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Unraveling Decision-Making Complexity: Artificial Intelligence versus Fuzzy AHP-TOPSIS[*]

Karar Verme Karmaşıklığının Çözülmesi: Yapay Zekâ ile Bulanık AHP-TOPSIS Karşılaştırması

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Ö Z

Bilgi çağının gelişimi ve üretim süreçlerinin otomasyonunun artmasıyla birlikte yöneticiler karar alma ve planlama faaliyetlerini desteklemek için giderek daha fazla gelişmiş bilgi sistemlerine yönelmektedir. Bu sistemlerin en yeni ve dikkat çekici örneklerden biri ise ileri düzey bir sohbet botu olan ChatGPT'dir. Bu bağlamda araştırma, geleneksel bir çok kriterli karar verme yöntemi olan bulanık AHP-TOPSIS ile yapay zeka tabanlı karar verme yaklaşımlarının karşılaştırmalı bir analizini sunmaktadır. Bu yönüyle çalışma, her iki yöntemi bir araya getirerek örgütsel karar verme kalitesini artırmayı amaçlayan yeni bir çerçeve geliştirmeyi amaçlamaktadır. Ayrıca, işe alım kararlarına odaklanarak ChatGPT tarafından üretilen çıktıları geleneksel yöntemlerle karşılaştırmaktadır. Araştırma bulguları neticesinde, ChatGPT gibi yapay zeka tabanlı sistemlerin geleneksel çok kriterli karar verme yöntemlerine göre daha isabetli kararlar verdiğine ulaşılmıştır. Dahası, yapay zeka tarafından verilen kararların, şirketin halihazırda yaptığı seçimlerle büyük ölçüde uyum sağlayarak tahmin doğruluğunu ve işe alım süreçlerini optimize etme potansiyelini gözler önüne sermektedir

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A B S T R A C T

In the era of the information age and increasing automation of production processes, managers are increasingly relying on advanced information systems to support their decision-making and planning activities. Among these systems, the emergence of chatbots—specifically ChatGPT, a state-of-the-art conversational agent—represents a significant development. This research presents a comparative analysis of fuzzy AHP-TOPSIS, a traditional MCDM, and AI-based decision-making approaches. A novel framework integrating both methods has been developed to enhance the quality of organizational decision-making. The study focuses on recruitment decisions, comparing outputs generated by ChatGPT with those derived from traditional approaches. Findings reveal that artificial intelligence, as demonstrated by ChatGPT, delivers more accurate and reliable decisions than conventional MCDM's. Moreover, these AI-generated decisions align closely with the actual selections made by the organization, showcasing their predictive accuracy and potential to optimize recruitment processes.

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1. Introduction

Industrial transformations represent pivotal moments in human history, profoundly impacting individuals and institutions across various sectors as technological advancements reshape commerce and lifestyles (Saatçioğlu et al., 2018; Soylu, 2018). The ever-evolving information technologies, spurred by Industry 4.0 and globalization, are digitally revolutionizing nearly every facet of our contemporary digital era (Keskinkılıç & Kuk, 2023). Consequently, the forthcoming evolution of labor conditions stands as a pressing inquiry (Zanzotto, 2019), given the myriad challenges, opportunities, and novel exigencies arising at each juncture of technological progression (Christensen et al., 2015). The Industry 4.0 paradigm and its constituent elements harbor transformative potential, poised to reshape existing job structures. Presently, Artificial Intelligence (AI) technologies and tools are rapidly advancing, exerting varied influences on operational frameworks and business paradigms. Hence, forecasting the ramifications of AI within Industry 4.0 on occupations and business frameworks has emerged as a critical endeavor (Kılıç & Atilla, 2024).

However, during this anticipatory phase, it is crucial to acknowledge that the increasing integration of Industry 4.0 and its components into production systems significantly affects human resource practices within organizations (Sgarbossa et al., 2020). Within this framework, the recognition of human resources as a paramount factor for organizational success has spurred strategic approaches among organizations toward personnel management (Cingöz & Akdoğan, 2013). Consequently, the human element assumes heightened significance as a strategic resource for organizations, with the rapid pace of technological advancements elevating the role of individuals within production processes. At this juncture, the meticulous selection of prospective team members, assessed by organizations for employment opportunities, becomes paramount.

In today's era of information abundance, characterized by the exponential growth of data stored in databases, data analytics methods have become indispensable tools for decision-makers, whether in personnel selection or other critical organizational decision-making scenarios (Ayçin & Aşan, 2021; Gedik, 2021). With the emergence of AI-based decision-making algorithms in recent years, there is a palpable curiosity surrounding the potential transformation of corporate decision-making processes. Traditionally, the data analytics process relied on tables, graphs, summaries, and search tools to uncover valuable insights, aiding decision makers by reflecting analysis results to the user. However, in today's landscape, managers increasingly utilize a diverse array of information systems equipped with analytical methodologies and capabilities to support their decision-making and planning activities. These information systems may encompass Multi-Criteria Decision-Making (MCDM) techniques or AI tools, showcasing the dynamic nature of decision support mechanisms. Notably, ChatGPT (Generative Pre-training Transformer), a chatbot, stands as a cutting-edge example of such knowledge systems.

In this study, the decision-making outputs generated by ChatGPT, an AI technology developed by OpenAI, were juxtaposed with the traditional recruitment approach and the computed MCDM method. This comparative analysis is motivated by the recognition that traditional managerial decision-making processes often harbor biases, leading to suboptimal outcomes. Statistical decision-making methodologies, devised to mitigate biases, hold significant relevance in managing decision-making processes effectively. The Fuzzy Analytic Hierarchy Process (AHP), a prominent MCDM technique in personnel selection, derives candidates' final scores by weighting criteria and computing candidates' scores based on these weightings. The Fuzzy AHP-TOPSIS method, a hybrid of Fuzzy AHP and Fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), involves calculating both positive ideal and negative ideal proximity scores and ranking candidates accordingly. This research undertakes a comparative analysis between Fuzzy AHP-TOPSIS and AI-based decision-making, culminating in the development of a comprehensive framework that encompasses both methodologies, optimizing organizational decision-making quality.

Like all components of Industry 4.0, AI is rapidly integrating into our daily lives with increasing momentum. As individuals, we are witnessing this transformative shift and closely following its advancements. From an organizational perspective, there is a concerted effort to integrate new technologies and AI into production processes to achieve a competitive advantage. This strategic approach will be explored further in the subsequent sections of this study. While numerous studies have examined this topic across various contexts, yielding diverse insights, this research offers a novel perspective. By addressing an unexplored aspect, it provides a significant contribution to the existing body of knowledge.

The existing literature extensively examines various decision-making techniques used in organizational processes, particularly in personnel selection. However, it has largely overlooked the perspectives of the counterparts involved in these decisions, a gap partly due to the limited capabilities of earlier AI tools. Today, chatbots have advanced into sophisticated language models capable of generating human-like responses. Against this backdrop, this research seeks to address a long-standing question about AI's decision-making capacity, shedding light on its future trajectory and development. By offering a fresh perspective, this study aims to enrich the literature and spark new discussions among researchers in this field. Additionally, it seeks to provide practical insights and recommendations for individuals and organizations, the key stakeholders in decision-making and personnel selection processes.

The study comprises six chapters in total. The introductory chapter provides a general overview, setting the stage for the research. The second chapter presents a comprehensive review of the existing literature and studies that have employed the methodology used in this research. The third chapter focuses on the theoretical and conceptual foundations, offering a detailed explanation of "ChatGPT, Fuzzy AHP-TOPSIS, and Decision Making." The fourth chapter outlines the research methodology, followed by the fifth chapter, which presents the findings of the study. Finally, the sixth chapter evaluates these findings, compares them with prior literature, identifies research limitations, offers recommendations for future studies, and concludes the research.

2. Literature and the Gap

This section of the study delves into previous studies in the literature. In this context, examples of studies utilizing fuzzy AHP and fuzzy TOPSIS methods are presented initially. This is crucial in demonstrating that the techniques employed in the study are widely favored methods in the literature, given their extensive applications across various fields and sample sets.

