



A Decision Support Model Proposal for the Employment Decisions of Mechanical Design Engineers

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Abstract

The quality of human resources is directly linked to a business's success or failure in the market. Consequently, the selection and effective utilization of human resources remain significant areas of research. Selecting the right personnel—particularly for roles within Research and Development (R&D) departments—presents a complex decision-making problem involving multiple criteria. This study focuses on the selection of a mechanical design engineer for an R&D department and proposes a decision-support model based on the Fuzzy Analytic Hierarchy Process (Fuzzy AHP). First, five main dimensions and eighteen criteria are identified through a systematic literature review. These dimensions and criteria are evaluated via pairwise comparisons by three R&D managers who are subject-matter experts and key decision-makers regarding R&D personnel recruitment. The resulting matrices are then weighted using the Fuzzy AHP method, thereby enabling the modeling of the uncertainty and subjectivity inherent in the selection process. The study reveals that technical competence (0.371) is the most critical dimension in selecting a mechanical design engineer, followed by creativity and innovation (0.190). By employing the Fuzzy AHP approach, the study establishes a systematic evaluation framework for R&D personnel selection, offering an objective and consistent tool for managers.

Keywords: Fuzzy AHP, R&D, Mechanical Design Engineer Selection, Multi-Criteria Decision Making

1. Introduction

Numerous internal and external factors influence the success or failure of business enterprises. In this regard, human resources constitute one of the most critical factors affecting a firm's market position and future (Barney, 1991, p. 99; Wolfson & Mathieu, 2021, p. 435; Wright, Dunford, & Snell, 2001, p. 701). Particularly within research and development departments, human resources play a pivotal role in a firm's long-term success or failure by influencing strategic variables such as product development and the speed of market introduction (Cohen & Levinthal, 1990, pp. 138-146; Kleiner-Schäfer & Liefner, 2021, pp. 976-980). Consequently, the proper selection of mechanical design engineers for research and development departments is of decisive importance for the firm to achieve its strategic objectives (Chinowsky & Byrd,

2001, p. 34; Erkarslan et al., 2011, p. 140; Yang et al., 2005, p. 155).

Selecting personnel involves a decision-making problem that requires taking multiple criteria into account. While some of these criteria can be measured objectively, others entail subjectivity and uncertainty. Moreover, traditional methods often overlook criteria characterized by subjectivity and uncertainty, proving inadequate in the candidate selection and evaluation processes (Aksakal et al., 2013, p. 68; Lievens et al., 2002, p. 580).

It is critical to support decision-making and evaluation processes regarding human resource selection through a framework that comprehensively addresses both objective criteria (such as education level and years of experience in the relevant field) and subjective ones (such as creativity and problem-solving skills) (Ijadi Maghsoodi et al., 2020; Jereb et al., 2005). It is possible to overcome these and similar limitations by developing a decision-support model based on the Fuzzy Analytic Hierarchy Process (Fuzzy AHP), a multi-criteria decision-making method. By synthesizing fuzzy set theory with the Analytic Hierarchy Process, the Fuzzy AHP method enables the numerical modeling of preferences expressed qualitatively by decision-makers; this yields more realistic results in areas—such as candidate selection—that involve a combination of tangible and intangible evaluation factors (Schmidt & Hunter, 1998, p. 267; Güngör et al., 2009, p. 641; Varmazyar & Nouri, 2013, p. 27).

This study aims to develop a decision-support model using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) for the selection of design engineers for an R&D department and to determine the weights of the dimensions and criteria constituting this model. In the study, dimensions and criteria are identified systematically based on existing literature regarding Fuzzy AHP and candidate selection, and these dimensions and criteria are expressed in terms of their degrees of importance derived from pairwise comparisons made by experts.

2. Purpose of the study and research questions

The recruitment process encompasses the identification, evaluation, and hiring of candidates suited to an organization's operational needs and plays a pivotal role in enabling the organization to achieve its strategic objectives (Gurbuz & Mert, 2011, pp. 1803, 1815-1818; Kim & Ployhart, 2018, pp. 46-47; Selase, 2018, pp. 284-285). Selecting the right candidate and ensuring they begin their role in the appropriate position impacts employee performance as well as the long-term performance of both the specific department and the organization as a whole. In this context, performance is not solely a matter of individual competence; it also depends on a multitude of factors that must be considered holistically—such as organizational culture, team dynamics, and the professional development opportunities offered to the employee (Jacobs & Washington, 2003, pp. 343-347; López-Cabarcos et al., 2022, pp. 361-367; Shahzad, 2014, pp. 222-225).

