

T.C.

MARMARA ÜNİVERSİTESİ

SOSYAL BİLİMLER ENSTİTÜSÜ

İŞLETME ANABİLİM DALI

YÖNETİCİLER İÇİN KARAR BİLİMLERİ (İNG.) BİLİM DALI

PERFORMANCE EVALUATION OF MATCHING ALGORITHMS IN A RECRUIMENT PLATFORM: MULTI-CRITERIA DECISION-MAKING APPROACH

Yüksek Lisans Tezi

OSMAN KAVAFOĞLU

İSTANBUL, 2024

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Tez Savunma Jürisi

1. Tez Danışmanı : Doç. Dr. Hüseyin Ekizler
2. Üye : Prof. Dr. Beril Durmuş
3. Üye : Dr. Öğr. Üyesi Ayşe Nur Adıgüzel Tüylü

ÖZET

BİR İŞE ALIM PLATFORMUNDA EŞLEŞTİRME ALGORİTMALARININ PERFORMANSLARININ DEĞERLENDİRİLMESİ: ÇOK KRİTERLİ KARAR VERME YAKLAŞIMI

Gelişen teknoloji ve imkanlar insan kaynakları yönetiminin organizasyonlar için önemini ve değerini artırmıştır. İnsan kaynakları yönetimi personel seçimi, maaş yönetimi, performans yönetimi, çalışanlara sağlanan faydaların yönetimi, çalışanların gelişimi ve eğitimlerinin yönetimi, strateji yönetimi, iş pazarı analizini ve personel kazanımı ve çıkışı fonksiyonlarını içermektedir. Bu tezde insan kaynakları yönetiminin personel seçimi fonksiyonunun üzerinde durulmuştur. İnsan kaynakları teknolojileri, süreçlerini iyileştirmek ve kolaylaştırmak için yapay zeka ve makine öğrenmesi çözümlerini uygulayan hızlı büyüyen bir sektör haline gelmiştir. Eşleştirme algoritmaları işe alım fonksiyonunu kolaylaştırmak amacıyla adaylarla iş ilanlarını eşleştirmeyi hedefleyen yapay zeka çözümleridir. Bu tezin amacı bir işe alma platformunda, iş arayan adaylarla ilanları eşleştirmek için kullanılabilecek eşleştirme algoritmalarının, uzmanların gözünden belirli kriterlere göre önemini araştırmak ve performanslarını değerlendirmektir. Bu amaç doğrultusunda bir işe alma platformunda, alanında uzman olan pazarlama, satış, ürün, müşteri deneyimi ve yazılım geliştirme departmanlarının yöneticilerine alternatif algoritmaların ve kriterlerin önem derecelerinin tespiti için ölçek çalışması yapılmıştır. Elde edilen veriler çok kriterli karar verme yöntemlerinden AHP, SWARA, VIKOR ve WASPAS metotları ile analiz edilmiş, Kendall uyum katsayısı ile istatiksel olarak test edilmiştir.

Çalışmanın ilk aşamasında kriterlerin uzmanlara göre önem dereceleri AHP ve SWARA metotu ile belirlenmiştir. İkinci aşamasında VIKOR ve WASPAS yöntemleri ile karşılaştırmalı olarak bu kriterlere göre uzmanların eşleştirme algoritmalarına dair tercihleri sıralanmıştır. Kullanılan metotların sıralama sonuçlarına bir değişikliğe sebep olup olmadığını belirlemek amacıyla Kendall uyum katsayısı yöntemi uygulanmıştır. Yapılan analiz sonucunda çalışmaya katılan uzmanlara göre en önemli kriter Kullanıcı Memnuniyeti kriteri olurken, seçilen kriterlere göre en önemli algoritma ise Doğal Dil İşleme temelli eşleştirme algoritması olmuştur. Kullanılan metotlardan bağımsız olarak bu veri setiyle aynı sonucun elde edileceği Kendall'ın uyumluluk testinin sonucu olarak bulunmuştur.

Anahtar Kelimeler: İşe alma, eşleştirme algoritmaları, AHP, VIKOR, SWARA, WASPAS

ABSTRACT

PERFORMANCE EVALUATION OF MATCHING ALGORITHMS IN A RECRUIMENT PLATFORM: MULTI-CRITERIA DECISION-MAKING APPROACH

Development of the technology and resources have increased the importance and value of human resources management for organizations. Human resources management encompasses functions such as recruitment and selection of staff, wage administration, performance management, benefits governance, professional growth and education, strategic human resources management, job market analysis, and staff retention and separation. This thesis focuses on the recruitment function of human resources management. Human resources technologies have become a fast-growing industry, applying artificial intelligence and machine learning solutions to improve and facilitate its processes. Matching algorithms are artificial intelligence solutions that aim to match job listings with candidates in order to facilitate the recruitment function. The aim of this thesis is to investigate and evaluate the importance and performance of algorithms that can be used to match listings with job seekers on a recruitment platform, based on the selected criterion and the data sourced from the perspective of subject-matter experts. To this end, on a recruitment platform, managers of marketing, sales, product, customer experience and software development departments who are experts in the field have been scaled to identify the importance of alternative algorithms and criterion. The data obtained were analyzed using the AHP, SWARA, VIKOR and WASPAS methods of multi-critical decision-making and statistically tested with Kendall's Coefficient of Concordance.

In the first stage of the study, the importance levels of the criteria according to subject-matter experts were determined by the AHP and SWARA methods. In the second step, with comparison, preferences of subject-matter experts for matching algorithms regarding the criteria are ranked utilizing VIKOR and WASPAS methods. In order to determine whether utilized methods caused any difference in ranking results, Kendall's Coefficient of Concordance test is applied. As a result of the analysis, according to the experts participating in the study, the most important criterion was the User Satisfaction, while the best algorithm regarding the criteria in the study was Natural Language Based matching algorithm. Kendall's Coefficient of Concordance showed that despite different MCDM methods, with this data set, results would be the same.

Keywords: recruitment, matching algorithms, AHP, VIKOR, SWARA, WASPAS

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ABBREVATIONS

AHP:	Analytical Hierarchy Process
AI:	Artificial Intelligence
ARAS:	The Additive Ratio Assessment
ATS:	Applicant Tracking Systems
BWM:	Best Worst Method
CI:	Consistency Index
CODAS:	Combinative Distance-based Assessment
COPRAS:	The Complex Proportional Assessment
CR:	Consistency Ratio
CRITIC:	Criteria Importance Through Intercriteria Correlation
CV:	Curriculum Vitae
DEMATEL:	Decision-Making Trial and Evaluation Laboratory
EDAS:	Evaluation based on Distance from Average Solution
FUCOM:	The Full Consistency Method
GRA:	Grey Relational Analysis
HR:	Human Resources
HRM:	Human Resources Management
MABAC:	Multi-Attributive Border Approximation Area Comparison
MADM:	Multi Attribute Decision-Making
MAIRCA:	Multi-Attribute Ideal–Real Comparative Analysis
MAUT:	Multi Attribute Utility Theory
MCDM:	Multi Criteria Decision-Making
ML:	Machine Learning

MODM:	Multi Objective Decision-Making
NLP:	Natural Language Processing
OCRA:	Operational Competitiveness Rating Analysis
OWA:	Ordered Weighted Averaging
PIPRECIA:	Pivot Pairwise Relative Criteria Importance Assessment
PSI:	Preference Selection Index
RI:	Randomly Generated Consistency Index
SAW:	Simple Additive Weighting
SMEs:	Subject-Matter Experts
SVM:	Support Vector Machines
SWARA:	Stepwise Weight Assessment Ratio Analysis
TODIM:	Tomada de Decisão Iterativa Multicritério
TOPSIS:	Technique for Order Performance by Similarity to Ideal Solution
VIKOR:	Vise Kriterijumska Optimizajica I Kompromisno Resenje
WASPAS:	Weighted Aggregates Sum Product Assessment
WPM:	Weighted Product Method
WSM:	Weighted Sum Method

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INTRODUCTION

Casprini et al. (2024) define human resources management as directing workplace relationships combined with obligations like accomplishing efficiency and success in job performance, improving individual expertise, skills, and perspectives, acknowledging worker necessities and demands, creating an inviting work environment, and unlocking individual and collaborative contributions for accomplishing business objectives.

Successful and effective human resource operations improve satisfaction among clients and staff members. This makes way to organizations often demonstrating greater innovation, efficiency, and a positive reputation in the business world (Tian et al., 2023).

According to Muscalu (2015), one of the human resources management functions, recruitment is critical for human resource management because it is the primary means of organizing the workforce. The recruiting process tries to bring in an acceptable number of people who meet employment requirements, allowing employers to select the best candidate for a specific post. Process includes locating, tracking, discovering, and recruiting people with the necessary professional qualifications to fill current and upcoming opportunities.

It is safe to state that the recruitment function has a greater impact on an organization's earnings and profit ratios than any other human resource's function. On top of that, poor recruitment decisions might result in not just underperforming employees but also a greater loss of potential. Turnover can have both direct and indirect repercussions, including as costs related with human replacement, as well as negative effects on customer service and mood. Optimizing recruiting techniques and hiring top talent can dramatically improve company performance (Pessach et al., 2020).

Study conducted by Daryani et al. (2020) states that online job postings on career sites and platforms help recruiters find a varied pool of candidates for open positions. But online recruitment comes with many challenges. High demand for employment supported with labor mobility and economic despair causes the trouble of thousands of resumes being submitted to organizations. Recruiters cannot manually review all resumes for the few open employment openings with a selection rate of less than %5.

Artificial intelligence solutions can improve efficiency, accountability, and equality in recruitment (Tian et al., 2023). Using artificial intelligence in recruitment can dramatically reduce costs, duration, and labor. The majority of Fortune 500 companies use applicant tracking systems. As a software application the

applicant tracking system handles the staffing and recruitment processes, as well as collects and stores resume data (Pant et al., 2022).

In this thesis, matching algorithms, an artificial intelligence-based solution method, are evaluated in the context of recruitment. The selected matching algorithm alternatives are rule-based, weighted score-based, skill-based, collaborative filtering-based, content-based filtering, clustering-based, machine learning-based and natural language processing-based matching algorithms. Selected alternative matching algorithms are evaluated regarding the following criteria: accuracy, efficiency, scalability, flexibility, user satisfaction, robustness, explainability and cost.

The aimed evaluation is conducted with subject-matter experts that are team managers in a recruitment platform. Participant subject-matter experts are the managers of departments such as product, sales, customer success, marketing, and software development, in the company that owns the recruitment platform, each possessing a median of decade experience in their respective fields.

Since the study includes several criteria and alternatives to make preferences the multi-criteria decision-making methodology is utilized to draw meaningful outcomes. AHP, SWARA, VIKOR and WASPAS techniques used to find the most significant criteria and the most important alternative regarding the evaluated criteria. Kendall's Coefficient of Concordance W is used to validate the results of rankings.

2. HUMAN RESOURCES AND RECRUITMENT

2.1 Human Resources Management

Human Resources Management (HRM) involves managing workplace relationships. The responsibility includes achieving productivity and efficacy in job performance, enhancing individual expertise, abilities, and mindsets, recognizing worker requirements and demands, creating a welcoming workplace, and unlocking individual and collaborative contributions to achieving business objectives (Casprini et al., 2024). HRM is crucial for improving management by recruiting personnel, implementing best practices, and facilitating change (Ridder & McCandless, 2010). It also involves managing people procedures within a business. This encompasses hiring and allocating employees, producing, and verifying new technology, and handling expenses and compensation systems (Ülgüt et al., 2024).

HRM includes hiring, performance evaluation, reward systems, and training/development. Evaluation procedure for staff hiring can be divided into subjective and objective. The subjective phase includes evaluations of personalities, stress and management style inventories, interviews, and supervisor scores, whereas the objective approach includes samples of work, demographic information such as sex and age, situational analysis tests, and ability exams (A. R. Mishra et al., 2020). Effective HRM fosters learning and personal growth opportunities (Đukić, 2022). As a crucial component of business process management, HRM enhances the profitability of an organization and rivalry. Successful and effective human resources (HR) procedures increase an organization's customer and employee satisfaction. In addition, the organization typically exhibits greater innovation, efficiency, and an upbeat image in the business environment. In the HRM industry, internet-based hiring systems are crucial for managing massive data problems. HR specialists need to be up to date with the rapidly evolving business trends and issues. To enhance business operations and efficiency, specialists need to pick up novel abilities and advancements (Tian et al., 2023).

2.2 Functions of Human Resources Management

Creating and carrying out strategic HR schemes, determining staff needs, employing and choosing the best candidates, providing training, assessing via performance evaluations, and, of course, encouraging to guarantee retention of staff are the components that lead to having the most effective staff attainable (Shtembari et al., 2022). According to research conducted by Aguinis et al. (2024),HRM functions varies

as follows: recruitment and selection of staff, wage administration, performance management, benefits governance, professional growth and education, strategic HRM, job market analysis, and staff retention and separation. In this thesis, we explain all functions but mainly focus on the recruitment function.

2.2.1 Wage Management

Wage management refers to managing HR and paying people for their labor. Employers want to fulfill their contractual obligations by paying their employees. This implies that employees and their employers have a contractual arrangement. Staff efficiency is heavily influenced by how they are compensated (Okeke et al., 2017). Wages are known as benefits offered to staff members in exchange for their employment or effort. Specifically, the phrase relates to money and tangible assets that may be measured in monetary terms. In its broadest sense, it refers to all types of financial earnings, as well as tangible goods and perks, which staff members obtain in exchange for their efforts. Wage refers to a bundle or total that includes basic pay, a variable salary, and additional benefits/social help. Base pay/salary is determined by calculating the monetary worth of labor using multiple approaches. Additional perks include components provided due to staff becoming associated with the organization. In contrast, wage management is a multi-phased mechanism and a shifting operation that refers to installing wage regulations that determine salaries based on the marketplace, creating base compensation and pay structures, and building reward systems (Demir & Acar, 2014).

Among the most important factors influencing the caliber and efficiency of the workforce is salary and compensation. From the hiring process to the commitment and retention stages, pay is an important consideration. The most suitable candidate won't be hired, the most talented employee won't be inspired to give it their all, the most competent person won't remain with the company, and in the most severe situation, the rate of departure will go up if the proper bundle isn't supplied. It is crucial that authorities devote their time and create the greatest program they can for the workers because all of these detrimental effects result in additional costs for the business. Among the most beneficial ways for the business to manage its workforce is through wages (Shtembari et al., 2022).

2.2.2 Performance Management

One of the most crucial HR procedures is performance management, which may direct worker performance and greatly enhance organizational success. Although performance management was initially intended for executives, professionals, and technical personnel, it is now widely utilized worldwide to evaluate

employees across all degrees. The attainment of the organization's strategic objectives through three fundamental principles, improving individual performance of workers, personal growth, and handling administrative responsibilities like compensation, has been narrowly characterized as performance management's primary goal (Neher & Maley, 2020). Performance management systems enable frequent communication, establishing targets, and performance evaluations. Workers benefit from ongoing assistance and coaching to be matched with corporate goals and inspired to operate optimally. These systems assist in monitoring and assessing worker efficiency and they strive to foster an atmosphere of constant growth (Nyathani, 2023). The preparation, input, and assessment operations are combined into a package known as performance management, which provides employees the resources, drive, and chance for bettering firm-level performance. The management processes consist of a series of arranging, feedback, and assessment actions designed to assist staff members in meeting performance standards (Bauwens et al., 2024).

By offering precise accountability and metrics for evaluating performance, performance management processes have been put into place as a way to control and gauge the output of workers or teams. The idea behind these procedures is that they help the business achieve its objectives and strategy, while providing an open structure that encourages all staff members to make individual or collective contributions to the strategic trajectory of the company (Becker et al., 2011). Measuring and monitoring company and staff performance is crucial for ensuring organizational success and sustainability. Performance management encompasses beyond just measuring and adapting staff efficiency. Executives collaborate with personnel to determine expectations, assess and analyze outcomes, and award progress. Their main objective is to favorably impact the success of the business. A performance management system aligns HRM processes to optimize present and potential staff performance, thereby affecting the success of the company (Den Hartog et al., 2004).

2.2.3 Benefits Governance

Benefits for staff, sometimes described as an intercompany wellbeing system, are initiatives provided by corporations to improve the well-being of staff members and their families. Legal welfare initiatives encompass medical insurance, retirement programs, job benefits, and compensation for workplace accidents. Unofficial welfare schemes involve monetary offerings, entertainment venues, house ownership assistance, and recreational endeavors such as sports and company outings (Yamamoto, 2011).

Since the 1990s, perks and benefits have increased their share in compensation cost of organization; estimates place their percentage at 20–30% for the United States, United Kingdom, and Australia, also 10–20% for several Western European countries. Benefits are generally understood to be non-wage compensation that isn't tied to performance. Benefit kinds also differ by organization and industry. They are impacted by factors in the labor market, like talent rivalry, and managerial beliefs about what would result in positive results for staff. Benefits are not usually customized for each worker; instead, they are frequently offered to a large group of staff members such as continuous personnel or staff who reach a particular pay level. Because of this, businesses can benefit from advantages of volume at a minimal expense (Laundon et al., 2019).

Benefits for staff members are crucial for both employers and employees when determining salary packages. Perks for workers significantly impact employment decisions and retention. Benefits gained through work, perceived equality, and incentives for staff members all contribute to employment happiness. A company seeks to lure talented individuals, inspiring and keeping them, enhancing motivation, supplying for their safety and wellness requirements, boosting happiness, enhancing the caliber of work life, while remaining competitive, and strengthening the perception of the company. In order to accomplish the intended outcome, administration has to meticulously evaluate the most appropriate advantages for the business, staff acceptability, overall expenses, available funds, and evaluation methods. The advantage of the benefit system or strategy should be flexible to adapt to shifting social situations (Ekere & Amah, 2014).

2.2.4 Professional Growth and Education

An organization identifies and employs talent, offering incentives, remuneration, and perks, in addition to mentoring and education. Corporations invest much in growth of talent, yet failing to create a strong retaining channel and to sustain employee drive can result in a talent drain or desertion to competitors, negatively impacting the company as a whole. Studies point out that education and skill growth impact organizational performance, including productivity, staff turnover, loyalty, and frequency of missing work (Wen-Tsann et al., 2015). Training the abilities of the upcoming generation of leaders is a key problem for firms in a worldwide, knowledge-driven economy, according to senior executives and HR specialists. Most firms prioritize learning and growth as part of their HR strategy. Staff growth is the extension of an individual's potential to perform efficiently in his or her current or potential job and workplace environment. Activities for staff development involve formal schooling, job experiences,

networking, and evaluation of traits, abilities, and talents to promote professional growth (Dachner et al., 2021).

Education and growth for staff have emerged as being among the key components within company initiation approaches. The business owners have become more motivated as a result of their investments in and emphasis on educational and professional growth programs. Moreover, it facilitates the development of a highly qualified workforce within corporations. Programs for learning and growth describe related strategies that the company uses to train staff members to increase performance and innovation. likewise, the techniques establish ambitious objectives for the development of the firm. The companies put on a constant effort and aim to make successful attempts to raise staff productivity standards. The training strategies cover a wide range of abilities, including advanced interpersonal skills, managerial abilities, and swift decision-making, and they might be useful in numerous scenarios that call for broader skill sets. These programs help executives close the gaps and strengthen shortcomings of staff within the company, which lowers risk variables and boosts productivity (Bhakuni & Saxena, 2023).

2.2.5 Strategic HRM

The strategic HRM function assesses if an organization's strategic goals directly influence its HRM approach and procedures. This practice examines how organizations integrate their strategic approach within their HRM structure. The common premise is that an organization's strategic direction has a significant impact on its HRM architecture. A straight approach to HRM focuses on its effectiveness in supporting organizational goals from the perspective of strategic planning. That is why HR practices ought to concentrate on the fundamental parts of the strategy in question (Ridder & McCandless, 2010).

The idea that the activities and procedures related to HR have an impact on how well the company performs is a key component of strategic HRM. Through the application of cutting-edge techniques, the Strategic HRM function affects the performance of the business. Creating and carrying out strategic HR plans, which include providing a remuneration and benefits bundle that fulfills employees' needs and motivates them to go above and beyond for the organization, are essential for attracting the greatest possible workforce. There are a lot of other factors to consider as well in strategic HRM such as when creating a pay plan corporate strategy, equity, enacted laws, and unions should be well thought out (Shtembari et al., 2022).

HRM strategies are adopted at the practical context to align with organization objectives. An HR strategy is the design that arises from critical decisions regarding managing HR, indicating management's primary objectives and the tools to achieve them. The proactive perspective views HRM as completely submissive

to organizational level initiatives, with the latter shaping HRM rules and procedures. After determining the corporate strategy, HRM regulations and procedures are adopted to promote the selected competitor strategy without additionally involving HRM professionals (Bratton, 2007).

2.2.6 Job Market Analysis

As an outcome of the proliferation of digital technology, there is a huge quantity of data available about the job market, offering useful knowledge into the demands of the workforce. This material contains details about job opportunities, necessary qualifications, position titles, wages, and additional information. Furthermore, resumes as well as online profiles of candidates offer insightful summaries of their training, background, and experience. Such initiatives have used job market analysis based on publicly accessible information. Characteristics of the workers, skill needs, and present and prospective job trends can all be learned from analyzing the labor market. The data can assist a variety of parties. Employment searchers can learn about present and anticipated hiring patterns, sought-after abilities, and predicted compensation. Organizations can utilize job market analysis to determine credentials for certain professions. Job market analysis may guide employment regulations, including workforce growth, education, and unemployment benefits. Recognizing both present and potential job patterns helps legislators distribute resources efficiently and design policies that promote new employment and development. Employment market research may help educators create courses and educational programs which are relevant to the employment market. Researchers can utilize job market evaluations to understand employment dynamics (Rahhal et al., 2024).

2.2.7 Staff Retention and Separation

To succeed, businesses must retain its true and committed staff members. The term staff retention describes the innovative strategies used by a company to reduce staff loss and increase productivity. Nowadays, the majority of companies have a significant difficulty in lowering staff turnover. Since most businesses are in fierce rivalry with one another to be the best, most view staff retention as a critical component. Staff turnover resulted in approximately 47.4 million United States citizens changing employment as a consequence of a business's insufficient loyalty and engagement capabilities (Bhakuni & Saxena, 2023).

Nowadays, there is a higher chance that firms will lose competent HR to rival organizations. Staff retention is the buzzword when it comes to HRM. In business management, the word acquires an entirely novel significance in addition to its generic definition, which is retaining, preserving, extension, and preventing

from stepping out. It refers to preserving staff in an organization. The retention term places emphasis on organizations as the primary agents, with retention being a particular managerial concern. This concern is known as retention management, which is characterized as the comprehensive set of HRM strategies aimed at keeping staff members who excel for an extended amount of time, allowing them to utilize or enhance their skills. Separation incurs immediate expenses including hiring, staff restructuring, training and education, and lower productivity. Even if the general workload stays constant, increasing the short-term pressure on the remaining staff may negatively impact their enthusiasm. Long-term employees may lose their organization-specific information, abilities, and expertise. Inevitably, organizations prioritize retaining high-performing staff (Yamamoto, 2011).

2.2.8 Recruitment

Recruiting is crucial for HRM as it is the primary means of arranging the workforce. The recruiting process aims to bring in an adequate quantity of individuals who match job criteria, allowing employers to pick the most suitable prospect for a certain position. HR recruitment involves locating, monitoring, discovering, and recruiting people who possess the requisite professional qualities to fill current and potential openings (Muscalu, 2015). Economic rotations, the spread of globalization, national diversity, and innovation produce fresh needs for companies, propelling the area of HR in unexpected ways. Such as talent management that involves anticipating an organization's hiring requirements and creating an approach that meets them (Stone & Deadrick, 2015). Recruitment is the process of preparation, hiring, assigning, and relocating employees (Tian et al., 2023).

The recruitment function is crucial for the HRM and constitutes the initial move into building competitiveness. Recruiting and retaining top personnel is a hard endeavor for companies. Hiring specialists could prove a hard and time-consuming endeavor for authorities and organizations. The most challenging aspect of HRM is finding the right candidate for the position. Recruitment processes vary by industry needs, involving submission of applications analysis, self-evaluation call screening, and industry-specific tests (e.g. ability, technical, programming, character, interest test). Industries typically utilize a variety of approaches to selection depending on job requirements, time, expenditure, precision, culture, and acceptance. The recruitment team has to match the role, departmental, and organizational qualities to the applicant's attributes. The recruitment team tailors the procedure to meet their specific demands at each stage (Sivaram & Ramar, 2010).

The process of recruiting is complex because it must strike a balance between the demand for haste and the demand for an honest and reliable assessment of candidates. Conventional approaches have found it difficult to keep up with the ever-evolving labor market, whereby new positions appear on a regular basis and the skills needed for those that already exist change. Furthermore, the sheer number of applications for jobs, particularly in industries with high population densities, can overburden HR, resulting in inefficiency and perhaps biased applicant selection. These difficulties highlight the necessity of an astute, flexible, and effective hiring procedure (Kurek et al., 2024).

