Assessment Model for Ranking Prospective Candidates for the Position of Production Supervisor in a Manufacturing Company

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Abstract

Human resources have a substantial influence on the success and progress of an organisation, and finding qualified candidates who meet the employment requirements is a common challenge for businesses. However, the average unemployment rate in any nation is typically very high, and together with the difficulty experienced by companies in terms of finding dependable personnel, this highlights the importance of an objective, organised approach to hiring new personnel. This paper proposes a multiple-criteria assessment model that allows a company to rank the fitness level of potential workers to production supervisor position in a manufacturing company. The methods used to evaluate prospective workers are multi-expert analytic hierarchy process (multi-expert AHP) and preference ranking organization method for enrichment evaluation (PROMETHEE). The criteria for selecting production supervisors were categorised into subjective and objective types, and were customised for use by company XYZ. The criteria weights were determined using Multi-expert AHP. The experts provided their scores for the significance of the criteria via pairwise comparisons; these scores were then aggregated based on their level of expertise in evaluating criteria, and the criteria weights were established. Finally, PROMETHEE was used to determine the ranking of the prospective candidates for the position of production supervisor in company XYZ.

Keywords: *Ranking, Promethee, Multi-expert AHP, expertise-based expert's importance weights*

1. Introduction

Human resources have a tremendous impact on the success and development of a company, and each company needs to make suitable choices when recruiting employees to fulfil its requirements. Unfortunately, many companies have trouble finding competent employees who are qualified for their positions and who meet the requirements outlined in the job description [1]. Conversely, a close fit between employee and task can improve employee satisfaction and motivation, thus raising business performance [2]. The difficulty experienced by companies in recruiting dependable employees and the necessity for a person-to-job fit demonstrate the need for a structured, systematic hiring process.

There are many different areas of expertise, and companies must specify suitable selection criteria for each field of employment. The case examined here is the position of production supervisor. In manufacturing organisations, production supervisors play a key role in distributing job responsibilities, supervising the performance of subordinates, and balancing the competing needs for performance, quality, and safety [3]. As members of middle management, production supervisors play a crucial role in facilitating interactions between upper management and their employees [4], and act as a link between strategic and operational decisions in every production organisation [5]. Their role as leaders of team member interchange can enhance job satisfaction [6], which in turn can improve supervisor-employee relationships [7].

The importance of production supervisors as middle managers necessitates the careful selection of personnel for these positions. Companies must use the right criteria in order to find employees who are suitable candidates for the job, in order to prevent issues in the production process and to reduce the risk of hiring incompetent staff members.

Competency mismatch is one of the main causes of firms hiring less dependable workers, and several researchers have reported measurements of this effect. Desjardins and Rubenson [8] directly measured and analysed the competency mismatch, while Allen and van der Velden [9] examined the impact of competence mismatch on employees' salaries and job satisfaction. Van der Velden and Bijlsda [10] estimated the level of competence mismatch by combining measurements of skill proficiency and self-assessment. Research related to self-assessment has been carried out by many researchers in various fields of work, such as quality control [11], banking services [12], and research and development [13]. Numerous academics have also focused on competence mismatch and fitness level measurements from the job seeker's perspective, in terms of selecting prospective firms. However, to minimise the risk of competence mismatch, a measurement tool is also required for use by the employer when recruiting dependable employees through a structured, systematic hiring process that is advantageous to both job seekers and employers. From the employer's perspective, a multi-criteria assessment model is required to determine a ranking of candidates and the criteria weights are applied. The criteria weights can be determined using various methods, including the analytical hierarchy process (AHP) [14], and the best-worst method [15], in which a single expert evaluates the criteria to obtain the weights. In regard to the AHP method, there have been previous articles on the determination of the criteria weights with more than one assessor [16]; however, the expertise of the assessors was not considered when aggregating their scores.