To ensure the healthy continuation of business operations, every department and employee carries out specific tasks, and the knowledge, skills, and competencies of the workforce vary according to their respective areas of expertise. In this context, R&D department employees engage in activities that require a high level of technical knowledge and skill. R&D mechanical design engineers—who determine the products brought to market and directly influence time-to-market—play a pivotal role in a company's competitive standing; they possess qualities such as the ability to generate new ideas, select optimal solutions by evaluating engineering and customer criteria against alternatives, and adapt to and integrate innovations into work processes. Consequently, the selection of a mechanical design engineer is critical: choosing the right person can lead to project success and the realization of the company's product goals, whereas selecting the wrong engineer can result in increased workforce turnover and project failure (Gurbuz & Mert, 2011, pp. 1813-1816; Kim & Ployhart, 2018, pp. 58-60; Selase, 2018, pp. 285, 287).

In light of the information provided, the aim of this study is to present a consistent, systematic, and objective evaluation model to decision-makers involved in the selection of mechanical design engineer candidates for an R&D department. This evaluation model is based on the Fuzzy Analytic Hierarchy



Process. Accordingly, the study aims to identify the dimensions and criteria to be considered in the selection of mechanical design engineers through a systematic literature review; to calculate the relative importance of these dimensions and criteria using pairwise comparisons involving three R&D managers responsible for hiring decisions; and, finally, to discuss the contributions of the proposed model to the candidate selection process.

In line with these objectives, the primary research questions addressed within the scope of the study are outlined below:

- What are the dimensions and/or criteria that can be evaluated for the selection of mechanical design engineers for R&D departments?
- How can the selection criteria for mechanical design engineers to be employed in R&D departments be categorized?

2. Methodology

The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) method forms the basis of the model proposed in this study for the selection of mechanical design engineers for R&D departments. As a multi-criteria decision-making method, Fuzzy AHP is preferred for the systematic and objective resolution of complex selection problems encountered when evaluating candidates for mechanical design engineering positions in R&D departments (Güngör et al., 2009, pp. 642–643; Liang & Wang, 1994, pp. 23–25; Kabak et al., 2012, pp. 3516–3517). This approach makes it possible to overcome limitations such as the uncertainty and ambiguity inherent in human evaluations. By synthesizing fuzzy set theory with AHP, Fuzzy AHP enables the numerical modeling of decision-makers' qualitative expressions. Consequently, it facilitates the achievement of more realistic results in areas heavily reliant on subjective and qualitative assessments—such as mechanical design engineer selection—while minimizing errors in observation and evaluation, as well as reducing uncertainties specific to the R&D department's evaluation processes (Huang et al., 2008, pp. 1041–1043; Dursun & Karsak, 2010, pp. 4325–4326; Hsu et al., 2003, pp. 540–542).

2.1. Process of determining dimensions and criteria

The set of dimensions and criteria for the study was derived in two stages. In the initial stage of determining these dimensions and criteria, the current literature regarding personnel selection—specifically concerning the performance evaluation of R&D department employees and the selection of design engineers—was reviewed. Additionally, studies focusing on the evaluation of candidates using the Fuzzy AHP method were taken into account. Through this process, a list of potential dimensions and criteria was established.

In the second stage of the process for determining dimensions and criteria, the compilation of dimensions and criteria obtained in the first stage underwent a preliminary evaluation by experts. Through this preliminary assessment, R&D managers—who are experts and decision-makers in personnel recruitment—evaluated the dimensions and criteria within the context of mechanical design engineering and adapted them to the research field. Criteria from the literature deemed unsuitable were eliminated, and the adaptation process was finalized by rephrasing the dimensions and criteria into terms clearly understood within the R&D department. As shown in Table 1, the final set of dimensions and criteria—consisting of five dimensions and eighteen criteria—aligns with previous studies in the literature.