For instance, Afshari et al. (2014) conducted a comprehensive literature review on the application of fuzzy decision-making techniques in personnel selection problems. Also, Kusumawardani and Agintiara (2015) explored the utilization of the fuzzy AHP-TOPSIS method in addressing human resource selection challenges. Furthermore, Moayeri et al., (2015), Erdem (2016) and Esmaili-Dooki et al., (2017) used the technique for personnel selection. Beside this, Kamble and Parveen (2018) investigated the application of fuzzy AHP-TOPSIS for selecting the best candidate from a pool of applicants in an academic institution and Deliktaş and Üstün (2018) studied the use of fuzzy AHP-TOPSIS in selecting an industrial engineer in a manufacturing company. In another study, the evaluation of human resources in science and technology across Asian countries (Chou et al., 2019) has been investigated.

In the realm of decision-making, there are studies where fuzzy AHP and fuzzy TOPSIS techniques are combined. Examples of such studies include partner selection processes (Wittstruck & Teuteberg, 2012) and determining suitable cloud solutions for managing big data projects (Boutkhoum et al., 2017). Also, a research on information technology personnel selection (Samanlioglu et al., 2018) and a study conducted in a private company in Pakistan (Janjua & Hassan, 2020). Additionally, Liu et al. (2020) conducted a literature review spanning from 2008 to 2020 focusing on studies in this domain.

Up to this point discussed, various examples of applications of fuzzy AHP and fuzzy TOPSIS methods across different samples have been provided. However, the primary issue that has spurred our research question and investigation is the examination of AI's decision-making behavior. It is crucial to delve into previous studies in the literature that have addressed this issue. For instance, in a study by Shrestha et al. (2019) compared human and AI-based decision-making, proposing a new framework that combines both modes to optimize organizational decision-making quality. Similarly, in another study by Araujo et al. (2020), perceptions regarding automatic decision-making by AI were evaluated. The study revealed that certain decisions made automatically by AI were either equal to or better than those made by human experts

There are also studies on the ChatGPT, which represents the AI aspect of our research in exploring AI decision-making behavior. For instance, a study (Perez-Soler et al., 2018), attempts were made to enhance collaborative modeling and group decision-making behavior using chatbots in social networks. In another one, Gilson et al. (2022) delved into ChatGPT's performance in medical licensing exams, revealing that the bot performed at the level of a third-year medical student. Additionally, due to the dialogic nature of its responses, ChatGPT demonstrated the ability to provide reasoning and contextual information in most of its answers.

In another study, Sobania et al. (2023) concluded that ChatGPT's error correction performance significantly outperformed standard program repair approaches and other error correction applications. However, Gao et al. (2022) found that when ChatGPT generated summaries for academic papers, the resulting summaries were often ambiguous and felt formulaic. On the other hand, Susnjak (2022) evaluated ChatGPT's capacity to handle high-level cognitive tasks and produce text that closely resembles human-generated content. The study revealed that ChatGPT can demonstrate critical thinking skills and generate highly realistic texts with minimal input. This capability raises concerns about the potential threat to the integrity of online exams, particularly in higher education settings where such exams are increasingly prevalent. Furthermore, the accuracy of ChatGPT in answering questions related to ophthalmology was evaluated in a research, achieving 55.8% and 42.7% accuracy in two simulation exams comprising 260 questions (Antaki et al., 2023).

In addition to the aforementioned studies, several others have evaluated the limitations and capabilities of ChatGPT. Dowling and Lucey (2023) highlighted ChatGPT's significant potential to aid finance research. Gozalo-Brizuela and Garrido-Merchan (2023) developed a taxonomy by categorizing the most popular generative AI models, contributing to the understanding of AI model classifications. Guo et al. (2023) conducted extensive human evaluations and linguistic analyses of ChatGPT-generated content, uncovering several intriguing insights. However, Jiao et al. (2023) focused on ChatGPT's translation quality and concluded that while it shows promise as a spoken language translator, it falls short compared to professional commercial systems. Furthermore, various studies have explored ChatGPT's applications in the medical field (Tu et al., 2023), machine learning model construction (Mitrovic et al., 2023), and mathematics (Frieder et al., 2023).

These studies represent the current literature on ChatGPT, the AI chatbot that sparked this study and serves as the basis for our research question. It is evident that research on ChatGPT, being a relatively new development, is still limited and nascent. Furthermore, while studies on decision-making behavior-central to our research question-are few and far between, there exists a notable absence of research on decision-making behavior specifically in personnel selection. This study aims to bridge this gap in the literature. Additionally, the study holds significance in envisioning the structure of decision-making behavior and personnel selection in the future world. Consequently, the study's findings are intended to offer insights for decision-makers and policymakers in organizations, particularly within human resources departments. Prior to starting the methodology, and findings evaluation, it is imperative to establish the theoretical groundwork that shapes the conceptual framework of the subject matter.

3. Conceptual Framework

Today, chatbots are ubiquitous, used across various aspects of daily life, particularly on messaging platforms and social networks, where their adoption has become widespread and streamlined. However, the integration of AI into chatbots remains relatively uncommon (Tebenkov & Prokhorov, 2021). This is due to chatbots being designed in two primary ways; first, by modeling conversational interactions necessary for executing specific tasks, and second, by modeling conversational content pertinent to those tasks. Examples of the former include tasks like flight reservations, product inquiries, and food orders and in the latter type of modeling, which involves the exchange of content between humans and bots (Hoon et al., 2020) which has been used in this study.

One of the prominent instances of content exchange between humans and bots is through NLP (Neuro-linguistic Programming)-based bots. In this framework, bots can undergo training using a diverse range of unlabeled data and subsequently be utilized for various tasks such as text or image generation (Antaki et al., 2023). ChatGPT (Chat Generative Pre-trained Transformer), a cutting-edge language model developed by OpenAI, stands out as a compelling example of this system within the AI domain in recent years. With its capability to produce text resembling human speech and address complex inquiries, ChatGPT has already made a substantial impact and is poised for continued rapid advancement in the foreseeable future (Aljanabi, 2023; Gordijn & Have, 2023; Jiao et al., 2023; Gao et al., 2022).

ChatGPT is a natural language processing model with 175 billion parameters, capable of generating responses that mimic human speech patterns. The system leverages deep learning algorithms trained on extensive datasets to produce human-like responses to user inputs (Gilson et al., 2022). Additionally, it is trained using a combination of reinforcement learning algorithms and human input across billions of parameters. This innovative structure and its associated advantages propelled the platform to reach one million users within its first week of public availability (Aljanabi et al., 2023; Dowling & Lucey, 2023; Guo et al., 2023; Aydın & Karaarslan, 2022).

As a versatile chatbot, ChatGPT is designed to address a broad spectrum of topics, rendering it a potentially valuable tool for customer service, chatbots, and various other applications (Gilson et al., 2022). However, it does come with notable limitations. The system may occasionally provide incorrect responses, exhibit sensitivity to arbitrary fluctuations in rapid speech, and lack the ability to systematically rectify ambiguous prompts (Gordijn & Have, 2023). Furthermore, the factors contributing to the limited popularity of such chatbots encompass the intricate and time-consuming learning process, alongside imperfect algorithms for handling human queries, which diminishes the efficacy of chatbots and erodes users' trust in them (Tebenkov & Prokhorov, 2021).

The system's capacity to analyze and comprehend vast volumes of information is paramount (Aljanabi, 2023). With the ongoing trend of automating business processes and the subsequent accumulation of substantial data in databases, big data analytics methodologies can leverage this trend to bolster decision-makers in their decision-making endeavors (Alaaeldin et al., 2021). Within this framework, the concept of machine learning emerges, predicated on the notion that analytical systems can learn to discern patterns and make decisions with minimal human intervention. This concept represents a data analysis approach wherein the analytical system learns iteratively while addressing numerous analogous problems and is harnessed to train chatbots for autonomous communication with users based on archived dialogues (Tebenkov & Prokhorov, 2021). AI trained through past interactions undergoes a learning curve and demonstrates decision-making capabilities independently. However, these capabilities exhibit variances compared to human decision-making processes (see Table 1). Therefore, exploring the nexus between AI and decision-making is of paramount importance (Jarrahi, 2018; Pomerol, 1997).