This paper presents a multiple-criteria assessment model for use by a company to rank the qualifications of prospective workers for the production supervisor job position in a manufacturing organisation. The methods used to evaluate prospective workers are multi-expert AHP and PROMETHEE. First, this research use multi-expert AHP to determine the criteria weights, in which experts provide scores for the significance of the criteria based on pairwise comparisons. These scores are then aggregated based on each expert's level of expertise in evaluating criteria, and the criteria weights are established. Finally, this research applies PROMETHEE to determine the ranking of the prospective candidates for the position of production supervisor with company XYZ.

This article is structured as follows. A theoretical background is provided in the next section, which is followed by an overview of the research methodology used, the results and discussion. Finally, our conclusions are presented.

2. Theoretical background

2.1. Multi-expert AHP

Thomas L. Saaty introduced the AHP method for multi-criteria decision making (MCDM) [17]. A complex multi-criteria problem is described in terms of a hierarchy in the AHP decision-making paradigm. The AHP hierarchy has a multi-level structure, with the objective representing the first level, the second level for criteria, and the alternative serve as the third level. This approach allows complex and multi-criteria problems to be divided into a hierarchical form so that they become structured and systematic.

If more than one expert are involved in the assessment, an aggregation process for the experts' scores is required. In this paper, the score weights for each expert were determined based on their expertise in making this type of assessment (expert judgment). Herowati et al. [18] combined the concept of expertise from Weiss et al. [19] with additive consistency for FPR [20] to create CWS indexes. In their article, they represented the expertise level of an assessor in the form of a CWS index. The expertise referred to in this paper is expert judgment, namely the ability to differentiate consistently [19], which requires repeated evaluations by experts. This repetition is facilitated by the additive consistency of the FPR $P = (p_{ij})$ with $p_{ij} \in [0,1]$, where each estimation for repetition can be obtained as shown in (1):

$$\varepsilon p_{ik}^{j} = p_{ij} + p_{jk} - \frac{1}{2}, j \neq i,k, \forall i,j,k = 1,2,\ldots,n \tag{1}$$

where p_{ij} represents the degree to which alternative *i* is preferred to alternative *j*; εp_{ik}^{j} is the estimator for p_{ik} using p_{ij} and p_{jk}; and there are (n−1) estimators for each p_{ik}.

The AHP method uses the multiplicative preference relations (MPR) approach to assessment. Herowati et al. [21] calculated the CWS index for each expert who provided an assessment in the form of MPR. These CWS indexes were then used to obtain expertise-based importance weights [22] based on three concepts, as described below:

1. Transform MPR to FPR using (2)
   The transformation between MPR to FPR, from $A = (a_{ij})$, $a_{ij} \in \left[\frac{1}{9}, 9\right]$ to $P = (p_{ij})$, $p_{ij} \in [0,1]$ [23]:
   $$p_{ij} = g(a_{ij}) = \frac{1}{2}.(1 + log_9\, a_{ij}) \tag{2}$$
   where a_{ij} represents the ratio to which alternative *i* is preferred alternative *j*.
2. Calculate the CWS index for each expert [18]

$$\text{CWS index} = \frac{\text{Discrimination}}{\text{Inconsistency}} = \frac{\text{Variance in the values of different alternatives}}{\text{Variance in the values of the same alternative}}$$

$$\text{CWS index} = \frac{\dfrac{\sum_{j=1}^{n} r(M_j - GM)^2}{n-1}}{\dfrac{\sum_{j=1}^{n}\sum_{i=1}^{r} (M_{ij} - M_j)^2}{n(r-1)}} \quad (3)$$

where:

r represents the replications number

M_j represents the mean of individual scores for case *j*

GM represents the grand mean of all scores

n represents the different cases number

M_{ij} represents the scores for *i*-th replication of case *j*,

3. Convert the experts' CWS indexes to get weights based on expertise
   Combine the ordered CWS indexes and linear basic unit monotonic function (LBUM) Q(R)=R. The total ordered CWS indexes in logarithmic scales were represented the horizontal axis of the LBUM (see [22] for more details).