Table 1. Dimensions, criteria, and necessary definitions for mechanical design engineer selection

Dimension	Criteria	Definition	References
Technical Competence (TY)	TY1: CAD/CAM/CAE Knowledge	Proficiency in computer-aided design, manufacturing, and engineering tools	Erkarslan vd., 2011, s. 138-139; Kovačić vd., 2018, s. 2-4; Zdorova vd., 2020, s. 2-5

	TY2: Knowledge of Materials	Knowledge of the properties and selection criteria of engineering materials	Deng & Edwards, 2007, s. 294-296; Ashby, 1989, s. 509-511; Krucken vd., 2017, s. 5-8
	TY3: Analysis and Simulation Skills	Ability to use simulation tools such as finite element analysis, fluid dynamics, etc.	Deng & Edwards, 2007, s. 300; Kovačić vd., 2018, s. 8-10
	TY4: Competence in Design Tools	Proficiency in current design software and platforms	Erkarslan vd., 2011, s. 139; Zdorova vd., 2020, s. 3-6; Kovačić vd., 2018, s. 4-6
Creativity and Innovation (YI)	YI1: Generating New Ideas (Concepts)	The ability to develop unique and innovative design concepts	Cropley, 2015, s. 163-164; Kobe & Goller, 2009, s. 133-135
	YI2: Improving Existing Designs	Ability to improve and optimize existing products/designs	Snider vd., 2016, s. 170-173; Cropley, 2015, s. 162
	YI3: Providing Innovative Solutions	The ability to come up with unconventional and creative solutions to complex problems	Snider vd., 2016, s. 180-182; Cropley, 2015, s. 164-165
	YI4: Adapting to New Technologies	The ability to adapt quickly to technological changes and a desire to learn new technologies	Petty, 1983, s. 9-12; Cropley, 2015, s. 168-169
Problem-Solving Skills (PC)	PC1: Analytical Skills	Ability to systematically analyze complex engineering problems	Ramadi vd., 2015, s. 40-42; Nilsson, 2010, s. 407-409; Yazdani vd., 2018, s. 3-5
	PC2: Research Skills	Access to technical information, the ability to conduct literature reviews and research	Igarashi vd., 2004, s. 1-3; Edvardsson Stiwe & Jungert, 2010, s. 535-537
	PC3: Planning (/Organizing) Skills	Planning the resolution process, organizing resources, and setting priorities	Güngör vd., 2009, s. 642-643; Çelikkilek & Tüysüz, 2018, s. 13-15
Teamwork and Communication (TC)	TC1: Interdisciplinary Practice	Ability to collaborate with different engineering disciplines	Ford & Riley, 2003, s. 184-186; Ramadi vd., 2015, s. 42-44; Gider & Urbančić, 2010, s. 268-270



	TC2: Verbal Communication	Presenting ideas effectively, active participation in technical meetings	Ramadi vd., 2015, s. 43-44; Ford & Riley, 2003, s. 187-189; Schulz vd., 1999, s. 385-387
	TC3: Written Communication	Technical reporting, documentation, and written communication skills	Ford & Riley, 2003, s. 188-190; Ramadi vd., 2015, s. 43-44; Palma vd., 2014, s. 3-5
	TC4: Interpersonal Skills	Team cohesion, empathy, and collaboration skills	Khusainova vd., 2020, s. 6-10; Schulz vd., 1999, s. 387-389
Project and Time Management (PY)	PY1: Project Management Skills	Project planning, monitoring, and control skills	Çelikbilek & Tüysüz, 2018, s. 14-16; Palma vd., 2014, s. 4-7; Gider & Urbančić, 2010, s. 269-271
	PY2: Time Management	Meeting deadlines, prioritization, and effective time management	Ramadi vd., 2015, s. 43-45; Kovačić vd., 2009, s. 705-707; Edvardsson Stiwné & Jungert, 2010, s. 540-541
	PY3: Use of Resources	The ability to efficiently manage budgets, equipment, and human resources	Güngör vd., 2009, s. 642-643; Gider & Urbančić, 2010, s. 269-270; Palma vd., 2014, s. 5-7