The recruitment function provides a bigger influence on an organization's earnings development and profit ratios than every other HR function. In addition, bad recruitment selections can result in not solely low-performing personnel but also higher loss of talent. Turnover can have both direct and indirect consequences, including expenditures associated with personnel substitution (e.g., interviews, rehiring, training, decreased productivity, and overtime), as well as negative effects on customer service and mood. Optimizing recruiting procedures and employing optimal personnel can significantly boost organizational performance. Nonetheless, recruitment demands not merely employing the most qualified candidates, but additionally satisfying additional company objectives. To have a balanced workforce, it's important to satisfy the demand for people in various areas, promote diversity in teams, and address workforce imbalances (Pessach et al., 2020).

The rise of broadband access has led to a shift in recruitment practices throughout major organizations. Online employment ads on career sites and platforms assist recruiters reach a diverse pool of candidates for open positions. While e-recruitment benefits both employers and candidates, it also presents new obstacles. Large firms and employment agencies frequently get thousands of resumes daily. The problem is exacerbated by increased labor mobility and economic despair, leading to a high demand for jobs. Recruiters cannot manually review all resumes for the few available job positions with a selection rate of below five percent. (Daryani et al., 2020). Whether or not the procedure is highly automated, when it performs poorly in matching or recruiting, the results can be severe for the prospects who become employees (or not). They may suffer from difficulty, mental health problems, and subpar work output as well as higher the expenditures for the company (Delecraz et al., 2022a).

Finding suitable candidates through resume evaluation is a crucial stage in the HR recruitment process. The volume of candidatures for various positions and a shortage of domain expertise to comprehend and appropriately match the technical expertise included in a resume to the opening's demands renders it difficult to evaluate resumes currently. In order to prevent wasting excessive amounts of time, money, or

employee effort on resume analyzing, organizations are under pressure to create an effective resume-filtering procedure. But without the right framework, many businesses evaluate applicants' qualifications through antiquated, ineffective methods. The keywords technique, which is frequently used in resume filtering, places a strong emphasis on examining individuals (Tian et al., 2023).

2.3 Importance of Human Resources Management

In order to set up competitive applications, HRM specialists must: (a) behave as a liaison within upper management and staff by answering inquiries, clarifying and upholding agreements, and assisting in the resolution of job-related issues; (b) counsel executives on policy-related issues, covering topics like harassment at work and equal job possibilities; (c) analyze and alter rewards and perks procedures; (d) carry out challenging hiring obligations, such as taking care of staffing shortages, arbitrating conflicts, terminating workers, and implementing disciplinary practices; and (e) represent the company at hearings and examinations regarding staff members. The significance of HRM requires a wide range of abilities, including technical expertise such as finance, enterprise resource planning and social abilities. This includes expertise in personnel supervising, management, legislation, governance, and education or training (Aguinis et al., 2024).

According to Stone & Deadrick (2015) HR practices ought to utilize general hiring to find talented candidates, design jobs with self-reliance and involvement in decision-making, apply collaborative frameworks for teamwork and creativity, prioritize education and professional growth, and offer incentives to promote staff recognition, creativity, and preservation. HR should prioritize retaining staff members and adapt to the diverse demands of skilled professionals. Although a few companies are adopting modern HR procedures, most continue to employ outdated methods that are in conflict with knowledge-oriented objectives.

Periodic efforts in precious and uncommon resources raise the potential of establishing essential competencies, which provide superior results that meet customers' demands or contribute to a competitive edge across the organizational area. Sufficient resources, whether within or managed by an organization, must be coupled with competences. Based on this angle, the blueprint of HRM originates from recognizing HR behavior significant to the organization's performance and converting these resources to strategic alternatives which are bolstered by HR practices. This approach connects the operations of HR to the distinctive features that create the base of HR. Staff are considered as valued resources who are essential to the performance of the organization as a whole. In this sense, they are an asset rather than an expenditure.

The operations must continually improve the vital and unique features of HR, such as talent and drive, to align with core competencies (Ridder & McCandless, 2010).

2.4 Recruitment Platforms

Organizations struggle with inconsistent resume formats among candidates. Individuals originate from many professions and experiences. Each candidate's resume reflects their diverse education, work experience, and distinctive presentation style. Resumes are unorganized documents in multiple file types (.pdf,.doc,.docx,.jpg,.txt), with content that does not follow established formats or layouts. Recruiters invest a significant amount of time reviewing resumes to choose suitable candidates due to the difficulty of reading them. These platforms' broad structure may not be suitable for all occupations due to its lack of domain-specificity. Recruiters utilize such formats to conduct keyword-based searches and shortlist prospects (Daryani et al., 2020). As more Curriculum Vitae (CV) gets submitted, HR departments might find it difficult to manually evaluate job applications. To quicken up the recruiting process, autonomous candidate evaluation methods demand an illustration of the HR department's decision-making procedure and thorough calibration by expert recruiters. This technique is difficult and susceptible to mistakes and needs to be performed whenever the criteria for selection vary (Faliagka et al., 2012).

A vast amount of data has been created recently by the rise in online job listings and resume submissions by job searchers as a result of recent advancements in online recruitment. The recommendation systems technology is essential to the successful job-candidate matching procedures made necessary by this plethora of information. Specifically, semantic technologies have demonstrated potential to improve online recruiting by directing how documents are processed and automating matching, which improves the quality of job recommendations (Kurek et al., 2024).

The ever-changing nature of employment has two key effects on recruitment. Candidates nowadays possess greater options and are far more inclined to switch jobs. Organizations are privy to a larger pool of applicants yet might require hiring more often and ensure candidates discover purpose in their jobs. These transformations create an ever-changing and complicated employment market, necessitating accurate and extensible matching across candidate characteristics and organizations hiring standards (person-job compatibility). As therefore, in order to expedite the matching of candidates with positions, digital middlemen like job sites, employment platforms, and consultancies as well as exclusive departments of corporations and independent contractors will become more and more significant in the hiring process (Grunenberg et al., 2024).

2.5 Human Resources Technologies

In the age of transformational employment, HR technology has become a pivotal point, offering the assistance and instruments required to manage transitions. HR technology includes interaction and teamwork platforms, applications for managing projects, and extensive systems of information to address diverse needs (Nyathani, 2023). HR technology refers to tools used to manage HR, including recruitment, retention, and management. Technological implementations can minimize the administrative workload for HR departments, allowing them to concentrate on more significant operations like supplying executives with knowledge to enable beneficial HR decision-making process (Bulmash, 2008).

2.5.1 Artificial Intelligence in Human Resource Management

As stated by Delecraz et al. (2022),HR technology is a rapidly evolving industry that uses Artificial Intelligence (AI) to accelerate and enhance HRM-related responsibilities, including staff benefit and payroll processing, hiring and talent administration, performance evaluation, re-skilling, and staff-based forecasting analysis. AI solutions are dependent on data used for training to make projections, judgments, and suggestions; thus, any biases or mistakes will be evident in the results. AI systems may heighten social prejudices, resulting in biased outcomes in HRM along with other domains such as law enforcement and finance. The models might have difficulty with data not included in their initial training. Limitations in data used to train might lead to inaccurate or biased forecasts in new or infrequent scenarios. Additionally, AI systems might have trouble adapting to changing situations or new knowledge due to redundant training data (Aguinis et al., 2024). AI in HR Tech refers to machine and deep learning algorithms that automate and enhance job matching with time. Algorithms may enhance performance in HRM by providing more rapidly, more precise, and reliable results using scientific and information technology breakthroughs from domains like Natural Language Processing (NLP) and behavioral sciences. Also, Machine Learning (ML) is capable of accurately evaluating candidate abilities and motivation, as well as anticipating job fit and performance. (Delecraz et al., 2022).

One of the most important aspects of HRM, the recruitment procedure, has changed significantly in the digital era. AI driven recruiting options are gradually replacing and supplementing conventional approaches, which are frequently laborious and reliant on judgment from individuals. AI technologies can help to partially automate the hiring procedure, which includes reviewing job postings, reviewing applicant CVs, shortlisting candidates, conducting interviews, and making employment offers. Existing job recommendation frameworks have built-in flaws that severely restrict their usefulness in dynamic hiring

situations. Their dependency on past data is the main cause of these restrictions, which makes it difficult to adjust to the quickly changing labor market and the creation of new positions. Despite their usefulness, conventional recommendation frameworks frequently fall short of accurately capturing the varied abilities of candidates and the complex needs of new job categories. This deficiency is especially noticeable when there is little past data for new jobs, leading to suggestions that are either biased or insufficient. Additionally, data biases in current models frequently cause suggestions to be skewed and injustices in the hiring process to persist. The absence of explainable AI in these models complicates decision-making, making it challenging to evaluate and enhance suggestions' equality and openness. (Kurek et al., 2024).

Prior attempts have been made to forecast recruiters' decisions. Accurate models for prediction could one day substitute human recruiters, saving significant resources. Recruiters' judgments are personal in nature, with human perceptions playing a significant role in recruitment and placement. Leveraging interpretable modeling techniques, which are referred to as explainable AI, can assist recruiters make better decisions by providing insight. A further field of research focuses on predicting employee turnover or performance after hiring. Although unbiased, post-hire forecasting attempts may be overdue in some circumstances for effective action (Pessach et al., 2020).

Despite scholars and professionals concentrating on the integration of HR systems with information technology and analytics for HR, there is not enough research done on the synthesis of AI, ML, and HRM. Solutions that utilize AI and ML are powerful instruments for helping business professionals make more intelligent choices. These intelligent systems possess the power to completely transform industry and society by learning a wide range of representations from unprocessed or minimally processed information. Nevertheless, a system could contain algorithms that are prone to a series of learning blunders that can cause exorbitant expenses and an abundance of trust among decision-makers. Likewise, it is difficult to describe such systems due to the enormous parameters and elevated levels of complexity of the model frameworks, which raises doubts regarding their future adoption and reliability. While AI can improve efficiency, accountability, and equality in recruitment, it's important to consider potential biases in the analytics process. AI biases may be anchored in models used for ML or related algorithms. For example, incorrect kernel selection in support vector machine algorithm might reduce efficiency and introduce biases or threats. Scarcity of certain data kinds can bias ML outcomes, favoring the majority over the minority. (Tian et al., 2023).

3. MATCHING ALGORITHMS

In 1962, Gale and Shapley introduced matching theory, a game theory-based mathematical paradigm. The phrase “matching” implies two objects which are adequately situated in tandem and share an identical appearance. Advancements in science and technology have created a plethora of demand-matching opportunities across several industries. As a result, locating, assessing, and operating resources has become more difficult. Likewise in an era of massive amounts of information being out there, gathering preferences for everyone is costly and practically unattainable. Hence, there are many matching systems being utilized across several areas and fields such as face recognition that uses picture matching, information retrieval that relies on text-based matching technologies and also matching for recommendation services (Ren et al., 2021). The typical matching procedure consists of four phases: data collecting, modeling, model computation, and matching outcomes (Yabin, 2022).

3.1 Matching Algorithms in Recruitment

The recruitment procedure involves examining job requirements, screening, and shortlisting qualified individuals. It focuses on hiring top talent with relevant skills. Recruiters are responsible for screening job seekers' resumes as the first step in the recruitment process. On a daily basis, companies with job openings receive countless emails from interested candidates. Recruiters find it challenging and time-consuming to manually review all CVs and select the best candidates for specific positions. Therefore, many platforms currently automatically scan resumes. Online recruiters use several approaches to discover top candidates for every role. Recruiting platforms go through an extensive number of resumes to find the greatest fit for vacant positions. These platforms' methods have yielded high precision and accuracy (Alamelu et al., 2021). More effective methods of connecting candidates with job descriptions must be looked into in order to improve resume matching effectiveness (Daryani et al., 2020).

Choosing the right candidate for a job listing might be critical depending on the nature of the position. As a result, the recruiter becomes anxious, and the applicants they choose may not be the best fit. Many efforts in mining texts along with other data science applications have focused on automating this matching process in order to tackle this issue and handle additional duties like rating and sorting candidates for employment. Mismatching arises when under-skill and over-qualification issues are not addressed. When someone is under-skilled, it indicates they don't have the necessary talents and skills to execute on their present work in a certain way. Overqualification occurs when a candidate's experience and work activities exceed the

required degree of knowledge for the position. The discrepancy affects the productivity of the candidates. Consequently, it causes actual economic and societal costs (Habous & Nfaoui, 2021).

Manual hiring is labor-intensive, time-consuming, expensive, and prone to missing out on qualified applicants. Plus, it's common for manual screening to miss opportunities to find candidates with the best qualifications and domains of expertise. Therefore, in order to choose the finest candidate, there is a tremendous demand for automated resume screening. The idea of utilizing AI in hiring is being floated, that is, empowering machines with intelligence for locating the best suitable applicants from all of the applicants. This could significantly save expenses, duration, and labor. For recruiting, a variety of businesses, like Microsoft and Google, use exclusive software. The majority of the Fortune 500 organizations employ applicant tracking systems (ATS). ATS is an automation program which handles the staffing and recruitment process along with gathering and storing resume data. By using AI and cutting-edge ML techniques to distinguish between qualified job prospects, ATS have significantly improved. However, its primary goal is to automate tracking and notify hiring managers and job applicants about hiring (Pant et al., 2022). ATS manages the recruiting process, including advertising job vacancies, maintaining resumes, and monitoring candidates throughout the recruitment phase. It automates recruiting processes to save time and improve efficiency (Nyathani, 2023).

Conventional employment applications rely on simple Boolean operations to match job seekers with employers based on their basic qualification data. However, this often results in irrelevant matches. To prevent such mismatching outcomes accurate and methodical solutions must be adopted (Lee et al., 2018). For a typical matching system procedure in a HR environment could be explained as follows: Data collection by gathering personal information from employees through interviews, performance evaluations, and job experience. Data modeling by cleaning, filtering, and processing data analysis tools to extract useful personnel characteristics. This data is afterwards abstracted and stored in a database to be used in future algorithm implementations. The most crucial step in the process is model computation, which involves training the cleaned data with several models to achieve a decent model. Matching outcomes refers to displaying the predicted data that the trained model predicts to the systems' members (Yabin, 2022).

The automatic algorithm for recommendations that identifies resumes as matches can be difficult for hiring managers to fully grasp. The majority of ML-Based hiring algorithms currently in use don't offer information about how to comprehend the results or whether their recommendation is skewed against any certain set of candidates (Tian et al., 2023).

3.2 Matching Algorithms for Recruitment

For this thesis selected alternative matching algorithms are as follows: rule-based matching algorithms, weighted score-based matching algorithms, skill-based matching algorithms, collaborative filtering-based matching algorithms, content-based filtering matching algorithms, clustering-based matching algorithms, ML-Based matching algorithms and NLP-Based matching algorithms.

3.2.1 Rule-Based Matching

Rule-based matching describes an algorithm that uses a set of rules to apply matching between variables. For recruitment function of HR, rule-based matching can be utilized to create matchings of candidates with job listings. For example, if a job calls for a specific education level, this kind of matching algorithm only links the candidates that have the required level of education to the job listing. The overall objective of an adequate matching algorithm is supposed to be to minimize match duration and storage cost. (Guo et al., 2022).

Based on research carried by Guo et al. (2022) rule-based matching algorithm can be used to data layer flow scheduling, a component of software-defined networks, as its effectiveness affects flow routing efficacy and scheduling as a whole. Flow routing duration and storage stress are greatly reduced in large-scale networks by lowering the storage overhead and processing time of rule matching. A decision tree specifically for rule matching issues can be created by combining ML techniques including reinforcement learning, decision trees, and recurrent neural network. Such a decision tree may satisfy the short matching duration and minimal storage overhead needed for extensive flow tables, as well as the 100% correctness needed by the Software-Defined Networking flow routing rule matching problem. The construction of the rule list is both the most important component and the largest task in a rule-based matching algorithm. Developing extensive rule sets may be quite costly and laborious (J. Li & Wang, 2015).

A study for identify resolution developed by J. Li & Wang (2015), classifies many of the resolution methods now in use into rule-based and ML categories. Numerous rule-based identification resolution techniques that rely on matching rules encoded by subject-matter experts (SMEs) have been proposed. In one instance, a straightforward criterion that requires two identification records to match only when their initial and last names, and birthdate are the same may be used to link cross-jurisdictional criminal histories. Or in another instance, if the first name matches the score of two identity records with the same birthdate and last name exceeds a certain level, the system will resolve them into a single identity record. On top of that, rules may be context-specific and not transferable to other domains.

Moreover, in a paper published by Wang et al. (2023), the industrial control equipment identification categorized into two. One is comparatively seasoned technique that uses rule matching to identify industrial control equipment. To identify the type of equipment that matches the data, industrial control equipment info is compared with the rule base. The rule basis is built using expert knowledge or past experience. The second category involves identifying devices using ML techniques. Study reveals the limitations of rule based matching stating that even though the rule-matching approach is simple to comprehend, straightforward to use, and quick to recognize; there are several drawbacks to the rule-matching-only approach. The caliber of the rule basis affects the recognition impact, and experience limits the matching rules (Y. Wang et al., 2023). This insight can be reflective of the rule-based matching's generalized advantages and disadvantages. To give an example to algorithms that can be tagged as rule-based IF-THEN rules and Boolean logic can be stated. The IF-THEN rules delineate the prerequisites and repercussions for an effect to occur, such as match a job listing to a candidate if candidate has certain requisite (Neyland & Möllers, 2018).

According to work provided by (Zohuri & Moghaddam, 2017) many unusual phenomena may be translated into bits and bytes thanks to Boolean logic, which was first created by George Boole in the mid-1800s. Boolean logic rather quite simple to grasp and describe. According to the law of the middle being excluded, the assumption that a given assertion P is either true or incorrect and cannot be anything in between. After that, these initial claims are combined employing the basic operators NOT, OR, AND to construct new, true or false, assertions. For instance, if a job listing requires a candidate with a master's degree, then following statement is true "Candidate with master's degree matches with the job requirements." and following statement is false "Candidate without master's degree matches with the job requirements".

3.2.2 Weighted Score-Based Matching

Weighted score-based matching describes assigning weights to various criterion and computing scores based on assigned weights. An example for recruitment in HR would be assigning weights of matching for criterion such as experience, skills, education, and location of a job listing and then scoring each candidate based on assigned weights.

In the paper developed by Sharath et al. (2019), weighted score-based matching is utilized for map matching, which is a tool to provide location resolutions that offer greater precision and trustworthiness. The map matching algorithm combines incorrect positions that are direct results of faulty global positioning system receivers and map data. There are four types of map matching algorithms: probabilistic, geometric,

topological, and advanced. There are three established weighting scores: vehicle direction, road link bearing, and raw location information closeness to road connections. By a conventional weight-based map matching algorithm, the varied road network elements are issued individual weighting scores. After weighing the relative relevance of the various weighting scores, the aggregate weighting score is used to calculate the likely position (Sharath et al., 2019). In another study on map matching that utilizes weighted score-based matching, weighted score matching algorithms are defined as provider of a score for every prospective segment according to the weighted average of scores for certain criteria. This enables identification and selection of the segment that possesses the highest score. The study defines the weighted score-based matching algorithms obtains agile responsiveness and are straightforward to implement but they suffer from a reduced level of success compared to more complex algorithms (Hashemi & Karimi, 2016). Logistic regression can perform well and quickly on certain low-dimensional datasets; however, it is prone to overfitting when dealing with high-dimensional data. Because logistic regression implies a linear relationship between input along with dependent parameters, it might find it difficult to deal with nonlinear data. Logistic regression exhibits somewhat favorable repeatability considering it is a version of quadratic programming (Tian et al., 2023).

3.2.3 Skill-Based Matching

Globalization has led to a larger pool of contenders for each job opening. Due to spike in switching jobs, decreased levels of position duration and larger workforce recruitment market became fiercely competitive. Possessing the right abilities for an area of expertise is vital, especially since skill demands change over time. The COVID-19 epidemic has spurred the adoption of technology while also causing enterprises to lay off staff. Aging professionals sometimes lack new technological abilities, resulting in limited possibilities for employment. In addition to technical talents, strong interpersonal skills have grown more essential. The changing marketplace for workers necessitates the acquisition of new skills, making it challenging to stay current. Consequently, there has emerged growing curiosity towards skill-based matching of applicants to positions since the ideal characteristics for specific roles are now less clear-cut and stable (de Groot et al., 2021). Skill matching has a key part in the recruitment procedure. It involves assessing a candidate's knowledge and required abilities to a job description to determine a relevant match. There are numerous methods for calculating such skill-based matching. Making the algorithm functional requires addressing the primary issues of delivering accurate outcomes in a computationally affordable way (Petrican et al., 2017).

3.2.4 Collaborative Filtering

Collaborative filtering is a broadly utilized recommendation method. Filtering provides the user with tailored suggestions according to the preferences and characteristics of other users. By using the user's navigational data, it can determine the characteristics of users. Then, considering such preferences or characteristics, a group of others who share the target user's tastes is identified; these individuals are typically described as the target user's neighbors. The target user then gets suggested goods that the neighboring users have expressed interest in. This technique needs a lot of evaluation data. Due to the fact that repeat purchases allow for the collection of a sizable number of user data, collaborative filtering utilized to propose items that are commonly purchased (Abdullah et al., 2013). Collaborative filtering algorithms suggest occupations based on users' historical behavior and comparable choices obtained from other users. This approach depends on user-job interactions rather than job content. The essential premise is that users who have previously agreed would do so again, therefore tasks that comparable people have enjoyed are proposed (Kurek et al., 2024).

According to the work of Schmitt et al. (2016), job and candidate matching mainly tackled by the cold-start issue of providing suggestions for fresh recruiters or job searchers. Cold-start issue describes once a candidate finds a job, the job search ends resulting in unrelated neighboring. Therefore, even though it may be rather ineffective for cold-start problem, collaborative filtering has been demonstrated to yield exceptional matching results for job and candidate matching.

Collaborative filtering employs both item-based and user-based algorithms, including neural networks, principal component analysis, and support vector machines (R. Mishra & Rathi, 2020). A forecast made via collaborative filtering is centered on user ratings. User interest is predicted by the algorithm through selecting and consolidation of input from users. Suppose that people are going to concur with other things if they find particular things to be of a high enough grade. As a result, this method may forecast user attitudes based on the chosen items' pattern of similarity (Chanavaltada et al., 2015).

In the procedure of creating matching systems, collaborative filtering is a popular suggestion algorithm that is also a content-independent predictive method. The fundamental concept is to match or forecast appropriate sources or employment for the target users based on the known interests or habits of the current user base. The conventional collaborative filtering matching method uses ratings from other users to match project resources or jobs with the target user. The matching procedure is as follows: Creating a person-position evaluation matrix, identifying comparable neighbors for users, pairing employees using the similarity calculation approach, the score value of a target user's interest level for anything may be

anticipated (Yabin, 2022). Matrix factorization is one of the most effective collaborative filtering techniques. Through user evaluations of objects, latent variables are retrieved using this approach. The fundamental notion is that important details are concealed within the ratings themselves (Strub et al., 2016).

3.2.5 Content-Based Filtering

Content-based filtering calculates a new rating by explicitly using the knowledge of the user and the item. User data could include things like age, gender, and friend graphs, among other things. Tags, a brief description, or the genre of the film can all be considered item data. For content-based filtering to function effectively, items demand complex engineering (Strub et al., 2016). Content-based systems for recommendation evaluate item content in order to identify subjects that seem especially interesting to the user. History plays a key role in content-based filtering by serving as the training set data for a ML algorithm that generates a user model (Pazzani & Billsus, 2007). Such algorithms propose employment based on job descriptions and user choices. The suggestion is generated by comparing the user's profile, which contains their abilities, previous expertise, and preferences, with the subject matter of the job listings, containing the necessary abilities, expertise level, and job positions. This method makes the assumption that jobs which the user has previously cherished will likewise be of interest (Kurek et al., 2024).

Content-based systems suffer from inflexibility, an absence of inherent semantic relations, and difficulties with scale. Various algorithms, such as K nearest neighbor, clustering, Bayesian clustering, and deep learning, are commonly utilized for content-based algorithms (R. Mishra & Rathi, 2020). Content-based filtering utilized to facilitate data extraction. Initially, words are manually allocated using a process that compares them with data in the client's profile. An algorithm for learning is then used to execute these comparisons and provide findings to the client. Term frequency and inverse document frequency are employed in data retrieval and content-based filtering systems. They determine the corresponding centrality of data. These systems use important words to describe products and create a personal profile to propose items based on the user's preferences. In other words, these algorithms strive to offer things that are like those that a user has preferred or is currently researching (Javed et al., 2021).

The content-based filtering relies only on user ratings to create personalized profiles, ensuring user independence. Specifically describing the content features or descriptions that lead to an item being in the list for recommendation, the content of the item is the main explanation for the algorithm’s way of working. These qualities can help determine the transparency of the content-based filtering. Content-based filtering and recommendation may endorse items that have not yet been evaluated by any users. As a result, they are

not affected by the first-rate constraint. Even though the apparent upsides of this method there have been findings that may be evaluated as shortcomings of the content-based filtering, such as the general unavailability of the necessary amount of data for content evaluation, the serendipity issue of how content-based filtering often suffer from lack of out of the box thinking which resulting similarities of past content with future recommendations or requirement of a sufficient number of evaluations to accurately identify user preferences and make suggestions, this may result in not delivering credible suggestions for new users or profiles due to lack of accessible past ratings or evaluations (Lops et al., 2011).