Table 1: Comparison of AI-Based and Human Decision Making

Decision-Making Conditions	AI-Based Decision Making	Human Decision Making
Specificity of the decision search space	Requires a well-specified decision search space with specific objective functions.	Accommodates a loosely defined decision search space.
Interpretability of the decision-	Complexity of the functional	Decisions are explainable and

making process and outcome	forms can make it difficult to interpret the decision process and outcomes.	interpretable, though vulnerable to retrospective sense-making.
Size of the alternative set	Accommodates large alternative sets.	Limited capacity to uniformly evaluate a large alternative set.
Decision-making speed	Comparatively fast. Limited tradeoff between speed and accuracy.	Comparatively slow. High trade-off between speed and accuracy.
Replicability of outcomes	Decision-making process and outcomes are highly replicable due to standard computational procedure.	Replicability is vulnerable to inter- and intra-individual factors such as differences in experience, attention, context, and emotional state of the decision maker.

Source: Shrestha et al., 2019.

In essence, decision-making entails selecting one option from among several alternatives (Dalbudak & Rençber, 2022) or making a choice between available options (Arslan & Demir, 2020). Simon (1955) defined decision-making as the process of selecting the alternative expected to yield the most favorable outcome. This process encompasses the identification and enumeration of alternatives, the assessment of their potential outcomes, and the comparison of their accuracy and efficacy (Shrestha et al., 2019). However, while pinpointing an exact definition for the term "decision" may be challenging, there is a general consensus that individuals have encountered this concept. Virtually every person, whether rightly or wrongly, engages in choosing between various alternatives and deliberates before arriving at a decision (Pomerol, 1997).

Decision-making holds significance not only on an individual level but also from an organizational standpoint. For instance, in today's competitive landscape, the selection of qualified individuals for specific roles, particularly senior positions, is pivotal to an organization's success (Ekşi, 2023; Esmaili-Dooki et al., 2017). Consequently, one of the strategically critical facets of human resource management is decision-making in personnel selection. This process, stemming from the necessity for personnel and aiming to match individuals with suitable positions, is an ongoing endeavor until the right candidate is identified. To complete the selection process, the pool of candidates must exceed the required number of employees. Subsequently, one applicant is chosen based on the organization's predefined criteria. The ability to select the appropriate personnel significantly influences a company's success (Deliktaş & Üstün, 2018; Özdemir et al., 2018). This underscores the strategic importance of decision-making behavior concerning personnel selection.

In the global market, modern organizations confront intense competition and given the escalating global competitiveness, the future survival of most companies hinges primarily on the commitment of their employees (Saad et al., 2016). Factors such as talent, knowledge, skills, and other capabilities exhibited by employees or staff significantly influence an organization's success. The primary goal of organizations is to explore more effective methods of ranking employees based on diverse competencies (Güngör et al., 2009).

This process is typically overseen by human resources departments within organizations. While some organizations opt for rigorous and costly selection procedures to identify the best candidates, others prioritize filling positions quickly and affordably based solely on information provided in application forms (Deliktaş & Üstün, 2018). However, selecting the right personnel helps avoid hiring "inadequate" employees, thereby saving time and resources that would otherwise be spent on training and developing misplaced hires (Özdemir et al., 2018). The objective of the selection process primarily revolves around evaluating differences among candidates and forecasting their future performance. Similar to many decision-making challenges, personnel selection is highly intricate. While individuals may struggle with quantitative predictions, they often excel at qualitative assessments, given their inclination to articulate emotions verbally. This is where fuzzy linguistic models prove valuable by translating verbal expressions into numerical ones. Consequently, certain MCDM methods based on fuzzy relations are employed to quantify the significance of each criterion (Venkatesh et al., 2019; Güngör et al., 2009).

MCDM serves as a valuable tool for addressing and analyzing complex real-time problems, owing to its unique capability to assess different alternatives based on various criteria, facilitating the selection of the optimal choice (Yılmaz & Ecemiş, 2022; Ağaç & Baki, 2016). MCDM problems encompass scenarios where multiple criteria are optimized, and the best alternative is chosen from a range of potential solution sets (Dalbudak & Rençber, 2022). This method is straightforward to comprehend and implement by managers, contributing to an enhancement in the decision-making process (Mutlu & Sarı, 2017).

In the literature, several widely favored MCDM methods have been selected for utilization in this study. The concepts, which will be elaborated on in detail regarding their application in the methodology section, are briefly introduced in this section. Among these, fuzzy AHP is primarily employed to ascertain the criteria weights, providing a robust and adaptable solution for tackling complex decision scenarios (Acar et al., 2018; Boutkhoum et al., 2017; Patil & Kant, 2014; Choudhary & Shankar, 2012; Heo et al., 2010). AHP is commonly utilized in situations where the options are well-defined, yet the factors influencing decision-making cannot be expressed quantitatively. The objective here is to determine the most appropriate option according to the specified criteria. In other words, the option that meets the defined criteria the most is tried to be determined (Mutlu & Sarı, 2017; Shukla et al., 2014).

However, practitioners often face challenges when assigning evaluation scores in AHP. Fuzzy AHP plays a crucial role in addressing this issue by mitigating subjective judgments that can lead to ambiguity (Cebeci, 2009) and helps overcome human bias and data clarity issues in decision-making (Liu et al., 2020), providing managers with flexibility when evaluating decision scenarios (Venkatesh et al., 2019). In the realm of human resources, it is utilized to aid in decision-making during the selection of optimal personnel, as it allows for the assessment of both qualitative and quantitative criteria in personnel selection processes (Esmaili-Dooki et al., 2017; Güngör et al., 2009).

Another technique employed in the study, TOPSIS, is essentially an index known as proximity to the positive ideal solution (PIS) and distance to the negative ideal solution (NIS). This method then selects the candidate with the maximum similarity to the positive ideal solution (Deliktaş & Üstün, 2018). TOPSIS, known for its user-friendliness (Boutkhoum et al., 2017), operates on the principle that the alternative chosen to address a MCDM problem should have the shortest distance to the positive ideal solution and the greatest distance to the negative ideal solution (Shukla et al., 2014; Choudhary & Shankar, 2012; Chen & Tzeng, 2004; Hwang & Yoon, 1981). Essentially, this technique employs a distance metric to identify the most efficient solutions from a pool of alternatives (Venkatesh et al., 2019). However, like any system, the TOPSIS method has its limitations, particularly in capturing the inherent uncertainty or inaccuracy within decision-making scenarios (Chen, 2000). To address these limitations, combining fuzzy set theory with the traditional TOPSIS method proves to be a more effective approach, allowing decision-makers to integrate incomplete and unquantifiable information (Boutkhoum et al., 2017).

In this study, the fuzzy AHP-TOPSIS method, a combination of both techniques, was utilized. Initially, the fuzzy AHP technique was employed to weigh the relative importance of personnel selection criteria in relation to each other. These weighted criteria were then used to evaluate each candidate's performance across various criteria. Subsequently, fuzzy TOPSIS was applied, where each candidate's score for proximity to the ideal solutions (both positive and negative) was calculated based on the assigned scores. The optimal candidate for recruitment should ideally be close to the positive ideal and distant from the negative ideal (Kusumawardani & Agintiara, 2015). This application of fuzzy set theory facilitates dealing with uncertainty and imprecision in decision-making processes (Nazim et al., 2022). Consequently, decision-makers can navigate the challenge of assigning clear values to evaluation scores and obtain numerical indicators of the significance of each performance characteristic (Güngör et al., 2009). In the literature, fuzzy AHP and fuzzy TOPSIS methods, commonly utilized in personnel selection and other domains, alongside the AI chatbot ChatGPT, which forms another aspect of this research, have been extensively studied. Thus, the subsequent section of this study systematically explores some of these studies, highlighting their key findings and critical aspects.

4.Implementation

In this section, several key elements of the research are succinctly summarized, including the study's purpose, methods for collecting and analyzing research data and as well as the study's field, universe, and sample. This overview lays the foundation for the subsequent analytical processes, preceding the presentation of study findings, and elucidates the methodological framework that underpins the study's application. By emphasizing a systematic approach in data collection and analysis, this methodological framework enhances academic rigor and offers a roadmap for the research journey.