2.2.Fuzzy AHP method

The study utilizes the fuzzy AHP method to quantitatively evaluate the dimensions and criteria to be presented to experts. The classical AHP method is not preferred because it is difficult to compare dimensions and criteria—particularly in the context of human resource selection—using precise numerical expressions. Furthermore, the classical AHP method cannot fully reflect uncertainties in the conversion of evaluations to precise numbers in accordance with qualitative expressions. Consequently, it is not possible to obtain satisfactory results using this method within the scope of this study (Aly & Vrána, 2008, p. 530; Bozbura et al., 2007, p. 1111). The Fuzzy AHP method combines fuzzy set theory with the AHP methodology to compare dimensions and criteria in human resource selection (Bozbura et al., 2007, p. 1103; Güngör et al., 2009, p. 642; Kahraman et al., 2003, p. 386). This makes it possible to provide a more realistic basis for evaluating qualitative statements that are difficult to express through precise numerical assessments (Dursun & Karsak, 2010, pp. 4324–4325; Güngör et al., 2009, p. 642). In this study, using triangular fuzzy numbers, three parameters—pessimistic, probable, and optimistic values—are defined for the evaluation of dimensions and criteria (Aly & Vrána, 2008, p. 531; Bozbura et al., 2007, p. 1104; Dursun & Karsak, 2010, p. 4325; Kahraman et al., 2003, p. 385). Thus, these three values enable the decision-maker to express uncertainty (Aly & Vrána, 2008, p. 531; Güngör et al., 2009, p. 642).

This study aims to present a model using the fuzzy AHP method and is based on expert opinions. Fuzzy AHP analysis based on expert opinions does not require a large sample size due to concerns about statistical generalizability (Chan et al., 2019, p. 1; Kubler et al., 2016, pp. 399–401; Morgan, 2014, p. 7179; Saaty & Özdemir, 2014, pp. 359–361). However, the research population consists of design experts in senior leadership/managerial positions at engineering firms operating in R&D departments—where at least five people work in the R&D department—who have directly influenced or made personnel hiring decisions at least once. The researchers comprising the sample for this study were selected using purposive sampling. Purposive sampling is a sampling method in which experts intentionally select participants who can contribute most to the research objectives, rather than selecting them based on probability. This approach

makes it possible to include participants who are experienced and competent in their respective fields and to evaluate the contributions they provide within the study (Saaty & Özdemir, 2014, pp. 366–368). In this context, the following criteria are considered when identifying and selecting potential participants for the study:

- The participant must work in the R&D department of a company,
- The participant must carry out their activities in an R&D department with at least five employees,
- The participant must have, at least once in the past, directly influenced the hiring decision or made that decision independently during the hiring process for candidates for positions in the R&D department,
- The participant must have had the authority, at least once in the past, to directly influence or make the hiring decision independently regarding candidates for positions in the R&D department,
- The participant must have at least 6 years of experience in design engineering within the R&D department,
 - If the participant agrees to voluntarily participate in the study, they will be eligible to be included in the study,
- The participant must be informed about the study prior to participating.

Prior to administering the paired comparison survey designed to collect data for the study, information regarding the study's purpose, methodology, and scale was provided to ensure the research was conducted in accordance with ethical standards. Furthermore, it was clearly explained that no personal data would be recorded or requested. The study proceeded with three experts who voluntarily consented to participate and met the criteria.

In this study, the 1–9 scale proposed by Saaty (1980) is used; however, during the evaluation phase, calculations are performed using the Fuzzy AHP rather than the classical AHP. In this respect, the data collection approach is the same as that of the classical AHP. The following steps were carried out to calculate the comparison data obtained using the Fuzzy AHP method:

- Most likely value, m : To calculate the most likely value, the values of the comparisons provided by the three experts are first calculated using the geometric mean. This allows the common trend among the three experts to be represented.
- The most optimistic value (u) and the least optimistic value (l): These values—which can also be expressed as the highest (u) and lowest (l)—ensure that a range is determined for each comparison. For example, if one of three experts assigns a value of 3 for a comparison and the other two assign a value of 4, the lowest value (l) is determined to be 3. For the same example, the highest value is determined to be 4. Here, the most likely value is the geometric mean, which is 3.634. Therefore, for the triangular fuzzy number, (l, m, u) is determined to be (3, 3.634, 4).
- Fuzzy AHP calculation method: The steps for fuzzy AHP calculations are based on Buckley's (1985, pp. 233–247) analysis method. The reason Buckley's calculation method is preferred over Chang's (1996, pp. 649–655) Fuzzy AHP calculation method is that information is transferred directly to the analysis via geometric means, without being summarized or interpreted. Thus, rather than comparing probabilities, the trend of participant evaluations and the tolerance range of this calculation are directly revealed (Buckley, 1985, pp. 233–247; Cebeci & Ruan, 2007, pp. 191–207; Buckley et al., 2001, pp. 48–64).