2.2 Alfares weighting method

The Alfares method of weighting was applied to get criteria/sub-criteria weights in the form of a ranking assessment [24], as represented in (4) and (5), normalised the results to give the weights of the criteria/sub-criteria.

$$v_{i,j} = 100 - S_n(r_{i,j} - 1) \quad (4)$$

$$S_n = 3.19514 + \frac{37.75756}{n} \quad (5)$$

where:

$v_{i,j}$ is the weight of criterion *j* assessed by expert *i* with ranking $r_{i,j}$

S_n is the weight reduction slope for criterion *n*

n is the criteria number (maximum 21)

2.3 Promethee

PROMETHEE is a ranking method for MCDM, where the aim is to determine which alternatives are dominated and which are dominant. The alternative that dominates the others will be the primary alternative, and will be the chosen one, whereas the alternative that is dominated will be the last to be chosen.

The order of alternatives is determined using the outranking method, in which the basic alternatives are compared with any alternatives that may arise in the future. The steps in PROMETHEE are as follows [25]:

1. Determine the available alternatives;
2. Normalise the value of each alternative;
3. Calculate the difference between alternatives for the same criterion;
4. Calculate the preference function;
5. Calculate the preference index;

6. Calculate the values of the leaving flows as well as the entering flows;
7. Create a partial pre-ordering, and then a complete pre-ordering.

3. Research methodology

The steps used to build the multiple-criteria assessment model for use by the company to rank the qualifications of prospective workers for the production supervisor job position were as follows:

1. Identify criteria for selecting prospective workers for the production supervisor job position from advertisements on the websites of 12 companies for the post of production supervisor. Group the criteria and reduce them using the Pareto 80/20 rule.
2. Adjust the criteria obtained in the first step based on the criteria used in company XYZ.
3. Determine weights for less than eight criteria/sub-criteria, as follows:
   a. Use MPR based on pairwise comparisons to elicit each expert's preferences for the criteria resulting from Step 2;
   b. Calculate the weights of criteria/sub-criteria for each expert.
4. Determine the weights for more than seven criteria/sub-criteria, as follows:
   a. Elicit the expert's preferences for evaluating the sub-criteria in the form of a ranking;
   b. Transform them using (4) and (5) to obtain the sub-criteria weights.
5. Determine the expertise-based weights for the expert's judgments via pairwise comparisons based on MPR:
   a. Use pairwise comparisons based on MPR to elicit the expert's preferences using the criteria resulting from Step 2:
   b. Transform them using (2) to unify the experts' evaluation scores in the form of FPR;
   c. Calculate the CWS index for each expert;
   d. Calculate the weights of the experts.
6. Aggregate the expert's criteria scores to form an FPR group score and obtain the criteria/sub-criteria weights.
7. Construct the multiple-criteria assessment model, which will be filled in by the company's expert for the potential candidates.
8. Apply PROMETHEE to obtain a ranking of the candidates.

4. Results and Discussion

4.1. Identification, grouping and reduction of criteria

The first step was to identify the criteria that would be applied to select prospective employees for the role of production supervisor from advertisements on the websites of 12 companies who were hiring for the post of production supervisor. We then grouped the criteria into objective and subjective types, reduced them using the Pareto 80/20 rule, and held discussions with the company to determine criteria that were suitable for further use in this company. The criteria and sub-criteria used in this ranking model are listed in Table 1.

4.2. Determination of criteria/sub-criteria weights for each expert

The criteria and sub-criteria weights for the experts are shown in Tables 2 and 3. All criteria were assessed by pairwise comparison based on MPR, and the weights were calculated using the AHP method for less than eight sub-criteria. There were more than seven sub-criteria for two criteria: eleven for the Work skill criterion and eight for Knowledge. The experts assessed these sub-criteria by ranking, the weights were calculated using the Alfares method shown in (4) and (5), and they were normalised. Tables 8 and 9 show the weights of the sub-criteria obtained for each expert by combining the weight of the criterion with the weights of the related sub-criteria. For example, the weight of the MS Office sub-criterion for Expert 2 is 0.074 x 0.226 = 0.017, as shown in row 3 and column 4 of Table 8.