4.1.Purpose of the Research

The primary objective of this study is to delineate the evolution and current status of AI. AI has garnered increasing significance, particularly with the advent of Industry 4.0, and its relevance continues to grow. Thus, there is a pressing need to assess awareness and perceptions surrounding AI, a task that necessitates a greater number and higher quality of scientific studies on the topic. Achieving this requires aligning research with current trends and closely tracking developments in the field.

The proliferation of studies on AI has introduced diverse perspectives on the concept. Notably, technologies such as ChatGPT have made remarkable advancements. ChatGPT has continuously innovated across various domains since its inception, showcasing diverse capabilities extensively discussed in the literature review section of this study. Given its decision-making mechanism akin to human intelligence and its ability to choose between options, delving into the intricacies of this subject has become imperative. Consequently, this study presents an application aimed at evaluating the decision-making capacity of ChatGPT, recognized as one of the most advanced and comprehensive AI tools in recent years.

This study acknowledges that organizations in the private sector must make selections among candidates during personnel selection processes. However, the accuracy of these choices can only be assessed over time, as the performance of hired employees unfolds. To aid in making informed decisions prior to the selection phase, various techniques like MCDM are indispensable. In this study, alongside Fuzzy AHP-TOPSIS, ChatGPT is also regarded as a decision-making technique, helping determine the most suitable candidates for specific positions within the company.

To achieve the study's objectives, the following research questions were addressed:

a) How compatible are the decisions made by ChatGPT in personnel selection with the candidates preferred by the company for employment?

b) How compatible are the decisions made by Fuzzy AHP-TOPSIS in personnel selection with the candidates preferred by the company for employment?

c) How well do the decisions made by ChatGPT in personnel selection align with the candidates recommended by Fuzzy AHP-TOPSIS?

Based on these research questions and the literature, specific questions were formulated for the chatbot during interviews. The bot was educated on the criteria for candidates applying for specific positions and subsequently asked which candidates it would prefer. The decisions made by the bot were then evaluated. These results were compared with the decisions made by the company during the employment of their selected candidates, as well as with the decisions derived from MCDM techniques.

4.2. Research Methodology

In the study, MCDM techniques were employed to assess the decision-making capability of ChatGPT. This was deemed necessary to establish a standard for evaluating the bot's decision-making effectiveness. As the accuracy of a decision becomes apparent over time or through comparison with decisions made by other decision-makers, utilizing specific methods becomes crucial. Therefore, in this section, a MCDM technique, the Fuzzy AHP-TOPSIS method is briefly outlined to provide readers with information and a clearer understanding of the subject.

In this context, it's important to understand what a fuzzy set entails. Fuzzy sets are represented using membership functions, which determine the membership of an element in a fuzzy set on a scale from 0 to 1. Each fuzzy basis set can be conceptualized as a fuzzy number, expressing an interval value with both lower and upper bounds. Fuzzy sets are essentially defined by membership functions, as they encapsulate the same concepts and ideas (Baykal & Beyan, 2004).

Fuzzy sets are often represented using membership functions, such as triangular, trapezoidal, bell curve, sigmoid, and Z-shaped functions. Fuzzy numbers are required to be both normal and convex, and they can be described using verbal expressions like approximate, more or less, or almost. Among fuzzy numbers, triangular and trapezoidal forms are commonly employed in practical applications (Bektur, 2021). For instance, a triangular fuzzy number denoted as ($a1$, $a2$, $a3$) consists of $a1$ as the lowest value on the left, $a2$ as the central or best possible value, and $a3$ as the highest value on the right. The membership function of a triangular fuzzy number $\mu\,\tilde{A}$ is typically represented as shown in formula

$$\mu_A(x) = \begin{cases} 0, & x < a_1 \\ \dfrac{x-a_1}{a_2-a_1} & a_1 \leq x \leq a_2 \\ \dfrac{-(x-a_3)}{a_3-a_2} & a_2 \leq x \leq a_3 \\ 0, & x > a_3 \end{cases} \tag{1}$$

Formula (1) shows the membership function of the triangular fuzzy number (m, l, u). Just as mathematical operations can be performed on natural numbers, mathematical operations can also be performed on fuzzy numbers.

$$\tilde{A} + \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$$

$$\tilde{A} - \tilde{B} = (a_1 - b_3, a_2 - b_2, a_3 - b_1)$$

$$\tilde{A}\,.\,\tilde{B} = (a_1\,.\,b_1, a_2\,.\,b_2, a_3.\,b_3)$$

$$\frac{\tilde{A}}{\tilde{B}} = (\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1})$$

$$\tilde{A}\,.\,k = (a_1\,.\,k\,, a_2\,.\,k, a_3.\,k)$$

$$\tilde{A}^{-1} = \left(\frac{1}{a_3.}, \frac{1}{a_2.}, \frac{1}{a_1.}\right) \tag{2}$$

AHP was first proposed by Myers and Alpert (1968) and was developed as a model by Saaty (1977) and made available for solving decision-making problems (Dalbudak & Rençber, 2022; Mutlu & Sarı, 2017; Kusumawardani & Agintiara, 2015; Ayhan, 2013). As we explained in the literature review section of our study, it is seen that the AHP method is widely used in solving decision problems encountered in many fields and businesses today.

Basically, AHP can be defined as a method of expressing the components and variables of a complex and poorly structured situation in a hierarchical order, assigning quantitative values to personal judgments regarding the comparative importance levels of each alternative, and synthesizing the priority levels of variables according to the results of the judgments obtained (Alp & Gündoğdu, 2012). AHP handles the decision problem in a hierarchical structure and allows the decision maker to apply data, experience, understanding and intuition in a correct and logical way by modeling a complex problem in a hierarchical structure by showing the relationship between goals, objectives (criteria), sub-criteria and alternatives (Karakış, 2019).

Classical AHP is criticized for its inability to model uncertainty and fuzziness. Unlike AHP in which exact values are used, in Fuzzy AHP, criteria evaluations and comparisons are made with fuzzy logic. In this context, fuzzy AHP was introduced to overcome this deficiency of classical AHP (Kabir & Hasin, 2011). In this study, the

Fuzzy AHP model based on the calculation of artificial order values of comparisons with triangular fuzzy numbers proposed by Chang (1996) was used. Chang's fuzzy AHP method is a preferred method because it does not require much mathematical calculation and classical AHP steps are applied (Karakış, 2019).

$$\boldsymbol{X = \{ x_1, x_2, x_3, x_4, \ldots\ldots\ldots\ldots x_n \}}$$

$$\boldsymbol{U = \{ u_1, u_2, u_3, u_4, \ldots\ldots\ldots\ldots u_n \}} \tag{3}$$

In this method, as shown in the formula above, when "x" is a set of criteria and "u" is a set of objectives, each criterion is taken and rank analysis is applied for each objective according to Chang's method. In other words, synthetic values are obtained for each objective according to each criterion. In this way, m synthetic values are obtained for each criterion, as many as the number of criteria. These values are shown as follows.

$$\boldsymbol{M_{gi}^1, M_{gi}^2, M_{gi}^3, \ldots\ldots\ldots\ldots M_{gi}^m} \qquad \boldsymbol{i = 1, 2, 3, \ldots\ldots. n}$$

$$\boldsymbol{M_{gi}^j (j = 1, 2, 3, \ldots\ldots m)} \quad triangle\ fuzzy\ number \tag{4}$$

The TOPSIS method, which can find voice as a method of ranking according to ideal solution, was developed by Hwang and Yoon (1981). The TOPSIS method, which is one of the MCDM techniques, is based on the decision of decision alternatives according to their distance from the positive ideal solution and negative ideal solution point (Dumanoğlu & Ergül, 2010). In this method, the alternative that offers the most appropriate solution is the alternative that is closest to the positive ideal solution. Ideal solution or most appropriate alternative is the solution which minimizes cost criterion while maximizing benefit criterion.