2.3.Fuzzy AHP analysis and findings

The pairwise comparison survey values obtained with the participation of experts are first calculated



using Buckley's (2001) analytical approach to derive the most likely values by taking geometric means (Buckley et al., 2001, pp. 48–64; Ramík & Korviny, 2010, pp. 1604–1613; Zhang, 2017, pp. 1083–1095). The experts' pairwise comparison values and the geometric means of these evaluations are detailed in Table 2. In the next step, the Fuzzy AHP Matrix of Dimensions, as shown in Table 3, is derived by including the most probable values along with the highest and lowest values.

Table 2. Fuzzy AHP calculation table for dimensions

Comparison No	Criterion on the Left (A)	Criterion on the Right (B)	Expert 1 U1	Expert 2 U2	Expert 3 U3	Geometric Mean Value
1	TY	YI	4,00	3,00	4,00	3,63
2	TY	PC	1,00	5,00	3,00	2,47
3	TY	TC	3,00	3,00	2,00	2,62
4	TY	PY	1,00	2,00	5,00	2,15
5	YI	PC	2,00	3,00	1,00	1,82
6	YI	TC	0,50	3,00	0,20	0,67
7	YI	PY	3,00	5,00	2,00	3,11
8	PC	TC	2,00	5,00	0,50	1,71
9	PC	PY	1,00	1,00	1,00	1,00
10	TC	PY	3,00	1,00	2,00	1,82

Table 3. Fuzzy AHP calculation table for dimensions

Criteria	TY-l	TY-m	TY-u	YI-l	YI-m	YI-u	PC-l	PC-m	PC-u	TC-l	TC-m	TC-u	PY-l	PY-m	PY-u
TY	1,000	1,000	1,000	3,000	3,630	4,000	1,000	2,470	5,000	2,000	2,620	3,000	1,000	2,150	5,000
YI	0,250	0,280	0,330	1,000	1,000	1,000	1,000	1,820	3,000	0,200	0,670	3,000	2,000	3,110	5,000
PC	0,200	0,400	1,000	0,330	0,550	0,550	1,000	1,000	1,000	0,500	1,710	5,000	1,000	1,000	1,000
TC	0,330	0,380	0,500	0,330	1,490	5,000	0,200	0,580	2,000	1,000	1,000	1,000	1,000	1,820	3,000
PY	0,200	1,470	1,000	0,200	0,320	0,500	1,000	1,000	1,000	0,330	0,550	1,000	1,000	1,000	1,000

In the next step, the geometric mean of the l, m, and u values in this matrix must be calculated for each row. This yields the geometric l, m, and u values for the dimensions. These geometric l, m, and u values are presented in Table 4 as Geo-l, Geo-m, and Geo-u. The sum of the Geo-l, Geo-m, and Geo-u values is subsequently required for the weight calculation process.

Table 4. Geometric means and column sums

Geo-l	Geo-m	Geo-u
1,431	2,191	3,129
0,631	1,012	1,715
0,505	0,822	1,380
0,465	0,902	1,719
0,421	0,607	0,871
Total Geo-l = 3,453	Total Geo-m = 5,535	Total Geo-u = 8,814

Fuzzy weights are derived by dividing the Geo-l, Geo-m, and Geo-u values in each row of the resulting table by the Total Geo-l, Total Geo-m, and Total Geo-u values, yielding the weight values W-l, W-m, and W-u. The row averages of these values represent the net weight values. Final weights are obtained by dividing the net weights by the sum of the net weight column. The sum of the final weight values equals 1. Thus, the final (or normalized) weight value for each dimension is determined. These values are presented in Table 5.