3.2.6 Clustering-Based Matching

Matching applicants and jobs with each other are a challenging undertaking that often involves categorizing occupations and concepts in the recruitment industry. The clustering procedure groups related data points into clusters depending on the variables that were observed. It maximizes similarities of data points between each cluster whilst boosting differences among groups. It is an unsupervised training technique, which translates to no prior understanding of the segmented data or cluster membership is required. For job and candidate matching two clustering-based can be utilized: K-means and hierarchical clustering (Thortstensson, 2020). Clustering techniques, which organize data into clusters so that similar instances are placed in one cluster and divergent data fall into separate clusters, have gained increased attention being an essential field of unsupervised learning (Dang et al., 2021).

K-means clustering is a continuous technique that divides data into K clusters according to centroids. It distributes data points to clusters with respect to so that the sum of the squared distances around the data points and the cluster's centroid is minimized (Makwana et al., 2013). K-means is a straightforward unsupervised learning technique for clustering challenges. The technique seeks to build k clusters of n objects with high intra-cluster similarity yet low inter-cluster similarity. The program randomly chooses k out of n objects and assigns one to each cluster to act as the mean or center. The remaining items are allocated to the cluster with the closest similarity based on their distance from the cluster mean. The technique involves computing a new mean per each cluster and iterating once the criteria function meets (Sivaram & Ramar, 2010). While this technique has the benefit of faster implementation, it faces challenges in determining and organizing group numbers. As a result, clusters are randomly ordered. Nevertheless, if two clusters fail to coordinate within a short distance, what distinguishes them might be difficult to detect (Wen-Tsann et al., 2015).

Hierarchical clustering creates a hierarchy of clusters. It might be from the top down or from the bottom up. A top-down strategy begins with every point of data in the same cluster and then iteratively splits clusters once all clusters are singletons. A from the bottom-up strategy, also known as agglomerative, operates in the reverse way around, beginning with all data points in their very own cluster. The process involves combining clusters that meet predetermined metrics or similarity levels (Reddy & Vinzamuri, 2014). The hierarchical approach is an agglomerative approach that divides samples into clusters based on categorization and then calculates the distance of adjacent points. The two nearest points are merged to form a single cluster (resulting in $n - 1$ clusters). That combination reduces the total amount of groups till all of the points are merged into a single group (Wen-Tsann et al., 2015).

Clustering-based matching algorithms can be utilized in a recruitment platform by making job recommendations and candidate matchings after identifying and categorizing users and job listings based on their respective characteristics.

3.2.7 Machine Learning Based Matching

ML is a key subfield of AI that enables computers to learn. It is an algorithm's capacity to accumulate and consolidate data from huge-scale observations, as well as learn novel data to better itself (Stone et al., 2024). ML, an important domain of AI, learns new data that can promote decision-making lacking explicitly stated rules by analyzing existing data. Given its completely data-driven exploration of knowledge and projections, it has gotten popular for handling not solely organized corporation data yet also unstructured vision, speech, and natural language data. Widespread use of ML enabled to learn, project and complete tasks even with dealing massive amounts of data (Tian et al., 2023). Interpretable ML modeling delivers valuable insights about applicant background and hiring decisions. These models generate odds for effective hiring per candidate and position. Implementing ML in HR might be challenging due to a lack of empirical data. In the majority of instances, the limited dataset struggles to sufficiently represent the population's attributes, making it difficult to train a trustworthy model. Limited datasets can lead to low support values for segments of the population, as just a few samples are connected with each anticipated or rule-based segment of the population, which leads to poor statistical significance. The issue becomes increasingly evident as the number of features increases (Pessach et al., 2020).

A paper provided by Faliagka et al. (2012) states that ML algorithms can be applied to improve candidate ranking, job matching, and user profiling in recruitment platforms. Algorithms such as decision trees, linear regression, regression trees or support vector regression prove to be favorable in such needs.

A decision tree algorithm creates a top-down tree structure by separating variables based on their differentiation capability. A decision tree is distinguished by its comprehensible learning mechanism, which involves breaking down the learning process into tree construction steps. Another ML algorithm neural network processes are designed to imitate the way the human brain processes data. With the rapid development of deep learning disciplines, it has been successful in processing vast volumes of data, especially big data, and in interpreting complex relationships. In contrast to Support Vector Machines (SVM) or random forests, it features a complex learning topology as a network of neurons, with each neuron having its own activation mechanism or data processing technique (Tian et al., 2023).

Regression trees utilize a divide-and-conquer strategy to segment predictive space, making them a feasible choice. The framework is similar to propositional decision trees, with internal nodes containing tests and leaves containing forecasts for class value. SVM are supervised learning algorithms that can be applied to problems with regression and classification. SVM's power lies in its kernel representation, enabling a nonlinear mapping from the input space to a higher-dimensional feature space. The goal is to identify a function that, given the unknown probability variation in the data, reduces the expected error, or the integral of a particular loss function. This reduces the chance of the projected function differing from the unknown original function (Faliagka et al., 2012).

Tian et al. (2023) stated that the strength of SVM is found in its inherent mapping of data into a high-dimensional space, which makes it possible to successfully differentiate data points with distinct labels via a linear function. Comparatively speaking, it performs more steadily and competitively than peer techniques like random forests. When it comes to learning, SVM also shows strong reproducibility when contrasted with deep learning and ensemble learning techniques, both whose characteristics include inherent unpredictability. It happens due to the fact that, although it is expected to be extremely uncommon, the single random choice case in SVM classification would be an incoming point that falls on the perfect hyperplane. Consequently, SVM is a strong option for segments such as a business in which learning reproducibility is highly required, engineering, or health, due to its favorable reproducibility.

In order to streamline the recruitment procedure and increase productivity by more precisely recognizing eligible resumes, smart resume systems for recommendations have been created in light of recent advancements in ML and NLP methodologies. Metaheuristic algorithms are replacing heuristic techniques in ML for HRM functions. The metaheuristic algorithms concentrate on using cutting-edge learning algorithms and methods for dealing with massive amounts of data to solve highly complicated issues (Tian et al., 2023).

3.2.8 Natural Language Processing Based Matching

NLP is the study of using computers to comprehend and modify natural language for practical purposes. NLP researchers study human language comprehension and utilization to build tools and approaches for computers to do particular assignments. Natural language comprehension is crucial to every NLP work. Building computer algorithms that recognize natural language entails three fundamental challenges: understanding the cognitive process, representing and interpreting linguistic input, and gaining global information. An NLP algorithm can start with determining the morphological components of a single word, then proceed ahead to the stage of a sentence (word sequence, syntax, meaning), and finally to the setting and topic (Chowdhury, 2020).

NLP is a collection of methods that combines cutting-edge computing and human understanding to enable computers to comprehend texts. NLP categorized into two categories: natural language generation and natural language understanding, which deal with the problem of producing and comprehending text. NLP technology like part of speech tagging, tokenization, stemming, and lemmatization is used for numerous activities such as system design and development (Habous & Nfaoui, 2021).

NLP applications are growing into more and more commonly utilized instruments for organizations looking to enhance their management and operations systems. They are used in many practical programs, including automating the identification of compliance validation and screening electronic health data in accordance with clinical recommendations. Text mining is a set of NLP-based methods for extracting meaningful data from websites, documents, and emails. These methods include word sense disambiguation, part-of-speech labeling, word formation, lemmatization, name entity mining, relationship extraction, and sentiment analysis. Additionally, BERT, a deep learning the vectorization process algorithm, effectively extracts coherent attributes from textual input. BERT, a bidirectional encoder, is capable of recording more context semantics as it takes leverage of the bidirectional training of transformer neural networks in vectorization (Tian et al., 2023).

Resumes are now automatically screened because of the time-consuming disadvantages, favoritism, and human prejudice associated with manual screening. Various techniques have been employed for keyword matching and resume parsing. The most common include resume summarization, ontology mapping trees, and information extraction followed by resume categorization. Essentially there have been advancements in NLP since the 1950s, text mining's development made the process of obtaining knowledge from resumes easier to understand (Pant et al., 2022).

3.3 Matching Algorithm Evaluation Criterion

According to its definition, matching is the act of taking two models (the starting point and the destination) as inputs and producing a set of matches within the components of these two models that satisfy a certain connection (Celonis et al., 2014). In this thesis following criterion are evaluated; accuracy, efficiency, scalability, flexibility, user satisfaction, robustness, explainability and cost.

3.3.1 Accuracy

Accuracy criteria is the ability of an algorithm to correctly match the most suitable candidates to job postings. Yin et al. (2019) discovered that layman's belief in a model is significantly impacted by its claimed accuracy on held-out data. However, this effect wanes and even vanishes if the measured accuracy is sufficiently inadequate once they have seen the model's accuracy in action. AI comprehension can occasionally be sacrificed in favor of AI accuracy, since some may view AI accuracy as a necessary condition, if not a substitute, for guaranteeing positive results. This could cause people to value accuracy more highly than comprehension even while they value comprehension on its own (Nussberger et al., 2022). Work by Yu et al. (2019) and Lai & Tan (2019) discovered that if high accuracy indicators emerge, as seen by both subjective feedback and more choices that align with the model's suggestions, people's trust in the algorithm increases.

If the goal is to instill trust in stakeholders, the accuracy of an algorithm in comparison to other possibilities must be a top priority (London, 2019).

3.3.2 Efficiency

Efficiency criteria is the amount of time and computer power needed for an algorithm to produce results. AI integration in hiring has advanced the process significantly by automating and improving a number of procedures. AI powered systems are capable of processing high application quantities, screening resumes faster than human reviewers, and using complex algorithms to determine a candidate's appropriateness. But for these systems to work well, they frequently need previous data. Their efficiency decreases in situations when data are scarce or nonexistent, as in the case of recently established jobs or special skill sets (Kurek et al., 2024). An algorithm's efficiency is typically strongly influenced by the accuracy of the input-data portrayal. Research has demonstrated that when compared to an inadequate data representation, an appropriate data representation yields better performance (Alzubaidi et al., 2021).

3.3.3 Scalability

Scalability is how well an algorithm performs as the size of the data increases. Possible kinds and values are used to describe the features or attributes of the data sets which are used with machine-learning algorithms. The type of machine learning algorithms that need to be used to extract useful information is dependent on the type of data. The analysis of large data sets can be challenging when the objective is to find more powerful patterns and details that support better insight, making decisions, and data processing automation. Regretfully, the new difficulties posed by big data, particularly scalability, were too great for the conventional methods of applying machine-learning algorithms (Alghunaim & Al-Baity, 2019). The majority of ML workloads are distributed and executed in parallel to reduce the runtime required by a given volume of data. The obstacle with scalability is to keep the processing rate constant without requiring a lot of physical hardware (Garate-Escamilla et al., 2019). Study by Zeebaree et al. (2024) delivered that, anticipatory scaling driven by AI offers a way to solve the cloud computing application scalability challenge with changing workloads. AI systems use historical usage data to predict needs properly for the future.

When creating and contrasting ML-based techniques, scalability is an essential consideration to make sure the outcomes are dependable and long-lasting. When the characteristic values in ML algorithms are more closely spaced, the approach has a better chance of being trained swiftly and effectively. On the other hand, if characteristic values or data points are dispersed, it will take longer to understand the data and the precision will drop. Scaling is therefore a technique for bringing data points nearer if the data carries any farther-off data points. Stated differently, scaling makes data units more universal, hence reducing the distance between them (Sharma, 2022).

3.3.4 Flexibility

Flexibility is the ability of an algorithm to adapt to different types of data and requirements. Flexibility in quantitative problem solving is an essential aspect of expertise in mathematics. The skill to use the most appropriate method for a particular issue or problem-solving scenario and the knowledge of alternative approaches to solving problems are frequently seen as the two main components of operational flexibility (H. Wang & Star, 2023). Flexibility takes into account not solely outstanding efficiency, but additionally the corresponding rise in performance from beginning with an average algorithm setup and the work required to achieve it. For instance, algorithm A might function effectively on certain circumstances, yet it fails to include any variables that may be used as handles to alter the algorithm, therefore it lacks the capacity for significant flexibility. On the other hand, Algorithm B might not function well with initial

parameters, but can be improved with modification. Therefore, algorithm A may seem preferable at first, but with proper tweaking, algorithm B may prove superior thanks to its versatility (Preuss, 2009). Flexibility refers to how an algorithm adapts to new data when retrained. A flexible system learns and changes as it is employed, resulting in different solutions for the same query over time as it addresses the issue more effectively (Tong et al., 2022).

3.3.5 User satisfaction

User satisfaction criteria is how satisfied users (both employers and candidates) are with the matches. Satisfaction can be described as a perceived discrepancy among previous projections and the actual execution following the use. Expectations are not met by achievement, which leads to dissatisfaction. Satisfaction is a result of perceived worth or quality, that users evaluate based on their experience and expectations (Uzir et al., 2021).

User satisfaction is a complex concept that depends on a number of variables, including the system's timeliness, accuracy, usability, and capacity to recognize and meet the demands of each unique user. A few crucial components that have a big influence on consumer satisfaction given as follows. The simplicity with which a product or algorithm can be used and interacted with by people. The speed at which users pick up on the system and become skilled with it. Quick reaction speeds and less loading time to enhance the user experience. Reliable operation free from frequent glitches or system breakdowns. The availability of features that are both desired and necessary to satisfy user needs. The data offered must be accurate and current. Users' flexibility to customize the system to suit their needs. Recommendations and material that are tailored to the tastes and actions of the user. Implementing procedures for users can leave feedback and view solutions. Confirmation that user data is managed safely and in accordance with privacy laws. Clear communication regarding the handling and security of user data. Ensuring a consistent user experience across various platforms and devices (Ekechi et al., 2024).

3.3.6 Robustness

Robustness criteria is the algorithm’s ability to handle noisy or incomplete data. In the work of Marcus (2020) robust AI defined as intelligence that can be relied upon to apply its understanding to a broad spectrum of challenges in a methodical and trustworthy manner, combining data from various sources in order to ensure it operates freely and dynamically regarding the world and transfer the information it learns

from one context to a different one in the manner that would be expected from an average adult, even though it does not have to be superhuman or self-improving.

When an algorithm's result delivers likely performance upon a testing set and the training one deemed close, it qualifies as robust. Robustness is not just another means of determining limitations on generalizations. It is true that a less strict definition of robustness is a prerequisite for the asymptotic generalizability of widespread learning algorithms. Although stability and robustness share some obvious similarities, they differ in certain ways. Robustness demands that a prediction rule respond similarly when tried on a sample that is similar to a training data, though stability demands that essentially identical sets of training data with one sample removed result in similar prediction rules (Marcus, 2020).

3.3.7 Explainability

Explainability is how well the algorithm’s decision-making process can be understood and explained. Fairness is the dearth of bias or preference against someone, or community based on their natural or learned attributes while making decisions. Thus, it is seen unfair when an algorithm produces results that are biased in favor of a specific set of individuals (Sogancioglu et al., 2023). Statistical and optimization-based ML algorithms have been widely successful in a variety of fields. Likewise deep-learning algorithms typically perform well in achieving generalization on newly distributed data that is similarly spread, they also have certain drawbacks, such as a dearth of explainability and a learning process that is difficult for humans to understand. Such algorithms for ML also have the trait of reflecting the data that they are dependent upon. In general, this might be advantageous, but in some specific fields, it might be a significant disadvantage. Take automated hiring platforms for instance. In this field, moral conduct is required, and inaccurate information is not tolerated. It is necessary to initiate appropriate action to ensure that AI behaves ethically, even when such behavior conflicts with potentially biased training data (Ortega et al., 2021).

AI is met with a great deal of mistrust, which is understandable given its novelty in our lives and being the work of humans. For example, deep learning has drawn criticism for its ability to approximate language and visual model weaknesses well. In NLP and visual identification, delusiveness and biasness have been revealed. Thus far, no solid answer to these issues has been discovered. It is imperative to promptly tackle the probable ethical dilemmas since apathy may result in unforeseen divisions and discrepancies in the society of the future. A right to explanation was included in the General Data Protection Regulation by the European Union to address any issues with the growing significance of algorithms. Because such trust criteria are difficult to define and measure, interpretability and explainability criteria are typically employed

as steppingstones. Being able to explain or convey an abstract idea into a domain in a way that is comprehensible to humans is known as interpretability in the domain of algorithms for ML whereas explainability is the synthesis of interpretable domain aspects that have helped a particular example led to a conclusion (Dosilovic et al., 2018).

Study conducted by Zhou et al. (2019), demonstrated that providing an explanation of how training data points affect forecasts greatly raised user trust in those results. In another study by Alam & Mueller (2021), the functions of explanations in AI-driven decision-making scenarios involving medical diagnosis. The findings indicate that the combination of example-based and visual explanations along with justifications had a considerably greater effect on patient satisfaction and trust than either type of explanation by itself or just text-based justifications. Wang & Yin (2021) contrasted several explanation kinds, including nearest neighbor, counterfactual, feature importance, and feature contribution, from the following viewpoints: enhancing people's comprehension of the AI model, assisting people in identifying model ambiguity, and bolstering people's measured confidence in the model. They emphasized how crucial it is to choose several AI explanation kinds when creating the best AI techniques for a given decision-making task.

Therefore, explainable AI in decision-making would encourage fair HRM procedures and use trust in the application of AI models. Explainable AI tackles black-box AI in favor of interpretable AI (Bhattacharya et al., 2022).

3.3.8 Cost

Cost criteria is the overall cost involved in implementing and running an algorithm. A key component of managing software projects to excellence is having a precise idea of the development and implementation process cost (Huang et al., 2015). ML algorithms provide forecasts, which are then frequently utilized to create policies or other plans of action that have an implementation cost (Tulabandhula & Rudin, 2013). ML algorithms encounter several obstacles in terms of implementation and durability. In the research made by Baier et al. (2019), these obstacles were classified into three broad categories: pre-installation, installation, and non-technical. Data quality, data volume, high-dimensional unbalanced data, encoded training data, data obtaining, data setup, technical liabilities, computing power, energy consumption, and data protection are all issues that must be addressed before to implementation. Deployment issues include high-frequency data, notion dispersion, continuous data verification, ongoing result validation, system resilience, deployment architectures, and expansion. Non-technical issues include

user-friendly instruments, legal limitations, outcome clarity and comprehension, confidence, the practical application of ML, and assessment measures.

In another study provided by Frontistis et al. (2023), while ML has the ability to boost system efficiency and management, various issues must be addressed before widespread deployment. High-quality data is essential for producing accurate and reliable ML models, as is the case with most AI techniques. While ML models can provide precise forecasts owing to their complexity, their comprehension and association with actual systems might restrict their use. ML models must be adaptable and give trustworthy simulations and predictions under diverse settings. ML systems must be adaptable to deliver trustworthy simulations and projections under many settings.

4. DECISION MAKING

Decision making involves selecting the optimal answer from several possibilities that reflect various considerations and assumptions. Decisions are formed within a setting that includes accessible knowledge, alternatives, scores, and preferences at the point of decision-making. The complexity of decision-making stems from the numerous factors used to evaluate alternatives (Chatterjee & Chakraborty, 2016).

4.1 Multi Criteria Decision Making

One well-known approach to decision-making is multi-criteria decision making (MCDM). It constitutes a subset of operational research approaches in general that address decision challenges when several criteria for choice are present. The primary model group is frequently referred to as MCDM (Zolfani & Saparauskas, 2013).

MCDM calls for rendering judgments based on many, often contradictory criteria, including both advantageous and not advantageous characteristics. Advancements in computer technology have enabled systematic examination of difficult MCDM problems, contributing to the discipline's growth. The growing adoption of information technology has led to a significant volume of data, forming MCDM crucial for business decision-making. MCDM offers a fair evaluation of options and removes sentiment from the decision-making process. It also prevents any one component from dominating others. Broadly, there are two sorts of MCDM issues: the first contains a limited number of alternate solutions, while the other kind has a limitless number. The number of viable solutions to problems involving choosing and evaluation is often limited. An MCDM issue is often defined by a $m \times n$ decision matrix, with each member a_{ij} representing the performance of the ith alternative against the jth criteria. As a result of the requirement for a structured strategy for facilitating decision making in circumstances containing numerous factors, a set of tools known as MCDM techniques has arisen to help in determining the optimal course of action (Chatterjee & Chakraborty, 2016).

MCDM entails selecting alternatives from a collection using mathematical techniques and logical judgments. A judgment is rendered on the most beneficial alternative after considering various criteria for assessment. MCDM is a key component of modern decision-making, management, and systems development. It is utilized extensively in several areas, including the fields of engineering, economics, medical, transportation, and administration (Pamučar et al., 2020). The overarching objective of any typical

MCDM study is to analyze and rank the options on hand using a predefined set of deciding criteria. A MCDM analysis consists of four main steps. In the very first step, decision-makers select appropriate criteria for evaluating options. Such a selection is often accomplished by examining the literature, using decision-makers' expertise, or requesting professional guidance. Decision-makers ought to pay adequate attention to this step because neglecting any significant criterion will end up resulting in an ineffective analysis. In the second step, decision-makers gather data or specific scores for every alternative based on previously selected criteria to create a decision matrix. Consider an MCDM issue with $ai = \{a1, a2, \ldots, am\}$ denoting the investigated options and $cj = \{c1, c2, \ldots, cn\}$ representing the assessment criteria. Equation expresses the generic form of the decision matrix, with Xmn representing the score of option m relative to criteria n. The third step is deciding the weight for every criterion. Treating all factors evenly is not sensible since every one of them may have varying degrees of value in a decision-making system. Finally, the last step involves aggregating the criterion weights and specific scores for each alternative into an overall rating. Overall ratings are used to rank options in order of preference (Krishnan et al., 2021).

MCDM is a popular multidisciplinary study area in business administration and operations research. There are two categories of MCDM: multi-attribute decision-making (MADM) and multi-objective decision-making (MODM). MADM often contains distinct decision factors and a limited number of options for examination. MODM aims to select the most beneficial option from many options while adhering to specific limitations. MODM assigns each criterion to a specific aim, while MADM assigns each criterion to a distinct property (Turskis et al., 2016).

4.1.1 Multi Objective Decision Making

The choosing process in MODM is facilitated by evaluating each alternative in relation to the established list of goals. The goals must be quantifiable, regardless of whether the measurement is limited to a nominal scale, and each choice option's results need to be evaluated. Choosing is facilitated by objective results, which serve as the foundation for comparing each of the options. In light of the several, occasionally competing, aims, multi-objective approaches appear to be a suitable tool for ranking or choosing several options from a collection of the accessible possibilities. MODM models range from straightforward strategies that require minimal data to those built around programming methodologies that demand in-depth knowledge for the various objectives and the stakeholder choices (Brauers et al., 2008). MODM techniques address multi objective optimization problems and assess continuous alternatives. The MODM approaches

look for the best solution by evaluating conflicts between several objectives (Thakkar, 2021). MODM techniques take contrasting objectives into account. The use of MODM approaches has grown in popularity, enabling decision-makers to take competing goals into account at the same time. These techniques, which include the TOPSIS, WSM, and WPM, allow trade-offs among requirements to be identified and lead to Pareto-optimal solutions (Sahoo & Shubhra Goswami, 2023).

4.1.2 Multi Attribute Decision Making

An essential part of contemporary decision science is MADM, often known as multi-objective decision making with limited alternatives. Engineering, business, economics, and military management are among the many domains in which the theory and practices of MADM have been widely used. These include deciding on investments, venture capital project assessment, establishment position, auctioning, support services, armed forces effectiveness of systems examination, growth comparing of manufacturing industries, comprehensive assessments of financial performance, etc. In essence, MADM is to use appropriate techniques to determine which alternative(s) from a limited number of options is/are the most desired based on a set of qualities (Xu, 2015). According to contemporary decision-making science, the MADM phenomena is crucial for finding solutions to issues that arise in day-to-day living (Zhang et al., 2022). The best-known MADM applications comprise a few of the ones listed following: TOPSIS, AHP, ELECTRE, VIKOR, SAW, COPRAS, SWARA and MOORA (Zolfani & Saparauskas, 2013).

The choosing process in MADM is facilitated by evaluating each choice in relation to a list of objectives. Features help the decision process by serving as the foundation for comparing the options. Consequently, it appears that multi-attribute approaches are a suitable tool for sorting or choosing several options from a collection of accessible qualities in light of the many, perhaps contradictory, attributes. Every choice option must have its results quantified, and the objectives need to be quantifiable regardless of whether the method of measurement is limited to the nominal scale (Turskis et al., 2016).