Fuzzy TOPSIS is a decision-making method used in the selection, ranking and evaluation of alternatives in quantitative and qualitative MCDM problems. In case the alternatives are quantitative data, determining the criteria weights in the TOPSIS method constitutes the subjective aspect of the method (Ishizaka & Nemery, 2013). In this context, it is seen that various decision-making methods such as AHP, ANP (Analytical Network Process) can be integrated into the TOPSIS method to determine the criteria weights in the method (Karakış, 2019).

During the application, decision makers express evaluations about decision criteria and alternatives linguistically and these are converted to fuzzy numbers and proximity coefficients calculated for alternatives (Karakış, 2019). With the help of the calculated closeness coefficients, the alternatives are ranked and the solution is presented. In this context, the linguistic evaluations developed by Chen (2000) and used in the evaluation of alternatives and their fuzzy number equivalents are shown in the findings section of the study.

In a group of K decision makers, the importance weight of the jth decision criterion affecting decision problem is calculated. A decision is made by ranking the alternatives according to their proximity coefficient values. If the proximity coefficient is equal to 1, the value of the alternative in question is equal to the fuzzy positive ideal solution, and if the proximity coefficient is equal to 0, the value of the alternative is equal to the fuzzy negative ideal solution (Çınar, 2011). Thus, technical explanations of the methods used in the research are included here. In this way, it is aimed to inform those interested in the subject in more detail about the inner aspects of the applied methods. After this part, information will be given about the universe and sample of the research.

4.3. Universe And Sample

This section discusses the practical implications of decisions made using ChatGPT and the Fuzzy AHP-TOPSIS method in specific sectors. Rather than focusing solely on theoretical decisions, it is crucial to assess how these decisions manifest in real-life scenarios. To achieve this, a private sector enterprise was selected as a case study. The enterprise, a sizable company with branches across the country, represents a significant presence in the industry. However, due to logistical constraints, it was impractical to implement the study nationwide. Therefore, the study focused on branches located in major industrial cities such as Ankara, İstanbul, İzmir, and Bursa.

Last year, branches of the same firm in Turkey's four largest cities undertook recruitment activities for new employees. Through interviews conducted with the human resources departments of these branches, we obtained information about candidates who applied for the manager position. It is important to note that personal information about the candidates was handled in compliance with privacy protection standards. The study adhered to academic research protocols and ethical guidelines. The data obtained from the human resources departments of the sampled branches facilitated the necessary procedures for introducing candidates into the decision-making process using ChatGPT and applying the Fuzzy AHP-TOPSIS technique.

In this context, the study was conducted at a local level, primarily due to the novelty of ChatGPT in academic testing within this field. Given its status as a new concept, the initial sample size was intentionally kept small. The study's findings can be viewed as a preliminary exploration, paving the way for future studies with larger budgets and broader samples. Given the early stages of AI applications, initial efforts often involve small-scale studies due to budget constraints. Therefore, the first application was conducted with a relatively limited sample size, aiming to provide insights for future research endeavors.

5. Findings

The presentation of research findings was achieved through a two-stage process. In the first stage, the Fuzzy AHP-TOPSIS application was conducted. Within this method, the Fuzzy AHP approach was used to determine the weights of criteria employed in personnel selection. Using the derived criterion weight values, the Fuzzy TOPSIS method was then utilized to rank personnel selection alternatives. The criteria were established based on input from four different experts in the field of human resources, categorized into four main headings: foreign language proficiency (K1), salary expectations (K2), experience (K3), and communication skills (K4). In this context, a table demonstrating the conversion of the identified criteria from linguistic expressions to fuzzy and inverse fuzzy numbers is presented below.

Table 2: Fuzzy numbers and inverse fuzzy numbers used in the application of the Fuzzy Ahp method

Saaty 1-9 Scale	Linguistic Expressions	Triangular Fuzzy Scale	Triangular Fuzzy Inverse Scale
1	Equal Importance	(1,1,1)	(1,1,1)
3	Slightly More Important	(1,3,5)	(0.20,0.33,1)
5	More Important	(3,5,7)	(0.14,0.20,0.33)
7	Strongly Important	(5,7,9)	(0.11,0.14,0.20)
9	Very Strongly Important	(7,9,11)	(0.09,0.11,0.14)

Source: Salomon & Gomes, 2024.

The values regarding the pairwise comparison results of the main criteria requested from human resource management experts are provided in Table 3 below. According to the experts, foreign language proficiency is considered strongly important compared to salary expectations, while experience is deemed very strongly important compared to foreign language proficiency. Additionally, communication skills are evaluated as more important than foreign language proficiency. The weighting of the identified criteria in the study was also determined based on these opinions and assessments.

Table 3: Fuzzy evaluation matrix

Criteria	K1	K2	K3	K4
K1	(1,1,1)	(5,7,9)	(1,3,5)	(0.14,0.20, 0.33)
K2	(0.11,0.14,0.20)	(1,1,1)	(0.09,0.11, 0.14)	(0.14,0.20, 0.33)
K3	(0.20,0.33,1)	(7,9,11)	(1,1,1)	(5,7,9)
K4	(3,5,7)	(3,5,7)	(0.11,0.14, 0.20)	(1,1,1)

The weights of the criteria were calculated following the steps of Fuzzy AHP. Using Steps 1 and 2, the Si values were computed. Based on these Si values, the weight vector w was obtained with the help of Equations 14, 15, and 16.

Table 4: Weights of criteria with Fuzzy AHP

Criteria	K1	K2	K3	K4
w	0,28511	0	0,432258	0,282632

Using the weights obtained from the Fuzzy AHP method, a decision combination was formed for candidate selection in Bursa, İstanbul, İzmir, and Ankara using the Fuzzy TOPSIS method, as shown in Table 5. Since salary expectations (K2) are cost-based, they are taken inversely. The distances of candidates to the positive ideal solution and negative ideal solution, along with the proximity coefficients calculated based on these values, were determined. A proximity coefficient closest to 1 indicates the most suitable candidate with the desired qualities, while a value closest to '0' indicates an unsuitable candidate.

Table 5: Fuzzy numbers used in fuzzy TOPSIS application

Saaty 1-9 Scale	Linguistic Expressions	Triangular Fuzzy Scale
1	Very Low	(1,1,3)
3	Low	(1,3,5)
5	Average	(3,5,7)
7	High	(5,7,9)
9	Very High	(7,9,11)

Importance weights of criteria shown in Table 5 were used in combination with the Fuzzy TOPSIS method to evaluate alternatives based on these criteria. A Fuzzy decision combination matrix was created for candidates based on the fuzzy number expressions of the verbal variables used by decision-makers for criteria-based evaluation of candidates (as shown in Table 5), as seen in Appendix 1.

Subsequently, using Equation 21 with the fuzzy decision combination matrix (Appendix 1), a normalized decision matrix is obtained. After calculating the normalized decision matrix, Equation 22, 23, 24, and 25 are used to calculate the weighted normalized decision matrix (Appendix 2) considering the importance weights of the criteria.

After calculating the weighted normalized fuzzy decision matrix, the fuzzy positive ideal solution and fuzzy negative ideal solution are determined using Equations 26, 27, and 28. To find the distances of alternatives from the calculated ideal solutions, Equations 29, 30, 31, and 32 are computed using the Vertex method (Appendix 3).

The ranking of alternatives based on the proximity coefficient CC_i values is presented in Appendix 4. If the proximity coefficient is equal to 1, the value of the alternative is equal to the fuzzy positive ideal solution; if the proximity coefficient is equal to 0, the value of the alternative is equal to the fuzzy negative ideal solution. Proximity coefficients between (0-0.2) are considered unacceptable, (0.2-0.4) carries high risk, (0.4-0.6) implies risk, (0.6-0.8) is deemed acceptable, and (0.8-1) should be preferred (Chen et al., 2006).

The evaluation of the preferences made by the model resulting from all these applications constitutes one aspect of this study. Additionally, AI comes into play to form the other aspect of the comparison. In the scope of this study, one of the most advanced AI tools of today, ChatGPT, is considered as a sample to assess the decision-making behavior of AI. As mentioned in the literature review section, ChatGPT, the most advanced version of chatbots today, has been the subject of significant research in many fields. These studies have revealed important findings regarding the bot's limitations and capabilities.