Table 5. Fuzzy weight values, net weight values, and final weights

W (l)	W (m)	W (u)	Net-Weight Values	Final Weights (Normalized Weight)
0,162	0,396	0,906	0,488	0,371
0,072	0,183	0,497	0,250	0,190
0,057	0,149	0,400	0,202	0,154
0,053	0,163	0,498	0,238	0,181
0,048	0,110	0,252	0,137	0,104
		Total	1,315	1,000

Once the global weights of the dimensions have been determined, the same procedures are applied to calculate the weights of the criteria contained within each dimension. After determining the normalized weights of the criteria, global weight values are obtained by multiplying each criterion's weight by the normalized weight of its respective dimension. Normalized weights indicate the relative importance of the criteria within their specific groups, whereas global weights express the importance of the criteria within the entire set of criteria. Tables 6 and 7 present the values obtained from the calculations for the dimensions and criteria.

Table 6. Order of importance of dimensions

Main Dimensions	Abbreviation	Fuzzy Weight (l, m, u)	Final Weights (Normalized Weight)	Priority
Technical Competence	TY	(0,162, 0,396, 0,906)	0,371	1
Creativity and Innovation	YI	(0,072, 0,183, 0,497)	0,190	2
Teamwork and Communication	TC	(0,053, 0,163, 0,498)	0,181	3
Problem-Solving Skills	PC	(0,057, 0,149, 0,400)	0,154	4
Project & Time Management	PY	(0,048, 0,110, 0,252)	0,104	5

Table 7. Ranking of criteria by global weights

Rank	Criteria	Code	Dimension	Global Weight
1	Knowledge of Materials	TY2	Technical Competence	0,199
2	Analysis and Simulation Skills	TY3	Technical Competence	0,092
3	Improving Existing Designs	YI2	Creativity and Innovation	0,075
4	Interdisciplinary Practice	TC1	Teamwork and Communication	0,074
5	Generating New Ideas (Concepts)	YI1	Creativity and Innovation	0,065
6	Research Skills	PC2	Problem-Solving Skills	0,063
7	Project Management Skills	PY1	Project and Time Management	0,058
8	Analytical Skills	PC1	Problem-Solving Skills	0,051
9	Verbal Communication	TC2	Teamwork and Communication	0,05
10	CAD/CAM/CAE Knowledge	TY1	Technical Competence	0,047



11	Interpersonal Skills	TC4	Teamwork and Communication	0,043
12	Planning (/Organizing) Skills	PC3	Problem-Solving Skills	0,04
13	Competence in Design Tool	TY4	Technical Competence	0,033
14	Providing Innovative Solutions	YI3	Creativity and Innovation	0,027
15	Time Management	PY2	Project and Time Management	0,027
16	Adapting to New Technologies	YI4	Creativity and Innovation	0,024
17	Use of Resources	PY3	Project and Time Management	0,019
18	Written Communication	TC3	Teamwork and Communication	0,013
				Toplam = 1,000

Subsequently, a sensitivity analysis is conducted to test the extent to which potential changes in the preferences expressed by participants alter the results—or, in other words, how a potential shift in responses affects the importance weights and, consequently, the degree of fragility or robustness of the study's findings. This makes it possible to assess the reliability of the model (Erkut & Tarımcılar, 1991, pp. 62–63; Triantaphyllou & Sánchez, 1997, pp. 152–153).

As part of the study, the sensitivity analysis observes how the ranking of the dimensions' importance changes in response to a $\pm 20\%$ variation in their weights. This approach makes it possible to identify the dimensions to which the model is sensitive (Triantaphyllou & Sánchez, 1997, pp. 156–158; Kaymak & van Nauta Lemke, 1998, pp. 171–173) and to determine whether such sensitivity significantly impacts the model's results (Erkut & Tarımcılar, 1991, pp. 72–75). Furthermore, it allows for the determination of the percentage range of variation within which the model remains valid for use (Buckley et al., 2001, pp. 49–52; Triantaphyllou & Sánchez, 1997, pp. 158–160).

In the sensitivity analysis, for a $\pm u\%$ change scenario regarding a criterion weight v , if the current weight g_v is expressed in terms of the new weight variable g'_v , the formula is as follows:

$$g'_v = g_v * (1+u)$$

For other criteria, the calculation is performed according to the formula below, provided that “ v ” and “ i ” represent distinct criteria:

$$g'_i = g_i * [(1-g'_v) / (1-g_v)]$$

Thus, new weights are obtained and can be compared with the existing importance ranking based on the original weights. The new weights, along with the rates of change, are presented in Table 8.