4.2 Weighting Methods

Finding criteria weight is a major challenge in multi-criteria analysis frameworks. Methodologies for establishing criterion weight have become the subject of many studies and scholarly debate for a lengthy period. The majority of scholars recommend classifying criterion weighting techniques as subjective or objective. The subjective approach to determining criterion weights may differ depending on the number of participants, techniques used, and ultimate weights. Subjective techniques frequently employ pairwise

comparing and ordering criterion. (Pamučar et al., 2018). Subjective techniques evaluate criteria based on feedback provided by decision makers or experts involved in the decision-making process. Subjective methods reveal decision makers' individual viewpoints and instincts, indicating their impact on the manner in which decisions are made. Objective methods use data from the original decision matrix to determine the weight of criteria, unlike subjective methods. Objective techniques reject decision makers' opinions (Žižovic et al., 2020). Distinctively from the two techniques there is a third one, the combined approach. The combined approach. involves combining subjective and objective weights using methods such as additive synthesis, multiplicative synthesis, subjective correction based on objective, range maximization, and others. This strategy tends to be more comprehensive but requires significant effort. Weighting methods can be subjective, objective, or a combination of the two. Considering these three approaches for weight assessment each one contains both advantages and downsides. Subjective and subjective-objective weighing systems need extensive surveys and professional consultations, which can be time-consuming and labor-intensive. As a result, they are considered not appropriate for fast, short-term assessment (Zhong et al., 2023).

Few of the common subjective weighing techniques include pairwise comparisons, DEMATEL, SIMOS, SWARA, FUCOM, KEMIRA, PIPRECIA and P-SWING. Subjective techniques may gain the upper hand by incorporating information from experienced decision-makers. Due to this advantage being based on decision-makers' prior beliefs, studies including afore mentioned techniques and more of them may contain skewed results. Inadequate awareness of the evaluated decision's situation might hinder decision-makers' ability to deliver the necessary level of knowledge. Delivering this kind of knowledge might get challenging when the MCDM challenge comprises several criteria. Objective procedures, as opposed to subjective methods, lack the requirement for decision-makers to provide any prior knowledge or judgment. These approaches are recognized for removing potential bias related with subjective judgment, resulting in increased objectivity. A few examples of objective approaches include entropy-based methods CRITIC, and the latest CILOS and IDOCRIW methods (Krishnan et al., 2021).

4.2.1 DEMATEL

The Science and Human Affairs Program of the Battelle Memorial Institute of Geneva established the Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach in 1972-1976 to address complex and interconnected problems. The DEMATEL technique can enhance comprehension of complex issues and identify potential fixes through a structured framework. This approach uses a cause-and-effect

diagram to pinpoint the interconnectedness of a system's constituents. Causes and effects diagram use digraphs, as opposed to directionless graphs, to illustrate the contextual connections and effect between items (Shieh et al., 2010).

Directed graphs (digraphs) prove more beneficial than directionless graphs given that they may demonstrate the directional connections among sub-systems. A digraph can depict a communication structure or a dominance relationship among individuals. The initial approach to DEMATEL was directed at the fragmented and hostile phenomena of global civilizations and sought integrative solutions. The DEMATEL technique has gained popularity in Japan due to its ease of understanding complex causal connections. The digraph depicts the contextual relationship between system components, with numerical values representing influence intensity. The DEMATEL approach creates a clear hierarchical model for the system by analyzing the causes and consequences of components Wu & Lee (2007).

DEMATEL's examination of component relationships provides a deeper knowledge about the system's structure and supports the resolution of com3plex challenges. DEMATEL uses graph theory to evaluate relationships and create a map for system elements. Examining the total-relation matrix of elements provides an expanded perspective of their interaction. DEMATEL has been effectively implemented in several domains, including service, environment, and evaluation (Zhang & Deng, 2019).

4.2.1.1 DEMATEL Method's Application Steps

DEMATEL is particularly helpful in examining the causal linkages between elements of the system. It could be employed to investigate and resolve complex and interwoven situations. It may verify the interconnected nature of elements and assist in the creation of a map to reflect related connections between them. This approach uses an impact relation diagram to identify the important components of a complicated system in addition to using matrices to turn the interconnected relationships to a causal sequence set (Si et al., 2018).

The application steps for DEMATEL method (W. Zhang & Deng, 2019) are as follows:

Step 1: Assume S is a system with n criteria, denoted as $s1, s2, \dots, sn$. The pair-wise comparison scale has four levels: 0, 1, 2, and 3, representing "No influence," "Low influence," and "High influence," and "Very high influence," accordingly.

Step 2: The first direct-relation matrix Z is a $n\ x\ n$ matrix created via pair-wise comparisons with regard to both influences and directions among criteria. z_{ij} represents the extent by which the criterion i affects the criterion j, i.e., $Z\ =\ [z_{ij}]_{nxn}.\ \ j, i.e., Z = \left[z_{ij}\right]_{nxn}$

Step 3: The normalized direct-relation matrix $X, i.e., X = \left[x_{ij}\right]_{nxn}$ and $0 \leq x_{ij} \leq 1$ can be deducted by:

$$x = \frac{z}{\max\limits_{1 \leq i \leq n} \sum_{j=1}^{n} z_{ij}}$$

Step 4: The total-relation matrix T can be obtained as follows:

$$T = \left(t_{ij}\right)_{nxn} = X(I - X)^{-1}$$

where the I denotes the identity matrix. t_{ij} represents the degree to which criteria i influences criterion j.

Step 5: In the total-relation matrix T, the sums of rows and columns are designated as D and R, respectively, with $D\ = [d_i]_{n\times 1}\ \ and\ R\ =\ [r_i]_{n\times 1}$, as shown below:

$$D = \sum_{j=1}^{n} t_{ij}$$

$$R = \sum_{j=1}^{n} t_{ij}$$

where $1\ \leq i\ \leq\ n, 1\ \leq\ j\ \leq\ n$ represents the sum of the direct and indirect effects of criteria i on other criteria, known as the influence degree of criteria i, and r_i denotes the degree to which criteria i is affected by the direct and indirect effects of other criteria.

Step 6: $R + D$ and $R - D$ can be calculated using R and D.

If $R - D\ >\ 0$, the factor is considered a causation factor.

If $R - D\ <\ 0$ the factor is an effect. Higher $R - D$ numbers indicate greater impact and prioritization, whereas smaller figures indicate less influence and lower prioritization. Higher $R\ +\ D$ numbers imply more significance, whereas smaller figures suggest less importance in the system.

4.2.2 Entropy

German physicist R. Clausius proposed the thermodynamic notion of entropy in 1865. It is an equilibrium parameter for matter and describes the chaos or disorder in a thermodynamic system. Shannon measured

the unpredictable nature of impulses in sources of information (information entropy) and introduced entropy into information theory in 1948. The entropy weight technique employs information theory to describe message uncertainty, assess assessment characteristics' capacity to communicate decision information, and determine relative weight amongst attributes. The judgment matrix may be used to compute the entropy weight (Chen, 2020).

The researchers have proposed a number of objective weighing techniques. The entropy approach is the most often utilized. Entropy is a measure of the degree of uncertainty provided by the discrete probability distribution in information theory. Data sets that have higher entropy levels turn out to be unpredictable. Entropy is a tool that may be used to ascertain the significance values, or the ranking of relevance, given a decision matrix with a certain quantity of information for options (Alp et al., 2015).

Zeleny (1982) was the initial author to propose using entropy to determine the weight of criterion in MCDM studies. As a result, entropy continues to be used in several scientific fields, including chemistry, mathematics, social sciences, and directed research. The decision matrix's assessment criteria may be weighted using the entropy weighting approach, which is an objective weighing technique. The high level of entropy shows that the relevant criteria is of paramount importance (Gök-Kısa & Perçin, 2018).

4.2.2.1 Entropy Method's Application Steps

Entropy approach has had a significant impact on the modeling and mapping of several natural disasters (Wu et al., 2022). Numerous disciplines, including health care, biology, geography, processing images, and engineering, have made extensive use of the entropy-based approach (Li et al., 2018). The results of the studies demonstrate that the entropy information greatly raises the algorithm's resilience and detection rate (Chen, 2020).

The essential equations (Gök-Kısa & Perçin, 2018) are outlined below:

Step 1: Data matrix normalization

Create a starter data matrix for the entropy weight assessment algorithm by assigning m evaluation items and n evaluation indications.

$$X = \begin{bmatrix} x_{11} & x_{12} \dots & x_{1n} \\ x_{21} & x_{2^2} \dots & x_{2n} \\ x_{n1} & x_{n2} \dots & x_{mn} \end{bmatrix} = (X_1\, X_2 \dots X_n)$$

Normalization of the matrix,

$$x_{ij}^{*} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}$$

Step 2: Calculating the entropy value (E_j)

$$E_j = -k \sum_{i=1}^{m} (x_{ij}^{*} \, In x_{ij}^{*})$$

$$k = (In(n))^{-1}$$

k: entropy coefficient

n: number of alternatives

Step 3: Calculating the uncertainty degree (d_j)

$$d_j = 1 - E_j$$

Step 4: Calculating the weight scores.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

4.2.3 SWARA

A number of novel MCDM techniques have been created by researchers and scientists in the past 15 years. Despite being a recently introduced technique, Stepwise Weight Assessment Ratio Analysis (SWARA) method has been applied to numerous problems, including logical settlement of conflicts, designing a product, manufacturing equipment selecting, choosing vendors, and the prioritization of sustainable development evaluation metrics for the energy system. Participants are able to more freely convey their opinions utilizing preset categories for stating choices when using the SWARA technique (Stanujkic et al., 2015).

The viewpoint of SWARA differs from that of other comparable techniques such as AHP, ANP, and FARE. SWARA provides decision-makers with the opportunity to prioritize their actions with respect to the state of both the environment and the economy at the time. According to this approach, the specialists' involvement is crucial. SMEs play a crucial part in the decision-making procedures for significant projects (Keršuliene et al., 2010).

It can be highlighted that one benefit of SWARA is the way the weights and criterions relative significance are calculated more logically. Every expert in the study selects the significance of every given criterion,

beginning with the initial till to last one, all parameters get sorted. An expert makes use of their own intuitive knowledge, wisdom, and expertise while participating in the sorting process. Using this strategy, first place is assigned to the one that is most significant according to the participants. The key component of this technique is the capacity to determine the consensus of experts on the important ratio of criteria to be considered in the process of establishing their significance. Therefore, this approach helps with collaborating and gathering of data from the SMEs. The SWARA approach is straightforward, and professionals may coordinate with ease. The primary benefit of this procedure for the decision-making process is that, in certain cases, priorities are established in accordance with national or corporate policy, negating the requirement for assessment in order to sort parameters (Zolfani & Saparauskas, 2013).

4.2.3.1 SWARA Method's Application Steps

SWARA is a popular approach for evaluating qualities that prioritizes expert opinion. This method is employed in conjunction with other procedures, which is thought to be a benefit of the methodology. Consequently, it is a popular strategy in MADM (Alinezhad & Khalili, 2019). Despite being a recently developed approach, it was applied to several issues such as supplier selection (Singh & Modgil, 2020), priority planning (Ghorshi Nezhad et al., 2015) and product effectiveness evaluation (Zavadskas et al., 2021).

In order to successfully determine the varying weights of criteria using the SWARA approach, necessary steps (Stanujkic et al., 2015) described below:

Step 1: Arranging and listing the criterion in descending order according to their predicted relevance. **Step 2:** Beginning with the second criteria, respondents assign the relevance of criterion j in comparison to the preceding criterion $(j-1)$. This ratio is also referred to as the Comparative importance of average value, or s_j (Keršuliene et al., 2010).

Step 3: Calculating the coefficient value k_j

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases}$$

Step 4: Assessing the recalculated weight q_j

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{k_j - 1}{k_j} & j > 1 \end{cases}$$

Step 5: Calculating the respected weights of the assessed criteria.

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k}$$

w_j represents the relative weight of j criteria.

4.2.4 CRITIC

The CRITIC (CRiteria Importance Through Intercriteria Correlation) approach is one of the most popular and commonly utilized objective techniques. The CRITIC approach employs the standard deviation of ranking criteria scores for each column and the correlation coefficients across each paired columns to identify criteria variations (Žižovic et al., 2020). The CRITIC technique assigns weight to criteria based on the level of dispersion and consistency. The dispersion level measures the difference in a criterion's values across assessment schemes. The degree of confidence reflects the quantity of information that is comparable across many criteria. Whenever a criterion displays a bigger dispersion and confidence level, its weight must increase (Zhong et al., 2023).

CRITIC method has shown that it offers significance by taking into account both the contrast intensity and the conflicting relationships across every choice criterion. The contrast intensity indicates the level of variation found in each criterion's specific scores. The CRITIC technique assigns a larger weight to criterions having a higher standard deviation or contrast intensity. The reasoning behind this situation is as follows. A criterion with higher variance in scores is likely to give data that is more helpful. In decision-making, criteria like this must be prioritized above those with similar scores. MCDM problems sometimes include competing criteria among the alternatives studied. Sometimes an option cannot fully fulfill all established requirements, resulting in a conflict among them. The CRITIC technique uses the Pearson correlation coefficient, ranging from -1 to 1, to account for contradictory correlations. Whenever the coefficient equals 0, it suggests both of the criteria exist independently. A negative coefficient suggests that both criteria progress in opposing directions. As the coefficient near zero, the conflict among the two criteria intensifies. A coefficient that is positive implies a parallel connection between two criteria. This indicates that the two criteria having a high positive coefficient exchange excessively data that is redundant. As a result, criterion with substantial positive correlations with other criteria provides no further details and is deemed minor in the overall decision system. Based on those grounds, the CRITIC technique assigns greater weight to a criterion containing more conflict or a smaller amount of redundancy. Due to these characteristics, CRITIC has been employed in a number of real-world scenarios (Krishnan et al., 2021).

4.2.4.1 CRITIC Method's Application Steps

The conversion of qualitative characteristics to quantitative ones and not requesting the characteristics being independent of each other is the main advantages of the CRITIC approach (Alinezhad & Khalili, 2019). The method has been applied to many fields such as safety evaluation (H. W. Wu et al., 2020), innovation performance assessment (Satici, 2021) and designing a power system (Chisale et al., 2023).

The application steps according to Akbulut (2020) for CRITIC are given below:

Step 1: Initializing the decision matrix.

$$X = \begin{bmatrix} x_{11} & x_{12} \dots & x_{1n} \\ x_{21} & x_{2^2} \dots & x_{2n} \\ x_{n^1} & x_{n2} \dots & x_{mn} \end{bmatrix}$$

Step 2: Matrix normalization

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}$$

Step 3: Calculating correlation ratios between criteria pairs to determine the degree of link between the assessment criteria.

$$p_{jk} = \frac{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j) \times (r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{m}(x_{ij} - \bar{x_j})^2 \times \sum_{i=1}^{m}(x_{ik} - \bar{x}_k)^2}} ; j, k = 1, \dots, n$$

Step 4: To represent the information amount for each assessment criterion the c_j value is estimated.

$$c_j = \sigma_j \sum_{k=1}^{n} (1 - p_{jk}) ; j = 1, \dots, n$$

σ_j represents the standard deviation value for each assessment criteria and calculated as follows.

$$\sigma_j = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} (x_{ij} - \bar{x}_j)^2} ; i = 1, \dots, m$$

Step 6: In this final step the weight degree for each assessment criteria is calculated as follows.

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} ; j = 1, \dots, n$$

The greatest value calculated is accepted as the best assessment criteria.

4.2.5 FUCOM

Pamučar et al. (2018) created The Full Consistency Method (FUCOM) approach to determine criterion weights (Durmić, 2019). FUCOM can precisely identify the weight coefficients of every item that are being compared. This method accurately determines the weight coefficients of every item compared at a specific level of hierarchy while maintaining comparative coherence. It minimizes mistakes in comparisons by limiting the number of compares and defining limitations for determining optimum criterion values. Method also validates models by producing error values for weight vectors based on divergence from complete consistency (Fazlollahtabar et al., 2019).

Then again, different techniques for assessing criterion weights, meet with excessiveness of the pairwise comparing, that opens the possibility for flaws in reasoning. The FUCOM methodological process reduces the apparent redundance drawback. This procedure allows for the accurate estimation of the weight coefficient values of all items that are jointly compared at a particular degree of the hierarchy while also meeting the constraints of comparison coherence (Pamučar et al., 2018).

4.2.5.1 FUCOM Method's Application Steps

While meeting comparative consistency requirements the accurate computation of the weight coefficients is made possible by FUCOM (Fazlollahtabar et al., 2019). The repetition of comparisons between pairs arises in the other methods (the BWM and AHP models) for computing the weights of criteria, making them not as susceptible to judgment mistakes; meanwhile, the FUCOM technique removes this issue (Pamučar et al., 2018).

The FUCOM method used in studies such as choice of vendors (Durmić et al., 2020), fighter aircraft selection (Van Hoan & Ha, 2020) and assessing the performance indicators (Badi et al., 2022).

Steps needed for FUCOM application according to Durmić (2019) are as follows:

Step 1: A predefined set of assessment criteria is evaluated based on their relevance, beginning with the greatest weight coefficient, and progressing to the lowest.

$$C = \{C_1, C_2, \dots, C_n\}$$

$$C_{j(1)} > C_{j(2)} > \cdots > C_{j(k)}$$

Step 2: This stage compares the listed criteria and determines their comparative priority ($\varphi_{k/(k+1)}, k = 1,2,\dots,n$ k being the criteria's rank).

$$\phi = \varphi_{1/2}, \varphi_{2/3}, \dots, \varphi_{k/(k+1)}$$

Step 3: This stage calculates the final weight coefficients for the assessment criterion $(w_1, w_2, \dots, w_n)^T$. The final weight coefficient values must have these two requirements; first the weight coefficient ratio equates to the observed criteria's comparison priority $\varphi_{k/(k+1)}$ as established in Step 2, indicating that the following criterion is fulfilled:

$$\frac{w_k}{w_{k+1}} = \varphi_{k/(k+1)}$$

Second, the weight coefficients ought to demonstrate mathematical transitivity.

$$\varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} = \varphi_{k/(k+2)}$$

Next, $\varphi_{k/(k+1)} = \frac{w_k}{w_{k+1}}$ and $\varphi_{(k+1)/(k+2)} = \frac{w_{k+1}}{w_{k+2}}$ $\frac{w_k}{w_{k+1}} \otimes \frac{w_{k+1}}{w_{k+2}} = \frac{w_k}{w_{k+2}}$

Hence, the second requirement is derived:

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)}$$

The final model for estimating the weight coefficients of assessment criteria is able to define based on the given parameters as follows:

Min χ

$$s.t.$$

$$\left| \frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)} \right| = \chi, \forall j$$

$$\left| \frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \right| = \chi, \forall j$$

$$\sum_{j=1}^{n} w_j = 1, \forall j$$

$$w_j \geq 0, \forall j$$

4.2.6 BWM

Best Worst Method (BWM) is one of the current weighting approaches that uses pairwise comparisons to determine criterion weights. The BWM addresses the inconsistency issue associated with pairwise comparisons by doing solely $2n - 3$ comparisons. The BWM has been employed in several real-world applications, including power, logistics management, transportation, production, education, investment, performance assessment, aviation, communication, medical care, financial technology, and tourism. This method was paired with other robust approaches to achieve improved outcomes (Pamučar et al., 2020).

Professor Rezaei presented the BWM in 2015. BWM, like Analytical Hierarchy Process, relies on pairwise comparisons between two criteria. BWM differs from AHP on the basis of pairwise comparing. BWM uses systematic pairwise comparisons instead of irregular ones. In BWM, decision-makers' feedback is being used to identify the best and worst criteria. The BWM solely conducts reference comparing, meaning that preferences of every criterion over the worst one and the preferences of the best one over all criterions. A restricted objective optimization problem is constructed utilizing the idea of the pairwise comparison score between both criteria must be as near to the ratio of their weights as achievable. After addressing the restricted objective optimization problem, the weights of the criteria may be determined. Hence, the BWM demonstrates significantly simpler functioning with a smaller unreliability in comparison with other weighting methods (You et al., 2017).

4.2.6.1 BWM Method's Application Steps

BWM method employs a systematic approach to pair-wise comparing of evaluated criteria (You et al., 2017). Its process is considerably less complicated and highly precise, as it avoids redundant and additional comparisons (Pamučar et al., 2020).

Choosing a cloud service provider (Youssef, 2020), assessment of Eastern European healthcare systems (Torkayesh et al., 2021) and a supply chain management application (Haseli et al., 2021) are some of the studies that employed the BWM methodology.

The procedure for BWM according to You et al. (2017) given below:

Step 1: Establishing a logical decision-making criteria structure that compares the performance of several alternatives, a decision-making system with n criteria, denoted as $\{C_1, C_2, \dots, C_n\}$.

Step 2: Determining the best C_B and the worst criteria C_W in the decision-making criteria system.

Step 3: Assessing the preference of C_B over the rest of the criterion by utilizing a 1-9 scale. The 1-9 scale illustrates the relative relevance of the best criterion to the remainders. Should the C_B equally significant as the compared criterion, the preference over that criterion is assigned a value of one. If the C_B is more significant than the selected criterion, a preference score of 9 given. A best-to-others vector $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$ may be derived, while a_{Bi} representing the preference of the best criteria C_B over criterion C_i.

Step 4: Same process using 1-9 scale for the preference of remainders over the worst criteria. Just as the same a worst-to-others vector $A_w = (a_{W1}, a_{W2}, \dots, a_{Wn})^T$ can be created, while a_{iw} representing the preference of C_i over C_B.

Step 5: The constrained objective optimization model is conducted by two equations given below:

$minmax_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jw} \right| \right\}$ for objective function,

$s.t. \begin{cases} \sum_j w_j = 1 \\ w_j \geq 0, for\ all\ j \end{cases}$ for constraint conditions.

w_B is the C_B's weight; w_{Bj} is the j's weight; a_{Bj} is the preference of the C_B over C_j; w_W is the C_W's weight; and a_{jw} is the preference of the C_W over C_j.

For the sake of running a practical mathematical computing equation for objective function can be shifted as below:

$$min\xi$$
$$s.t. \begin{cases} \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, for\ all\ j \\ \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, for\ all\ j \end{cases}$$

where ξ is the auxiliary parameter. By solving both the constraint conditions and shifted objective function equations, the optimum weights for all given criterion and the optimum auxiliary parameter ξ^* may be acquired.

4.2.7 AHP

In 1980, Saaty proposed the Analytical Hierarchy Process (AHP). This approach determines the weights (significances) of hierarchically non-structured or specific level of hierarchy criteria in comparison with the criteria at more advanced levels. The evaluation for comparing is qualitative and straightforward to

implement. It influences whether a particular criterion is of greater significance than another and assigns precedence accordingly. The procedure converts qualitative assessments of experts into quantitative evaluations. The AHP approach determines the level of consistency for every expert's evaluation. The Consistency Index (CI) refers to a relationship: The matrix's consistency increases as the consistency index decreases. The AHP technique has a mathematical foundation and may be used to determine the relevance of target objects based on expert estimations. Yet it has several limitations that arise with the number of criteria evaluated. When evaluating the relevance of a set of criteria regarding an object, experts ought to benchmark their value against different sets of criteria. Addressing numerous criteria creates a challenge. Only a handful of experts have successfully avoided conflicts when answering the AHP surveys for the first time. The procedure's weaknesses are highlighted by frequent breaches of its assessment criteria's temporariness (Podvezko, 2009).

AHP is one of the multivariate analysis methods used to decrease the unpredictability of subjective assessments. The purpose is to identify the trade-off in complicated decision-making scenarios, for instance, evaluating unidentical objectives based on various criteria (Gaudenzi & Borghesi, 2006). The procedure enables decision-makers to organize complicated situations into hierarchical or integrated layers. Typically, the hierarchy includes three layers: the objective, the criteria, and the alternatives. This strategy reduces complexity and speeds up the process of making decisions by providing a structure for challenging scenarios like selection problems (Hruška et al., 2014).

4.2.7.1 AHP Method's Application Steps

One of the main disadvantages of the AHP method is the complexity of the application steps even in the smaller studies, additionally AHP suffers from the setbacks that are caused by the flaws of pairwise comparison in general (Munier & Hontoria, 2021).

The AHP is a widely utilized method in the literature such as in road selection (Han et al., 2020), warship selection (dos Santos et al., 2021) and evaluation of landslide hazards (Panchal & Shrivastava, 2022).

Application steps of AHP are given below according to Goswami & Mitra (2020) and dos Santos et al. (2021):

Step 1: Objective declaration, selection of criteria, and alternatives.

Step 2: Creation of a matrix for pairwise comparisons.

Step 3: The normalization process of the matrix for pairwise comparisons.

$$N_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{i_j}}$$

Step 4: The consistency of every single criterion is ascertained by multiplying the row average matrix by the pair-wise comparison matrix.

Step 5: Assessing the consistency by calculating CI and Consistency Ratio (CR). RI is consistency index value that is generated randomly.

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

$$CR = \frac{CI}{RI}$$

4.2.8 PIPRECIA

In 2017, Stanujkic et al. introduced the PIvot Pairwise RElative Criteria Importance Assessment (PIPRECIA) technique, a considerably recent multi-criteria decision-making model. This approach is primarily used to determine the weights of evaluation criteria, but it may also be used to solve MCDM challenges, such as alternative assessment and choosing the best alternative (Stanujkic et al., 2021).

