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Big Five Personality Traits in the Selection of Retention Strategies in the IT-ITES Industry: A Fuzzy MCDM Approach

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Abstract

Purpose: The potential of any organization to flourish while sustaining competition and delivering excellent service depends upon its human capital. There is no one-size-fits-all approach to retaining employees, as every individual is unique, necessitating the use of multiple strategies. Multi-criteria decision-making (MCDM) methods are employed to rank employee retention techniques based on each personality. This study contributes to Decision Sciences by developing and validating a hybrid Fuzzy Analytic Hierarchy Process (FAHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) framework that systematically links the Big Five Personality traits with specific retention strategies under conditions of uncertainty, thereby providing a quantifiable tool for strategic human resource management.

Design/methodology/approach: Expert opinions have been obtained with the objective of determining the most effective strategy based on each type. Based on the recommendations of experts, Organizational Culture, Inclusion and Belongingness, Employee Engagement, Employee Empowerment, and Employee Well-Being were taken into account as alternatives. The Big 5 traits, Openness to new experiences, Conscientiousness, Extroversion, Agreeableness, and Neuroticism, are used as criterion factors. The criterion weights established using FAHP were ranked using FTOPSIS. Sensitivity analysis was conducted to test the robustness and stability of the proposed method.

Findings: The Consistency Ratio of the fuzzy influence matrix was within the specified value, hence the scores given by the experts were valid and reliable. The study identified that Conscientiousness was the most preferred trait according to HR experts. Based on the criteria, i.e., Big Five personalities, organizational culture is ranked number one among the retention techniques to be employed for retention. Sensitivity analysis was performed and proved the reliability of the data.

Practical implications: Based upon the results of the model, organizations can customize their model with other personality types as criteria and build their own set of alternatives. By experimenting with various MCDM approaches, researchers may widen the scope of their investigation. Different sectors, combinations of factors, and geographical locations can be used for the studies.

Social implications: The study highlights that Fuzzy MCDM techniques can be used to predict retention techniques using personality. The algorithms and variables create a base for further restructuring that could be used irrespective of industry and organization.

Originality/value: The study broadens the scope of the literature by using mathematical models. A decision-making model has been customized for deciding upon employee retention strategies based on employee Personalities that are pertinent to the IT&ITES organizations in India.

Keywords: FAHP, Employee retention, FTOPSIS, Big Five personality.

JEL Classifications: C3, C6, M1

Paper type: Research paper

1. Introduction

One may wonder why there should be retention, considering all of the recent layoffs. Retaining the rest of the talent would be vital since they are already acquainted with the organisation and its operations. Despite innovations in technology such as generative AI, organizations continue to need human touch. Without a doubt, machines cannot take the place of people as they lack empathy and feelings. According to Holtom et al. (2008), “having outstanding personnel is crucial not just for present-day needs but also for the future”. The IT and ITES industries in India employ more than 3 million people (Pallathadka et al., 2022). India is currently the most sought-after nation in the world for IT and ITES companies contemplating offshore work. This sector holds a prominent place in the global economy and has steadily contributed to the expansion of exports, the creation of new job opportunities. Unfortunately, it has a drastic turnover rate compared to other sectors. High attrition rates have a detrimental effect as the workforce plays an integral part in the efficient use of principal resources, which in turn impacts the performance and efficiency of the organization (Park et al., 2021). According to the Ministry of Electronics & Information Technology (2025), the IT and ITES sectors contributed approximately 7.5% to India’s GDP, with projections indicating a rise to 7.9%, and an anticipated market size of USD 245 billion in FY24–25, of which USD 194 billion is expected from exports. Gartner forecasts suggest that employee turnover within these sectors may be 50–75% higher than historical averages. Moreover, recruitment timelines have lengthened by approximately 18% compared to pre-pandemic benchmarks. Attrition rates in 2023 ranged between 15% and 18%, with Business Insider reporting an increase to nearly 18–20% by September 2024. Data for Q1 of 2024 indicated an overall turnover of 21%, a figure projected to escalate through mid-2025. Recent research highlights how delays in hiring and workforce disengagement have amplified the urgency for strategic retention frameworks (Mirčetić et al., 2024). Alarming, employee turnover costs reached approximately ₹45,000 crore in Q3FY2024 alone (Ministry of Electronics & Information Technology, 2025). Industries struggling with employee attrition have to come up with innovative techniques and understand the antecedents of retention that cause the employees who are skilled and competent to be embedded in the organization (Hadj, 2020; Halim et al., 2020). It is up to organizations to enhance acquisition and retention as a result of a number of advancements, such as globalization, innovations in technology, and a boom in intellectual labour.

In this competitive era, contemporary approaches such as diversity, integration, employee engagement, empowerment, and career advancement help to retain employees (Cloutier et al., 2015). Individuals tend to be more opportunistic while remaining less loyal to their companies due to the availability of jobs in the labour market (Park et al., 2021). Turnover has been extensively investigated for almost three decades, and there is a plethora of literature available. While there are numerous causes why people leave their jobs, the present investigation explores the sequence of events preceding those grounds. This study considers the analysis of the various factors of retention and how they can impact each personality trait to remain in the organization. The help of experts in the area of Talent & Human Resource management was sought to decide and draw upon factors that can increase retention. The MCDM approach helps to assist with challenging decision-making situations, especially when there is an extensive range of alternatives and criteria. The effectiveness of expert-driven criteria selection has also been validated in recent studies using MCDM to address HR performance and staffing issues (Gupta & Bhargava, 2025; Rudsari & Fakhrhosseini, 2024). Employing a hybrid MCDM framework,

the current research assigns weighted importance to each criterion and ranks the alternatives accordingly to identify the most effective strategy for minimizing turnover and enhancing employee retention (Kusumawardani & Agintiara, 2015). The application of Multi-Criteria Decision-Making (MCDM) methodologies facilitates structured decision-making in complex scenarios characterized by multiple and often conflicting criteria (Mariadoss & Augustin, 2023a; Salehzadeh & Ziaeiian, 2024). Drawing upon an extensive literature review (Chatzoudes & Chatzoglou, 2022; Das & Baruah, 2013; Griffeth et al., 2000; Holtom et al., 2008; Kumar et al., 2025; Kyndt et al., 2009; Milman, 2003; Sadeghzadeh et al., 2025; Stokes et al., 2013), the five organizational retention strategies were identified as potential alternatives. Five alternatives and criteria are used in this study, so the best technique employed would be the MCDM methods to select the optimal solution. The best retention factor based on each personality trait is calculated by assigning weights for each alternative or the variable that is considered as a criterion for the decision-making problem (Sudarsanam et al., 2022).

In this article, a hybrid strategy for selecting retention factors to control turnover and retain personnel is used. Much of the existing work emphasizes leadership, communication, and job satisfaction, while giving comparatively less attention to personality as a key driver of retention. Yet personality traits have been consistently recognized as one of the primary factors influencing turnover (Timmerman, 2006), and remain underutilized in shaping systematic retention practices. While FAHP has been widely applied in Human Resource Management, its potential to connect the Big Five Personality traits with retention strategies has not been fully explored, as shown in Table 1.

Table 1. Criteria-based MCDM approaches in HR

| Problem Addressed | Author(s) | Year | MCDM method |
|--|-------------------------|------|--|
| Organizational efficiency | Kumar et al. | 2025 | Fuzzy SWARA and MOORA |
| Employee selection | Sadeghzadeh et al. | 2025 | Fuzzy Analytic Network Process |
| Evaluating the green human resource management practices | Gupta and Bhargava | 2025 | AHP-EDAS |
| Job satisfaction comprises psychosocial risks | Sarbat | 2024 | PIPRECIA-S |
| Decision-making in human resource management | Salehzadeh and Ziaeiian | 2024 | AHP |
| Recruitment | Taylan et al. | 2024 | FTOPSIS, FuzzyVIKOR, Fuzzy PROMETHEE-Trapezoidal Fuzzy Numbers |
| Stakeholders' perspective towards employability | Bhattacharjee et al. | 2023 | Hybrid FAHP-TOPSIS |
| Identifying key human resources challenges in start-up companies | Priyanka et al. | 2023 | Fuzzy DEMATEL |
| Prioritizing the antecedents of employer branding | Chopra et al. | 2023 | FAHP |
| Selection of appropriate age management techniques | Ji et al. | 2023 | AHP, ANP, WINGS |
| Overcoming barriers to integrated management systems | Darzi | 2023 | G-AHP, F-TOPSIS |

| via developing guiding principles | | | |
|-----------------------------------|-----------------------------|------|--------------------------------------|
| Leader retention | Magan et al. | 2023 | Spherical FAHP |
| Personnel selection | Li et al. | 2022 | LGBWM and IFN |
| Employee Turnover | Pourkhodabakhsh et al. | 2022 | Best worst method |
| HRIS | Esangbedo et al. | 2021 | Grey PA-FUCOM |
| Employee Retention | Yildis et al. | 2020 | Spherical FAHP |
| Talent Identification Process | Lai and Ishizaka | 2019 | AHP |
| Human Resource Selection | Sutrisno | 2019 | FMCDM, SAW |
| Applications in HRM | D'Urso and Masi | 2015 | FAHP |
| Human Resource Selection | Kusumawardari and Agintiara | 2015 | ANP& Choquet integral |
| Performance Evaluation | Gürbüz and Albayrak | 2014 | SVM & TOPSIS |
| Recruitment | Li et al. | 2010 | SVM & TOPSIS |
| Training provider evaluation | Ignatius | 2010 | AHP-Fuzzy PROMETHEE, and AHP-FTOPSIS |

Notes: Literature on applications of MCDM in HR

Most prior studies, as in Table 1, as suggested, rely on a single MCDM approach, whereas hybrid methods provide comprehensive insights that have received limited attention. These gaps reveal the absence of a structured, evidence-based framework. It moves beyond generalized and instead offers targeted, personality-sensitive approaches to employee retention. To address this limitation, the present study introduces a hybrid model that integrates FAHP and the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) to systematically link the Big Five Personality traits with suitable retention strategies. FAHP is first employed to determine the relative importance of personality traits in influencing retention, and FTOPSIS is then used to evaluate and rank strategies such as Organizational Culture, Employee Well-Being, Engagement, Inclusion, and Belongingness, according to their alignment with Big Five Personality Traits. Consistency ratio checks and sensitivity analysis are incorporated to enhance methodological rigor and ensure the reliability of the findings. Theoretically, the study advances the literature by bridging the gap between personality research and decision-making models, offering a replicable framework that strengthens the connection between individual differences and retention outcomes. The remainder of this paper is organized as follows: Section 2 presents a comprehensive literature review on turnover, personality traits, and retention strategies. Section 3 details the methodology, including the hybrid FAHP-FTOPSIS framework and data collection from experts. Section 4 discusses the findings, including criterion weights, rankings, and sensitivity analysis. Section 5 explores practical and social implications, originality, and value. Finally, Section 6 provides conclusions, limitations, and directions for future research.

2. Literature Review

To justify the selection of the criteria variables and alternatives, the following section presents a comprehensive literature review that examines the key factors contributing to employee turnover and those that significantly influence employee retention.

2.1 Turnover

A topic studied and researched for more than two centuries has also remained a key focus of personnel research by psychologists (Porter & Steers, 1973). It continues to taunt every industry without clues or solutions. “The Great Resignation 2020 to date” is evidence of this. “Turnover is generally thought to be a function of negative job attitudes combined with an ability to secure employment elsewhere”. Employee turnover and retention strategies evolved around the year 1917 when employees started to quit jobs because of pay dissatisfaction (Miller et al., 1979). Later in the 1930s, research was carried out, and results showed that employees decided to terminate if fathers were in skilled jobs (Hom et al., 2017). Turnover in any organization may be employee-oriented (voluntary) or organisation-oriented (involuntary). However, it is an expensive affair for both the organization that has invested resources in training and for the individual who must devote their energy and time to finding and settling into a new job (Farris, 1971).