In this study, conversations were conducted with ChatGPT's latest and paid version, GPT-4, to address the decision-making capacity of AI. During the conversations with the bot, a brief introduction about the topic was initially provided. Subsequently, it was explained that information about candidates with specific criteria for personnel selection in a business would be provided, and the bot was informed about how its decision would be made within this context. Then, the bot was presented with the necessary information about the candidates based on the defined criteria, and it was asked which candidates it would choose. However, to assess the consistency of the decisions made by AI, this decision process was repeated with different conversations on different days. In this context, the conversations revealed consistent responses with minor differences.

The table below includes the decisions made as a result of these applications, which constitute the two aspects of the study, along with the company's own selections. The tables are divided into two parts: the first part includes decisions for candidates employed in Bursa and İzmir, while the second part includes decisions for candidates employed in Ankara and İstanbul. To facilitate data visibility and avoid unnecessary page length, information about candidates not selected in any of the three parts is not included in the table. Readers who wish to explore the topic in more detail can find the detailed versions of the tables in the appendices section.

Table 6: Comparison of Results (Bursa)

Bursa	CC_i	Company's Choice	F-AHP-TOPSIS	ChatGPT
BA2	0,67	✓		✓
BA4	0,42			✓
BA11	0,88	✓	✓	
BA12	0,84	✓	✓	✓
BA16	072	✓		
BA20	0,84		✓	
BA22	0,16			✓
BA28	0,88		✓	
BA35	0,40			✓
BA36	0,90	✓	✓	
BA39	0,83	✓	✓	
BA40	0,73			✓
BA42	0,73			
BA44	0,80		✓	✓
BA47	0,80	✓		

The company operating in Bursa has employed 7 out of 47 candidates. As a result of Fuzzy AHP-TOPSIS, 7 candidates were identified, and ChatGPT was asked to select 7 candidates accordingly. When comparing the decisions made by Fuzzy AHP-TOPSIS with those made by the company, it is observed that they have common decisions for candidates BA11, BA12, BA36 and BA39. According to ChatGPT's decisions, there are common decision for only candidate BA12. It can be said that the decisions made by Fuzzy AHP-TOPSIS are successful compared to ChatGPT's decisions. Additionally, an interesting situation arises here. Although Fuzzy AHP-TOPSIS and ChatGPT suggest a candidate who should be preferred but the company did not employ (BA44). If we interpret the data based on numbers, it is seen that this candidate, although having good qualifications on paper in terms of criteria, were not preferred by the company. This could be due to various factors such as social, cultural, customary, or demographic reasons. The underlying reasons behind such situations can only be determined through more in-depth or comprehensive research. Due to time and financial constraints in this study, conducting a more in-depth evaluation was not possible.

Table 7: Comparison of Results (İzmir)

İzmir	CC_i	Company's Choice	F-AHP-TOPSIS	ChatGPT
ZA6	0,70	✓		
ZA9	0,53			✓
ZA11	0,72	✓		✓
ZA16	0,80	✓	✓	✓
ZA20	0,82		✓	
ZA25	0,82		✓	

The situation in İzmir provides a clearer picture. Both the company and Fuzzy AHP-TOPSIS, as well as ChatGPT, agreed on 1 out of 3 employed candidates (ZA16). This indicates that this candidate stood out among 33 applicants as suitable for the company based on their qualifications and other characteristics. For the remaining candidates, the company preferred ZA6 and ZA11, Fuzzy AHP-TOPSIS preferred ZA20 and ZA25, and ChatGPT preferred ZA9 and ZA11. For candidate ZA11, both compay decision and ChatGPT's decision are same. But for this candidate, Fuzzy AHP-TOPSIS made different decision and did not suggest to choose this person. Hence, in terms of decision-making methods and AI success in the İzmir sample, it is evident that ChatGPT's decision are better. Due to the limited number of applicants and positions available for employment, the evaluation of results has been restricted to this extent. Perhaps more comprehensive findings can be obtained in the future with larger samples. Therefore, the table below illustrates how the results shaped up for Ankara and İstanbul.

Table 8: Comparison of Results (Ankara)

Ankara	CC_i	Company's Choice	F-AHP-TOPSIS	ChatGPT
AA3	0,73	✓		
AA6	0,82		✓	✓
AA10	0,80		✓	
AA13	0,80	✓	✓	✓
AA20	0,80	✓	✓	✓
AA22	0,70	✓		✓
AA24	0,66	✓		✓
AA28	0,88		✓	✓
AA36	0,84		✓	✓
AA48	0,82		✓	
AA51	0,59	✓		
AA54	0,81	✓		
AA57	0,61	✓		
AA58	0,68			✓

In terms of Ankara, the findings are as follows. The company has employed 8 out of 67 candidates. When comparing the decisions made by Fuzzy AHP-TOPSIS and ChatGPT with those made by the company, it is observed that they have common decisions for candidates AA13 and AA20. That means both AI and Fuzzy AHP-TOPSIS correctly guessed 2 candicates which company has been decided to employ. Apart from this, according to ChatGPT's decisions, 2 candidates (AA13, AA20, AA22, and AA24) were selected in common with the company. It is noted that 2 of these candidates (AA13 and AA20) were preferred in all 3 scenarios. Additionally, unlike Bursa, it is seen that ChatGPT's decisions are more successful than Fuzzy AHP-TOPSIS. Furthermore, similarly to previous cases, there are candidates that both Fuzzy AHP-TOPSIS and ChatGPT suggest to be preferred, but the company did not employ (AA6, AA28, and AA36).

Table 9: Comparison of Results (İstanbul)

İstanbul	CC_i	Company's Choice	F-AHP-TOPSIS	ChatGPT
İA2	0,81	✓	✓	✓
İA5	0,65	✓		
İA6	0,77		✓	
İA12	0,69	✓	✓	✓
İA18	0,06			✓
İA19	0,19			✓
İA22	0,73	✓	✓	✓
İA29	0,69		✓	
İA30	0,69	✓		
İA42	0,64			✓
İA44	0,69	✓		
İA48	0,65	✓		✓
İA49	0,77		✓	
İA51	0,70		✓	

Regarding İstanbul, the company has employed 7 out of 53 candidates. When comparing the decisions made by Fuzzy AHP-TOPSIS with those made by the company, it is observed that they have common decisions for candidates İA2, İA12, and İA22. According to ChatGPT's decisions, 4 candidates (İA2, İA12, İA22, and İA48) were selected in common with the company. Among these candidates, 3 (İA2, İA12, and İA22) were preferred in all 3 scenarios. Similar to Ankara and unlike Bursa, it is also seen that ChatGPT's decisions are more successful than Fuzzy AHP-TOPSIS. However, unlike Bursa and Ankara, there are no candidates suggested by both Fuzzy AHP-TOPSIS and ChatGPT that the company did not employ. Apart from common decisions, preferences for candidates differ in cases where they are not selected in common, similar to İzmir.

When all these findings are considered, it is seen that the decisions made exhibit many differences within themselves. Looking at the overall application conducted in 4 different cities, it is observed that Fuzzy AHP-TOPSIS achieved more successful decisions in Bursa, while ChatGPT's decisions were more accurate in Ankara, İstanbul and İzmir. In some cases, candidates suggested by both Fuzzy AHP-TOPSIS and ChatGPT were not employed by the company.

It is impossible to fully understand all the variability shown above with the available data. This is because the current application is based only on the numerical transformation of linguistic expressions of criteria, so conclusions and findings are limited for now. There could be many reasons underlying this situation. Having good qualifications on paper alone may not be sufficient for employees to be hired. In the professional business world, alongside the qualifications of candidates, many factors such as social, cultural, customary, and demographic aspects can also be influential in employing personnel. The reasons behind these and similar situations can only be determined through more in-depth or comprehensive research. Due to time and financial constraints in this study, conducting a more in-depth evaluation was not possible. This concludes the findings of the study, and the next section includes overall evaluations within the research scope and discussions of the research findings with the past studies in the literature.