PIPRECIA technique is an adoption of the SWARA. The very first step for application of SWARA method, is selecting criteria and ordering them in a decreasing sequence of predicted relevance. In order to achieve this SWARA prerequisites or assumes that every participant in the assessment must jointly decide on the relevance of the criterion. By considering that SWARA technique may not be suitable for resolving some challenges. Hence, Stanujkic et al. (2017) presented the PIPRECIA technique, which doesn't demand the consensus of respondents for assessing the relevance of criteria. This enables PIPRECIA approach to use interactive surveys to collect respondents' evaluations (Jauković-Jocić et al., 2020).

The PIPRECIA model operates effectively for defining criteria, particularly in a group decision-making setting. Since the SWARA method requires preliminary sorting based on predicted significance, it consequently earns lack of authorization for a collective decision-making process. Modifications of PIPRECIA simplify and clarify the notion of significance (Đukić, 2022).

4.2.8.1 PIPRECIA Method's Application Steps

The PIPRECIA approach takes into account the respondents' expectations regarding the importance of the criteria without needing their permission (Jauković-Jocić et al., 2020). It enables the clear and concise statement of significance and doesn't demand the preceding ranking of criteria (Đukić, 2022).

The PIPRECIA method is utilized in studies such as quality evaluation (Jauković-Jocić et al., 2020), cause assessment (Stević et al., 2022) and competition analysis (Đalić et al., 2020).

According to Jauković-Jocić et al. (2020) the PIPRECIA techniques computation steps are given below:

Step 1: Ascertain the collection of significant assessment criteria and arrange the items in order of decreasing importance according to predicted relevance. Ordering the criteria, however, is optional and can be skipped.

Step 2: Determine the relative significance sj by following the steps below, beginning with the second criteria.

$$s_j = \begin{cases} > 1 & when\ C_j > C_{j-1} \\ 1 & when\ C_j = C_{j-1} \\ < 1 & when\ C_j < C_{j-1} \end{cases}$$

where Cj indicates the importance of criteria j and $Cj-1$ indicates the importance of the criterion that came before it, $j-1$.

Step 3: To find the coefficient kj:

$$kj = \begin{cases} 1 & if\ j = 1 \\ 2 - sj & if\ j > 1 \end{cases}$$

Step 4: Calculate the recalculated weight qj as follows:

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{q_{j-1}}{k_j} & j > 1 \end{cases}$$

Step 5: Determine the relative weights of the criteria wj as follows:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k}$$

where n denotes the number of the criteria.

4.3 Ranking Methods

Ranking alternatives by applying a rigorous mathematical process for analyzing numerical values is one of the steps of MCDM analysis process. MCDM approaches for ranking are able to handle various degrees of selected issue complexities. This makes it difficult for the decision-maker to choose the best approach given the typical issue features at hand. Every approach has advantages, disadvantages, and applications. This results in a phenomenon called the uneven alternative ranking brought on by various MCDM techniques. One of the main criticisms of the techniques used in MCDM is that various approaches yield different outcomes whenever employed to the exact same issue because of these variances. One of the main restrictions on using the MCDM approaches is because the parameters and alternatives at an everyday scenario are changing, the priority or ranking produced by the MCDM approach could not hold true over an extended period of time. For this reason, it is important to supplement the MCDM results with a thorough sensitivity study (Thakkar, 2021). MCDM techniques offer organized structures for decision-making through ranking the alternatives. Mixing the MCDM with data-driven techniques including large-scale data analysis, machine learning methods, and algorithms for optimization, resulted in increased precision when ranking alternatives with MCDM techniques (Sahoo & Shubhra Goswami, 2023).

4.3.1 ARAS

The Additive Ratio Assessment (ARAS) approach is designed to manage scenarios in which the assessment data consists of several units of measure. The approach contains five steps: formalizing the decision-making matrix, normalizing the data, calculating the normalized weighted matrix, determining the optimality function and utility degree, and deriving the final ranking. The ARAS technique simplifies complicated decision-making by using an indicator of relative value (utility degree) to identify the best choice and reduce the impact of multiple units of measure (Hatefi et al., 2021).

4.3.1.1 ARAS Method's Application Steps

The main characteristic of the ARAS approach that sets it apart from various other MCDM techniques is that it yields proportionate rating outcomes that are objective (Özkan & Ağ, 2021). The rather recent approach ARAS has individual attributes which qualitative ones must be transformed into quantitative ones (Alinezhad & Khalili, 2019).

The ARAS approach has been utilized in various fields such as choosing the option for foundation installments (Zavadskas et al., 2010), performance evaluation of corporate sustainability (Özkan & Ağ, 2021) and sorting of factoring companies (Özbek & Erol, 2017).

Final computation steps are given below according to Alinezhad & Khalili (2019):

Step 1: Initial step is creating the decision matrix.

Step 2: Normalization of the decision matrix.

$$r_{ij} = \frac{r_{ij}}{\sum_{i=0}^{m} r_{ij}}; j = 1, \dots, n$$

Step 3: Weighting the normalized decision matrix.

$$\hat{r}_{ij} = r_{ij}^{*} \cdot \omega_j; i = o, 1, \dots, m$$

Step 4: Calculating the Optimality Function which is accepted as the higher the better.

$$S_i = \sum_{j=1}^{n} \hat{r}_{ij}$$

Step 5: Obtaining the Utility Degree, which is between 0 and 1, for alternative sorting.

$$k_i = \frac{S_i}{v_o}; i = o, 1, \dots, m$$

4.3.2 WASPAS

Zavadskas et al. proposed Weighted Aggregates Sum Product Assessment (WASPAS). It recognizes the distinct mix of two well-known techniques to MCDM: the Weighted Sum Method (WSM) and the Weighted Product Method (WPM). The WASPAS approach helps handle complicated issues in multicriteria decision making (Lukić et al., 2021). The process involves determining the relative relevance of each characteristic, evaluating and prioritizing options. The WASPAS technique comes with the following features: it is considered a compensating approach, the attributes are independent, qualitative qualities are translated to quantitative attributes (Alinezhad & Khalili, 2019).

4.3.2.1 WASPAS Method's Application Steps

The main advantage of the WASPAS method is that it uses the combination of two techniques WSM and WPM. This technique's another primary benefit is its robustness over rank inversion of the alternatives under consideration. Additionally, it is discovered that this approach possesses the special capacity to address optimization issues with single and multiple responses in a range of machining processes. This approach may be effectively used because it is fairly broad and just requires basic, strong mathematics (Chakraborty & Zavadskas, 2014).

The WASPAS technique has been employed in many studies such as decision making in manufacturing (Chakraborty & Zavadskas, 2014), choosing the best water-abrasive cutting procedure variables (Radomska-Zalas, 2023) and choosing suppliers for a firm that manufactures polyvinyl chloride carpentry (Stojić et al., 2018).

The application steps of the WASPAS method according to Radomska-Zalas (2023) and Alinezhad & Khalili (2019) given below:

Step 1: Normalization of the decision matrix after creating one.

$$r_{ij}^{*} = \frac{r_{ij}}{\max_{i} r_{ij}}$$

$$r_{ij}^{*} = \frac{\min_{i} r_{ij}}{r_{ij}}$$

Step 2: Calculating the WSM, the total relative weight.

$$Q_i^{(1)} = \sum_{j=1}^{n} r_{ij}^{*} \cdot w_j$$

Step 3: Calculating the WPM, multiplied relative weight.

$$Q_i^{(2)} = \prod_{j=1}^{n} \left(r_{ij}^{*}\right)^{w_j}$$

Step 4: The Joint Generalized Criterion to generalize the WSM and the WPM methods is calculated.

$$Q_i = 0.5\left(Q_i^{(1)} + Q_i^{(2)}\right) = 0.5\left(\sum_{j=1}^{n} r_{ij}^{*}.w_j + \prod_{j=1}^{n} (r_{ij}^{*})^{w_j}\right)$$

For higher validation the following equation is used.

$$Q_i = \lambda \sum_{j=1}^{n} r_{ij}^{*}.w_j + (1-\lambda) \prod_{j=1}^{n} (r_{ij}^{*})^{w_j}$$

Step 5: Final sorting of the alternatives by Q_i values.

4.3.3. CODAS

In Combinative Distance-based Assessment (CODAS) technique, the attractiveness of options is judged utilizing two variables. The first and major metric is connected to the Euclidean distance between alternatives to the negative ideal. Utilizing this form of distance necessitates a l^2 −norm indifference space for criterion. The Taxicab distance serves as a secondary supplemental metric and is connected to the l^1 −norm indifference space. It is obvious that the option with higher distances from the negative-ideal solution is preferred. In this strategy, if two options that are incomparable based on Euclidean distance, the Taxicab distance is utilized as a supplemental measure. Though the CODAS prefers the l^2 −norm indifference space, it may also evaluate two other forms of indifference spaces (Turskis et al., 2016).

4.3.3.1 CODAS Method's Application Steps

CODAS distinguishes itself compared to other MCDM approaches by utilizing distance from negative optimum point by Euclidean and Taxicab measures to evaluate an alternative's overall effectiveness (Turskis et al., 2016).

As a rather recent method CODAS, has been applied in different study areas as a MCDM method such as green supplier selection (C. Wei et al., 2021), online shopping platform evaluation (Lei, Wei, & Chen, 2021) and a fuzzy extension to market segment assessment (Ghorabaee et al., 2017).

Application steps for CODAS method is given below based on the study conducted by Turskis et al. (2016):

Step 1: Conducting the decision matrix.

Step 2: Normalizing the conducted decision matrix.

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{\max\limits_i x_{ij}} & if\ j \in N_b \\ \min\limits_i x_{ij} & \\ \dfrac{i}{x_{ij}} & if\ j \in N_c \end{cases}$$

Where Nb is benefit and Nc is cost criteria.

Step 3: Conducting the weighted normalized matrix.

$$r_{ij} = w_j n_{ij}$$

Step 4: Calculating the negative-ideal point.

$$ns = [ns_j]_{1\times m}$$

$$ns_j = \min_i r_{ij}$$

Step 5: Finding the Euclidean and Taxicab distances from the negative-ideal point.

$$E_i = \sqrt{\sum_{j=1}^{m} (r_{ij} - ns_j)^2}$$

$$T_i = \sum_{j=1}^{m} |r_{ij} - ns_j|$$

Step 6: Creating the relative evaluation matrix.

$$R_a = [h_{ik}]_{nxn}$$

$$h_{ik} = (E_i - E_k) + (\psi(E_i - E_k) \times (T_i - T_k))$$

Where $k \in \{1,2,\ldots,n\}$ and ψ represents a barrier value to detect the equivalence of the two alternatives' Euclidean distances, which is described as:

$$\psi(x) = \begin{cases} 1 & if \quad |x| \geq \tau \\ 0 & if \quad |x| < \tau \end{cases}$$

The barrier value in this equation which the decision-maker can select is denoted by τ. Using this option to a number between 0.01 and 0.05 is advised. If the Euclidean distance between two options is smaller than τ, the Taxicab distance is used to compare them.

Step 7: Finding the evaluation rate of alternatives.

$$H_i = \sum_{k=1}^{n} h_{ik}$$

Step 8: Sorting the alternatives in a decreasing order by evaluation rates.

4.3.4 PSI

Maniya and Bhatt created the Preference Selection Index (PSI) approach in 2010. The PSI approach resolves disputes and determines the relative relevance of each property. The PSI technique relies on statistical notions and requires minimum calculations, eliminating the requirement for weight values for each parameter (T. F. Waruwu & Mesran, 2021). The method's primary benefit is that, like other MCDM approaches, when comparing criteria, it assigns a relative priority to the criteria and doesn't demand criterion weights. In this regard, the approach is highly beneficial for weighing the problem's criteria. For the creation of preference selection index resulting from a collection of processes in the approach, a given score is generated, and the alternatives are sorted from best to worst (Tuş & Aytaç Adalı, 2018).

4.3.4.1 PSI Method's Application Steps

The primary benefit of the PSI technique is in its ability to eliminate the need for weighting criteria or assigning relevance ratings to criteria during comparison. As a result, it is particularly helpful when there is disagreement on how to allocate weights to the problem (Tuş & Aytaç Adalı, 2018).

Studies utilized PSI method vary in different fields some examples of them are creating a decision support system for student scholarships (Arifin & Saputro, 2022), assessing the performance of young lecturers (F. T. Waruwu, 2021) and examination of a solar combi system for various consumption situations (Lotfabadi et al., 2022).

According to Tuş & Aytaç Adalı (2018), PSI method's computation steps are given below.

Step 1: Creating and normalizing the decision matrix in accordance with the type of the criterion.

Step 2: Calculating the normalized mean performance value for each criterion.

$$\bar{x}_j^* = \frac{1}{m}\sum_{i=1}^{m} x_{ij}^*$$

Step 3: Finding the preference variation value.

$$PV_j = \sum_{i=1}^{m}\left(x_{ij}^* - \bar{x}_{ij}^*\right)^2$$

Step 4: Finding the deviation pf preference value for each criterion.

$$\phi_j = \left(1 - PV_j\right)$$

Step 5: Calculating the weight value for each criterion.

$$w_j = \frac{\phi_j}{\sum_{j=1}^{n} \phi_j}$$

Step 6: Finding the preference selection index.

$$I_i = \sum_{j=1}^{n} x_{ij}^{*} \cdot w_j$$

Step 7: The alternative that has the highest preference selection index value is accepted as the best alternative.

4.3.5 MABAC

Pamucar and Cirovic introduced the Multi-Attributive Border Approximation Area Comparison (MABAC) approach in 2015. This approach relies on defining the distance between alternatives from the approximate border area. Each alternative is analyzed and graded based on the difference in distance. MABAC is a compensating method, with non-dependent attributes, that qualitative ones are translated into quantitative attributes (Alinezhad & Khalili, 2019). The MABAC multi-criteria framework offers several benefits, including reliable outcomes when units of measurement for displaying criteria scores shift, stable remedies when criteria formulation changes such as a change from a benefit to cost type, and suitability to address complex issues that possess various alternatives and criterion thanks to method's simplicity on mathematical side (Torkayesh et al., 2023).

4.3.5.1 MABAC Method's Application Steps

Following its introduction in 2015, the MABAC approach has emerged as one of the increasingly often produced MCDM techniques. The increasing number of papers utilizing the MABAC indicates the need for trustworthy instruments for making decisions on intricate and multifaceted issues. The most common application area that MABAC and its expansions have been utilized to solve is supply chain and logistics. The defense sector, tourism, energy management, finance, and HRM are additional significant application areas that employ MABAC to address various decision-making issues (Torkayesh et al., 2023). The logistics center's handling and transportation resource choices (Pamučar & Ćirović, 2015) and group decision-making with multiple qualities (J. Wang et al., 2020) are some examples of the MABAC's application.

According to Torkayesh et al. (2023) and Alinezhad & Khalili (2019), MABAC's computation steps are as follows.

Step 1: Creating the normalized decision matrix for benefit and cost criteria.

$$r_{ij}^{*} = \frac{r_{ij} - r_i^{-}}{r_i^{+} - r_i^{-}}$$

$$r_{ij}^{*} = \frac{r_{ij} - r_i^{+}}{r_i^{-} - r_i^{+}}$$

Step 2: Weighting the normalized decision matrix.

$$\hat{r}_{ij} = w_j + r_{ij}^{*} w_j$$

Step 3: Computing the matrix border approximation are values.

$$g_j = \left(\prod_{i=1}^{m} \hat{r}_{ij} \right)^{1/m}$$

An $n\ x\ 1$ matrix is produced by calculating the values of the boundary approximation area matrix.

Step 4: The distance between alternatives and the border approximation area is calculated based on the border approximation area matrix amounts and weighted normalized scores for every attribute.

$$q_{ij} = \hat{r}_{ij} - g_j$$

Step 5: The total distance of each choice from the boundary approximation area is computed.

$$S_i = \sum_{j=1}^{n} q_{ij}$$

Step 6: The final ranking of the options is obtained by calculating, from the previous step, the total distances of each alternative from the approximate border area in descending order.

4.3.6 MAIRCA

Pamucar et al. (2018) proposed the Multi-Attribute Ideal–Real Comparative Analysis (MAIRCA) approach that centers on distinguishing the theoretical and practical effects. MAIRCA's unique linear normalizing technique ensures accurate and consistent results. MAIRCA is a powerful mathematical tool and solution method that may be used with other approaches. The following are the advantages of the MAIRCA method:

It can address challenges with multiple criteria for assessment and alternatives, it can deal with qualitative as well as quantitative assessment criteria, it is straightforward to comprehend and function, and the algorithm that it uses generates reliable outcomes (Ecer, 2022).

The MAIRCA approach is centered on discovering disparities among ideal and empirical scores. The total of disparities is estimated for each condition. The estimated total score is the overall disparity among each alternative identified. The concluding step involves rating the alternatives. The top choice in the ranking is the one with the lowest disparity in score. This alternative has the closest possible scores to the ideal score on multiple criteria (Aksoy, 2021).

4.3.6.1 MAIRCA Method's Application Steps

Despite being a widely used technique in MCDM due to how it yields very dependable findings and is a useful mathematical instrument, MAIRCA is unable to adequately convey the uncertainty and obscurity of experts (Ecer, 2022). This approach has the benefit of allowing for both qualitative and quantitative objectives (Nguyen et al., 2022). MAIRCA method is utilized in various study areas such as assessment of supplier performance (Chatterjee et al., 2018), coronavirus vaccination preference (Ecer, 2022) and location selection for under water crossing of tanks (Tešić & Božanić, 2018).

MAIRCA's computation steps are given below according to work of Aksoy (2021) and Nguyen et al. (2022).

Step 1: Creating the initial decision matrix.

Step 2: Figuring out the preferences using the P_{Aj} alternative selection method. It is regarded as though there isn't a favorite among the alternatives. Following that, the criteria's priority stays the same and is as follows:

$$P_{Aj} = \frac{1}{m}$$

Step 3: Developing the theoretical ranking matrix Tp, where n is the total amount of criterion and m is the total amount of alternatives. Tp is a multiplication of the criteria weights Wij by the order of priority of the alternatives P_{Aj} to determine the elements of the mxn matrix.

$$t_{Pij} = p_{Aj} \cdot w_j$$

Step 4: Developing the matrix of real rating t_{rij} for benefit and cost criterion.

$$t_{rij} = t_{Pij}.\left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}\right)$$

$$t_{rij} = t_{Pij}.\left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+}\right)$$

Step 5: Finding the total gap matrix.

$$g_{ij} = t_{Pij} - t_{rij}$$

Step 6: The process of determining the ultimate values of criterion functions by alternatives.

$$Q_i = \sum_{i=1}^{m} g_{ij}$$

4.3.7 EDAS

Ghorabaee et al. (2015) shared the Evaluation based on Distance from Average Solution (EDAS) analysis technique. This approach is useful in situations with contradicting attributes since it calculates the distance between each alternative and the ideal value to determine the best option. This approach is classified as a compensating method. The attributes are all independent of one another and need to be changed from qualitative to quantitative (Alinezhad & Khalili, 2019).

The EDAS technique determines the optimal alternative through its distance from the average solution. Two metrics for alternative acceptability must be calculated: positive distance from average and negative distance from average. The most effective choice in the EDAS approach is decided by its distance from the average value. The decision-makers are not obligated to identify ideal and lowest points answers. That's the benefit of the EDAS technique (Kundakcı, 2019).

4.3.7.1 EDAS Method's Application Steps

The EDAS technique is a rather recent solution of MCDM, it has advantages of straightforward usage and application also it is helpful in decision-making situations where there are competing criteria. There are some studies that employed the EDAS method such as green supplier selection (G. Wei et al., 2021), a fuzzy application of EDAS to assessment of green building energy saving projects (Liang, 2020) and choosing a 3D printer (Lei, Wei, Shen, et al., 2021).

The mathematical application steps of the EDAS method are given below (Kundakcı, 2019).

Step 1: Conducting the initial decision matrix.

Step 2: Calculating the average solution.

$$AV_{j^-} - \frac{\sum_{i=1}^{n} X_{ij}}{n}$$

Step 3: Finding the positive and negative distances from the average.

For benefit,

$$PDA_{ij} = \frac{max\left(0, \left(X_{ij} - AV_j\right)\right)}{AV_j}$$

$$NDA_{ij} = \frac{max\left(0, \left(AV_j - X_{ij}\right)\right)}{AV_j}$$

For cost,

$$PDA_{ij} = \frac{max\left(0, \left(AV_j - X_{ij}\right)\right)}{AV_j}$$

$$NDA_{ij} = \frac{max\left(0, \left(X_{ij} - AV_j\right)\right)}{AV_j}$$

Step 4: Calculating weighted sum of positive and negative distances from the average for alternatives.

$$SP_i = \sum_{j=1}^{m} w_j PDA_{ij}$$

$$SN_i = \sum_{j=1}^{m} w_j NDA_{ij}$$

Step 5: Normalizing the weighted sum values for alternatives.

$$NSP_i = \frac{SP_i}{max(SP_i)}$$

$$NSN_i = 1 - \frac{SP_i}{max(SN_i)}$$

Step 6: Obtaining the appraisal score for alternatives.

$$AS_i = \frac{1}{2}(NSP_i + NSN_i)$$

Step 7: Ranking the alternatives in a decreasing order based on each respective appraisal score value, highest is accepted as the best.

4.3.8 SAW

The SAW (Simple Additive Weighting) technique is additionally referred to as the weighted summing approach. To get the overall score for an alternative, multiply the score by the weight of each attribute (Cahyapratama & Sarno, 2018). The technique, also known as weighted sum, is used to solve problems in decision support systems, evaluating each alternative based on its performance score across all attributes. The SAW provides a more accurate evaluation by considering criteria and predefined preferences (Devi & Sihotang, 2019).

4.3.8.1 SAW Method's Application Steps

The SAW method can function effectively in line with current weights, scores, criteria, as the outcomes are going to be more accurate and objective. The most popular approach for handling the MADM problems is the SAW technique (Amalia & Alita, 2023). Considering the technique is not too complex, this technique is among the easiest to execute (Sumaizar et al., 2021). The SAW technique is a popular strategy for selecting and making decisions. This approach is advantageous because to its versatility and sensitivity (Siregar et al., 2022). There are many studies that used the SAW method such as identifying the standout students (Amalia & Alita, 2023), deciding on transportation-related delivery priorities (Sumaizar et al., 2021) and picking the recipients for food aid (Siregar et al., 2022).

The mathematical computation steps for the SAW method based on the works of Cahyapratama & Sarno (2018) and Devi & Sihotang (2019) are given below.

Step 1: Creating the initial decision matrix.

Step 2: Normalizing the decision matrix with respect to cost and benefit criterion.

$$R_{ij} = \frac{x_{ij}}{\max x_{ij}}$$

$$R_{ij} = \frac{minx_{ij}}{x_{ij}}$$

Step 3: Obtaining the preference value by summing the multiplied normalization values with relative weights.

$$V_i = \sum_{j=1}^{n} w_i R_{ij}$$

Step 4: Ordering the preference values in a decreasing manner which the greatest is considered as the best alternative.

4.3.9 VIKOR

Opricovic introduced the Vise Kriterijumska Optimizajica I Kompromisno Resenje (VIKOR) technique in 1998. This approach is a compromise method in compensating models, where the nearest option to the optimum answer is selected by the subgroup. The approach ranks and selects options with opposing features, resulting in a compromise solution that contributes to the decision maker's final conclusion. This is a compensating strategy that requires independent qualities and the conversion of qualitative to quantitative features (Alinezhad & Khalili, 2019).

The VIKOR approach is a beneficial MCDM tool, especially when the decision maker is unable or unaware of how to articulate their preferences at the start of system design. The resulting compromise solution is acceptable because it maximizes the majority's group utility while minimizing the opponent's individual regret. A compromise of solutions may act as the foundation for talks, taking into account the decision maker's choice for criterion weights. The VIKOR approach quantifies the performance evaluations of alternatives in terms of a collection of criteria as crisp values. However, under many conditions, crisp data are insufficient to mimic real-world scenarios. When faced with competing scenarios or criteria, decision makers should take into account imprecise or confusing evidence (Chatterjee & Chakraborty, 2016).

The VIKOR approach was created to optimize complicated systems using several criteria. The algorithm generates an alternate rank list, a compromise solution, and weight stability differs for the desired stability using the original weights. This strategy focuses on arranging and picking a set of options in the presence of competing criteria. The multi-criteria ranking index measures closeness to the ideal answer. This strategy is successful when decision-makers are unable to articulate their preferences early in system design. This strategy involves arranging and selecting from several options. It provides an alternative answer for situations with competing criteria, assisting decision-makers in reaching a final choice (Hezer et al., 2021).

4.3.9.1 VIKOR Method's Application Steps

The VIKOR method's straightforward and understandable computational processes have made it quite popular among decision-makers. The definition of the positive and negative ideal points forms the foundation of the VIKOR approach (Chatterjee & Chakraborty, 2016). The VIKOR technique proves to be advantageous when decision makers cannot make the decision at the initial step of creation of a system (Perdana et al., 2023). VIKOR is a very popular method in the MCDM field, there are many studies and analyses conducted with VIKOR such examples of them are improving the efficiency of the gas pipeline network (Gharieb et al., 2023), assessment of citizens' satisfaction levels (Yıldırım & Yıldırım, 2022) and financial risk assessment of sustainable supply chains (Wang et al., 2023).