Extensive empirical research has been conducted to provide a conceptual framework for predicting and measuring employee turnover. The creation of numerous conceptual models that attempt to describe the process of turnover has been a key development in the research on employee turnover in recent years. The models aim to identify significant variables and indicate correlations between them in the process of leaving (Jackofsky, 1984). Each model discovered new constructs compared to the previous models, and new perspectives for research were suggested (Lee & Mowday, 1987). Personality is one of the many factors that impact turnover intention, as discussed by Zimmerman (2008). The SEM model to explore factors that cause intention to quit and found that it is impacted by personality and its effect on their level of satisfaction at work (Mahoney et al., 2020). According to Allen, one of the antecedents of perceived organisational support is personal character, which implies that the personality of the individual influences turnover behaviour (Allen et al., 2003).

2.2 Personality (OCEAN: Openness, Conscientiousness, Extroversion, Agreeableness, Neuroticism)

During the fourth century, the ideologies of philosophers like Plato, Aristotle, and Descartes influenced the emergence of personality. They define personality as the fundamental aspect that influences the way individuals behave and respond. It began as an applied activity and is intended to address issues that arise in real-time (Hogan & Sherman, 2020). Psychologists like Sigmund Freud, Alfred Adler, Carl Jung, and several others have made significant contributions to the psychology of personality, and their work may be attributed historically to these renowned philosophers. The Psychoanalytic Personality Theory was developed by Sigmund Freud. The layers of personality identified by Freud in his theory - the Id, Ego, and Superego- were subsequently incorporated into the Fundamentals of Personality theories. According to Carl Jung's theory of personality, the two primary components of personality types are the perceiving function, which is based on rational sense and instinct, and the two judging functions, thinking and feelings, which are further split into extraversion and introversion. Individual perception and judgment were used to further develop this idea, as in the MBTI (Zhang et al., 2021).

Gordon Allport (1937) contrasted personality with “persona,” a mask worn by ancient Roman actors to represent a specific character. According to Allport, ‘personality is the dynamic organisation within the individual of those psychophysical systems that determines his unique adjustment to his environment’. Cattell’s perspective on personality was based on common and unique characteristics. Cattell (1943) divided it into dynamic, social, non-dynamic, co-nascent, logical, and other forms of traits. Fiske based his study on Cattell’s work and observed the development of these traits. Fiske named the recurrent factors in his study as social adaptability (agreeableness), conscientiousness, and emotional control (Fiske, 1949). In addition to these characteristics, McCrae and Costa (1987) interpreted several other characteristics, including individuals who were open and extroverted. Hom et al. (1992) stated that Steers and Mowday’s model of turnover may have several causes; personality may also be taken into consideration, as behaviour is an offshoot of an individual’s attributes. The Cusp model charts the trajectory of behavioural changes from employment retention to termination (Sheridan & Abelson, 1983). According to Jackofsky (1984), the turnover model, an individual’s personal characteristics, such as personality, determine the fulfillment of their job, which determines how they perform and their desire for movement. Among the factors influencing turnover are individual traits, especially personality (Lee & Mowday, 1987).

In recent times, turnover has been characterised as persistent patterns in people’s feelings, thoughts, and behaviours (Wu et al., 2024). Each of these traits is associated with turnover and retention. It is critical to understand how individuals act and react in an organization. In this study, the interconnectivity of each Big Five personality trait with turnover and retention can be observed, as in the findings of Zimmerman (2008). Personality impacts the pattern of an individual’s response to various external stimuli and shapes the work-based attitudes (Costa & McCrae, 1992). Personality enables predicting the employees who are at flight risk and use apprehensive techniques (Zhang & Yang, 2023) that can help retain them (Tett & Meyer, 1993). Personality helps identify person-job fit (Chen & Liang, 2023) and how an individual’s values align with the organization's culture (Azimi et al., 2023; Morgeson et al., 2005). Job crafting based on personality can reduce misfit and tailor roles based on it, increasing work performance (Tims et al., 2013).

Extrovert (E) traits include being outspoken, expressive, confident, friendly, and outgoing (Barrick & Mount, 1991). They are content with their present predicament, have positive feelings about their organisation, and feel integrated (McCrae & Costa, 1987). On the other hand, their desire to seek alternative opportunities outside the organisation could be strong because of their large social contacts. Individuals who demonstrate the trait of *Agreeableness (A)* were helpful, generous, selfless, and courteous (McCrae & Costa, 1987). Employees with these traits are committed and have no intention to quit. The adaptability and reliance dimensions of being agreeable may be due to the impact of the individual’s perception of an organisation and the behaviours that emanate from it (Zimmerman, 2008). They have favourable feelings about their workplace, which intensifies the effect and serves as an encouragement to stay (Mobley et al., 1979). Invariably, they act impulsively and spontaneously respond to their stimuli and quit their job in extreme conditions (Mitchell et al., 2001). Timeliness, conformity, and efficient use of time are attributes that might be connected to people who are *Conscientious (C)*. Individuals with this trait exhibit organised, prudent, diligent, and dependable behaviours. Conscientious people have moral and ethical motivating factors that prevent them from having turnover intention (Maertz & Campion, 2004). Strong religious convictions lead them to

believe that a breach of trust and moral obligation causes individuals to feel guilty about leaving their organization (Blau & Ryan, 1997). Leavers are aggressive, independent, very motivated to achieve, self-assured, and gregarious, which makes them prone to turnover. Eysenck and Eysenck (1963) coined the term “*Neuroticism*” (*N*) after revising it to “*Emotional stability*”. Emotionally stable individuals are content, secure, and satisfied with themselves. High trait negativity directly impacts job satisfaction. They frequently exhibit emotions such as anxiety and nervousness, as well as a pessimistic perspective regarding the outside world and self (Watson & Clark, 1984). They are incapable of handling stress or adapting to diverse environments, and their sense of insecurity causes them to leave, especially early on in their career (Zimmerman, 2008). Empirical pieces of evidence support that highly neurotic people give up on stress-inducing goals and career decisions (Organ, 1994). The qualities of creativity, culture, curiosity, originality, open-mindedness, and artistic sensitivity were indicative of *Openness(O)* (Barrick & Mount, 1991). Individuals who were very open to diverse encounters might appreciate switching careers simply because they consider them as opportunities for learning as well as personal enhancement (Zimmerman, 2008). The HOBOS and wanderlust syndrome, in which people feel the need to relocate and change employment in search of better possibilities, regardless of their emotions towards their present employment, are additional examples of it (Ghiselli, 1974). Each of these traits is associated with turnover and retention. They play a vital role in determining how individuals act and react within an organization. This study reveals the interconnectivity of each trait of Big Five personality to its impact on turnover and retention.

2.3 Employee Engagement (EE)

Employee Engagement is a driving factor behind the accomplishment of organizational objectives and success because engaged workers comprehend their roles within their organization. Employee engagement is “the harnessing of the organization members’ selves to their work roles in engagement, people employ and express themselves, physically, cognitively, and emotionally during role performances”. Engaged employees have “fire in their bellies” for the positions they hold and for their organization (Baumruk, 2004). The engagement of individuals in a work setup is a crucial element for being competent and productive. Another perspective states that an employee's degree of engagement is possibly determined by the extent of emotional and cognitive involvement, without which they become disengaged, a dangerous symptom where they withdraw and lose connections emotionally (Kahn, 1990). In summary, employee engagement is a driving factor behind the accomplishment of organizational objectives and success because engaged workers are loyal and spread positivity within their organization, increasing retention.

2.4 Well-being at work (EWB)

Most human beings spend at least one-third of their lives at work. Individuals' experiences at work—physical, emotional, mental, or social impact their performance and longevity in the organization. Employees who were emotionally and cognitively engaged with their work were happy and tended to exhibit greater commitment to the organization (Bellamkonda & Pattusamy, 2022). Sometimes it has a spillover into personal lives that disrupts work-life balance, damaging their health and mental well-being. Employers realize that employee satisfaction is a critical component of productivity, considering that employee commitment and competence directly impact an organization's success.

Work that engages employees with interest, complexity, and challenges leads to higher job satisfaction, higher levels of engagement, and higher job performance (Gelencsér et al., 2023). The well-being of their employees is becoming important to employers worldwide as they make decisions about remote, hybrid, and in-office work arrangements. Workers' resilience is increasing, which makes their well-being more of a concern. Over the past 20 years, this topic has received more attention because employees were under constant pressure to meet excessively demanding deadlines. Well-being can be understood from different perspectives (i) subjective well-being, which is positive; (ii) negative affect and cognitive evaluation of satisfaction; (iii) psychological well-being, i.e., affective well-being (Wright, 2006). *Well-being at work* also constitutes social relationships and relationships with supervisors. Happy employees perform better and are less likely to quit than those who are unhappy and do not perform up to standards. This shows us how well-being can initiate positive feelings and emotions that help an individual to thrive mentally and psychologically, both on the job and as an individual.

2.5 Inclusion & Belongingness(I&B)

Another proven significant predictor of turnover is whether an individual's aspirations and ideals related to a job were matched by their institutional encounter and personal objectives. The ideals come first because the individual chooses whether to remain or discontinue based on them. When employees commence new roles, individuals carry a lot of preconceptions because everyone has a distinctive set of standards based on their opinions (Lee & Mowday, 1987). Staying or departing is impacted by a broad spectrum of variables. One of the prime factors is employment expectation, also referred to as met expectations. It also focuses on the values of an individual that influence affective response towards the job. Affect influences one's intent and desire to stay or leave. Affective responses to one's job and the organization contribute to contentment in the workplace, involvement, and organisational spontaneity, which in turn affect employee retention or attrition (Hom et al., 1992). In summary, it is revealed by the literature that an organization that fosters an Inclusive work culture and creates an environment of Belongingness paves the way for a more dedicated, committed, and productive workforce.

2.6 Organizational Culture (OC)

Academicians and managers worldwide are intrigued with the topic of culture that persists in the organization because a strong *Culture* can be one of the factors that increases internal branding and, in turn, helps in retention, and the end result is satisfied customers and a successful organization (Kerr & Slocum, 2005). It has been predicted by HR practitioners and researchers that diversity should be prioritized, and there should be more investments in DEI to sustain in the current scenario. Thorngate (2002), in his book, states that culture can be aesthetics, and working environment relationships among employees. Kerr and Slocum (2005) describe that culture is an intangible and subtle phenomenon that is hard to manage or influence. Corporate culture's norms and values were expressed and upheld via reward systems. A noxious or unpleasant atmosphere at work could demoralise individuals. Employees may be demotivated, low on productivity, and have high attrition rates. Strategic changes cannot take place if it is not supported by organizational values and norms, which are an integral part of organizational culture (Kerr & Slocum, 2005). Various strategies create psychological climates that foster various degrees of employee commitment and longevity (Sheridan, 1992). It can be concluded

that organizational culture plays a crucial role in retention since it influences job satisfaction and commitment of the employee (Islam et al., 2022).

2.7 Employee Empowerment (E Emp)

Employee Empowerment has become necessary in recent times due to high turnover rates and downsizing. Increasing employee involvement, commitment, and enhancing employee contributions amidst these for a successful organization can be achieved through employee empowerment. When employees feel empowered in their roles, it increases job satisfaction, which is believed to be one of the main factors in employee retention over centuries (Jena & Nayak, 2023). Conger and Kanungo (1988), in their study, highlighted that autocratic management and a lack of autonomy can deprive staff members of recognition, control, and decision-making abilities. Defining rigorous corporate goals can reduce self-efficacy. Bureaucracy and segmentation triggered by authoritarianism can lead to disparities in the distribution of organisational power. Delegation and employee empowerment have a positive correlation, while centralization and employee empowerment have a negative correlation. Empowerment creates transformation and might result in impactful psychological experiences (Menon, 2001). Assessing psychological empowerment is an invaluable instrument for comprehending and enhancing individuals' work experiences, resulting in favourable organisational consequences (Spreitzer et al., 2017). To sum up, the implementation of employee empowerment can effectively improve retention rates by cultivating a favourable work atmosphere, boosting satisfaction with work, and facilitating advancement in their careers (Islam et al., 2022).