Table 1. Criteria and Sub-criteria Used in the Ranking Model

Subjective Criteria	Sub-criteria	Objective Criteria	Sub-criteria
Software mastery	MS Office	Education	-
	ERP	GPA	-
	SAP	Age	-
	AutoCAD	Gender	-
Work skills	Communication	Assignment plan	-
	Leadership	Knowledge	PPIC planning
	Analytics		Work planning
	Teamwork		Able to use measurement tools & read technical drawings
	Individual skills		Material management
	Problem solving		Quality Control
	Creativity		5R and continuous improvement
	Fast learner		ISO 9001:2015
	Smart		CCPPKRTB (Make Healthy Supply product)
	Highly motivated	`	
	Systematic		
Attitude	Assertive		
	Disciplined		
	Honest		
	Responsible		
Work flexibility	Work in shifts		

Table 2. Criteria Weights Given by Each Expert

Subjective Criteria	Expert 1	Expert 2
Software mastery	0.077	0.074
Work skills	0.217	0.285
Attitude	0.334	0.321
Work flexibility	0.372	0.321
Objective Criteria		
Education	0.069	0.269
GPA	0.297	0.224
Age	0.103	0.111
Gender	0.124	0.048
Assignment plan	0.128	0.065
Knowledge	0.279	0.282

Table 3. Sub-criteria weights given by each expert

Subjective criteria	Sub-criteria	Expert 1	Expert 2
Software Mastery	MS Office	0.317	0.226
	ERP	0.078	0.094
	SAP	0.181	0.064
	AutoCAD	0.424	0.616
Work Skills	Communication	0.121	0.136
	Leadership	0.097	0.091
	Analytics	0.089	0.100
	Teamwork	0.113	0.127
	Individual skill	0.105	0.055
	Problem solving	0.089	0.109
	Creativity	0.073	0.064
	Fast learner	0.089	0.118
	Smart	0.081	0.046
	Highly motivated	0.065	0.082
	Systematic	0.081	0.073
Attitude	Assertive	0.128	0.133
	Disciplined	0.121	0.133
	Honest	0.427	0.582
	Responsible	0.325	0.152
Knowledge	PPIC planning	0.139	0.169
	Work planning	0.139	0.156
	Measuring ability	0.139	0.144
	Material management	0.119	0.131
	Quality control	0.129	0.119
	5R & continuous improvement	0.108	0.106
	ISO 9001:2015	0.108	0.094
	CCPPKRTB	0.119	0.081

4.3. Expertise-based weights for experts

The weights of the criteria and sub-criteria in Tables 2 and 3 were aggregated. In this study, we employed expertise-based weights from experts as shown in Step 5 above. Table 4 shows the results for the subjective criteria scores for Expert 1 from a pairwise comparison of MPR and FPR. We transform the MPR to FPR for each element of the matrix using (2). As an example, the transformation for the preferences of Expert 1 when comparing Criteria 3 and 1 is: $p_{31} = g(a_{31}) = \frac{1}{2}(1+log_9 a_{31}) = \frac{1}{2}(1+log_9 6) = 0.908$

Table 4. Criteria Scores for Expert 1 Using MPR and FPR

MPR	FPR
$\begin{bmatrix} 1 & 0.5 & 0.167 & 0.2 \\ 2 & 1 & 1 & 0.5 \\ \mathbf{6} & 1 & 1 & 1 \\ 5 & 2 & 1 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.5 & 0.342 & 0.092 & 0.134 \\ 0.658 & 0.5 & 0.5 & 0.342 \\ \mathbf{0.908} & 0.5 & 0.5 & 0.5 \\ 0.866 & 0.658 & 0.5 & 0.5 \end{bmatrix}$