6. Conclusions

Selecting the right employees for specific roles has become a critical factor in today's competitive landscape. Advancements in information technologies have further enhanced the potential to achieve this goal. This study examines whether the ongoing transformation in information technologies has practical implications for decision-making processes. In this context, the study explores both Fuzzy AHP-TOPSIS, a MCDM technique, and ChatGPT, an AI-powered chatbot, to assess their effectiveness.

While the literature review section of this study provides a detailed discussion, this section highlights key points from previous studies and compares them with the findings of the current research. This comparative analysis is crucial for better understanding and evaluating the study's contribution to the existing literature. Accordingly, the findings on the decision-making behavior of the Fuzzy AHP-TOPSIS technique are examined first, followed by an evaluation of ChatGPT's decision-making behavior.

When the results of the studies in the literature that preferred the Fuzzy AHP-TOPSIS method in personnel selection are evaluated, it is found that in some studies, the method produces results that match or are very close to the actual decision (Esmaili-Dooki et al., 2017; Kusumawardani & Agintiara, 2015; Ablhamid et al., 2013), while in some studies (Janjua & Hassan, 2020; Chou et al., 2019), the method produces both successful and unsuccessful results. However, in some studies, the decisions made by the method do not match the real personnel selection decisions (Samanlioglu et al., 2018). In this study, it can be said that although the fuzzy AHP-TOPSIS method cannot exactly identify the candidates that the company prefers to employ, it has achieved quite successful results (32%), similar to the studies in the literature.

In the studies discussed until this section, examples of decision-making applications of fuzzy AHP and fuzzy TOPSIS methods have been given. In terms of observing the decision-making behavior of AI, which constitutes the other part of the research question, it is necessary to compare the findings in the literature with the research findings. In some studies in the literature (Araujo et al., 2020; Shrestha et al., 2019), it has been observed that the decisions made by AI are equal to or better than humans. In this research, AI made suggestions and choosed to employ 10 candidates among 25 which is equal to %40 success rate and more than MCDM techniques. This situation is similar to literature findings and seen that successful results have been achieved in studies on the decision-making behavior of ChatGPT (Antaki et al., 2023; Sobania et al., 2023; Gilson et al., 2022).

When all these findings and comparisons are evaluated, it can be said that the personnel selection decisions made in real life are compatible with the decisions made with MCDM techniques and AI. According to the findings, both Fuzzy AHP-TOPSIS and ChatGPT correctly predicted 14 of the 25 personnel employed (56%) in all branches of the company. When factors such as the attitude of human resources departments in personnel selection, policies that may vary according to branches, attitudes and expectations of managers, local norms, cultural differences are taken into consideration, it can be thought that the success rate of these predictions is actually higher. This is because both MCDM and AI make decisions based on data that can only be computerized and based on mathematical models. For this reason, it is not yet possible to fully determine the impact of human emotional, mental, sociological, cultural and similar elements of the decision-making process. This situation can only be evaluated in more detail with more in-depth studies at the organizational level. Therefore, in this study, it can be said that both Fuzzy AHP-TOPSIS and ChatGPT give generally satisfactory results in the application of decision making in the personnel selection process.

Here, it is important to note that some candidates recommended for employment by both ChatGPT and Fuzzy AHP-TOPSIS, through a consensus decision, were ultimately not hired by the company. This group constitutes 5 individuals (20%) of the total candidates. Despite being recommended by both decision-making technique and AI, these candidates were not employed. This outcome stands out as one of the significant findings of the research.

Future studies in this field could benefit from examining the influence of local values, as highlighted in the findings of this research. Incorporating the perspectives of participants working at the national level alongside those from the same region as the recruiting branch could enhance the quality of the research. This approach would allow for an exploration of how national and regional cultures influence staff selection and highlight differences in values between the two. Additionally, given the potential for cultural, sociological, and other variations on an international scale, large-scale research is recommended to provide broader insights.

Another important consideration for future research is whether AI can be utilized to support the application of MCDM approaches. This raises the question of whether decision-making techniques, which are fundamentally based on mathematical calculations and data, can be effectively integrated with digital tools. With advancements in information technologies, the development of AI-supported MCDM applications may become a reality. For instance, this study prompts the question of what a ChatGPT-supported Fuzzy AHP-TOPSIS decision-making process might look like and whether it is feasible. These questions provide a valuable direction for future research and exploration.

As with any study, this research faced several limitations. The first was the lack of financial support, as the study was conducted solely with the authors' personal budgets. Additionally, companies were reluctant to share personnel information, even though no private details were requested, which hindered data collection and limited the sample size.

Also, a limitation encountered in the methodological section of the study relates to the technique applied. The Chen method results in the weights being reduced to "0," which constitutes a limitation of the study. Researchers aiming to conduct studies in this field are encouraged to consider this issue and explore alternative methods to address it in future research.

Another limitation stems from the nascent nature of AI technologies, which are still in their early stages of development. Consequently, the data obtained from the company was used as criteria for the AI tool, which was then tasked with making a decision. Unlike mathematical decision-making applications, this AI tool was not pre-trained. Addressing this limitation in the early stages of the study could improve future research, where more advanced and trainable AI systems might be utilized. With continued advancements in AI, it may become possible to conduct more extensive and robust studies in the future.

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Appendices

In this section, additional supporting materials, which are considered important for the implementation of the research, are included. In order not to increase the number of pages in the study and not to cause complexity, only a part of the data is shared in this section. Those who need the entire data for scientific research can contact the authors via their e-mail addresses and request the whole.

Appendix 1: Fuzzy decision combinations

Bursa	K1	K2	K3	K4
BA1	(1,1,3)	(1,1,3)	(1,3,5)	(1,3,5)
BA2	(3,5,7)	(1,3,5)	(7,9,11)	(1,3,5)
BA3	(1,3,5)	(3,5,7)	(1,3,5)	(1,3,5)
BA4	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)
BA5	(3,5,7)	(1,3,5)	(1,1,3)	(3,5,7)
BA6	(5,7,9)	(5,7,9)	(1,1,3)	(3,5,7)
BA7	(3,5,7)	(3,5,7)	(1,3,5)	(1,1,3)
BA8	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,11)
BA9	(1,3,5)	(7,9,11)	(3,5,7)	(5,7,9)
BA10	(5,7,9)	(3,5,7)	(3,5,7)	(1,3,5)

İstanbul	K1	K2	K3	K4
İA1	(1,3,5)	(3,5,7)	(1,3,5)	(1,3,5)
İA2	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,11)
İA3	(1,1,3)	(3,5,7)	(5,7,9)	(1,3,5)
İA4	(1,1,3)	(1,1,3)	(1,3,5)	(1,1,3)
İA5	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)
İA6	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)
İA7	(3,5,7)	(1,1,3)	(1,3,5)	(1,3,5)
İA8	(1,3,5)	(3,5,7)	(1,1,3)	(3,5,7)
İA9	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)
İA10	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)

İzmir	K1	K2	K3	K4
ZA1	(5,7,9)	(1,3,5)	(3,5,7)	(3,5,7)
ZA2	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,11)
ZA3	(1,3,5)	(3,5,7)	(5,7,9)	(3,5,7)
ZA4	(1,3,5)	(1,1,3)	(1,3,5)	(1,3,5)
ZA5	(1,1,3)	(5,7,9)	(3,5,7)	(3,5,7)
ZA6	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)
ZA7	(1,3,5)	(3,5,7)	(3,5,7)	(3,5,7)
ZA8	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)
ZA9	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)
ZA10	(5,7,9)	(3,5,7)	(1,1,3)	(1,1,3)

Ankara	K1	K2	K3	K4
AA1	(3,5,7)	(3,5,7)	(1,3,5)	(1,1,3)
AA2	(3,5,7)	(7,9,11)	(5,7,9)	(5,7,9)
AA3	(1,3,5)	(3,5,7)	(7,9,11)	(5,7,9)
AA4	(1,3,5)	(1,3,5)	(1,1,3)	(3,5,7)
AA5	(5,7,9)	(3,5,7)	(1,3,5)	(1,3,5)
AA6	(3,5,7)	(3,5,7)	(7,9,11)	(5,7,9)
AA7	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)
AA8	(5,7,9)	(5,7,9)	(3,5,7)	(1,3,5)
AA9	(5,7,9)	(7,9,11)	(3,5,7)	(5,7,9)
AA10	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)