2.8 Theoretical framework

This study's decision-making model for employee retention is anchored in two foundational theories: Social Exchange Theory (SET) and the Theory of Planned Behaviour (TPB). These theories offer psychological and behavioural justifications for the inclusion of specific employee traits (criteria) and retention strategies (alternatives) in the model. The criteria used were the Big Five personality traits - Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience, while the alternatives include Organizational Culture, Inclusion and Belongingness, Employee Empowerment, Employee Engagement, and Employee Well-Being.

Social Exchange Theory

Blau and Ryan (1997) and Cropanzano and Mitchell (2005) are based on the idea that relationships, whether personal or organizational, are maintained when the benefits received are perceived to outweigh the costs. In workplace settings, this means employees were more likely to stay if they believed their efforts and loyalty were being reciprocated through support, resources, recognition, and opportunities. In our model, each retention strategy reflects a different form of organizational reciprocity. For instance, organizational culture provides a supportive climate, inclusion and belongingness offer emotional safety, empowerment reflects trust, engagement promotes connection, and well-being supports the holistic needs of employees. These alternatives represent the tangible "returns" that employees receive in exchange for their contributions, making them central to SET's application in retention.

The Theory of Planned Behaviour

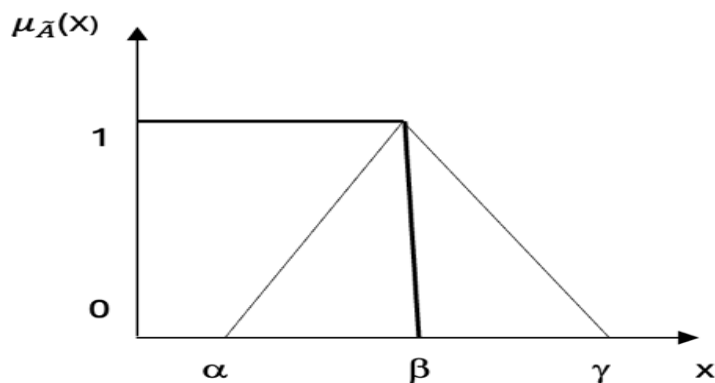
Ajzen (1991) offers another perspective for understanding employee retention. TPB suggests that behaviour is guided by three main components: attitudes toward the behaviour, subjective norms, and perceived behavioural control. In the context of employment, whether an individual intends to stay or leave is influenced by their internal evaluations and external perceptions of the workplace. This theory supports the inclusion of personality traits as the model's criteria. For example, employees high in Conscientiousness were often disciplined and reliable, aligning closely with strategies like Empowerment and Engagement. Those high in Neuroticism, who were more sensitive to stress or instability, may place greater value on Well-being and Inclusion. Employees with high Extraversion may thrive in vibrant Organizational Cultures, while Agreeableness and Openness to Experience may shape how individuals perceive Inclusive or Dynamic environments. The Big Five traits thus shape how employees form behavioural intentions and respond to different retention strategies.

By integrating these theories, the model bridges conceptual insight and decision-making application. Using a questionnaire, input was collected from experts to weigh the relative importance of each personality trait, capturing linguistic uncertainty common in human judgments. These weights were then fed into the FTOPSIS to rank the retention strategies, identifying those that best align with different employee profiles. This hybrid model not only reflects core theoretical constructs but also provides HR decision-makers with a practical, structured tool to personalize retention efforts in diverse organizational settings.

3. Methodology

As a solution to the ambiguity of human thought, Zadeh (1965) converted language into numbers with the help of *fuzzy sets*. "A fuzzy set, introduced, allows elements to have degrees of membership, ranging between 0 and 1. Triangular fuzzy numbers (TFNs) were used in this study for their simplicity, flexibility, and ability to handle imprecise human assessments.

Figure 1. Triangular Fuzzy number



Note: α = lower bound, β = peak point, γ = upper bound (where membership falls back to 0)
Membership degree function of a triangular fuzzy number, Source: Mariadoss and Augustin (2023a)

The membership degree function of a triangular fuzzy number, as shown in Figure 1, can be expressed as $\tilde{a} = a^l, a^m, a^u$ where a^l is the lower limit (α), a^m is the middle limit (β), and a^u is the upper limit (γ),

which satisfies $a^l \leq a^m \leq a^u$. TFNs provide a simple yet effective way to represent approximate values through a triplet (l, m, u) indicating the lower, middle, and upper bounds.” Sometimes, making decisions and solving problems were too complex and difficult to quantify (Huy et al., 2023). Fuzzy set theory resembles human reasoning to generate decisions using approximate information and uncertainty. Fuzzy set theory groups data without accurately defined limits. The versatility of addressing practical issues that invariably involve some degree of inaccuracy and variation in the factors and characteristics evaluated and analysed for the application is the positive aspect of applying precise mathematical and analytical approaches to fuzzy techniques. In decision-making contexts involving subjective expert judgments, such as evaluating personality traits for retention, fuzzy numbers effectively capture linguistic ambiguity (Kahraman et al., 2003). In the present study, expert judgments were collected using the standard Saaty 1–9 scale, commonly used in AHP-based decision-making methods. Although this scale gives numerical values, it is ordinal in nature, meaning it shows the order of preference but does not assume equal differences between points. This can create challenges, especially in human-related decision-making, where expert opinions are often subjective, imprecise, and uncertain. To manage this, fuzzy set theory was used to improve the handling of expert input. The ratings were converted into triangular fuzzy numbers (TFNs), which allow a range of values to better reflect the uncertainty in expert opinions. These fuzzy values were later defuzzified to produce clear numbers that could be used for ranking the options using the FTOPSIS method.

The use of fuzzy logic to handle ordinal expert input is well supported in human resource and decision-making research studies, as given in Table 1, like Sadeghzadeh et al.(2025) applied Fuzzy Analytical Process for employee selection; Taylan et al. (2024) applied FTOPSIS, VIKOR, and PROMETHEE to recruitment decisions; Bhattacharjee et al. (2023) used FAHP-TOPSIS to evaluate employability; Chopra et al. (2023) applied FAHP to study employer branding, and D’Urso and Masi (2015) studied the application of MCDM techniques in HR. Also, Magan et al. (2023) and Yildiz et al. (2020) used spherical FAHP to address employee and leader retention. These studies show that fuzzy MCDM methods were suitable for handling ordinal and uncertain expert input, supporting their use in this study.

An extensive literature review has been conducted to validate the reasons for the selection of criteria and variables. The recent work has been highlighted in Table 1. To effectively prioritize the identified criteria and support decision-making in addressing this gap, the study employs the FAHP and FTOPSIS.

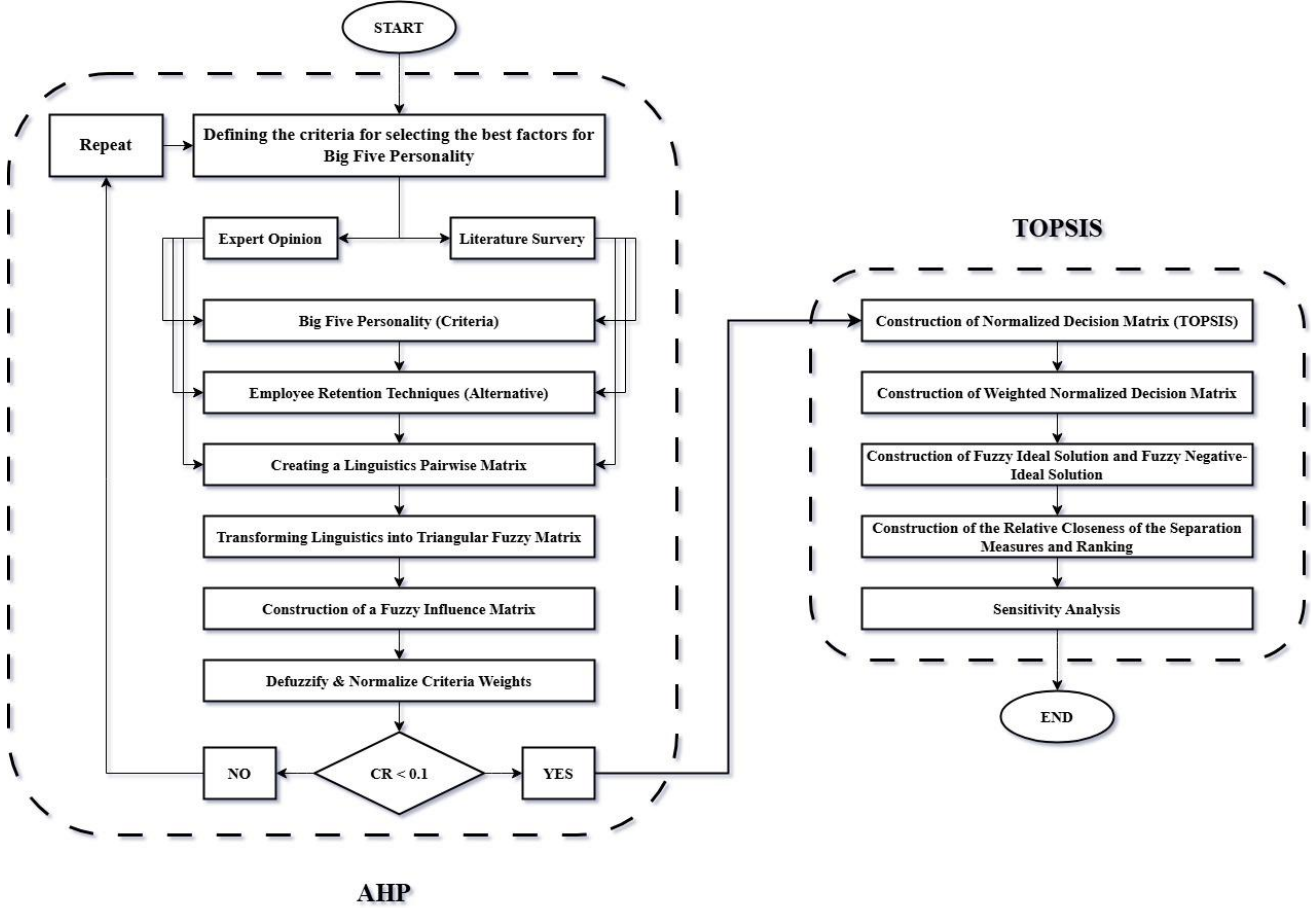
3.1 Fuzzy Logic for Decision-Making Under Uncertainty

3.1.1 FAHP Method

FAHP is one of the most powerful tools to solve complex MCDM problems. The pairwise comparison matrix used in this method is $(n \times n)$, where n is the number of criterion variables. The conversion from the linguistic scale to a Triangular Fuzzy number scale provided by Wu et al. (2024) is being used to create triangular fuzzy numbers in the comparison matrix for the criteria and for the comparison matrix of retention factor alternatives for each of the criteria. Consistency of the Expert's opinion and comparative weights is ensured through a crucial step by obtaining the Consistency Index and the Consistency Ratio (Modanloo et al., 2019). The RI value for the 5x5 matrix ($n=5$) is 1.11, and the CR

value should be less than 0.1 for consistency (Sudarsanam et al., 2022). Big Five personality traits were the employed criteria for this study, whereas Organizational culture, Inclusiveness and Belongingness, Employee engagement, Employee Empowerment, and Employee Well-being were used as alternatives. The process of obtaining weights and ranks is shown in Figure 2.

Figure 2. A schematic figure for the proposed method



Note: Proposed Schematic Framework, CR-Consistency Ratio, Source: Authors

The FAHP method is used to compute the criteria weights. The following steps comprise the FAHP technique.

Step 1: Construct the linguistic pair-wise comparison matrix.