The mathematical steps for VIKOR method application are given below based on the studies of Chatterjee & Chakraborty (2016) and Perdana et al. (2023).

Step 1: Creating the decision matrix and determining each criterion's maximum and minimum values.

Step 2: Normalizing the decision matrix.

$$R_{ij} = \left(\frac{X_j^+ - X_{ij}}{X_j^+ - X_j^-}\right)$$

X_j^+ is the maximum value of the criterion (minimum if the criterion is cost).

X_j^- is the minimum value of the criterion (maximum if the criterion is benefit).

Step 3: Multiplying each normalized value for each criterion with weights.

$$W_{ij} = r_{ij}.w_j$$

Step 4: Calculating the sum of the alternatives

$$S_i = \sum_{j=1}^{n} W_{ij}$$

Step 5: Obtaining the worst group score.

$$R_i = maxj\left[w_j\left(\frac{X_j^+ - X_{ij}}{X_j^+ - X_j^-}\right)\right]$$

Step 6: Calculating the index scores.

$$Q_i = \left[\frac{S_i - S^+}{S^+ - S^-}\right] V + \left[\frac{R_i - R^+}{R^+ - R^-}\right] (1 - v)$$

S^- is the minimum of S_i.

S^+ is the maximum of S_i.

R^- is the minimum of R_i.

R^+ is the maximum of R_i.

v is accepted as 0.5. v value is between 0 and 1. The compromise can be chosen by veto (v < 0.5), consensus (v = 0.5), or voting by majority (v > 0.5). More precisely, a procedure for making decisions that can employ the approach of maximizing group utility is represented by v equal to unity; on the other hand, a procedure that can employ a minimum individual regret strategy, which is identified within the maximum individual regret criteria, for each alternative is represented by v equal to zero. The decision specialist typically determines the value of v externally, which impacts the order of the alternatives.

Step 7: Ranking the alternatives and inspection of the conditions.

The alternatives are ranked based on their respective S_i, R_i and Q_i values. Then two conditions are checked based on the rules given below.

Condition 1: Acceptable Advantage

$$Q(A2) - Q(A1) \geq DQ$$

$Q(A2)$ is the second-best alternative, $Q(A1)$ is the first best alternative and $DQ = 1/(n-1)$ where n is the number of alternatives.

Condition 2: Acceptable Stability

The alternative $A1$ has to be accepted as best alternative in the rankings of S_i and R_i.

The following compromise options is put up in the event that one or more of the aforementioned requirements is not met:

First if Condition 2 is the only one that is not met alternatives $A1$ and $A2$ as accepted best, secondly if Condition 1 is the only one that is not met alternatives are ranked as $A1, A2, \ldots, A^N$. A^N is obtained as follows for maximum N,

$$Q(A^N) - Q(A1) < DQ$$

4.3.10 TOPSIS

Hwang and Yoon's Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) approach, created in 1981, is the second most common MCDM technique after Saaty's AHP (1980). This method is effective for complex situations with several criteria and options due to its simplicity and adaptability. The TOPSIS estimation steps involve normalizing the decision matrix, calculating the weighted normalized decision matrix, identifying the positive ideal and negative ideal solutions, estimating the difference or distance of each alternative from positive ideal solution and negative ideal solution, determining the ranking index, and ranking the preference order (Çelikbilek & Tüysüz, 2020).

TOPSIS logic is sound and apprehensible; calculation methods are simple; the idea allows for the search of the most suitable alternatives for each criterion in an easy mathematical format; and significance weights are included into comparative processes. Nevertheless, the TOPSIS technique has several limitations. A drawback with TOPSIS is the possibility of rank inversion. By adding or removing alternatives from a decision issue, the order of preference shifts. Total rank inversion occurs when the order of preferences is completely reversed. This means that the most desirable alternative turns into the least favorable once an alternative is added or removed from the procedure. This occurrence may not be tolerated in some situations (García-Cascales & Lamata, 2012).

The approach evaluates options based on the gap between positive and negative optimal outcomes. When making a selection, an option should be near to the ideal answer rather than the non-ideal. The option that is nearest to the positive ideal outcome is likewise viewed as the one farthest from the ideal negative outcome. The TOPSIS approach identifies the optimal option that is nearest to the positive ideal option. Also, the TOPSIS approach assists in evaluating decision-making units (Hezer et al., 2021).

4.3.10.1 TOPSIS Method’s Application Steps

The TOPSIS method has many advantages such as straightforward usage, yet it suffers from a possible order inversion when additional alternatives are considered which may result in complete opposite results (García-Cascales & Lamata, 2012). Despite this setback the TOPSIS technique has been widely utilized in MCDM field. Some studies that employed TOPSIS are selection of green supplier in food industry (Hajiaghaei-Keshteli et al., 2023) , conducting a suitability assessment system (Li et al., 2022) and evaluation of sustainable cities and communities (Wątróbski et al., 2022).

The computation steps necessary for the TOPSIS method are given below based on the study primed by Li et al. (2022).

Step 1: Conducting the initial decision matrix.

Step 2: Normalizing the decision matrix with respect to beneficial and non-beneficial criteria.

$$y_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}$$

$$y_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}$$

Step 3: Weighting the normalized decision matrix.

$$z_{ij} = w_j \times y_{ij}$$

Step 4: Obtaining the positive and negative ideal solution scores.

$$Z^+ = \{Z_1^+, Z_2^+, \dots, Z_n^+\} = \{\max Z_{ij}\}$$

$$Z^- = \{Z_1^-, Z_2^-, \dots, Z_n^-\} = \{\min Z_{ij}\}$$

Step 5: The distances to the ideal solution scores, for both positive and negative, are calculated.

$$S_i^+ = \sqrt{\sum_{i=1}^{n} (Z_{ij} - Z_j^+)}$$

$$S_i^- = \sqrt{\sum_{i=1}^{n} (Z_{ij} - Z_j^-)}$$

Step 6: Finding the coefficient of the closeness.

$$C_i = \frac{S_i^-}{S_i^- + S_i^+}$$

4.3.11 GRA

Deng introduced the Grey Relational Analysis (GRA) approach, which is frequently utilized to tackle uncertainty issues with discrete data and inadequate information. The GRA technique is a prominent approach for analyzing correlations between discrete data sets and making judgments in numerous attributes (Hou, 2010).

GRA is capable of identifying the relationship between a sequence of references and its comparison sequences. The optimal comparison option may be determined by further analyzing the related grades. Grey relational analysis measures similarity between finite sequences (Chang & Yeh, 2005).

GRA is a multifactorial statistical analysis approach that addresses partial, inadequate and imprecise data challenges and may be used to manage the interaction between distinct objectives. This approach uses several calculations based on the purpose and orientation. Data pretreatment converts original sequences into similar ones, allowing simulation results to be standardized between 0 and 1. GRA may employ a variety of formulae depending on the objective features of the original sequence. The ideal value of an original sequence is the minimum, indicating that the lower, the greater (Shan et al., 2020).

At its core, the GRA compares the similarities of alternatives to a reference set series that need selection, either all of them or none of them. The alternatives with the highest resemblance to the reference series are judged the best. This technique allows for comparisons and decision-making with minimum information. In brief, it is the process of producing, digging, and obtaining relevant data from partly identified data as well as data that is already present. The expression grey implies ambiguous data, values, or systems. Disturbance in data, both external and internal, might restrict the system's scope. Grey systems provide the benefit of using less data to analyze or compute the behavior of an uncertain system. While there are certain analogies between grey and fuzzy systems, the fuzzy method calls for cognitive research components, whereas grey systems rely on insufficient data (Škrinjarić, 2020).

4.3.11.1 GRA Method’s Application Steps

The GRA approach has several advantages, including being based on real data, having clear and uncomplicated computations, and being an effective decision-making tool in corporate settings (Hou, 2010). This method permits these kinds of comparisons and decision-making with the least amount of accessible information (Škrinjarić, 2020). There are many studies that employs the GRA method such as the assessment for quality levels of services in agricultural e-commerce (Zhang & Wang, 2022), choosing agricultural machinery (Lu et al., 2022), and analyzing the performance of building ventilations (Yuce et al., 2022).

The application steps are given below based on the study conducted by Yuce et al. (2022).

Step 1: Creating the initial decision matrix.

Step 2: Normalizing the decision matrix with respect to higher, lower and nominal value.

$$y_i(k) = \frac{x_i^0(k) - min\, x_i^0(k)}{max\, x_i^0(k) - min\, x_i^0(k)}$$

$$y_i(k) = \frac{max\, x_i^0(k) - x_i^0(k)}{max\, x_i^0(k) - min\, x_i^0(k)}$$

$$y_i(k) = 1 - \frac{|\, x_i^0(k) - x^0|}{max\, x_i^0(k) - x^0}$$

Step 3: In this step normalized values are compared to a selected value. This step requires the selection of normalization methods given above, for this step lower value normalization is selected. Grey relational coefficient is calculated as follows.

$$\xi_i(k) = \frac{\Delta_{min} + \varphi\Delta_{max}}{\Delta_{0i}(k) + \varphi\Delta_{max}}$$

$$\Delta_{0i}(k) = y_0(k) - y_i(k)$$

$$\Delta_{max} = max_{\forall ji} max_{\forall k} y_0(k) - y_i(k)$$

$$\Delta_{min} = min_{\forall j \varepsilon i} min_{\forall k} y_0(k) - y_i(k)$$

φ coefficient has a value between 0 and 1 and it is accepted as 0.5 in the literature.

Step 4: The grey relational degree is calculated.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} w_k \xi_i(k)$$

4.3.12 COPRAS

Zavadskas and Kaklauskas initially presented the The Complex Proportional Assessment (COPRAS) approach for making multiple-criteria decisions. The COPRAS technique employs a sequential ranking and evaluation procedure for alternatives in terms of relevance and usefulness degree. COPRAS approach can be considered simpler to operate than alternative approaches like AHP and TOPSIS due to its reduced computation requirements. COPRAS is capable of computing both maximizing and minimizing criteria and it can also compute qualitative and quantitative criteria. The COPRAS approach distinguishes itself from other multi-criteria decision-making methods by demonstrating utility degree. When comparing options, it can show which is more effective or worse (Organ & Engin, 2016).

COPRAS evaluates and compares options to determine which is superior. This strategy is useful for maximizing or minimizing criteria in assessments that include many criteria. The COPRAS approach sorts and assesses options based on significance and usefulness degree (Hezer et al., 2021). As it is proposed in 1994, the COPRAS is a compensating approach in which characteristics are independent and qualitative elements can be turned into quantifiable parameters (Alinezhad & Khalili, 2019).

4.3.12.1 COPRAS Method's Application Steps

The main benefits of the COPRAS method are the straightforward application, obtaining both optimal and non-optimal solution points and it can generate results in a rather short duration of time (Kumari & Mishra, 2020). There are many studies that utilizes the COPRAS method as a MCDM technique such as selection of a green supplier (Kumari & Mishra, 2020), determining the best alternative option for fuel (Narayanamoorthy et al., 2021), and choosing a product for biodegradable dynamic plastic (Kang et al., 2023).

The application steps for COPRAS method as follows (Organ & Engin, 2016).

Step 1: Creating the initial decision matrix.

Step 2: Normalizing the initial decision matrix.

$$\tilde{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Step 3: Conducting the weighted normalized decision matrix.

$$D' = d_{ij} = x_{ij}^{*} \cdot w_j$$

Step 4: Finding the maximizing and minimizing indexes of each alternative.

$$S_{i+} = \sum_{j=1}^{k} d_{ij}$$

$$S_{i-} = \sum_{j=k+1}^{n} d_{ij}$$

Step 5: Computation for finding the alternative's weights.

$$Q_i = S_{+i} + \frac{\min\limits_i \quad \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{\min\limits_i S_{-i}}{S_{-i}}}$$

Step 6: The relative weight of the evaluated alternatives determines the order of ranking. The alternative containing the largest relative weight is prioritized and considered the most desirable alternative.

$$A^* = \left\{ A_i | \max\limits_i Q_i \right\}$$

Step 7: Determining the performance index score for alternatives. The alternative that reaches the score of 100 is considered best.

$$P_i = \frac{Q_i}{Q\max} \cdot 100\%$$

4.3.13 MAUT

Keeney and Raiffa mainly introduced the Multi Attribute Utility Theory (MAUT) in 1976. The core notion behind MAUT is the concept that in each choice issue, there exists a real valued function or utility that needs to be maximized. MAUT allows decision-makers to evaluate all possibilities at the same time. The utility function, specified across a collection of criteria, reflects the decisionmaker's choices. In MAUT, the effectiveness of options is calculated using the utility value produced from a single attribute utility function. After calculating the integrated utility for every other option, the decision maker rates them all. Following calculating the integrated utility for every option, the decision maker rates them all (Aytaç Adalı & Tuş Işık, 2017).

MAUT transforms multiple preferences into quantities on a scale of zero to one, with zero becoming the poorest option and one reflecting the greatest. This permits straightforward comparisons of different sizes. The MAUT is generally used to tackle difficult issues with multiple criteria and outcomes. Decision makers evaluate results according to their utility, or relative attractiveness. The ultimate result is a ranked list of alternative assessments (Taufik et al., 2021).

It provides decision makers with flexibility to achieve greater precision and achievable outcomes. This approach is a compensating method, and the traits are independent of one another. Qualitative qualities are translated into quantitative attributes (Alinezhad & Khalili, 2019). The MAUT technique highlights alternatives with the greatest overall utility value and ranks alternatives accordingly (Karakış, 2021).

4.3.13.1 MAUT Method's Application Steps

The primary benefit of the MAUT is respecting the possible uncertainties. It may be assigned a utility, which is a feature that many MCDM techniques do not take into consideration (Taufik et al., 2021). Several decision issues are solved using MAUT technique, particularly in the social science and engineering domains (Karakış, 2021). Such solution examples are diplomat selection (Taufik et al., 2021), deciding on new branch location (Mesran et al., 2024) and airlines' financial performance assessment (Sümerli Sarıgül et al., 2023).

According to Aytaç Adalı & Tuş Işık (2017) and Karakış (2021) the application steps for MAUT technique are given below.

Step 1: Defining the criteria, the alternatives and conducting the decision matrix.

$$X = \begin{bmatrix} x_{11} & x_{12} \dots & x_{1n} \\ x_{21} & x_{2^2} \dots & x_{2n} \\ x_{n1} & x_{n2} \dots & x_{mn} \end{bmatrix}$$

Step 2: Normalization of the decision matrix with respect to beneficial and non-beneficial criterion.

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}$$

Step 3: In order to compute the relevance weights of the criterion, the standard deviation is computed using correlation coefficients between the criteria.

$$w_j = \frac{C_j}{\sum_{i=1}^{n} C_j}$$

The w_j is the weight of the criteria, j is the rate of priority and C_j is the index score of criteria j. The standard deviation of criterion j and the correlation coefficient among the criteria.

$$C_j = \sigma_j \sum_{i_{\dot{x}}=1}^{n} (1 - p_{jk})$$

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x_{ij} - \bar{x}\right)^2}$$

$$p_{jk} = \frac{\sum_{i=1}^{m}\left(x_{ij} - \bar{x_j}\right)\left(x_{ik} - \bar{x}_k\right)}{\sqrt{\sum_{i=1}^{m}\left(x_{ij} - x_j\right)^2 \sum_{i=1}^{m}(x_{ik} - \bar{x}_k)^2}}$$

p_{jk} is the average value of the criteria and σ_j is the standard deviation value of the criteria.

4.3.14 OWA Operator

MCDM issues can benefit from several aggregating operators, including weighted averaging, weighted geometric, and Ordered Weighted Averaging (OWA). Yager suggested the OWA operator in 1988. This is a parameterized class for mean type aggregation operators. Determining the weights of OWA operators yields specific aggregation operators like max, arithmetic average, and min. Its efficiency has led to widespread application in disciplines like ML. Implementing the method of the OWA operator consists of three steps: First input values are sorted in decreasing order. Then the relative weights of the reorganized input values are computed in an effective way. And lastly the generated weights are used to aggregate the reorganized input values to a single value. Determining the weights of rearranged input values is crucial for OWA operators, as employing varied weighting data might lead to inconsistent ranking outcomes. The weights for the OWA operator can be calculated objectively by not accounting for the complicated data distribution features of input values. While the distribution supposition techniques presume that the OWA operator weights are distributed according to a variety of frequently utilized probability density functions. Despite having strong theoretical underpinnings and desired qualities, the optimal notion is impractical as real OWA operator weights often fail to correspond to probability density functions in real-world circumstances (Lin et al., 2020).

The OWA methodology has been presented as one of the combined techniques in the context of multicriteria decision-making procedures, which has its foundation on fuzzy set theory. The OWA technique uses order weights that are distinct from standard weights. The standard weights are allocated to the criteria utilized, whereas the order weights are issued to the criteria's values as pixels by pixels. This strategy is also very adaptable to the demands and focus of decision-makers (Hajizadeh et al., 2020).

OWA ensures equality by overweighing the least pleased items. OWA's unique qualities include individual utility monotonicity, resulting in Pareto efficiency for OWA-optimum solutions. Monotonicity in utility transfers between richer and poorer agents reduces inequities and ensures equality in OWA optimum systems (Mogtit et al., 2020).

4.3.14.1 OWA Operator Method's Application Steps

The OWA Operator offers a distinct approach to decision-making with many kinds of risks (Mokarram et al., 2021). OWA has been used in many studies such as modeling for urban development (Ghasemkhani et al., 2020), location prediction (Mokarram et al., 2021) and assessment of failure risk (Chang & Cheng, 2011).

According to Jin et al. (2019) the application steps given below.

Step 1: Creating a decision matrix.

$$X = [X_{ij}]_{mxn} = X = \begin{bmatrix} x_{11} & x_{12} \dots & x_{1n} \\ x_{21} & x_{2^2} \dots & x_{2n} \\ x_{n1} & x_{n2} \dots & x_{mn} \end{bmatrix}$$

Step 2: Normalization of the decision matrix.

For benefit criteria.

$$r_{ij} = \frac{x_{ij}}{max x_{ij}}$$

For cost criteria.

$$r_{ij} = \frac{min x_{ij}}{x_{ij}}$$

Step 3: Calculation of OWA values for each alternative.

$$Z_i(w) = OWA(w)(r_{i1}, r_{i2}, \dots, r_{im}) = \sum_{j=1}^{m} w_j b_{ij}$$

b_{ij} = normalized values arranged in decreasing order of value.

4.3.15 TODIM

Gomes and Lima's Tomada de Decisão Iterativa Multicritério (TODIM) technique, built around prospect theory, is a successful approach to make behavioral decisions. The TODIM's key benefit is that it considers the decision maker's psychological characteristics. Primarily due to its ability to capture loss and gain despite uncertainties from a point of reference and decision makers' sensitivity to loss. The whole rationality decision making prioritizes utility maximization, whereas the TODIM technique prioritizes value function maximization. As a result, the TODIM approach is an effective tool to reach behavioral decisions with restricted rationality (Huang et al., 2017).

TODIM is straightforward to implement as well as comprehend compared to other MCDM approaches like evolutionary algorithms. TODIM is additionally easy to code using any high-level language, including MATLAB, Stata, and SAS. TODIM is centered around prospect theory, that describes the way people determine actions in the midst of uncertainty. The hypothesis highlights that people react asymmetrically to gains and losses. Losses alongside comparable gains have a larger absolute value. This response level differential may be quantified in TODIM using an attenuation factor (Alali & Tolga, 2019).

The TODIM technique first appeared in 1992. The approach involves calculating the entire value of every option to determine its superiority over others, followed by ranking them appropriately. This approach falls under the category of compensating tools. The qualities are independent of one another. Qualitative qualities require being transformed to quantitative attributes (Alinezhad & Khalili, 2019).

4.3.15.1 TODIM Method’s Application Steps

Compared to other MCDM techniques like evolutionary algorithms, TODIM is thought to be more straightforward, easy to use, and understandable for practitioners (Alali & Tolga, 2019). Yet this method contains two paradoxes regarding the weights of the criteria. One occurs if a multicriteria approach yields an unfavorable result that some decision makers find unexpected or strange, and the other paradox occurs when the overall performance of the alternatives changes with a manipulation to the criterion weights the relationships between the alternatives with the changing weight vector is differentiates (Llamazares, 2018). The TODIM technique has been utilized in many different fields such as a selection for mining technique (Dehghani et al., 2017), an analysis for natural gas destination in Brazil (Gomes et al., 2009) and portfolio allocation (Alali & Tolga, 2019).

The application steps for the TODIM method are given below based on the studies Llamazares (2018) and Alinezhad & Khalili (2019).

Step 1: Creating the normalized decision matrix for beneficial and non-beneficial criterion.

Step 2: Obtaining the relative weight.

$$w_{kr} = \frac{w_k}{w_r}$$

Step 3: Calculating the dominance degree for each alternative.

$$\Phi_k(A_i, A_j) = \begin{cases} \sqrt{\dfrac{w_{kr}(z_{ik} - z_{jk})}{\sum_{\iota=1}^{m} w_{\iota r}}} & if\ z_{ik} \geq z_{jk} \\ -\dfrac{1}{\theta}\sqrt{\dfrac{(\sum_{\iota=1}^{m} w_{\iota r})(z_{ik} - z_{jk})}{w_{kr}}} & if\ z_{ik} < z_{jk} \end{cases}$$

With the help of this parameter, decision maker is able to rank the alternatives based on benefits and costs: the best solutions are those that produce greater benefits for big values of θ, and the best solutions with smaller losses for small values of θ.

Step 4: Overall degree of dominance for each alternative is calculated as follows.

$$\Phi(A_i, A_j) = \sum_{k=1}^{m} \Phi_k(A_i, A_j)$$

Step 5: Overall performance for each alternative is determined.

$$\Phi(A_i) = \sum_{j=1}^{n} \Phi(A_i, A_j)$$

Step 6: Normalized overall performance for each alternative is determined.

$$\xi(A_i) = \frac{\Phi(A_i) - min_{j \in N}\Phi(A_j)}{max_{j \in N}\Phi(A_j) - min_{j \in N}\Phi(A_j)}$$

Step 7: Alternatives are sorted based on the normalized overall performance values.

$$A_i \geq A_j \Leftrightarrow \xi(A_i) \geq \xi(A_j)$$

4.3.16 OCRA

The Operational Competitiveness Rating Analysis (OCRA) technique is one of the MCDM approaches that is used for comparing competing alternatives. The technique takes a simple approach to integrate decision makers' preferences for the corresponding importance of criteria. Parkan introduced the OCRA technique in 1991. The OCRA approach is useful for MCDM scenarios in which criteria weights vary by alternatives while certain criteria aren't relevant to all alternates. This strategy distinguishes between helpful (maximizing) and unhelpful (minimizing) criteria, preventing knowledge loss throughout decision-making, and then combines these scores to generate operational competitiveness scores. The OCRA technique is nonparametric, meaning it does not require further variables to calculate (Madić et al., 2015).

OCRA, utilizes a nonparametric approach to analyze comparative effectiveness. This application is beneficial and user-friendly for comparing and contrasting various decision items and areas. Furthermore, monitoring and evaluating decision function over time. The OCRA practice evaluates options according to positive and negative criteria, resulting in a competitive evaluating that prevents data loss when decision-making (Wijaya et al., 2022).

OCRA approach had additional modifications by Parkan and Wu in 1997, 1999, and 2000. Initially, this approach was designed to assess the comparative effectiveness of a group of production units that employ resources to generate value-added products. Afterwards was utilized to handle multi-criteria decision-making issues. The OCRA procedure is straightforward and considers decision makers' preferences for determining the relevance of criteria. It is beneficial when individual criteria are weighted differently based on the alternatives, as certain criteria aren't necessarily relevant to all alternatives (Lukić & Zekić, 2021).

4.3.16.1 OCRA Method’s Application Steps

The positive aspect of this approach is that it treats the not advantageous (minimization) and advantageous (maximization) criteria independently, which aids in preventing information loss for the decision-makers. Also, incorporating further parameters, like in VIKOR, has no effect on the calculating process (Madić et al., 2015). The OCRA technique is employed in many MCDM studies such as selection of electronic devices (Özdağoğlu & Çirkin, 2019), a gray application of OCRA for personnel selection (Ulutaş et al., 2020) and online sales platform selection (Wijaya et al., 2022).

The calculation steps of the OCRA method are as follows (Wijaya et al., 2022).

Step 1: Creation of the decision matrix.

Step 2: Computing the preference rating based just on the alternatives' performance values in relation to the cost criterion.

$$\bar{I}_i = \sum_j^g wj \frac{max(x_{ij}) - x_{ij}}{min(x_{ij})}$$

Step 3: Ascertain each alternative's linear preference ranking in relation to the criterion that has to be minimized, cost.

$$\bar{I}_i = \bar{I}_i - \min(\bar{I}_i)$$

Step 4: Preference ratings in relation to the beneficial factors are established in this stage.

$$\bar{O}_i = \sum_{j=g+1}^{n} wj \frac{x_{ij} - min(x_{ij})}{min(x_{ij})}$$

Step 5: Finding the linear preference score for the beneficial criterion.

$$\bar{\bar{O}}_\iota = \bar{O}_\iota - min(\bar{O}_\iota)$$

Step 6: The competitor alternatives' total preference values are computed.

$$P_i = \bar{\bar{I}}_\iota + \bar{\bar{O}}_\iota - min(\overline{\overline{I_m}} + \overline{\overline{O_m}})$$

Step 7: Total preference scores are used to determine the ranking of all available alternatives. First position goes to the option with the best overall performance score.