Table 8. Sensitivity analysis table, $\pm 20\%$ change scenario, and new weight values

Change Scenario	Changed Dimension	Rate of Change	New TY	New Value	YI	New Value	TC	New Value	PC	New Value	PY
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0	-	%0	0,371	0,19	0,181	0,154	0,104
1	TY	+%20	0,445	0,168	0,16	0,136	0,092
2	TY	-%20	0,297	0,211	0,202	0,172	0,116
3	YI	+%20	0,355	0,228	0,174	0,148	0,1
4	YI	-%20	0,388	0,152	0,189	0,161	0,109
5	TC	+%20	0,362	0,185	0,217	0,15	0,101
6	TC	-%20	0,38	0,195	0,145	0,158	0,107
7	PC	+%20	0,363	0,186	0,177	0,185	0,102
8	PC	-%20	0,38	0,195	0,185	0,123	0,106
9	PY	+%20	0,365	0,187	0,178	0,151	0,125
10	PY	-%20	0,378	0,193	0,184	0,157	0,083

By comparing the newly obtained weight values across the change scenarios, it is necessary to check whether there are any shifts in the ranking of the dimensions. This comparison of importance rankings is conducted between the ranking prior to the application of change scenarios and the ranking after their application. In this context, a shift in ranking between CI (Creativity and Innovation) and TW (Teamwork) is observed only for Change Scenario 3 and Change Scenario 5.

An examination of the state of these two weight values prior to the modification reveals a difference of 0.009 between them. Consequently, a 20% variation can lead to a change in their relative ranking in these two scenarios. This results in Table 9, the "Dimension Importance Ranking Table Based on Change Scenarios," which allows for the observation of changes in rankings. Thus, the sensitivity analysis results demonstrate the model's robustness in the face of 20% variations.

Table 9. Ranking table of dimension importance based on change scenarios

Change Scenario	Changing Dimension	Difference %	1. Row	2. Row	3. Row	4. Row	5. Row
0	-	%0	TY	YI	TC	PC	PY
1	TY	+%20	TY	YI	TC	PC	PY
2	TY	-%20	TY	Y	TC	PC	PY
3	YI	+%20	TY	TC	YI	PC	PY



4	YI	-%20	TY	YI	TC	PC	PY
5	TC	+%20	TY	TC	YI	PC	PY
6	TC	-%20	TY	YI	TC	PC	PY
7	PC	+%20	TY	YI	TC	PC	PY
8	PC	-%20	TY	YI	TC	PC	PY
9	PY	+%20	TY	YI	TC	PC	PY
10	PY	-%20	TY	YI	TC	PC	PY

3. Conclusion, discussion, and recommendations

This study presents a model for selecting a mechanical design engineer for the R&D department using Buckley's Fuzzy AHP method, which is based on the geometric mean. This model identifies the dimensions and criteria for selecting mechanical design engineers through pairwise comparisons conducted by experts with experience in personnel selection for the R&D department, as well as knowledge, competence, and experience. In this regard, the resulting model contributes to the literature as a tool that can be used for decision support.

Considering the findings of the study, it is evident that the technical competence dimension ranks first by a wide margin, including in every change scenario analyzed in the sensitivity analysis. This result is to be expected, as it aligns with the primary activities of mechanical design engineers within the organization. Other studies in the literature also support the validity of this finding, indicating that technical competencies hold similarly high importance for R&D positions (Chen, 2009, pp. 5796–5803; Robinson et al., 2005, pp. 123–153). The fact that “materials knowledge” and “analysis skills”—two criteria within the technical competence dimension—have the highest overall weights demonstrates the strategic importance of these two competencies from a professional standpoint in mechanical design engineering. While material knowledge is important in many areas, such as manufacturability and cost, analysis and simulation skills are important in terms of providing insights into the extent to which the specified engineering conditions can meet the expected design outcomes.