This linguistic pair-wise comparison matrix $[x_{ij}]_{n \times n}$ demonstrates the influencing level between i^{th} criteria and the j^{th} criteria (Chen & Pham, 2000).

$$\hat{X} = [x_{ij}]_{n \times n} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ \begin{matrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{matrix} & \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nn} \end{bmatrix} \end{matrix}, \tag{1}$$

where $i, j = 1, 2, \dots, n$, $\hat{X}=[x_{ij}]_{n \times n}$ represent the fuzzy influence matrix; C_1, C_2, \dots, C_n denote the criteria or factors considered in the decision-making process, x_{ij} represents the fuzzy influence value

or the pairwise comparison value between criterion C_i and criterion C_j , and n is the total number of criteria considered in the evaluation.

Step 2: Create a triangular fuzzy decision matrix.

Using a triangular fuzzy scale, the linguistic pair-wise comparison matrix ($\widehat{\mathbf{X}}$) is transformed into a fuzzy pair-wise comparison matrix ($\widetilde{\mathbf{X}}$). The matrix is a fuzzy pair-wise comparison matrix with an equal number of rows and columns.

$$\widetilde{\mathbf{X}} = \begin{matrix} & C_1 & C_2 & \cdots & C_n \\ \begin{matrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{matrix} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & \tilde{x}_{nn} \end{bmatrix} \end{matrix}, \quad (2)$$

where $\tilde{x}_{ij} = (l_k, m_k, u_k)$ is a fuzzy number ($l_k < m_k < u_k, i = 1, 2, \dots, n, j = 1, 2, \dots, n, k = 1, 2, \dots, n$). This matrix also has a reciprocal value for every diagonal. The formula for reciprocal is

$$\tilde{x}_{ji} = (l_k, m_k, u_k)^{-1} = \left(\frac{1}{u_k}, \frac{1}{m_k}, \frac{1}{l_k} \right), \quad (3)$$

where \tilde{x}_{ji} represents the fuzzy reciprocal value; $l_k, m_k, and u_k$ denote the triangular fuzzy number; l_k is the lower limit of criteria i and j ; m_k is the most likely value (the peak) of the fuzzy comparison; u_k is the upper limit of the fuzzy comparison.

Step 3: Calculate the criteria weight.

The fuzzy Geometric Mean is used to determine the criteria weight (Salehzadeh & Ziaieian, 2024). The geometric mean was selected for defuzzification due to its multiplicative compatibility and ability to reduce distortion from extreme values, as recommended in MCDM literature (Buckley, 1985; Modanloo et al., 2019).

$$r_i = C_1 \otimes C_2 \otimes \dots \otimes C_n = \left(\prod_{i=1}^n l_i, \prod_{i=1}^n m_i, \prod_{i=1}^n u_i \right)^{1/n}; \quad (4)$$

$$r_i = \sqrt[3]{l_1 * l_2 * l_3}, \sqrt[3]{m_1 * m_2 * m_3}, \sqrt[3]{u_1 * u_2 * u_3},$$

where r_i represents the geometric mean fuzzy synthetic extent for each criterion; C_1, C_2, \dots, C_n are the fuzzy comparison values for each criterion; \otimes denotes the fuzzy multiplication operator, which is used to combine the fuzzy comparison values across all criteria; $l_i, m_i, and u_i$ are the lower, middle, and upper values of the fuzzy comparison for criterion i ; and \prod denotes the product operator across all criteria.

Fuzzy geometric mean value is calculated using the above formula, and the weight vectors are used to calculate $W' = (d'(C_1), d'(C_2), \dots, d'(C_n))$, where $C_i, i=1, 2, \dots, 5$ are the evaluation criteria (Saaty, 1987). The weight vectors provide the prioritized weights of the evaluation criteria. The geometric mean

provides a mathematically consistent method for aggregating expert judgments and is less sensitive to extreme values than the arithmetic mean, making it suitable for fuzzy pairwise comparisons (Buckley, 1985).

Step 4: Defuzzify criteria weights.

The criteria weight is in the form of a triangular fuzzy number. In this case, COA is used to extract the defuzzification value. (Sudarsanam et al., 2022)

$$w_i = \left(\frac{l + m + u}{3} \right), \tag{5}$$

where w_i is denotes the geometric mean fuzzy synthetic extent calculated using the centre of area formula. Also, l denotes the smallest possible value, m denotes the most promising value, and u denotes the largest possible value of the fuzzy triangular number r_i which is defined in Step 3.

Step 5: Normalize the criteria weight.

The normalized weight vectors are $W = (d(A_1), d(A_2), \dots, d(A_5))$ where W is a non-fuzzy number. The summation of all the criteria weight is $0 \leq x_{ij} \leq 1$. The criteria were normalized by (Mariadoss & Augustin, 2023a)

$$N_i = \frac{w_i}{\sum_{i=1}^n w_i}, \tag{6}$$

where N_i represents the normalized weight of criterion i , w_i is the geometric mean fuzzy synthetic extent of criterion i , and $\sum_{i=1}^n w_i$ denotes the sum of the fuzzy synthetic extents for all criteria.

Step 6: Check for Consistency.

The consistency ratio for each of the matrices is computed as follows:

The Eigen vector is computed for the comparison matrix. To calculate the eigenvector, we use the following equation: $w_i = \frac{\hat{a}_i}{n}$ is the eigen vector, where \hat{a}_i is the sum of the matrix normalization values for i^{th} row, and n is the order of the matrix. The λ_{\max} is computed as the matrix m of the Sum Vector (column-wise sum of the comparison matrix) and the eigen vector (Sudarsanam et al., 2022)

- Consistency index is computed by $CI = (\lambda_{\max} - n) / (n - 1)$ where n is the order of the comparison matrix. If the CI value is more than zero, then the matrix is tested for inconsistency.
- The test for inconsistency involved computing the ratio of CI and a random generator value. The RI value is listed in Table 2. The value varies for each of the orders of the matrix

Table 2. Random Index values

| | | | | | | | | | | |
|----|---|---|------|-----|------|------|------|------|------|------|
| N | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| RI | 0 | 0 | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

- $CR = CI / RI$ (a consistency ratio of less than 0.1 is acceptable). For those matrices with a CR value of more than 0.1, the entries in the comparison matrices need to be revised until a CR value of less than 0.1 is attained.

3.1.2 FTOPSIS method

TOPSIS helps to rank the alternatives in both conception and application. “It attempts to choose alternatives that simultaneously have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution” (Behzadian et al., 2012). In this study, we aim to select the best factors that promote retention, i.e., the alternatives. The collected data is analysed using FTOPSIS. This method was employed to give rank to the alternatives for establishing an optional level of process parameters with respect to multiple criteria (Modanloo et al., 2019). This study has employed alternatives that comprise five employee retention factors, and their criterion factors are the Big Five Personality traits. The alternatives include Organizational Culture, Inclusion and Belongingness, Employee Engagement, Employee Empowerment, and Employee Well-being. The criteria include Extroversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to experience. In this study, Conscientiousness, Agreeableness, and Extraversion were considered as benefit criteria, reflecting traits that enhance retention, whereas Openness and Neuroticism were treated as cost criteria, representing traits that may negatively influence retention outcomes. The normalization process was therefore applied accordingly to account for both benefit and cost attributes. This method is a description of the experiments carried out and conclusions drawn therefrom.

The algorithm of the FTOPSIS method is provided below:

Step 1: Construction of a normalized decision matrix.

In the FTOPSIS environment, simpler scales were used for transforming the criteria scales into a comparable scale (Jahanshahloo et al., 2006).

$$\hat{x}_d = [x_{ij}^d]_{m \times n} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} \hat{x}_{11}^d & \hat{x}_{12}^d & \dots & \hat{x}_{1n}^d \\ \hat{x}_{21}^d & \hat{x}_{22}^d & \dots & \hat{x}_{2n}^d \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{m1}^d & \hat{x}_{m2}^d & \dots & \hat{x}_{mn}^d \end{bmatrix} & \end{matrix}, \quad (7)$$

where $i = 1, 2, \dots, m, j = 1, 2, \dots, n$; \hat{x}_d is the defuzzified decision matrix; $[x_{ij}^d]_{m \times n}$ denotes the defuzzified value of the element in the matrix at row i and column j , where m is the number of alternatives and n is the number of criteria, $m \times n$ indicates the size of the decision matrix, m = total number of alternatives (A_1, A_2, \dots, A_m), n = total number of criteria (C_1, C_2, \dots, C_n), A_1, A_2, \dots, A_m represent the alternatives, C_1, C_2, \dots, C_n represent the criteria used for evaluation; and $x_{11}^d, x_{12}^d, \dots, x_{mn}^d$ represent the defuzzified scores.

Step 2: Converting the linguistic matrix into a triangulated fuzzy matrix.

$$\hat{x}_d = [x_{ij}^d]_{m \times n} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 & \hat{x}_{11}^d & \hat{x}_{12}^d & \dots & \hat{x}_{1n}^d \\ A_2 & \hat{x}_{21}^d & \hat{x}_{22}^d & \dots & \hat{x}_{2n}^d \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & \hat{x}_{m1}^d & \hat{x}_{m2}^d & \dots & \hat{x}_{mn}^d \end{matrix}, \quad (8)$$

where $\tilde{x}_{ij}^d = (a^l, a^m, a^u)$ is the formula used to create the triangular fuzzy matrix for the alternatives (i), $i = 1, 2, \dots, m$, and criteria (j), $j = 1, 2, \dots, n$. (Buckley, 1985).

Step 3: Consolidated triangular fuzzy matrix.

$$\hat{X} = [\hat{X}_{ij}]_{m \times n} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 & \hat{x}_{11} & \hat{x}_{12} & \dots & \hat{x}_{1n} \\ A_2 & \hat{x}_{21} & \hat{x}_{22} & \dots & \hat{x}_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & \hat{x}_{m1} & \hat{x}_{m2} & \dots & \hat{x}_{mn} \end{matrix}, \quad (9)$$

where the alternatives (i) $i = 1, 2, \dots, m$, and criteria (j), $j = 1, 2, \dots, n$.

Step 4: Defuzzify the decision matrix.

$$X = [X_{ij}]_{m \times n} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 & x_{11} & x_{12} & \dots & x_{1n} \\ A_2 & x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & x_{m1} & x_{m2} & \dots & x_{mn} \end{matrix}, \quad (10)$$

To defuzzify the decision matrix, the formula for the Centre of Area (COA) is used below:

$$x_{ij} = \left(\frac{l_{ij} + m_{ij} + n_{ij}}{3} \right),$$

where l_{ij} denotes the smallest possible value, m_{ij} denotes the most promising value, and n_{ij} denotes the largest possible value of the fuzzy triangular number \hat{x}_{ij} which is represented as (l_{ij}, m_{ij}, n_{ij}) .

Step 5: Normalization of the decision matrix.

The equation was computed using the beneficial and non-beneficial criteria, (Mariadoss & Augustin, 2023a)

$$\begin{aligned} r_{ij} &= \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad i = 1, 2, \dots, m, j = 1, 2, \dots, n; \\ r_{ij} &= \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad i = 1, 2, \dots, m, j = 1, 2, \dots, n, \end{aligned} \quad (11)$$

where r_{ij} represents the fuzzy normalized value of the performance score for alternative i with respect to criterion j , x_{ij} is the original performance score for alternative i and criterion j , and $\min(x_{ij})$, $\max(x_{ij})$ are the minimum and maximum performance scores for criterion j across all alternatives.

Step 6: Construct the weighted normalized decision matrix.

$$\widetilde{v}_{ij} = \widetilde{w}_j * \widetilde{r}_{ij}, \quad (12)$$

where $j = 1, 2, \dots, m$, $i = 1, 2, \dots, n$; w_j represents the criteria weight of j , \widetilde{v}_{ij} represents the fuzzy weighted normalized value of the alternative i with respect to criterion j , \widetilde{w}_j represents the fuzzy weight of criterion j , and \widetilde{r}_{ij} represents the fuzzy normalized performance score of alternative i with respect to criterion j (Saaty, 2008).

Step 7: Computation of the separation measure.