5. FINDINGS AND ANALYSES

In this section, goal of the study, research design and analyses of the thesis are shared.

5.1 Goal of the Study

This study aimed to rank matching-based algorithms on recruitment platforms according to the aspects that expert managers in product, marketing, customer experience, sales, and software development would consider most important. Experts in their respective domains—product, marketing, customer success, sales, and software development—with a median of ten years of experience were involved in the study to achieve this goal. The matching algorithms that are considered as alternatives in this study are rule-based, weighted score-based, skill-based, collaborative filtering, content-based filtering, clustering-based, ML–based, NLP-based. The evaluation criteria for matching algorithm alternatives are accuracy, efficiency, scalability, flexibility, user satisfaction, robustness, explainability and cost. Besides cost criteria, every criterion is considered as beneficial, cost criteria regarded as non-beneficial.

By utilizing two different weight assessment methods and two different ranking methods of MCDM, it is aimed to identify if the results contain any correlation or similarity with the same data set.

5.2 Research Design

In this study, participants were selected from a company that manages an online recruitment platform which promotes a horizontal organization where team managers have power, influence, and knowledge that extends beyond their own areas of expertise. Selected participants are product, sales, customer success, marketing and software development team managers who each possess a median of decade of experience in their resume. Each participant is considered as a SME within their respective expertise and considered resourceful and knowledgeable in their coworkers' fields. Therefore, it is believed that their viewpoints would provide meaningful results.

Provided data by SMEs is used in various ways. First for determining weights with AHP method, each participant scored each criterion within themselves using the AHP scale. The geometric mean is calculated for each score provided by each SME for each criterion. This matrix used as the decision matrix in the study for weight assessment.

Secondly, for weight determination with SWARA method, each SME ranked each criterion according to their importance and gave score between 0 and 1 for each criterions' importance.

Finally, to rate various matching algorithms utilizing VIKOR and WASPAS approaches, each SME assigned a score of 1 to 100 to each criterion. This matrix served as the fundamental decision matrix for ranking techniques VIKOR and WASPAS, with the means calculated for each data point.

The research design is intended to determine whether there is a correlation among distinct findings as well as how the outcomes vary from one another, using two separate approaches for criterion weight assessment and two distinctive approaches for ranking the alternatives in order to discover the best matching algorithm alternative. For purposes of comparing the outcomes, data analysis and the mathematical calculations were performed. The comparison is conducted in the following order: VIKOR with AHP weights, VIKOR with SWARA weights, WASPAS with AHP weights, and WASPAS with SWARA weights.

Following the outcomes of the decision-making approaches, Kendall's Coefficient of Concordance is employed to demonstrate the degree of agreement between the MCDM methods used in this research.

For better understanding of the tables used in all method, criteria in the study have been organized and summarized in Table 1.

Table 1: Criterion

C1	Accuracy	Beneficial
C2	Efficiency	Beneficial
C3	Scalability	Beneficial
C4	Flexibility	Beneficial
C5	User satisfaction	Beneficial
C6	Robustness	Beneficial
C7	Explainability	Beneficial
C8	Cost	Non- Beneficial

Likewise, matching algorithm alternatives in the study have been organized in Table 2.

Table 2: Alternatives

A1	Rule-Based
A2	Weighted Score-Based
A3	Skill-Based
A4	Collaborative Filtering
A5	Content-Based Filtering
A6	Clustering-Based
A7	ML-Based
A8	NLP-Based

5.3 Analysis

For the analysis of the study MCDM methods AHP, SWARA and VIKOR were selected. SMEs were assigned with filling out an AHP-based pairwise comparison matrix. Six SME compared each criterion using the AHP scale, based on their viewpoints. Each criterion's weight was estimated using the provided data. Second, each importance level was rated according to the criteria and ranked for the SWARA technique. Lastly, the SMEs evaluated each algorithm afterward, taking into account every criterion, to produce a decision matrix. This matrix later utilized in VIKOR and WASPAS methods. In final step Kendall's Coefficient of Concordance is calculated and compared each result obtained by AHP-VIKOR, AHP-WASPAS, SWARA-VIKOR and SWARA-WASPAS in order to find that does the results for different weighting and ranking methods share a correlation.

In this section, steps of analysis are shared. In first step weights for each criterion determined by AHP and SWARA. In second step each alternative matching algorithm is ranked using VIKOR and WASPAS. Sorting results compared and analyzed with Kendall's W.

5.3.1 Determination of Weights

In this study both AHP and SWARA methods utilized to determine relative weights of the criterion.

The relative importance of the components in a hierarchy is expressed via pairwise comparisons in the two approaches. However, relative to the SWARA, which has a substantially lesser needed number of

comparisons, the AHP approach demands a substantially higher amount of pairwise comparisons given the exact same set of criterions. The consistency of completed comparisons may suffer when employing the AHP approach. But the AHP approach incorporates an effort to verify the consistency of executed comparisons, making it simple to identify the insufficient response. The SWARA approach follows a different process. The SWARA approach is more appealing to employ since it requires a substantially smaller quantity of comparisons. Another distinction among them is the usage of predetermined scales to convey preferences. The AHP approach typically uses a nine-point scale, whereas the SWARA technique allows respondents more latitude for conveying their opinions (Stanujkic et al., 2015). Considering the advantages and disadvantages of both of these approaches, in this study the selection goal of these methods was to find if there is a difference in results using both methodologies with our data set.

5.3.1.1 AHP

At first step of this study, AHP method utilized to find the weights of the selected criteria. Participant SMEs gave scaled values to each criteria comparison. Scale used in this stage is given in Table 3.

Table 3: AHP Scale

Intensity of Importance	Definition
1	Equal importance
3	Somewhat more important
5	Much more important
7	Very much more important
9	Absolutely more important
2,4,6,8	Intermediate values between two adjacent judgments

The comparison matrix and criteria weights were established based on the data provided by SMEs using the scale in Table 3.

The starter matrix is given in Table 4. The geometric mean was used to generate the findings from the comparison matrices.

Table 4: Decision Matrix for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1,000	0,907	0,971	1,070	0,281	1,558	0,577	0,945
C2	1,103	1,000	0,812	1,165	0,237	0,523	0,393	0,618
C3	1,029	1,232	1,000	0,400	0,206	0,316	0,322	0,602
C4	0,935	0,858	2,501	1,000	0,243	0,483	0,331	0,501
C5	3,557	4,223	4,857	4,116	1,000	4,044	1,661	0,570
C6	0,642	1,913	3,166	2,070	0,247	1,000	0,585	0,567
C7	1,732	2,542	3,107	3,018	0,602	2,466	1,000	0,496
C8	1,058	1,619	1,661	1,995	1,754	1,763	2,018	1,000

And weighted scores were derived for each choice in Table 4. Calculated weights are shown in Table 5.

Table 5: Weights of Criterion with AHP

Criteria	Weights
C1	0,091
C2	0,070
C3	0,062
C4	0,073
C5	0,258
C6	0,104
C7	0,160
C8	0,181

Consistency measurements of these weights are assessed once the weights for each criterion have been determined. Comparison matrix is multiplied with each weight, then each row is summarized, data table can be found in Appendix 1. Summarized values are then divided by each respective weight. Divided values are then summarized again to find the value λ_{max}.

Table 6: Consistency Ratio Calculation

λ	CI	RI	CR = CI/RI	CR < 0.1
8,662	0,095	1,404	0,067	TRUE

CI value is calculated by λ_{max} minus number of criteria divided by number of criteria minus one. With respective RI index value CR is processed by dividing the CI with index value. A comparison matrix with a reasonable degree of consistency is indicated by a CR of less than 0.10. If not, the matrix is inconsistent, and its value needs to be changed. After computations CR value found as 0.06 which is under the limit for accepting the weights calculated by AHP as consistent.

5.3.1.2 SWARA

The SWARA approach is chosen since the application stages are deemed simple to follow, being relatively a recent method and its' enabling of latitude for its participants to express their opinions.

The SMEs were asked to rank each criterion for their perceived importance in Table 7.

Table 7: Ranking Criteria Based on Expected Significance

	SME1	SME2	SME3	SME4	SME5	SME6
C1	2	8	8	1	5	4
C2	5	6	7	2	8	8
C3	8	7	6	3	7	6
C4	7	5	5	4	6	5
C5	1	1	3	5	1	1
C6	6	3	4	6	4	3
C7	4	4	2	7	2	2
C8	3	2	1	8	3	7

Each rank is scored a point between 0 and 1 by SMEs in Table 8.

Table 8: Scoring Relative Importance of Criterion

	SME1	SME2	SME3	SME4	SME5	SME6
C1	0,90	0,30	0,30	1,00	0,60	0,70
C2	0,60	0,50	0,40	0,90	0,30	0,30
C3	0,30	0,40	0,50	0,80	0,40	0,50
C4	0,40	0,60	0,60	0,70	0,50	0,60
C5	1,00	1,00	0,80	0,60	1,00	1,00
C6	0,50	0,80	0,70	0,50	0,70	0,80
C7	0,70	0,70	0,90	0,40	0,90	0,90
C8	0,80	0,90	1,00	0,30	0,80	0,40

The SWARA's subsequent actions are calculated. Results for values of $\overline{P}_i$, S_i, C_i, $S_i^{'}$ can be found in the Appendix 2. The following Table 9 lists the weights determined using the SWARA method:

Table 9: Weights of Criterion with SWARA

Criteria	Final Weight Values (ω_j)
C1	0,122
C2	0,107
C3	0,106
C4	0,114
C5	0,157
C6	0,126
C7	0,137
C8	0,130

5.3.2 Evaluation of Matching Algorithms

The two approaches were applied in order to optimize the choice of both the highest and lowest ratings and provide an objective judgment (Rahayu & Rahmadani, 2020).

The VIKOR approach uses a near-ideal answer and evaluates alternatives based on established criteria. It rates alternatives to find the optimal compromise solution and is effective when the decision maker lacks the capacity to make decisions during the development of the system. The WASPAS technique mixes a pairwise comparison and various preferences to choose the optimal alternative. It is user-friendly, offers easy comprehension of the findings, and takes into account the relative importance of each factor (Perdana et al., 2023).

Given the benefits and drawbacks of both MCDM ranking approaches, they are selected in this study to determine whether there would be a difference in results with our data set.

The decision matrix used in VIKOR and WASPAS methods created by calculating mean of each score given by each SME between 1 and 100 to alternative matching algorithms for each criterion evaluated in the thesis. Scores provided by SMEs given in Appendix 3. The overall decision matrix with calculated mean values shown in Table 10.

Table 10: Decision Matrix for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	87,50	70,83	60,83	65,83	81,67	65,83	81,67	74,17
A2	87,50	75,83	73,33	70,83	87,50	67,50	78,33	71,67
A3	90,00	73,33	70,00	69,17	89,17	73,33	80,83	79,17
A4	78,33	64,17	74,17	66,67	80,00	70,00	66,67	70,00
A5	82,50	73,33	80,00	72,50	81,67	71,67	69,17	65,00
A6	82,50	66,67	79,17	70,83	81,67	75,83	72,50	70,00
A7	90,00	78,33	86,67	85,00	89,17	83,33	80,00	84,17
A8	93,33	85,83	86,67	85,83	90,83	84,17	82,50	84,17

Best and worst values of decision matrix is given in Table 11.

Table 11: Best and Worst Criteria Values

	A1	A2	A3	A4	A5	A6	A7	A8
f_j^*	93,33	85,83	86,67	85,83	90,83	84,17	82,50	65,00
f_j^-	78,33	64,17	60,83	65,83	80,00	65,83	66,67	84,17

5.3.2.1 VIKOR

Both weights obtained by AHP and SWARA methods used in VIKOR technique and then results compared.

5.3.2.1.1 VIKOR with AHP Weights

The decision matrix for VIKOR is provided by participants in Table 10. Regarding the criterion, each participant assigned a score for every matching algorithm choice ranging from 1 to 100. All criterion considered as beneficial except the cost criteria. In Table 11 the best (f_j^*) and the worst criteria (f_j^-) values are shown.

Next, the decision matrix normalized and weighted by $W\frac{(f_i^*-f_i)}{(f_i^*-f_i^-)}$ can be found in Appendix 3.

Weights of AHP is given in Table 5.

With weighted normalized decision matrix values S_i, R_i and Q_i calculated. In order to find the Q_i values the VIKOR value (v) is accepted as 0.5 at first, after considering the rankings for 0.5, calculations for $v >$ 0.5 is conducted. The minimum and maximum values of S_i and R_i are used for determining Q_i values and overall rankings. Minimum value of S_i means the maximum group utility where the minimum R_i is the minimum individual regret of the opponent.

Final rankings and values given in Table 12 with v = 0.8.

Table 12: Si, Ri and Qi for VIKOR-AHP

Alternatives	S_i	R_i	Q_i	Rank
A1	0,637	0,218	0,733	7
A2	0,434	0,095	0,323	3
A3	0,413	0,134	0,344	4
A4	0,808	0,258	1,000	8
A5	0,596	0,218	0,681	5
A6	0,615	0,218	0,706	6
A7	0,298	0,181	0,255	2
A8	0,181	0,181	0,105	1

The alternatives are sorted in accordance with their respective S_i, R_i and Q_i values. A8 has the least small Q_i value and A7 has the second smallest Q_i value.

Following the creation of a compromise solution, it is discovered that the Acceptable Advantage criterion is met when v accepted as 0.8 and not met when v is accepted as 0.5. Calculations are computed with following equations $Q(A_2) - Q(A_1) \geq DQ$ and $DQ = 1 / (j - 1)$.

Q_i value for A7 reduced from Q_i value for A8 is not bigger or equal to DQ value which is calculated by dividing 1 to number of alternatives minus 1.

Table 13: Acceptable Advantage for VIKOR-AHP

$\boldsymbol{Q(A2) - Q(A1)}$	0.150
	$\geq$
$\boldsymbol{DQ}$	0.143

Nonetheless for different v values, Acceptable Consistency criteria are fulfilled since A8 has the smallest S_i values.

Table 14: Acceptable Consistency for VIKOR-AHP

	S_i	R_i
A8 (NLP-Based)	0,181	0,181
Minimum	0,181	0,095

Consequently, according the VIKOR method calculated with weights provided by AHP method, A8 which is NLP-Based matching algorithm is the best alternative matching algorithm.

Additionally, computations of VIKOR is conducted with both v value as 0.5 and 0.6, and resulting rankings given in below in Table 15.

Table 15: Rankings with v = 0.5 and v = 0.6 for VIKOR-AHP

Alternatives	$v = 0.5$	$v = 0.6$
A1	7	7
A2	1	2
A3	3	3
A4	8	8
A5	5	5
A6	6	6
A7	4	4
A8	2	1

These results indicate that Weighted Score-Based and Skill-Based algorithms are acceptable as best among alternative matching algorithms.

5.3.2.1.2 VIKOR with SWARA Weights

Same steps of VIKOR computed with weights obtained by SWARA technique. The decision matrix for VIKOR is provided by participants in Table 10. In Table 11, the best (f_j^*) and the worst criteria (f_j^-) values are shown.

Next, the decision matrix normalized and weighted by $w\frac{(f_i^*-f_i)}{(f_i^*-f_i^-)}$, can be found in Appendix 3. Weights, used for weighted normalized matrix, of SWARA is given in Table 9.

After creating the weighted normalized decision matrix values S_i, R_i and Q_i calculated. VIKOR value (v) accepted as 0.5 at first, but like AHP with VIKOR, higher v values resulted in similar rankings. Therefore, also for VIKOR with SWARA weights results v is accepted 0.8. The minimum and maximum values of S_i and R_i are used for Q_i calculation.

Table 16: Si, Ri and Qi for VIKOR-SWARA

Alternatives	S_i	R_i	Q_i	Rank
A1	0,671	0,133	0,751	7
A2	0,482	0,115	0,470	4
A3	0,462	0,096	0,387	3
A4	0,816	0,157	1,000	8
A5	0,588	0,133	0,655	5
A6	0,610	0,133	0,681	6
A7	0,251	0,130	0,252	2
A8	0,130	0,130	0,111	1

A8 has the least small Q_i value and A7 has the second smallest Q_i value.

After making compromise solution, Acceptable Advantage criteria is not fulfilled, Q_i value for A7 reduced from Q_i value for A8 is not bigger or equal to DQ value which is calculated by dividing 1 to number of alternatives minus 1.

Table 17: Acceptable Advantage for VIKOR-SWARA

$\boldsymbol{Q(A2) - Q(A1)}$	0.141
$\geq$	
$\boldsymbol{DQ}$	0.143

Nevertheless, Acceptable Consistency condition is fulfilled since A8 also has the smallest S_i value.

Table 18: Acceptable Consistency for VIKOR-SWARA

	$\boldsymbol{Si}$	$\boldsymbol{Ri}$
A8 (NLP-Based)	0,130	0,130
Minimum	0,130	0,096

In order to define the best alternative algorithms VIKOR methodology suggests creating a compromised joint best solution set. Because the acceptable advantage condition is met (see in Table 17) but acceptable consistency condition is not fulfilled (see in Table 18) the $Q(A_m) - Q(A_1) < DQ$ condition is checked.

Table 19: Compromised Joint Best Solution Set for VIKOR-SWARA

CONDITION							**STATUS**
Acceptable Advantage				0.141 ≥ 0.143			FALSE
Acceptable Consistency				A8 has the smallest S_i or R_i value.			TRUE
$\boldsymbol{Q(A_m) - Q(A_1) < DQ}$							
Q(A8) - Q(A8)	**Q(A7) - Q(A8)**	**Q(A3)- Q(A8)**	**Q(A2)- Q(A8)**	**Q(A5)- Q(A8)**	**Q(A6)- Q(A8)**	**Q(A1)- Q(A8)**	**Q(A4)- Q(A8)**
0,000	0,141	0,272	0,358	0,520	0,549	0,624	0,877
TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

The m value for $v = 0.8$ accepted as 2 (Karakul Kayahan & Özaydın, 2019). Joint best solution is A8 and A7.

Consequently, according the VIKOR method calculated with weights provided by SWARA method, A8 which is NLP-Based matching algorithm is the best alternative matching algorithm. ML-Based algorithm is the second best alternative matching algorithm.

Computations of VIKOR is conducted with both v value as 0.5 and 0.6, resulting rankings given in below:

Table 20: Rankings with v = 0.5 and v = 0.6 for VIKOR-SWARA

Alternatives	$v = 0.5$	$v = 0.6$
A1	7	7
A2	4	4
A3	1	2
A4	8	8
A5	5	5
A6	6	6
A7	3	3
A8	2	1

These results indicate that NLP-Based and Skill-Based algorithms are acceptable as best among alternative matching algorithms.

5.3.2.2 WASPAS

WASPAS combines the Weighted Sum Model (WSM) with Weighted Product Model (WPM). The process involves determining the relative relevance of each criterion, evaluating and prioritizing alternatives (Alinezhad & Khalili, 2019).

Both weights obtained by AHP and SWARA methods, used in WASPAS technique and then results are compared. Normalized decision matrix that is used in both WASPAS analyses is given below in Table 21.

Table 21: Normalized Decision Matrix for WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0,938	0,825	0,702	0,767	0,899	0,782	0,990	0,876
A2	0,938	0,883	0,846	0,825	0,963	0,802	0,949	0,907
A3	0,964	0,854	0,808	0,806	0,982	0,871	0,980	0,821
A4	0,839	0,748	0,856	0,777	0,881	0,832	0,808	0,929
A5	0,884	0,854	0,923	0,845	0,899	0,851	0,838	1,000
A6	0,884	0,777	0,913	0,825	0,899	0,901	0,879	0,929
A7	0,964	0,913	1,000	0,990	0,982	0,990	0,970	0,772
A8	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0,772

This matrix conducted by dividing each criteria value given in Table 10 to the best values (maximum for beneficial, minimum for non-beneficial) of each criterion given in Table 11.

5.3.2.2.1 WASPAS with AHP Weights

After the normalization of the decision matrix WSM table (Table 22) is created by multiplying each normalized value with weights assessed by AHP method (given in Table 5). The Additive Relative Importance $Q_i^{(1)}$ value is calculated with summarizing each WSM value of alternative algorithms. It is employed to ascertain each alternative's additive relative importance based on weighted normalized data (Alinezhad & Khalili, 2019).

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Table 22: WSM with AHP Weights

	C1	C2	C3	C4	C5	C6	C7	C8	$Q_i^{(1)}$
A1	0,086	0,058	0,043	0,056	0,232	0,082	0,159	0,158	0,874
A2	0,086	0,062	0,052	0,060	0,248	0,084	0,152	0,164	0,909
A3	0,088	0,060	0,050	0,059	0,253	0,091	0,157	0,148	0,907
A4	0,077	0,052	0,053	0,057	0,227	0,087	0,130	0,168	0,850
A5	0,081	0,060	0,057	0,062	0,232	0,089	0,134	0,181	0,896
A6	0,081	0,055	0,056	0,060	0,232	0,094	0,141	0,168	0,887
A7	0,088	0,064	0,062	0,073	0,253	0,103	0,156	0,140	0,938
A8	0,091	0,070	0,062	0,073	0,258	0,104	0,160	0,140	0,959

Next, the WPM table (Table 23) is created by multiplying each normalized value with weights assessed by AHP method (given in Table 5). The Multiplicative Relative Importance $Q_i^{(2)}$ value is calculated with multiplying each WSM value of alternative algorithms. It is applied to ascertain the weighted normalized data of each alternative's multiplicative relative importance (Alinezhad & Khalili, 2019).

Table 23: WPM with AHP Weights

	C1	C2	C3	C4	C5	C6	C7	C8	$Q_i^{(2)}$
A1	0,994	0,987	0,978	0,981	0,973	0,975	0,998	0,976	0,870
A2	0,994	0,991	0,990	0,986	0,990	0,977	0,992	0,983	0,907
A3	0,997	0,989	0,987	0,984	0,995	0,986	0,997	0,965	0,904
A4	0,984	0,980	0,990	0,982	0,968	0,981	0,966	0,987	0,849
A5	0,989	0,989	0,995	0,988	0,973	0,983	0,972	1,000	0,894
A6	0,989	0,982	0,994	0,986	0,973	0,989	0,979	0,987	0,886
A7	0,997	0,994	1,000	0,999	0,995	0,999	0,995	0,954	0,934
A8	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0,954	0,954

For the final rankings the Joint Generalized Criterion Q matrix is conducted. It is suggested for combination and generalization of multiplicative and additive procedures. For the calculations λ value is accepted as 0.5. And the computations are made with following equation:

$$Q_i = \lambda Q_i^{(1)} + (1 - \lambda) Q_i^{(2)}$$

Table 24: Qi for WASPAS with AHP Weights

	$Q_i^{(1)}$	$Q_i^{(2)}$	Q_i
A1	0,874	0,870	0,872
A2	0,909	0,907	0,908
A3	0,907	0,904	0,905
A4	0,850	0,849	0,849
A5	0,896	0,894	0,895
A6	0,887	0,886	0,886
A7	0,938	0,934	0,936
A8	0,959	0,954	0,957

By ranking the final Q_i values we can find the best alternative matching algorithm order in Table 25 below:

Table 25: Final Rankings for WASPAS with AHP Weights

	Q_i	Ranks
Rule-Based	0,872	7
Weighted Score-Based	0,908	3
Skill-Based	0,905	4
Collaborative Filtering	0,849	8
Content-Based Filtering	0,895	5
Clustering Algorithms	0,886	6
ML-Based	0,936	2
NLP-Based	0,957	1

In conclusion, for WASPAS with AHP weights analysis best alternative for matching algorithms found as is A8 which is NLP-Based matching algorithm. Number two is ML-Based matching algorithm.

5.3.2.2.2 WASPAS with SWARA Weights

Same steps for WASPAS conducted with weights obtained by SWARA technique. Normalized decision matrix for the WASPAS method is given in Table 21. Weights of SWARA is given in Table 9.

Using this matrix the table for WSM method is created by multiplying each normalized value with SWARA weights. The Additive Relative Importance $Q_i^{(1)}$ value is calculated with summarizing each WSM value of alternative algorithms.

Table 26: WSM with SWARA Weights

	C1	C2	C3	C4	C5	C6	C7	C8	$Q_i^{(1)}$
A1	0,114	0,089	0,074	0,088	0,141	0,099	0,135	0,114	0,855
A2	0,114	0,095	0,089	0,094	0,152	0,101	0,130	0,118	0,894
A3	0,118	0,092	0,085	0,092	0,154	0,110	0,134	0,107	0,892
A4	0,102	0,080	0,090	0,089	0,139	0,105	0,111	0,121	0,837
A5	0,108	0,092	0,097	0,097	0,141	0,107	0,115	0,130	0,888
A6	0,108	0,083	0,096	0,094	0,141	0,114	0,120	0,121	0,878
A7	0,118	0,098	0,106	0,113	0,154	0,125	0,133	0,101	0,947
A8	0,122	0,107	0,106	0,114	0,157	0,126	0,137	0,101	0,970

Next, the WPM table is created by multiplying each normalized value with weights assessed by SWARA method (given in Table 9). The Multiplicative Relative Importance $Q_i^{(2)}$ value is calculated with multiplying each WSM value of alternative algorithms.