The two dimensions ranked second and third—creativity and innovation, and teamwork and communication—carry nearly equal weight based on the values derived from expert opinions and analysis results. The critical issue highlighted by both dimensions is the generation of alternative solutions. Tasks that are sometimes primarily undertaken by mechanical design engineers are resolved through the contribution of the company's institutional memory, while at other times they are resolved through the competencies of mechanical design engineers, as expressed by the creativity and innovation dimension. The fact that these two dimensions have similar values suggests that they cannot be considered independently of one another in the execution of tasks. Indeed, the criteria of the creativity and innovation dimension—such as improving designs and generating new ideas—along with the criteria of the teamwork and communication dimension—such as interdisciplinary collaboration and verbal communication—are considered qualities that cannot be treated separately for the successful completion of today's R&D projects. This aligns with the organizational dual competence theory in the literature.

The criteria included in the study—represented by the last two dimensions in the order of

importance—are also important qualifications for mechanical design engineers working in the R&D department. It can be said that these dimensions and criteria, which appear less important than others in the research findings, reflect the perspectives of experts working at the management level. Accordingly, a mechanical design engineer possessing technical competence and creativity should naturally also possess problem-solving skills. For this reason, these dimensions and criteria may have been assigned a lower weight (Robinson et al., 2005, pp. 131–132; Valentine et al., 2017, pp. 1309–1310). On the other hand, the reason the project and time management dimension and criteria are considered less important than other dimensions and criteria may stem from the fact that these are seen as qualities that can be acquired over time. At this stage, it should be noted that team leaders and managers assume responsibility and support mechanical design engineers in the areas of project and time management (Ortiz-Marcos et al., 2013, p. 89).

When the study's findings are evaluated based on the ranking of importance, the combined weight of the top six criteria reaches fifty percent. This indicates that material knowledge, analysis and simulation capabilities, design improvement, interdisciplinary collaboration, the generation of new ideas, and research skills are the most critical criteria to assess when selecting mechanical design engineer candidates. A common characteristic of these top six criteria—which account for fifty percent of the total weight—is that they are rooted in knowledge and experience and are intrinsic to the individual. The remaining criteria on the list, conversely, are those that can be developed through organizational adaptation and internal company activities. Consequently, this natural fifty-percent split highlights a distinction in the criteria that companies can consider when seeking either experienced mechanical design engineers or hiring recent graduates for the role. Thus, companies can take into account both the specific expectations associated with the position level and the relative weights of the criteria listed here when evaluating candidates for mechanical design engineering roles.

The model developed in this study offers a clear framework for the selection of mechanical design engineer candidates. This systematically constructed framework has the potential to shape approaches regarding the evaluation of the relevant dimensions and criteria. However, as with any study, this one has its limitations. The study does not provide specific tools for enterprises to evaluate the relevant dimensions and criteria. Furthermore, the relative importance assigned to the dimensions and criteria within the framework does not guarantee optimal results for every enterprise seeking to hire a mechanical design engineer. Dynamic internal and external factors that shift during the course of business operations are not addressed within the scope of the model. The model's validity may vary from one enterprise to another, depending on factors such as the evaluators' competence and intent, the specific conditions facing the enterprise, and various other influences. Another limitation is that the model has not been tested within an actual business setting. The research has not been validated through testing in real-world candidate selection processes or through assessments involving long-term performance or employee satisfaction.

Efforts to address these limitations form the basis for future research proposals. Briefly stated, the research proposals involve testing the developed model within business organizations and investigating and testing tools to evaluate the relevant dimensions and criteria.

The model proposed in this study is a decision-support model characterized by a strong academic foundation, a systematic and objective approach, and the ability to address—with a 20% sensitivity rate—the attributes that minimize uncertainties in the recruitment processes for mechanical design engineers. The findings indicate that the model serves as a viable framework for R&D departments when selecting mechanical design engineers. The research contributes to the literature by presenting a decision-support model for selecting mechanical design engineers for R&D departments through a fuzzy AHP analysis utilizing Buckley's geometric mean approach. This computational approach, which has rarely been employed in the academic literature, offers a methodological contribution. Furthermore, while providing a practical framework for decision-makers during the evaluation phase, the study also enriches the literature on the fuzzy AHP method, a technique used in multi-criteria decision-making.



Author Contributions

The sole author is responsible for conceptualizing, collecting, and analyzing data, and writing and editing the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

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