Ideal separation and Negative-ideal separation are calculated by Chen and Pham (2000).

$$\begin{aligned} A_i^+ &= \sum_{j=1}^n s(\widetilde{v}_{ij}^+, \widetilde{v}_j^+), \quad i = 1, 2, \dots, m; \\ A_i^- &= \sum_{j=1}^n s(\widetilde{v}_{ij}^-, \widetilde{v}_j^-), \quad i = 1, 2, \dots, m, \end{aligned} \quad (13)$$

where $s(\widetilde{v}_{ij}^+, \widetilde{v}_j^+)$ and $s(\widetilde{v}_{ij}^-, \widetilde{v}_j^-)$ are distance measurements.

Step 8: Distance Measure.

The distance measure is calculated using the vertex method provided below:

$$s(\widetilde{x}_{ij}, \widetilde{y}_{ij}) = \sqrt{[(x_{ij}^1 - y_{ij}^1)^2 + (x_{ij}^2 - y_{ij}^2)^2 + (x_{ij}^3 - y_{ij}^3)^2]}, \quad (14)$$

where $s(\widetilde{x}_{ij}, \widetilde{y}_{ij})$ denotes the distance between two fuzzy numbers, x_{ij}^1 denotes the fuzzy performance value of alternative i with respect to criterion j , and y_{ij}^1 denotes the fuzzy ideal (positive or negative) solution value for criterion j .

Step 9: Ranking Alternatives.

The ranks are calculated using the formula

$$c_i = \frac{A_i^-}{A_i^- + A_i^+}, \quad i = 1, 2, \dots, m, \quad (15)$$

where c_i is the closeness coefficient of alternative i , A_i^- is the distance of alternative i from the fuzzy negative ideal solution, and A_i^+ is the distance of alternative i from the fuzzy positive ideal solution

Step 10: Sensitivity analysis.

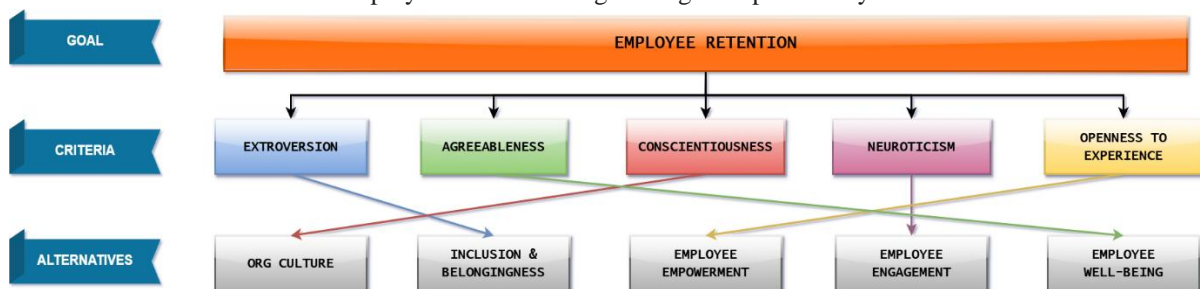
To ensure the robustness, reliability, and stability of the ranks. Multiply the different sets of criteria weights by the normalized decision matrix and obtain ranks.

The steps in the above section are applied in the following case study for making a decision upon identifying the right retention technique for each Big Five personality trait. With the methodological framework established, the following section presents the data collection process and its practical application through a case study in the IT& ITES sector

4. Data and Case Application

Employees who possess the right personality attributes that make them committed are likely to perform better and grow with the organization. Retaining such employees is becoming a challenge due to the abundant availability of jobs in the market that seem lucrative and the change in values of the upcoming generations. In IT & ITES, high employee turnover has a detrimental effect on both the organization's quality and finances (Pallathadka et al., 2022). The organisation will suffer greatly from the increased costs that are associated with onboarding new employees and from the lost time and output while they learn (Park et al., 2021). Furthermore, a high turnover rate lowers workforce morale. Despite technology developments such as generative AI, the IT & ITES business remains skill-based and dependent on human intervention.

Figure 3. Hierarchical structure of employee retention using the Big Five personality



Source: Authors, Personality-based retention framework.

This study presents an insightful measure for deciding upon employee retention variables based on Big Five Personality traits, as highlighted in Figure 3. The literature review gives a detailed understanding of each trait that helps in customizing the retention techniques for each of them. This study has used FAHP and FTOPSIS to match specific personality profiles with effective retention techniques. The study focuses on the IT & ITES sector and discovered that it is challenging to retain its task force. As part of the research ethics, the names of the companies are not revealed. The individual's personality may be crucial during recruitment for person-job fit analysis, but may appear unimportant while considering retention. This study emphasizes that personality is one of the primary factors responsible for a person's behaviour; hence, it has been studied for retention as well.

HR practitioners and experts were asked to rank the retention strategies carefully. A multi-criteria decision-making problem requires several experts. The study involved five experts, *E1*, *E2*, *E3*, *E4*, and *E5*, who gave opinions on employee retention factors against the Big Five personality traits.

Table 3. Detailed Expert information

| Expert | Title | Education | Experience |
|--------|------------------------|-------------------------------------|------------|
| E1 | Branch Head-HR | Master's in Business Administration | 25 yrs. |
| E2 | VP-HR | Master's in Hospitality Management | 27 yrs. |
| E3 | Senior HR Manager | Master's in Business Administration | 21 yrs. |
| E4 | HR Practitioner | Master's in Business Administration | 11 yrs. |
| E5 | Deputy General Manager | Doctorate in Management | 22 yrs. |

Source: Authors

Table 3 lists the title, educational qualifications, and experience of each expert. The research was conducted through an online survey of 5 experts. Data was gathered from various parts of India, with the responses from HR Practitioners or experts in the field of Human Resource Management. Obtaining an expert sample with a diverse organisational history was the primary objective of the sampling procedure. The experts in this case represent a wide range of backgrounds- (intellectual, physical), industries (services, manufacturing, IT), and roles (middle management, senior manager, vice president). To be qualified to take part in the survey, a person needed to meet two requirements: they were required to be working when they participated, as well as possess extensive experience. During August and September of 2023, a simple random sample method was used to reach as many experts as possible. The initial five views were obtained. The survey was made accessible through e-mails, accompanied by an overview outlining the goals of this investigation and the prerequisites for completing it. The experts were tasked to prioritize each of the parameters and alternatives (Huy et al., 2023) using a five-point rating system. A set of experts was denoted using the letter $E = [E1, E2, \dots, En]$.

This section develops a diagnosis system to predict the ideal personality by integrating the FAHP and FTOPSIS techniques. The proposed method is developed collaboratively with the opinion of HR and industry experts. Importantly, FAHP is employed to calculate the weights of the personalities by establishing interconnections among them.

5. Result and Analysis

5.1 FAHP

The pairwise comparison judgments from five experts were first averaged, then fuzzified into triangular fuzzy numbers, and subsequently aggregated using the fuzzy geometric mean to construct the fuzzy pairwise comparison matrix for FAHP.

Table 4. Group Decision Matrix

| | E | A | C | N | O |
|---|------|------|------|---|------|
| E | 1 | 0.33 | 0.11 | 4 | 3 |
| A | 3 | 1 | 0.2 | 7 | 4 |
| C | 9 | 5 | 1 | 9 | 8 |
| N | 0.25 | 0.14 | 0.11 | 1 | 0.33 |
| O | 0.33 | 0.25 | 0.12 | 3 | 1 |

Notes: Combined Expert responses E is Extroversion, A is Agreeableness, C is Conscientiousness, N is Neuroticism, O is Openness.

Source: Authors

The group decision matrix from Table 4 was created by combining the expert responses and taking an average to lessen the encumbrance of extensive tables. FAHP analysis was performed on the group decision matrix. (Wind & Saaty, 1980)

Table 5. Defined linguistic variables for the evaluation of information (criteria)

| Linguistic Variables | Abbreviation | TFN |
|----------------------|--------------|-------|
| No influence | NI | 1,1,1 |
| Very low influence | VL | 2,3,4 |
| Low influence | LI | 4,5,6 |
| High influence | HI | 6,7,8 |
| Very high influence | VH | 9,9,9 |

Notes: TFN-Triangular Fuzzy Numbers. Source: Authors

For comparison, a linguistic scale in Table 5 is used and converted into fuzzy numbers. The fuzzy number scale developed by the authors in Table 5 will be used to quantify the linguistic criteria comparison ratings provided by the experts.

Table 6. Fuzzy direct-influence criteria comparison matrices

| Decision Makers | Criteria | C1 | C2 | C3 | C4 | C5 |
|-----------------|----------|----|----|----|----|----|
| E1 | C1 | NI | VH | L | VL | NI |
| | C2 | L | NI | VH | NI | LI |
| | C3 | VL | NI | NI | LI | HI |
| | C4 | HI | LI | NI | NI | VL |
| | C5 | NI | VH | VH | VL | NI |
| E2 | C1 | NI | LI | VH | NI | NI |
| | C2 | NI | NI | VH | VL | HI |
| | C3 | VL | NI | NI | LI | NI |
| | C4 | HI | NI | VH | HI | LI |
| | C5 | NI | LI | VL | NI | NI |
| E3 | C1 | NI | LI | VL | NI | VH |
| | C2 | NI | NI | LI | VH | VL |
| | C3 | LI | NI | NI | H | LI |
| | C4 | NI | H | VL | NI | VL |
| | C5 | VH | NI | VL | LI | NI |
| E4 | C1 | NI | VL | LI | NI | VH |
| | C2 | HI | NI | LI | VH | HI |
| | C3 | HI | VL | NI | NI | VH |
| | C4 | HI | VL | LI | NI | NI |
| | C5 | HI | VL | LI | VH | NI |
| E5 | C1 | NI | VH | LI | VL | NI |
| | C2 | HI | NI | LI | VL | NI |
| | C3 | HI | VH | NI | VL | NI |
| | C4 | HI | VH | LI | NI | NI |
| | C5 | HI | VH | LI | VL | NI |

Notes: Linguistic Matrix for evaluation of information: NI- No Influence, VL-Very Low, LI-Low Influence, HI-High Influence, VH-Very High Influence, E is Expert, C is Criteria. Source: Authors.

Table 6 presents the criteria comparison ratings (linguistic ratings) provided by five experts based on their judgments. The linguistic ratings will be converted into Triangular Fuzzy Numbers (TFNs) to quantify subjective assessments systematically.

Table 7. Triangular Fuzzy Pairwise Comparison Matrix

| | E | | | A | | | C | | | N | | | O | | |
|---|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| E | 1.00 | 1.00 | 1.00 | 0.25 | 0.33 | 0.5 | 0.13 | 0.11 | 0.14 | 3.00 | 4.00 | 5.00 | 2.00 | 3.00 | 4.00 |
| A | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 | 0.17 | 0.20 | 0.25 | 6.00 | 7.00 | 8.00 | 3.00 | 4.00 | 5.00 |
| C | 9.00 | 9.00 | 9.00 | 4.00 | 5.00 | 6.00 | 1.00 | 1.00 | 1.00 | 9.00 | 9.00 | 9.00 | 7.00 | 8.00 | 9.00 |
| N | 0.20 | 0.25 | 0.33 | 0.13 | 0.14 | 0.17 | 0.11 | 0.11 | 0.13 | 1.00 | 1.00 | 1.00 | 0.25 | 0.33 | 0.50 |
| O | 0.50 | 0.33 | 1.00 | 0.20 | 0.25 | 0.33 | 0.11 | 0.13 | 0.14 | 2.00 | 3.00 | 4.00 | 1.00 | 1.00 | 1.00 |

Notes: E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Fuzzy Triangulated matrix from Equations 2 and 3.

This matrix highlights the degree of influence of one criterion over the other that can be analysed on the fuzzy scale of (lower-minimum value, middle-most likely value, and upper values-maximum value) as in Table 7. The linguistic variables (qualitative parameters) were phrases in natural language used to quantify vague terms (Sudarsanam et al., 2022). First, linguistic ratings were assigned and then converted into numerical values (quantitative) as in Equation 1. This matrix, as in Table 7, provides the average expert fuzzy number rating (the five expert linguistic ratings as in Table 6 are converted to a fuzzy number scale using Table 5).