Table 27: WPM with SWARA Weights

	C1	C2	C3	C4	C5	C6	C7	C8	$Q_i^{(2)}$
A1	0,992	0,980	0,963	0,970	0,983	0,969	0,999	0,983	0,850
A2	0,992	0,987	0,983	0,978	0,994	0,973	0,993	0,987	0,892
A3	0,996	0,983	0,978	0,976	0,997	0,983	0,997	0,975	0,889
A4	0,979	0,969	0,984	0,971	0,980	0,977	0,971	0,990	0,835
A5	0,985	0,983	0,992	0,981	0,983	0,980	0,976	1,000	0,886
A6	0,985	0,973	0,990	0,978	0,983	0,987	0,982	0,990	0,877
A7	0,996	0,990	1,000	0,999	0,997	0,999	0,996	0,967	0,944
A8	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0,967	0,967

For the final rankings the Joint Generalized Criterion Q matrix is conducted. It is suggested for combination and generalization of multiplicative and additive procedures. For the calculations λ value is accepted as 0.5. And the computations are made with following equation:

$$Q_i = \lambda Q_i^{(1)} + (1 - \lambda) Q_i^{(2)}$$

Table 28: Qi for WASPAS with SWARA Weights

	$Q_i^{(1)}$	$Q_i^{(2)}$	Q_i
A1	0,855	0,850	0,852
A2	0,894	0,892	0,893
A3	0,892	0,889	0,891
A4	0,837	0,835	0,836
A5	0,888	0,886	0,887
A6	0,878	0,877	0,878
A7	0,947	0,944	0,946
A8	0,970	0,967	0,969

By ranking the final Q_i values we can find the best alternative matching algorithm order in Table 29 below:

Table 29: Final Rankings for WASPAS with SWARA Weights

	Q_i	Ranks
Rule-Based	0,852	7
Weighted Score-Based	0,893	3
Skill-Based	0,891	4
Collaborative Filtering	0,836	8
Content-Based Filtering	0,887	5
Clustering Algorithms	0,878	6
ML-Based	0,946	2
NLP-Based	0,969	1

In conclusion, for WASPAS with SWARA weights analysis best alternative for matching algorithms is founds as A8 which is NLP-Based matching algorithm, same as WASPAS with AHP weights. Likewise, the number two best matching algorithm is ML-Based matching algorithm.

5.3.3 Comparison of Rankings of MCDM Methods with Kendall's Coefficient of Concordance

Kendall's coefficient of concordance (W) is a metric that evaluates participants' agreement considering ranks (Gearhart et al., 2013). The range of values for W is 0 to 1, with a value of 1 indicating complete correlation among two rankings set (Patel et al., 2020).

In this part of the study the significance of the degree of agreement among sets of rankings of matching algorithm alternatives based on matching algorithm criterion is shared. If the acquired W value is considered high (0.70 or more), it is accepted that matching algorithm criterion have the direct influence on the architecture of ranking sets, independent of the rankings of algorithms and weightings of criteria. If the anticipated result of W is considered low (less than 0.70) then it can be stated that the rankings of matching algorithm alternatives cannot be explained solely on selected matching algorithm criteria. Therefore, in the situation of low W value, various other ranking techniques and different weights of criteria shall additionally perform an impact on the arrangement of ranking groups.

The initial comparison matrix for calculating the Kendall's W is given below in Table 30.

Table 30: Overall Ranking of Matching Algorithms Using Different Methods

	$v = 0.8$		$\lambda = 0.5$	
Rank	**VIKOR-AHP**	**VIKOR-SWARA**	**WASPAS-AHP**	**WASPAS-SWARA**
1	NLP-Based	NLP-Based	NLP-Based	NLP-Based
2	ML-Based	ML-Based	ML-Based	ML-Based
3	Weighted Score-Based	Skill-Based	Weighted Score-Based	Weighted Score-Based
4	Skill-Based	Weighted Score-Based	Skill-Based	Skill-Based
5	Content-Based Filtering	Content-Based Filtering	Content-Based Filtering	Content-Based Filtering
6	Clustering-Based	Clustering-Based	Clustering-Based	Clustering-Based
7	Rule-Based	Rule-Based	Rule-Based	Rule-Based
8	Collaborative Filtering-Based	Collaborative Filtering-Based	Collaborative Filtering-Based	Collaborative Filtering-Based

Comparison matrix for VIKOR value accepted as 0.5 is given in Table 31.

Table 31: Overall Ranking of Matching Algorithms Using Different Methods (v = 0.5)

	$v = 0.5$		$\lambda = 0.5$	
Rank	**VIKOR-AHP**	**VIKOR-SWARA**	**WASPAS-AHP**	**WASPAS-SWARA**
1	Weighted Score-Based	Skill-Based	NLP-Based	NLP-Based
2	NLP-Based	NLP-Based	ML-Based	ML-Based
3	Skill-Based	ML-Based	Weighted Score-Based	Weighted Score-Based
4	ML-Based	Weighted Score-Based	Skill-Based	Skill-Based
5	Content-Based Filtering	Content-Based Filtering	Content-Based Filtering	Content-Based Filtering
6	Clustering-Based	Clustering-Based	Clustering-Based	Clustering-Based
7	Rule-Based	Rule-Based	Rule-Based	Rule-Based
8	Collaborative Filtering-Based	Collaborative Filtering-Based	Collaborative Filtering-Based	Collaborative Filtering-Based

Calculation steps for W are given below according to Alkharabsheh & Duleba (2021).

$$Ri = \sum_{j=1}^{m} r_{ij}$$

Ri is the overall combined ranking for each criterion.

m is the number of evaluation methods sorting n criteria.

$$R_i = \frac{m(n+1)}{2}$$

$$S = \sum_{j=1}^{n} (R_i - R)^2$$

S is the deviation of the sum-of-squares statistic across the row sums of ordering Ri.

R is the mean of the Ri values.

After that, Kendall's W, can be calculated using following formula:

$$W = \frac{12S}{m^2(n^3 - n)}$$

Chi-square can be calculated with:

$$m(n-1)W$$

Degree of freedom is $n - 1$ and with obtained values p-value is calculated in order to reject or accept the H_0.

H_0: $The\ rankings\ of\ objects\ are\ indepedent\ of\ one\ another$.

With given rankings and steps the coefficient W is calculated in Table 32.

Table 32: Final Kendall's Coefficient of Concordance Results

	n	m	Kendall's W	Chi-Square	Degree of Freedom	p-Value	H_0
VIKOR $v = 0.5$	8	4	0.9137	25.5833	7	0.0006	**Rejected**
VIKOR $v = 0.8$	8	4	0.9911	27.7500	7	0.0002	**Rejected**

As shown in table 32 for both v values W is higher than 0.70, which means that independently from the used MCDM methodologies alternative matching algorithms with selected criterions would show similar results.

Following that statement, in both cases the H_0 is rejected. Rejection means that despite the fact that there are two distinct sorting processes and two distinct weighing processes, they do not have a significant difference according to Kendall's with this data set and therefore are not very different from one another. The alternatives and criteria used in this study shared similar outcomes regardless of different ranking approaches, hence the Natural Language Process Based matching algorithm is accepted as the best alternative.

CONCLUSION

Recent developments of AI led many scholars and organizations do research on how to utilize AI in their respective fields and beyond. Finding solutions for many already existent and recently emerged problems in various fields have become possible thanks to advanced findings and rapid implementation of AI based solutions. HR is one of the researched areas by scholars and organizations in this context.

Nowadays many people who seek jobs are making their search solely in online platforms. Even though this is not the only way to find jobs, because of recruitment platforms who offer countless job listings across all industries, most candidates prefer to seek jobs online. This situation has both advantages and disadvantages. One main disadvantage is for platforms is it is really difficult to evaluate all the resumes that are submitted and find or at least suggest the most suitable candidates to their customer, the employer organization. Due to this problem, complex algorithms must be implemented in order to handle high application volumes and enhance the caliber of candidate selection.

This disadvantage is a general problem in recruitment whether there are thousands of applicants or not, finding a suitable matched candidate is a challenge on its own. Therefore, many recruitment platforms utilize ATS systems that are powered with matching algorithms. Matching algorithms are one of the solution development results of AI. Existent ATS systems can match candidates to job listings more efficiently and accurately.

In this thesis, main study is conducted for assessing the matching algorithms' significance rates with selected criteria according to SMEs working for a recruitment platform. Aim of the study was to explore the importance levels of criteria and the most suitable alternative for the matching algorithm-based solutions and to find out if there is a difference in outcome using AHP and SWARA for weight assessment with VIKOR and WASPAS for ranking alternatives with the same data set. The study's conclusions may offer platform developers and HR professionals insightful information on how to improve their recruiting solutions.

Criteria and the alternatives evaluated in the study were selected by researching the literature. The primary consideration for selecting both alternatives and criteria was scope broadness. Precisely, alternatives and criteria that supports more broadness of scope is preferred. The MCDM techniques employed in the analysis were chosen with consideration for four factors: first, AHP's widespread acceptance and capacity to facilitate pairwise comparisons; second, SWARA's user-friendliness and expert judgment; third, VIKOR's

broad applicability and emphasis on alternative ranking and selection; and fourth WASPAS's combination of WSM and WPM that enables higher accuracy and its robustness with ease of use. In order to find out and identify the correlation between the results of utilized MCDM applications Kendall's Concordance of Coefficient W is selected since it can manage multiple sorting results and used in many applications for validating MCDM results. This thorough method of research allows a robust assessment of the efficacy of the matching algorithms.

In the analysis, two different VIKOR values used. One is as 0.5 and the other is as 0.8. Hence, rankings for VIKOR had four distinct results. For WASPAS method two identical ranking results were obtained with AHP and SWARA weights.

In the rankings for VIKOR value as 0.5 with AHP weights best alternative matching algorithm was the Weighted Score-Based. However, in the rankings for VIKOR value as 0.5 with SWARA weights best alternative matching algorithm was the Skill-Based. In the rest two ranking results (VIKOR value as 0.8) of VIKOR the number one was the NLP-Based matching algorithm. Hence, in overall results NLP-Based matching algorithms had ranked as first most and the ML-Based matching algorithms ranked as second most. This demonstrates the great potential that NLP-Based and ML-Based algorithms have to enhance recruitment results.

The obtained results validated by Kendall's W, in which found that accepting the VIKOR value as 0.8 had higher W value (W = 0.9911) than accepting it as 0.5 (W = 0.9137). This indicates that ranking results are more consistent in our data set with VIKOR value as 0.8.

The high values of W showed that for this study there is similarity in results, independent of the utilized MCDM techniques. The constancy of these outcomes highlights the dependability of the selected techniques in evaluating matching algorithm performance.

With the weight assessment methodologies that are worked in the study, most important criteria according to data provided by SMEs as follows: User satisfaction, cost, explainability and robustness. Secondly, the matching algorithm alternatives that are most performant regarding the selected criteria are as follows: NLP-Based matching algorithm, ML-Based matching algorithm, Weighted Score-Based matching algorithm and Skill-Based matching algorithm.

Despite this study's thorough methodology, there are certain limitations to be aware of. Main limitation of the study is even though the analysis resulted is meaningful, it is relatively subjective. This is due to challenge of obtaining a performance data for each evaluated matching algorithm in practice. This study

only compared matching algorithms regarding the importance of criteria provided by participant SMEs. Despite the prioritizing the scope broadness while employing, the selected criteria may not have addressed every essential facet of matching algorithms. The results of this study could swiftly turn out of date due to the lightning-fast speed at which AI is developing. Continual investigation is required to stay abreast of the most recent advancements and their consequences for recruitment platforms.

Even though in the analyses VIKOR value is accepted as 0.8, results with 0.5 and some higher values showed that alternatives Weighted Score-Based and Skill-Based are very close to be regarded as the best alternatives. This result is found interesting since the recruitment platform that its managers participated in the study is currently utilizing a matching algorithm for ATS mainly built on Weighted Score-Based and Skill-Based matching. However, combining the results of VIKOR and WASPAS, with respect to Kendall's W correlation acceptance, NLP-Based and ML-Based matching algorithms are accepted as the best matching algorithm alternatives based on the data provided by the same SMEs. This implies that while more complex algorithms such as NLP and ML have great potential for future application, simpler techniques are still in use today.

This would be due to the capacity and comprehensiveness of the SMEs towards the matching algorithm systems and AI based HR solutions. Even though in their own platform they don't utilize what they believe the best, they acknowledge their power and importance. An important point towards future works from this insight could be that this study proved a point that if an AI solution characterizes with high level of complexity to comprehend, to implement and to transform into an actual solution that is functional and measurable, even though it could be counted as the best option it is not preferred as the first option over an alternative that may produce lower desired outcomes with easier implementation and lower complexity. This emphasizes how difficult it can be to implement cutting-edge AI solutions in practice even though they come with numerous positive aspects.

Several suggestions for further studies are made in light of the study's shortcomings and conclusions. For every matching algorithm under evaluation, real performance data should be gathered in future research. This will give comparisons a more objective foundation and enable researchers to confirm the algorithms' efficacy in practical settings. Investigations into how candidates and recruiters use various matching algorithms should be carried out. The research' insights can be used to improve the user experience by optimizing the algorithms according to the needs of users. Continuous improvement should be done on bettering the matching algorithms that are currently in use by adding new AI methods and taking note of new trends in data. This ongoing development can support the preservation of the significance and efficacy

of ATS solutions. Research comparing various types of jobs and industries may offer a more comprehensive understanding of the efficacy of distinct matching algorithms. These studies can highlight needs unique to a given industry and direct the creation of customized solutions. Researching the incorporation of hybrid models, which incorporate the advantages of several different algorithms, may help create ATS systems that are more reliable and adaptable. For instance, integrating Weighted Score-Based and Skill-Based methods with NLP-Based and ML-Based algorithms could lead to better outcomes. Given the variety of industries where issues about equality and fairness remain, more research into the topics of justice and bias within HRM and AI is required. It could prove crucial to investigate typical situations or elements that either exacerbate or mitigate bias and users' or workers' sense of justice, in near future.

In conclusion, regardless of the different ranking and weighting methods used in this thesis, the outcomes consistently indicated that NLP-Based matching algorithm should be preferred. In this aspect, the participant SMEs were advised to apply NLP-Based matching algorithm to their existent ATS system in their recruitment platform in order to achieve better matching results that can be offered to both recruiters and candidates.

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APPENDIX

Appendix 1: AHP

Data of SME 1 for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	7	9	5	1/5	4	5	3
C2	1/7	1	5	5	1/7	3	1/2	1/3
C3	1/9	1/5	1	1	1/9	1/8	1/5	1/7
C4	1/5	1/5	1	1	1/9	4	1/7	1/7
C5	5	7	9	9	1	9	7	1/3
C6	1/4	1/3	8	1/4	1/9	1	1/5	1/5
C7	1/5	2	5	7	1/7	5	1	1/3
C8	1/3	3	7	7	3	5	3	1

Data of SME 2 for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	1/7	1/5	1/7	1/9	1/7	1/3	1/7
C2	7	1	1/5	5	1/9	1/7	1/3	1/7
C3	5	5	1	1/5	1/9	1/9	1/3	1/5
C4	7	1/5	5	1	1/9	1/9	1/3	1/5
C5	9	9	9	9	1	9	9	1/9
C6	7	7	9	9	1/9	1	1/3	1/5
C7	3	3	3	3	1/9	3	1	1/3
C8	7	7	5	5	9	5	3	1

Data of SME 3 for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	1/9	1/9	1/5	1/9	1/7	1/9	1/9
C2	9	1	1/7	1/5	1/9	1/7	1/9	1/9
C3	9	7	1	1/7	1/9	1/3	1/5	1/9
C4	5	5	7	1	1/5	1/7	1/9	1/9
C5	9	9	9	5	1	1/3	1/9	1/9
C6	7	7	3	7	3	1	3	1/9
C7	9	9	5	9	9	3	1	1/9
C8	9	9	9	9	9	9	9	1

Data of SME 4 for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	5	7	7	7	5	5	9
C2	1/5	1	3	3	3	3	3	7
C3	1/7	1/3	1	3	3	3	3	5
C4	1/7	1/3	1/3	1	3	3	3	5
C5	1/7	1/3	1/3	1/3	1	3	3	5
C6	1/5	1/3	1/3	1/3	1/3	1	3	3
C7	1/5	1/3	1/3	1/3	1/3	1/3	1	3
C8	1/9	1/7	1/5	1/5	1/5	1/3	1/3	1

Data of SME 5 for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	1/3	1/5	1/2	1/5	7	1/5	1/3
C2	3	1	2	1/2	1/6	1/3	1/5	1/2
C3	5	1/2	1	1/3	1/6	1/2	1/4	1/3
C4	2	2	3	1	1/4	1/3	1/4	1/3
C5	5	6	6	4	1	6	5	1/3
C6	1/7	3	2	3	1/6	1	1/3	1/2
C7	5	5	4	4	1/5	3	1	2
C8	3	2	3	3	3	2	1/2	1

Data of SME 6 for AHP

	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	3	3	3	1/7	5	1/5	5
C2	1/3	1	1/3	1/3	1/5	1/3	1/3	3
C3	1/3	3	1	1/7	1/9	1/7	1/9	9
C4	1/3	3	7	1	1/9	1/5	1/3	3
C5	7	5	9	9	1	9	1/5	5
C6	1/5	3	7	5	1/9	1	1/5	5
C7	5	3	9	3	5	5	1	1/5
C8	1/5	1/3	1/9	1/3	1/5	1/5	5	1

Weights of AHP

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	Weights
C1	0,0999	0,0639	0,0582	0,0608	0,0998	0,0843	0,1118	0,1454	0,0905
C2	0,1102	0,0705	0,0447	0,0795	0,0465	0,0512	0,0699	0,1034	0,0720
C3	0,0945	0,0868	0,0551	0,0273	0,0404	0,0309	0,0477	0,1210	0,0630
C4	0,1122	0,0605	0,1377	0,0682	0,0477	0,0473	0,0491	0,1008	0,0779
C5	0,1965	0,2975	0,2674	0,2808	0,1964	0,2745	0,1881	0,1146	0,2270
C6	0,1160	0,1348	0,1743	0,1413	0,0700	0,0979	0,0866	0,1141	0,1169
C7	0,1324	0,1491	0,1711	0,2060	0,1546	0,2414	0,1481	0,0996	0,1628
C8	0,1382	0,1370	0,0915	0,1361	0,3445	0,1726	0,2988	0,2011	0,1900

Weighted Normalized Matrix of AHP

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	Sum
C1	0,091	0,064	0,060	0,078	0,073	0,163	0,093	0,171	0,792
C2	0,101	0,070	0,050	0,085	0,061	0,055	0,063	0,112	0,597
C3	0,094	0,087	0,062	0,029	0,053	0,033	0,052	0,109	0,518
C4	0,085	0,060	0,154	0,073	0,063	0,050	0,053	0,091	0,630
C5	0,325	0,296	0,299	0,301	0,258	0,422	0,266	0,103	2,272
C6	0,059	0,134	0,195	0,152	0,064	0,104	0,094	0,103	0,904
C7	0,158	0,178	0,191	0,221	0,155	0,257	0,160	0,090	1,412
C8	0,097	0,114	0,102	0,146	0,453	0,184	0,324	0,181	1,600

Appendix 2: SWARA

Values of $\overline{P}_i$, S_i, C_i, S'_i				
Criteria Order	**Mean Importance Score $\overline{P}_i$**	**Compared Importance Value of Mean S_i**	**Coefficient C_i**	**Recalculated Weight S'_i**
C5	0,900		1,000	1,000
C7	0,750	0,150	1,150	0,870
C8	0,700	0,050	1,050	0,828
C6	0,667	0,033	1,033	0,801
C1	0,633	0,033	1,033	0,776
C4	0,567	0,067	1,067	0,727
C2	0,500	0,067	1,067	0,682
C3	0,483	0,017	1,017	0,670

Appendix 3: VIKOR and WASPAS

Data of SME 1 for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	80	50	45	65	75	45	70	70
A2	80	75	50	60	80	50	65	70
A3	75	80	50	60	75	55	70	80
A4	70	75	45	50	70	50	65	80
A5	85	85	75	70	75	65	70	60
A6	80	80	80	65	80	65	75	70
A7	85	80	80	70	75	75	80	85
A8	90	90	85	80	85	85	80	85

Data of SME 2 for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	100	100	100	100	100	100	100	100
A2	100	100	100	100	100	100	100	100
A3	100	100	100	100	100	100	100	100
A4	70	70	70	70	70	70	70	70
A5	70	70	70	70	70	70	70	70
A6	70	70	70	70	70	70	70	70
A7	80	80	80	80	80	80	80	80
A8	100	100	100	100	100	100	100	100

Data of SME 3 for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	100	100	50	50	50	75	75	100
A2	100	100	100	75	75	75	80	100
A3	100	100	100	75	75	75	80	100
A4	100	100	90	50	75	75	80	100
A5	100	100	100	75	75	75	75	100
A6	100	100	90	90	75	100	90	100
A7	100	100	100	100	90	100	100	100
A8	100	100	100	100	90	100	100	100

Data of SME 4 for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	80	85	70	50	75	80	95	45
A2	85	75	80	70	80	75	90	50
A3	90	80	75	65	90	70	75	70
A4	80	70	85	80	80	75	65	60
A5	80	75	70	75	75	70	90	60
A6	70	60	85	80	70	65	60	65
A7	100	65	90	90	95	80	55	75
A8	95	70	75	85	85	75	70	65

Data of SME 5 for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	75	50	70	60	90	75	80	80
A2	80	55	80	70	90	75	85	80
A3	90	60	85	70	95	90	90	85
A4	80	60	85	80	95	80	90	90
A5	80	60	85	85	95	80	90	90
A6	85	70	90	90	95	85	90	95
A7	95	85	90	90	95	95	95	95
A8	95	85	90	90	95	95	95	95

Data of SME 6 for VIKOR and WASPAS

	C1	C2	C3	C4	C5	C6	C7	C8
A1	90	40	30	70	100	20	70	50
A2	80	50	30	50	100	30	50	30
A3	85	20	10	45	100	50	70	40
A4	70	10	70	70	90	70	30	20
A5	80	50	80	60	100	70	20	10
A6	90	20	60	30	100	70	50	20
A7	80	60	80	80	100	70	70	70
A8	80	70	70	60	90	50	50	60

VIKOR - AHP Weighted Normalized Decision Matrix

Criteria/Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	0,036	0,049	0,062	0,073	0,218	0,104	0,008	0,086
A2	0,036	0,032	0,032	0,055	0,079	0,095	0,042	0,063
A3	0,020	0,041	0,040	0,061	0,040	0,062	0,017	0,134
A4	0,091	0,070	0,030	0,070	0,258	0,081	0,160	0,047
A5	0,066	0,041	0,016	0,049	0,218	0,071	0,135	0,000
A6	0,066	0,062	0,018	0,055	0,218	0,047	0,101	0,047
A7	0,020	0,024	0,000	0,003	0,040	0,005	0,025	0,181
A8	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,181

VIKOR - SWARA Weighted Normalized Decision Matrix

Criteria/Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	0,047	0,074	0,106	0,114	0,133	0,126	0,007	0,062
A2	0,047	0,050	0,054	0,086	0,048	0,115	0,036	0,045
A3	0,027	0,062	0,068	0,095	0,024	0,075	0,014	0,096
A4	0,122	0,107	0,051	0,110	0,157	0,097	0,137	0,034
A5	0,088	0,062	0,027	0,076	0,133	0,086	0,115	0,000
A6	0,088	0,095	0,031	0,086	0,133	0,057	0,086	0,034
A7	0,027	0,037	0,000	0,005	0,024	0,006	0,022	0,130
A8	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,130

Appendix 4: Kendall's Coefficient of Concordance W

	$v = 0.5$		$\lambda = 0.5$	
Rank	**VIKOR-AHP**	**VIKOR-SWARA**	**WASPAS-AHP**	**WASPAS-SWARA**
1	Weighted Score-Based	Skill-Based	NLP-Based	NLP-Based
2	NLP-Based	NLP-Based	ML-Based	ML-Based
3	Skill-Based	ML-Based	Weighted Score-Based	Weighted Score-Based
4	ML-Based	Weighted Score-Based	Skill-Based	Skill-Based
5	Content-Based Filtering	Content-Based Filtering	Content-Based Filtering	Content-Based Filtering
6	Clustering-Based	Clustering-Based	Clustering-Based	Clustering-Based
7	Rule-Based	Rule-Based	Rule-Based	Rule-Based
8	Collaborative Filtering-Based	Collaborative Filtering-Based	Collaborative Filtering-Based	Collaborative Filtering-Based