Appendix 2: Weighted normalized fuzzy decision matrices

Bursa	K1	K2	K3	K4
BA1	(0.03,0.03,0.10)	(0,0,0)	(0.04,012,0.20)	(0.03,0.08,0.10)
BA2	(0.10,0.16,0.22)	(0,0,0)	(0.28,035,0.43)	(0.03,0.08,0.10)
BA3	(0.03,0.10,0.16)	(0,0,0)	(0.04,012,0.20)	(0.03,0.08,0.10)
BA4	(0.16,0.22,0.29)	(0,0,0)	(0.04,012,0.20)	(0.03,0.08,0.10)
BA5	(0.10,0.16,0.22)	(0,0,0)	(0.04,0.04,0.12)	(0.08,0.13,0.20)
BA6	(0.16,0.22,0.29)	(0,0,0)	(0.04,0.04,0.12)	(0.08,0.13,0.20)
BA7	(0.10,0.16,0.22)	(0,0,0)	(0.04,012,0.20)	(0.03,0.03,0.10)
BA8	(0.10,0.16,0.22)	(0,0,0)	(0.20,0.28,0.35)	(0.18,0.23,0.30)
BA9	(0.03,0.10,0.16)	(0,0,0)	(0.12,0.20,0.28)	(0.13,0.18,0.20)
BA10	(0.16,0.22,0.29)	(0,0,0)	(0.12,0.20,0.28)	(0.03,0.08,0.10)

İstanbul	K1	K2	K3	K4
İA1	(0.03,0.08,0.13)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.08,0.13)
İA2	(0.13,0.18,0.23)	(0,0,0)	(0.20,0.28,0.35)	(0.18,0.23,0.28)
İA3	(0.03,0.03,0.08)	(0,0,0)	(0.20,0.28,0.35)	(0.03,0.08,0.13)
İA4	(0.03,0.03,0.08)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.03,0.08)
İA5	(0.08,0.13,0.18)	(0,0,0)	(0.20,0.28,0.35)	(0.13,0.18,0.23)
İA6	(0.08,0.13,0.18)	(0,0,0)	(0.28,0.35,0.43)	(0.13,0.18,0.23)
İA7	(0.08,0.13,0.18)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.08,0.13)
İA8	(0.03,0.08,0.13)	(0,0,0)	(0.04,0.04,0.12)	(0.08,0.13,0.18)
İA9	(0.08,0.13,0.18)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.08,0.13)
İA10	(0.08,0.13,0.18)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.08,0.13)

İzmir	K1	K2	K3	K4
ZA1	(0.16,0.22,0.29)	(0,0,0)	(0.12,0.20,0.28)	(0.08,0.13,0.18)
ZA2	(0.10,0.16,0.22)	(0,0,0)	(0.12,0.20,0.28)	(0.18,0.23,0.28)
ZA3	(0.03,0.10,0.16)	(0,0,0)	(0.20,0.28,0.35)	(0.08,0.13,0.18))
ZA4	(0.03,0.10,0.16)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.08,013)
ZA5	(0.03,0.03,0,10)	(0,0,0)	(0.12,0.20,0.28)	(0.08,0.13,0.18)
ZA6	(0.10,0.16,0.22)	(0,0,0)	(0.20,0.28,0.35)	(0.13,0.18,0.23)
ZA7	(0.03,0.10,0.16)	(0,0,0)	(0.12,0.20,0.28)	(0.08,0.13,0.18)
ZA8	(0.03,0.10,0.16)	(0,0,0)	(0.20,0.28,0.35)	(0.08,0.13,0.18)
ZA9	(0.03,0.10,0.16)	(0,0,0)	(0.20,0.28,0.35)	(0.08,0.13,0.18)
ZA10	(0.16,0.22,0.29)	(0,0,0)	(0.04,0.04,0.12)	(0.03,0.03,0.08)

Ankara	K1	K2	K3	K4
AA1	(0.10,0.16,0.22)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.03,0.08)
AA2	(0.10,0.16,0.22)	(0,0,0)	(0.20,0.28,0.35)	(0.13,0.18,0.23)
AA3	(0.03,0.10,0.16)	(0,0,0)	(0.28,0.35,0.43)	(0.13,0.18,0.23)
AA4	(0.03,0.10,0.16)	(0,0,0)	(0.04,0.04,0.12)	(0.08,0.13,0.18)
AA5	(0.16,0.22,0.29)	(0,0,0)	(0.04,0.12,0.20)	(0.03,0.08,0.13)
AA6	(0.10,0.16,0.22)	(0,0,0)	(0.28,0.35,0.43)	(0.13,0.18,0.23)
AA7	(0.16,0.22,0.29)	(0,0,0)	(0.20,0.28,0.35)	(0.08,0.13,0.18)
AA8	(0.16,0.22,0.29)	(0,0,0)	(0.12,0.20,0.28)	(0.03,0.08,0.13)
AA9	(0.16,0.22,0.29)	(0,0,0)	(0.12,0.20,0.28)	(0.13,0.18,0.23)
AA10	(0.16,0.22,0.29)	(0,0,0)	(0.20,0.28,0.35)	(0.13,0.18,0.23)

Appendix 3: Distances of alternatives to the ideal solution and closeness coefficient

Bursa	d*+	d*-	CC_i
BA1	0,56	0,11	0,16
BA2	0,22	0,44	0,67
BA3	0,52	0,16	0,23
BA4	0,39	0,28	0,42
BA5	0,46	0,20	0,30
BA6	0,39	0,26	0,40
BA7	0,49	0,17	0,26
BA8	0,14	0,51	0,78
BA9	0,34	0,33	0,49
BA10	0,31	0,35	0,53

İstanbul	d*+	d*-	CC_i
İA1	0,55	0,15	0,21
İA2	0,13	0,54	0,81
İA3	0,42	0,25	0,38
İA4	0,62	0,06	0,09
İA5	0,23	0,44	0,65
İA6	0,16	0,52	0,77
İA7	0,49	0,20	0,28
İA8	0,55	0,13	0,19
İA9	0,49	0,20	0,28
İA10	0,49	0,20	0,28

İzmir	d*+	d*-	CC_i
ZA1	0,26	0,40	0,60
ZA2	0,22	0,44	0,66
ZA3	0,31	0,35	0,53
ZA4	0,52	0,16	0,23
ZA5	0,43	0,23	0,34
ZA6	0,19	0,46	0,70
ZA7	0,39	0,28	0,42
ZA8	0,31	0,35	0,53
ZA9	0,31	0,35	0,53
ZA10	0,48	0,17	0,26

Ankara	d*+	d*-	CC_i
AA1	0,49	0,17	0,26
AA2	0,19	0,46	0,70
AA3	0,18	0,48	0,73
AA4	0,52	0,14	0,21
AA5	0,39	0,28	0,42
AA6	0,11	0,54	0,82
AA7	0,18	0,47	0,72
AA8	0,31	0,35	0,53
AA9	0,21	0,45	0,68
AA10	0,13	0,52	0,80

Appendix 4: Predisposition coefficient ranking

Order	Bursa	CC_i	İstanbul	CC_i
1	BA36	0,90	İA2	0,81
2	BA11	0,88	İA49	0,77
3	BA28	0,88	İA6	0,77
4	BA12	0,84	İA22	0,73
5	BA20	0,84	İA51	0,7
6	BA39	0,82	İA12	0,69
7	BA44	0,80	İA29	0,69
8	BA46	0,80	İA30	0,69
9	BA47	0,80	İA44	0,69
10	BA36	0,90	İA50	0,66

Order	İzmir	CC_i	Ankara	CC_i
1	ZA20	0,82	AA28	0,88
2	ZA25	0,82	AA36	0,84
3	ZA16	0,8	AA6	0,82
4	ZA32	0,8	AA48	0,82
5	ZA11	0,72	AA54	0,81
6	ZA6	0,7	AA10	0,80
7	ZA2	0,66	AA13	0,80
8	ZA17	0,65	AA20	0,80
9	ZA19	0,65	AA25	0,75
10	ZA24	0,61	AA61	0,75