Table 8. Fuzzy number matrix using Geometric Mean

| Criteria | l | m | u |
|----------|------|------|------|
| E | 0.72 | 0.85 | 1.07 |
| A | 1.43 | 1.76 | 2.09 |
| C | 4.69 | 5.04 | 5.35 |
| N | 0.23 | 0.27 | 0.32 |
| O | 0.47 | 0.50 | 0.72 |

Notes: E-Experts, E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Fuzzy Number is obtained from Equation 4 using geometric mean.

The fuzzy geometric mean results in Table 8 indicate that Conscientiousness is the most influential personality trait in the decision process, followed by Agreeableness, Openness, Extraversion, and Neuroticism. Due to uncertainty, Triangulated Fuzzy Numbers created using Equations 2 and 3 are used to represent values that an element can take. It is expressed by (l, m, u) . Experts may not be able to provide a precise number, so we use TFN. The calculations are done using Equation 2 to arrive at the fuzzy number matrix in Table 8. Calculating criteria weights is obtained by using the Geometric Mean as described in Equation 4.

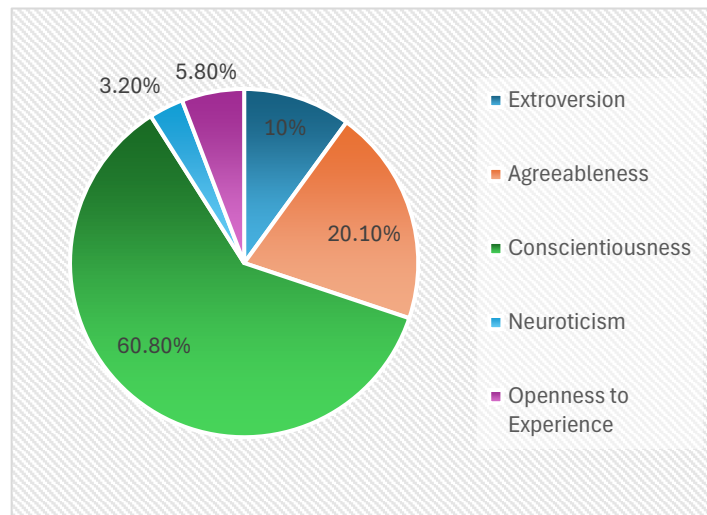
Table 9. Criteria Weights-Normalized

| Criteria | E | A | C | N | O |
|----------|--------|--------|--------|--------|--------|
| Wi | 0.1035 | 0.2071 | 0.5911 | 0.0322 | 0.0661 |

Notes: E-Experts, E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Criteria weights were derived using Equations 5 and 6 by normalizing it.

The weights are defuzzified in Table 9 using the centre of Area formula in Equation 6, and the criteria weights in Table 9 and Figure 7 have been obtained.

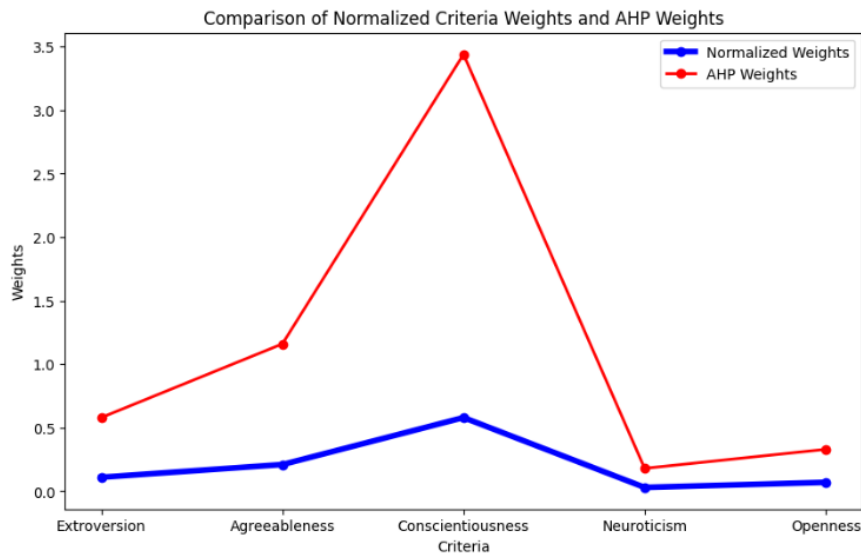
Figure 4. Criteria Priority



Source: Priority of Criteria Weights Authors

We may infer from Figure 4 that the most favourable personality attribute that promotes retention is conscientiousness (60.80%), which is followed by agreeableness (20.10%) and extroversion (10.00%). This indicates that openness (5.80%) and neuroticism (3.20%) are traits that are susceptible to turnover.

Figure 5. Weighted Criteria weights and Normalized weights (Source: Authors)



Based on Figure 5, conscientiousness is the attribute strongly linked to retention, followed by agreeableness and extroversion. It was observed that traits like neuroticism and openness to new experiences impede retention. The priority vector matrix represents the priorities of each criterion, which are derived from the fuzzy pairwise comparison matrix, indicating the relative importance of each criterion. We then normalize the criteria weights using the formula, as in Equation 6, $N = \frac{w_i}{\sum_{i=1}^n w_i}$ so that the summation of the criteria is $0 \leq x_{ij} \leq 1$ is highlighted in Table 9 and Figure 5.

Figure 6. Criteria Weights
Weights of Criteria, Source: Authors
AHP Weights of Big Five Personality Traits

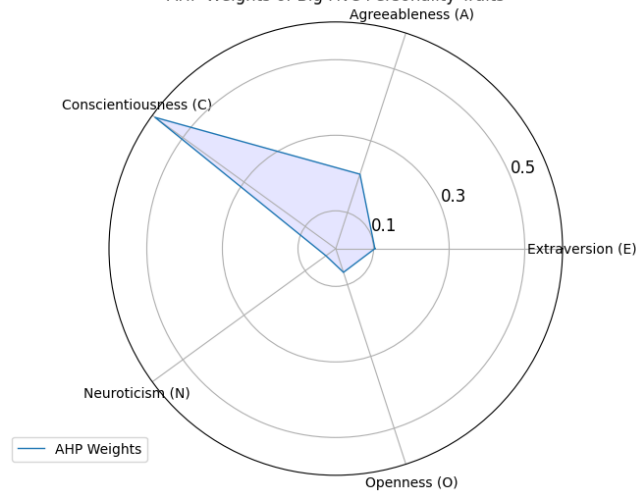


Figure 6 shows that Conscientiousness holds the strongest weight among personality traits, while Neuroticism has the least influence in the decision-making model.

Table 10. Consistency Ratio for Decision Matrix.

| λ_{\max} | CI | RI | CR | Consistency |
|------------------|------|------|------|-------------|
| 5.39 | 0.10 | 1.12 | 0.08 | CR < 0.1 |

Note: λ_{\max} is the computed maximum eigenvalue, CI is the Consistency Index, RI is the Random Index number from Table 2, and CR is the Consistency Ratio (Reliability).

To overcome bias and inconsistency of human discretion, the consistency ratio is used, from which we can draw logic and reliability. This consistency check is a critical diagnostic step in the AHP methodology to ensure the reliability of expert judgments. The $CR = \text{Consistency Index} / RI$ (a consistency ratio of less than 0.1 is acceptable) (Saaty, T. L., 1977, 1980, 1986, 1990, 2008). The iterations are repeated till we arrive at $CR < 0.1$, which is mentioned in Table 10. This result was arrived at after 6 iterations, allowing experts to review their opinions to improve consistency and to increase the robustness of the decisions. The Consistency matrix checks the reliability of the pairwise comparison matrix and quantifies the opinions of the experts, and is mentioned in Table 10. We find that the Consistency Ratio is 0.08, which is less than 0.1, indicating the consistency and reliability in the comparison matrix. Since the Consistency Ratio is 8% which is below the specified 10% the weights are robust, error-free, and bias-free. The consistency index was calculated using a random generator value from Table 2. The value varies for each order of the matrix.

5.2 FTOPSIS

The alternatives include Organizational Culture, Inclusion and Belongingness, Employee Engagement, Employee Empowerment, and Employee Well-being. This study aims to select the best factors that promote retention, i.e., the alternatives. After careful analysis, an extensive literature survey, and taking into consideration the expert opinions, the retention strategies selected were found to be most suitable for the current scenario. The linguistic decision matrix is created on expert opinion, as in Table 11.

Table 11. Evaluation rating of competitive alternatives

| Decision Makers | Alternatives | Criteria | | | | |
|-----------------|--------------|----------|----|----|----|----|
| | | E | A | C | N | O |
| E1 | E Emp | H | H | A | L | VL |
| | EWB | A | H | H | VL | L |
| | OC | L | VL | H | A | H |
| | EE | H | A | VL | H | L |
| | I&B | VL | H | H | L | A |
| E2 | E Emp | H | A | H | L | VL |
| | EWB | VL | L | H | A | H |
| | OC | L | A | H | H | VL |
| | EE | H | VL | H | L | A |
| | I&B | VL | A | L | H | H |
| E3 | E Emp | H | A | L | VL | H |
| | EWB | VL | H | A | H | L |
| | OC | L | VL | H | H | A |
| | EE | VL | H | A | H | L |
| | I&B | H | VL | L | A | H |
| E4 | E Emp | H | L | A | VL | H |
| | EWB | H | L | A | H | VL |
| | OC | H | L | A | VL | H |
| | EE | H | L | H | A | VL |
| | I&B | H | L | A | H | VL |
| E5 | E Emp | H | H | A | L | VL |
| | EWB | H | H | A | L | VL |
| | OC | H | H | A | L | VL |
| | EE | H | H | A | L | VL |
| | I&B | H | H | A | L | VL |

Notes: E Emp-Employee Empowerment, EWB-Employee Well-being, OC-Organizational Culture, EE-Employee Engagement, I&B-Inclusion & Belongingness, E-Experts, E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Source-Authors

Table 11 provides the expert criteria ratings of five alternatives for each of the five experts. The alternatives and the criteria are listed in the notes above.

Table 12. Defined linguistic variables for evaluation information (Alternatives)

| Linguistic Variables | Abbreviation | TFN |
|----------------------|--------------|---------|
| Very low | VL | (1,1,3) |
| Low | L | (1,3,5) |
| Medium | M | (3,5,7) |
| High | H | (5,7,9) |
| Very High | VH | (7,9,9) |

Note: Linguistic variables

Table 12 provides the linguistic to fuzzy number conversion scale for the criteria ratings for each of the alternatives. In the FTOPSIS environment, simpler scales are used for transforming the criteria scales into a comparable scale and then converted as a triangular fuzzy matrix as in Table 12, and a weighted normalized decision matrix is created using Equations 9 and 10. In FTOPSIS, arithmetic operations like fuzzy number addition, subtraction, multiplication by scalars, and distance

measurement (e.g., Euclidean or vertex method) are applied to aggregate decision matrices and compute closeness coefficients (Chen & Pham, 2000).

Table 13. Triangulated Fuzzy numbers for criteria & Alternatives

| Decision Makers | Alternatives | Criteria | | | | |
|-----------------|--------------|----------|---------|---------|---------|---------|
| | | E | A | C | N | O |
| E1 | E Emp | (5,7,9) | (7,9,9) | (3,5,7) | (1,3,5) | (1,1,3) |
| | EWB | (3,5,7) | (5,7,9) | (7,9,9) | (1,1,3) | (1,3,5) |
| | OC | (1,3,5) | (1,1,3) | (7,9,9) | (3,5,7) | (5,7,9) |
| | EE | (7,9,9) | (3,5,7) | (1,1,3) | (5,7,9) | (1,3,5) |
| | I&B | (1,1,3) | (7,9,9) | (5,7,9) | (1,3,5) | (3,5,7) |
| E2 | E Emp | (5,7,9) | (3,5,7) | (7,9,9) | (1,3,5) | (1,1,3) |
| | EWB | (1,1,3) | (1,3,5) | (7,9,9) | (3,5,7) | (5,7,9) |
| | OC | (1,3,5) | (3,5,7) | (7,9,9) | (5,7,9) | (1,1,3) |
| | EE | (5,7,9) | (1,1,3) | (7,9,9) | (1,3,5) | (3,5,7) |
| | I&B | (1,1,3) | (3,5,7) | (1,3,5) | (5,7,9) | (7,9,9) |
| E3 | E Emp | (5,7,9) | (3,5,7) | (1,3,5) | (1,1,3) | (7,9,9) |
| | EWB | (1,1,3) | (5,7,9) | (3,5,7) | (7,9,9) | (1,3,5) |
| | OC | (1,3,5) | (1,1,3) | (7,9,9) | (5,7,9) | (3,5,7) |
| | EE | (1,1,3) | (7,9,9) | (3,5,7) | (5,7,9) | (1,3,5) |
| | I&B | (7,9,9) | (1,1,3) | (1,3,5) | (3,5,7) | (5,7,9) |
| E4 | E Emp | (5,7,9) | (1,3,5) | (3,5,7) | (1,1,3) | (7,9,9) |
| | EWB | (5,7,9) | (1,3,5) | (3,5,7) | (7,9,9) | (1,1,3) |
| | OC | (5,7,9) | (1,3,5) | (3,5,7) | (1,1,3) | (7,9,9) |
| | EE | (5,7,9) | (1,3,5) | (7,9,9) | (3,5,7) | (1,1,3) |
| | I&B | (5,7,9) | (1,3,5) | (3,5,7) | (7,9,9) | (1,1,3) |
| E5 | E Emp | (5,7,9) | (7,9,9) | (3,5,7) | (1,3,5) | (1,1,3) |
| | EWB | (5,7,9) | (7,9,9) | (3,5,7) | (1,3,5) | (1,1,3) |
| | OC | (5,7,9) | (7,9,9) | (3,5,7) | (1,3,5) | (1,1,3) |
| | EE | (5,7,9) | (7,9,9) | (3,5,7) | (1,3,5) | (1,1,3) |
| | I&B | (5,7,9) | (7,9,9) | (3,5,7) | (1,3,5) | (1,1,3) |

Notes: Triangulated Fuzzy numbers for criteria & Alternatives from Table 11. E Emp-Employee Empowerment, EWB-Employee Well-being, OC-Organizational Culture, EE-Employee Engagement, I&B-Inclusion & Belongingness, E-Experts, E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Source-Authors

All the expert opinions are aggregated into one single matrix as shown in Table 13. The formula used to obtain the vector-normalized decision matrix is given in Equation 8.

Table 14. Triangulated Fuzzy Decision Matrix

| Alternatives | Criteria | | | | |
|--------------|------------------|------------------|------------------|------------------|------------------|
| | E | A | C | N | O |
| E Emp | (5.00,7.00,9.00) | (1.00,6.20,9.00) | (1.00,5.40,9.00) | (1.00,2.20,5.00) | (1.00,4.20,9.00) |
| EWB | (1.00,4.20,9.00) | (1.00,5.80,9.00) | (3.00,6.60,9.00) | (1.00,3.80,9.00) | (1.00,4.60,9.00) |
| OC | (1.00,4.60,9.00) | (1.00,3.80,9.00) | (3.00,7.40,9.00) | (1.00,4.60,9.00) | (1.00,4.60,9.00) |
| EE | (1.00,6.20,9.00) | (1.00,5.40,9.00) | (1.00,5.80,9.00) | (1.00,5.00,9.00) | 1.00,2.60,7.00 |
| I&B | (1.00,5.00,9.00) | (1.00,5.40,9.00) | (1.00,4.60,9.00) | (1.00,5.40,9.00) | 1.00,4.60,9.00 |

Notes: E-Experts, E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Triangulated Fuzzy Decision Matrix derived from Equation 8.

The corresponding criterion weights are multiplied by each column to obtain the weighted normalized decision matrix, which is obtained by Equation 11 and given in Tables 14 and 15.

Table 15. Weighted normalized fuzzy decision matrix

| Criteria | E | A | C | N | O |
|----------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| E Emp | 0.0575, 0.1035, 0.1863 | 0.0230, 0.2071, 1.8639 | 0.0656, 0.4315, 1.7733 | 0.0036, 0.0131, 0.1610 | 0.0073, 0.0603, 0.5949 |
| EWB | 0.0115, 0.0621, 0.1863 | 0.0230, 0.1936, 1.8639 | 0.1968, 0.5273, 1.7733 | 0.0036, 0.0227, 0.2898 | 0.0073, 0.0661, 0.5949 |
| OC | 0.0115, 0.0680, 0.1863 | 0.0230, 0.1270, 1.8639 | 0.1968, 0.5911, 1.7733 | 0.0036, 0.0274, 0.2898 | 0.0073, 0.0661, 0.5949 |
| EE | 0.0115, 0.0917, 0.1863 | 0.0230, 0.1804, 1.8639 | 0.0656, 0.4634, 1.7733 | 0.0036, 0.0298, 0.2898 | 0.0073, 0.0373, 0.4627 |
| I&B | 0.0115, 0.0739, 0.1863 | 0.0230, 0.1804, 1.8639 | 0.0656, 0.3677, 1.7733 | 0.0036, 0.0322, 0.2898 | 0.0073, 0.0661, 0.5949 |

Notes: E-Experts, E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness, Weighted normalized fuzzy decision matrix derived from Equations 10-12.

The weighted normalized fuzzy decision matrix, as shown in Table 15, is computed to standardize and weight the fuzzy criteria values for fair comparison, revealing that Conscientiousness dominates across all criteria while Neuroticism remains least influential. The formula used is $\tilde{v}_{ij} = \tilde{w}_j * \tilde{r}_{ij}$, $j = 1, 2, \dots, m$ and $i = 1, 2, \dots, n$.

Table 16. Fuzzy positive ideal solution and fuzzy negative ideal solution

| | Extroversion | Agreeableness | Conscientiousness | Neuroticism | Openness to experience |
|----|---------------------------|---------------------------|---------------------------|---------------------------|----------------------------|
| A+ | 0.0575, 0.1035, 0.1863 | 0.0230, 0.2071, 1.8639 | 0.1968, 0.5911, 1.7733 | 0.0036, 0.0322, 0.2898 | 0.0073, 0.0661, 0.5949) |
| A- | 0.0115, 0.0621, 0.1863 | 0.0230, 0.1270, 1.8639 | 0.0656, 0.3677, 1.7733 | 0.0036, 0.0131, 0.1610 | 0.0073, 0.0373, 0.4627 |

Note: Fuzzy positive ideal solution and fuzzy negative ideal solution derived using Equation 13. A_i^- - distance of alternative from the fuzzy negative ideal solution; A_i^+ - distance of alternative from the fuzzy positive ideal solution

The positive ideal solution and negative ideal solution are calculated as shown in Table 16. A^+ is calculated by $\max(v_{ij})$ for beneficial criteria, $A^- \min(v_{ij})$ for non-beneficial criteria using Equations 14 and 15 (Jahanshahloo et al., 2006).

Table 17. Closeness coefficient and ranking

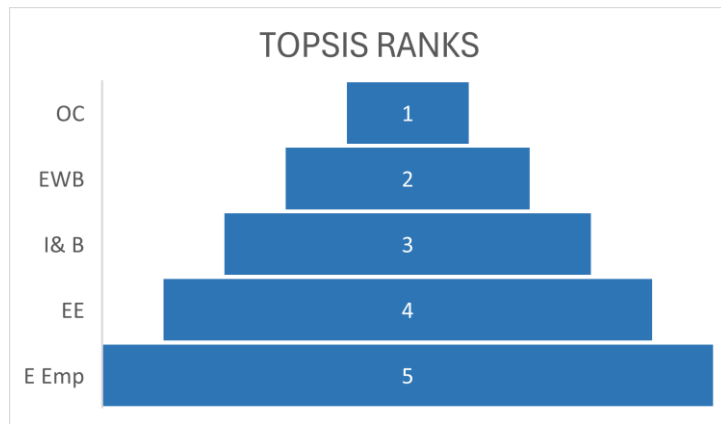
| Alternatives | A+ | A- | Ci | Ranking |
|--------------|------|------|-------|---------|
| OC | 1.38 | 3.62 | 0.724 | 1 |
| EWB | 1.42 | 3.58 | 0.716 | 2 |
| I& B | 1.47 | 3.53 | 0.706 | 3 |
| EE | 1.45 | 3.55 | 0.71 | 4 |
| E Emp | 1.51 | 3.49 | 0.698 | 5 |

Note: Closeness coefficient and ranking derived using Equations 14 and 15. A^- is the distance of the alternative from the fuzzy negative ideal solution; A^+ is the distance of the alternative from the fuzzy positive ideal solution; and C_i is the closeness index.

The distance between the positive ideal solution and the negative ideal solution is calculated using the Euclidean distance and indicated as C_i , as in Table 17, using Equations 16 and 17.

Using FTOPSIS, it is identified that Organizational Culture has the highest impact on retention, as highlighted in Figure 7. Employee well-being is ranked second.

Figure 7. TOPSIS Ranking



Note: Rank of the Alternatives, Source-Authors

Inclusion and Belongingness have been identified as the third factor impacting employee retention. Employee engagement and empowerment have been identified to take the last two positions in the FTOPSIS ranking, as shown in Figure 7. The results with respect to each method are mentioned in the above Tables.

5.3 Sensitivity Analysis

Sensitivity analysis is done to understand how the criterion weights (input parameters) impact the decision-making and outcome. The robustness of the ranks is analysed by changing the weights in small quantities to ensure reliability, as shown in Table 18. Sensitivity analysis offers a stronger form of validation than many alternative approaches because it directly evaluates how robust the FTOPSIS rankings remain when input weights or judgments are varied. Unlike single-point diagnostic measures, which only assess internal consistency at one level, sensitivity analysis reveals the stability of results across multiple scenarios, ensuring that the framework is not overly dependent on specific assumptions or subjective inputs. This makes it particularly well-suited for expert-driven MCDM studies, where reliability under uncertainty is crucial. Identifying the most important criteria helps in focusing on them and reducing complexity in decision-making.

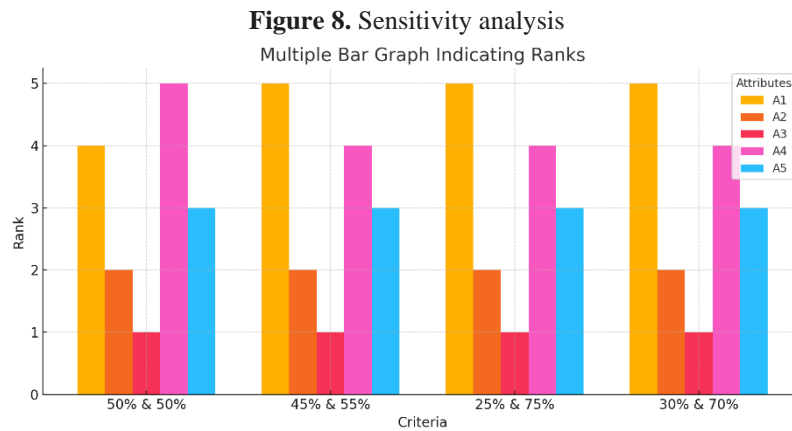
Table 18. Sensitivity Analysis

| Original Wi (criteria) | Alternatives | 50%&50% | 45%&55% | 25%&75% | 30%&70% |
|---------------------------|--------------|---------|---------|---------|---------|
| 0.1035 | A1 | 0.5560 | 0.52075 | 0.5225 | 0.529 |
| 0.2071 | A2 | 0.5693 | 0.55825 | 0.5733 | 0.5662 |
| 0.5911 | A3 | 0.5700 | 0.5625 | 0.5813 | 0.5715 |
| 0.0322 | A4 | 0.5400 | 0.52375 | 0.5288 | 0.5274 |
| 0.0661 | A5 | 0.5553 | 0.55525 | 0.5533 | 0.5485 |

Note: Testing rank consistencies over different weights

Table 18 provides the result of the sensitivity analysis done by changing the weightage assigned to a group of criteria. In the first scenario, all the weights were assigned equal weights, 50% & 50%, and it is represented in the first column. In the second scenario, the first three criteria (E, A, C) were assigned 45% weightage, and the other two criteria (N, O) were assigned 55% weightage. In the third

scenario, 25% weightage was assigned to the first three criteria (E, A, C) and 75% to the other two criteria (N, O). In the final scenario, the first three criteria (E, A, C) were assigned 30% weightage, and the other two criteria (N, O) were assigned 70% weightage.



Note: Sensitivity analysis tested for robustness and stability, source: authors.

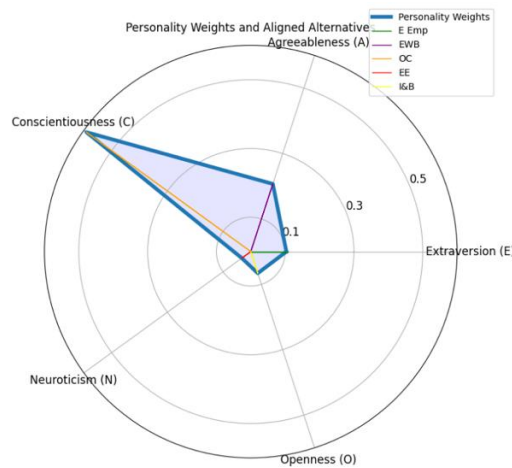
From the analysis stated in Figure 8, we can understand that Organizational culture is ranked first, and it is stable even when the weights are altered, showing the robustness and stability of the ranks. Employee well-being is ranked No. 2, and it is stable across different weights. Inclusion and belongingness have not changed over the input weights. This proves that the ranks given are robust and stable with any minor changes with regard to the criteria weights. This case study demonstrates the effectiveness of using FAHP and FTOPSIS to identify employee retention techniques using Big Five Personality Traits. Personalized retention strategies, informed by personality assessments, can lead to higher job satisfaction and reduced turnover. The following discussion interprets these findings in the context of existing literature and theoretical perspectives, highlighting their implications, relevance, and contributions to the field.

6. Discussions

This study develops a hybrid FAHP–FTOPSIS framework that links the Big Five personality traits with suitable employee retention strategies under uncertainty. It study claims novelty in decision sciences by applying fuzzy MCDM methods to model individualized retention preferences. The framework offers a quantitative, evidence-based tool for strategic human resource management. Using the FAHP method, the weights for the personalities are calculated based on expert opinion. The highest-ranking personality type is *Conscientiousness*. Individuals of this personality type are reliable and trustworthy, promoting peace and harmony within the team and the organization as a whole. They feel that they have an increased obligation to remain dependable and committed to a company. Individuals who score well on *Agreeableness* tend to be highly engaged and have favourable emotional profiles. Increased perceived contractual duties to stay may also result from the compliance and dependency components of agreeableness because one's intention and desire to remain or depart are influenced by affect. People who score highly on *Openness* may have more favourable attitudes towards learning experiences and a willingness to learn, which may motivate them to look for possibilities inside the organization or leave the organization for better opportunities. *Extroverts* are mostly people who feel good about their organization and are embedded within. Employees who exhibit *Neuroticism* and feel discontent at their place of employment are more likely to quit. Since they

can't handle stress or adapt to diverse environments, their sense of insecurity causes them to leave, especially early on in their career. As presented in Table 18, the rank values remained relatively consistent across different weight distributions, confirming that the FTOPSIS model is robust and not overly sensitive to moderate fluctuations in criteria importance. This diagnostic check strengthens the credibility of the model by demonstrating that its outputs are not artifacts of specific weight assumptions but reflect a stable preference structure.

Figure 9. Personality weights and aligned alternatives



Note: Criteria and alternatives alignment, Source-Authors

Figure 9 indicates the weights obtained by each trait of the Big Five Personality model and the ranks of each alternative. The FTOPSIS method was applied to find distances between the highest and the lowest value of alternatives, and ranking was done according to those values obtained. Table 17 and Figure 8 indicate that Organizational Culture is the top-ranked alternative because strong cultures can contribute to higher internal branding, which in turn improves retention. Toxic cultures can ruin the growth and success of any organization and can be the most suitable strategy for *conscientiousness*. The study also emphasizes the effectiveness of employing FAHP for assigning weights to the Big Five Personality traits and FTOPSIS for ranking employee retention strategies. These methodological approaches are particularly adept at handling subjective judgments and uncertainty, which are often inherent in human decision-making processes.

Most human beings spend at least one-third of their life at work. Individuals' experience at work—physical, emotional, mental, or social impacts their performance and longevity in the organization. By fostering *psychological and physical well-being*, it is possible to retain individuals with the agreeableness trait, and it is ranked second among alternatives. *Inclusive* work culture and creating an environment of belongingness pave the way for a more dedicated, committed, and productive workforce. Individuals with the *extroversion* trait can be retained using this technique. *Employee Engagement* in a work setup is a crucial element for being competent and productive is ranked fourth and is most suited to individuals with *Neuroticism*. *Empowering* individuals is a potential way of retaining them on board and is ranked fifth among alternatives. Feeling empowered in their professions increases the likelihood of having a feeling of contentment towards their jobs and workplace because of the prospects for professional growth. *Employee empowerment* is most suitable for individuals with the *openness* trait. To ensure consistency, the weights are altered in small quantities in order to evaluate

the stability of the ranks. In this study, it is identified that the decision matrix given by the experts was reliable, and organizational culture, Employee well-being, and Inclusion & belongingness have retained the *top three ranks* even after the weights were altered several times. Sensitivity analysis in this study acts as a critical diagnostic tool to evaluate the stability and reliability of the FTOPSIS model. By systematically altering the weights of the decision criteria, particularly the beneficial traits (Extraversion, Agreeableness, and Conscientiousness) versus the remaining traits (Neuroticism and Openness), we assessed how minor changes in input parameters influenced the final ranking of alternatives.

6.1 Limitations

Although this study successfully met its research objectives, it is important to acknowledge certain limitations that provide pathways for future exploration. Primarily, the study was confined to the Indian IT & ITES sector, which, while significant, represents a unique organizational and cultural context. This specificity may limit the generalizability of findings to other business environments and cultural backgrounds where workplace dynamics and employee expectations may differ considerably.

7. Conclusion

Human capital constitutes one of the most inevitable resources. On the one hand, moonlighting (Choudhary & Saini, 2021) results in stress and a diminished dedication to the principal job, which might impede employee retention. On the other hand, organisations find that keeping their workforce becomes a top priority during slumps in the economy. Recessions have a significant effect on retaining personnel on board. As a result of factors like insecure employment, financially unstable circumstances, or fewer prospects for career advancement, workers may be more prone to quit during a recession. This study examined the antecedents that impact the longevity of employees in several organizations in India from the Information Technology and enabled services sector, which has implications for human capital management. Additionally, the analysis highlights which criteria exert the most influence on decision outcomes, allowing practitioners to streamline focus on high-impact traits and reduce decision-making complexity. Therefore, the sensitivity analysis not only reinforces model robustness but also supports informed strategic decisions in real-world HR scenarios where subjective judgment often varies. Consequently, while the present study contributes significant insights into prioritizing employee retention strategies within the Indian IT sector, it also highlights its originality in applying a hybrid FAHP–FTOPSIS model to this specific HR problem

7.1 Theoretical Contribution

In order to understand employee retention decisions, this study makes a theoretical contribution by incorporating the Theory of Planned Behaviour and Social Exchange Theory into a Fuzzy multi-criteria decision-making framework. It improves knowledge of how behavioural intentions are shaped by personality factors and how organisational reciprocity affects retention outcomes. A freshly developed set of factors, supported by theories, particularly the ever-evolving Social Exchange theory that is based around loyalty and commitment, has been examined in this study. When an employee is well-cared for in all facets of their employment to ensure their longevity in the organization, relationships within the organization become established (Cropanzano & Mitchell, 2005). It makes

sense if the company has a strong, inclusive culture that provides the best possible work environment for employees, including empowerment and well-being. It is highly suggested that businesses make a greater effort to support the well-being of their employees and give them a sense of inclusion, providing them with an environment that allows them to assume responsibility for their jobs. Providing a fully engaged workplace is of the utmost significance as it is necessary to achieve employee retention .

7.2 Practical Contribution

According to the study, to improve employee retention rates, companies should carefully consider the qualities of potential hires and consider whom to place in key positions within the company. They should also give their staff members enough training and ensure their psychological wellness, which makes them feel included and engaged. In IT & ITES, high employee turnover has a detrimental effect on both the organization's quality and finances. The organisation will suffer greatly from the increased costs that are associated with onboarding new employees and from the lost time and output while they learn, a high turnover rate lowers workforce morale. According to this research, MCDM enables approaches that enable an extensive assessment of the apt retention strategies for each personality, resulting in decisions that are well-informed and increase employee embeddedness. Firstly, the study broadens the scope of the literature by using mathematical models to predict retention strategies for each Big Five personality trait. Using Personality and employee retention strategies, a decision-making model customized to the Indian IT & ITES industry has been developed. Secondly, this article contributes to how retention strategies can be specifically applied to each personality, and it is a particularly novel combination. The study highlights how the implications of Fuzzy MCDM techniques can be used to predict retention strategies using personality. The algorithms and variables create a base for further restructuring that could be used irrespective of industry and organizations. This study examined the antecedents that impact the longevity of employees in the organization in India for the Information Technology & IT-enabled services sector, which has implications for human capital management. The results of the study can help employers build customized decision-making models for their organization. Based upon this model, organizations can build it with their customized criteria and alternatives for the new employees who are from a different generation. Employers and practitioners can use this as a reference for establishing a benchmark in employee retention for their respective organizations.

7.3 Future Directions

Extending this research to diverse industries and geographical regions would allow for comparative analyses and a more comprehensive understanding of how personality traits impact retention strategies across various cultural and organizational settings. While the variables included in the study were carefully selected based on a thorough literature review and expert validation, the rapidly evolving landscape of the technology sector, marked by digital transformation, hybrid work models, and shifting employee expectations, suggests that additional variables may be crucial in understanding employee retention in contemporary contexts. Integrating emerging elements such as technology adoption, remote work adaptability, and digital collaboration into future studies could enhance predictive accuracy and contextual relevance. Future research could also benefit from conducting statistical hypothesis testing on the FAHP-derived weights and the FTOPSIS-generated rankings to solidify the reliability of the prioritization framework. Also, other MCDM methods like VIKOR, COPRAS could

be used for decision making with regard to Personality and Retention research. Comparative studies across technologically advanced and underdeveloped nations could reveal critical contextual differences, offering insights into how technological infrastructure and socio-economic conditions shape employee retention strategies. Such investigations would not only validate the current study's findings but also contribute to a deeper, context-sensitive understanding of the factors influencing employee commitment and embeddedness in varying economic and technological landscapes.

Abbreviations

E-Extroversion, A-Agreeableness, C-Conscientiousness, N-Neuroticism, O-Openness-(OCEAN), OC-organizational culture, EWB-Employee well-being, I&B -Inclusion &Belongingness, EE-Employee Engagement, E Emp-Employee empowerment, FAHP-Fuzzy Analytical Hierarchy Process, FTOPSIS-fuzzy Technique for order Preference by similarity to Ideal Solution, MCDM-Multi Criteria Decision-Making

Data availability statement

On request, the data set corresponding to the study can be obtained from the corresponding author.

Declaration of Conflict of Interest: The authors declare that they have no conflict of interest.

Ethical approval: This article does not require ethical approval, as the experts voluntarily agreed to participate in the survey and provide their responses. No personal information was collected; only professional experiences and opinions were shared.

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