Table 5 illustrates the CWS indexes calculation for Expert-1. It can be seen that there are two estimated values for each matrix element as shown in (1), and the CWS index for Expert-1 is 78.386, calculated using (3).

$$\text{CWS-INDEX} = \frac{\dfrac{\sum_{j=1}^{n} r(M_j - GM)^2}{n-1}}{\dfrac{\sum_{j=1}^{n}\sum_{i=1}^{r} (M_{ij} - M_j)^2}{n(r-1)}} = \frac{\frac{10.979}{(12-1)}}{\frac{0.306}{12(3-1)}} = 78.386$$

Table 5. Calculation of CWS index for expert 1

p_{ij}	Real values	Estimated values		M_j	$r(M_j - GM)^2$	$\sum_{i=1}^{r}(M_{ij} - M_j)^2$
p_{12}	0.342	0.092	0.291	0.242	0.176	0.035
p_{13}	0.092	0.342	0.134	0.189	0.108	0.036
p_{14}	0.134	0.185	0.092	0.137	0.056	0.004
p_{21}	0.658	0.908	0.709	0.758	1.724	0.035
p_{23}	0.500	0.250	0.342	0.364	0.398	0.032
p_{24}	0.342	0.291	0.500	0.378	0.428	0.024
p_{31}	0.908	0.658	0.866	0.811	1.971	0.036
p_{32}	0.908	0.658	0.866	0.636	1.213	0.032
p_{34}	0.500	0.750	0.658	0.461	0.638	0.022
p_{41}	0.500	0.541	0.342	0.863	2.235	0.004
p_{42}	0.866	0.815	0.908	0.622	1.161	0.024
p_{43}	0.658	0.709	0.500	0.539	0.871	0.022
TOTAL					10.979	0.306

In a similar way, we can obtain the CWS index for Expert 2. The results for the CWS indexes for Experts 1 and 2 for the subjective criteria were 78.386 and 254.174, respectively. The experts were then ranked, from the expert with the highest CWS index to the expert with the lowest, as displayed in Table 6 and described in [21], and we then obtained the expertise-based weights for the experts. Finally, the weights assigned by the experts to the objective and subjective criteria are given in Table 7.

Table 6. Calculation of experts' weights for subjective criteria

	Expert 2	**Expert 1**
CWS index	265.174	78.382
P = Log (CWS index)	2.424	1.894
Q = Accumulated(P)	2.424	4.318
R = Normalised(Q)	0.561	1
S(R) = R^α	0.561	1
DM importance weights	**0.561**	**0.439**

Table 7. Experts' weights for subjective and objective criteria

Criteria	**Expert 1**	**Expert 2**
Subjective criteria	43.9%	56.1 %
Objective criteria	38.8%	61.2 %

4.4. Aggregation of the experts' scores to get the criteria/sub-criteria weights

The sub-criteria weights from Experts 1 and 2 were combined using expertise-based weights to get the final weights, as shown in the fifth columns of Tables 8 and 9.

4.5. Multiple-criteria assessment model

The ranking model consists of two types of components, objective and subjective components. For each type, candidate scores were combined using the criteria weights derived from the final weights in Tables 8 and 9. After consulting with the company's experts, a rubric was developed for the value of each sub-criterion. Table 10 shows the objective components of the model, and the subjective components are shown in Table 11. Interviewer in the interview and testing session should use this rubric to calculate the appropriate value for each sub-criterion for each candidate, and the total objective and subjective scores for a candidate are then the aggregate of each criterion's scores.

Table 8. Objective criteria and sub-criteria weights for both experts

Criteria	**Sub-criteria**	**Sub-criteria weights**		
		Expert 1	**Expert 2**	**Final**
Education	-	0.069	0.269	0.147
GPA	-	0.297	0.224	0.269
Age	-	0.103	0.111	0.106
Gender	-	0.124	0.048	0.095
Assignment plan	-	0.128	0.065	0.103
Knowledge	PPIC planning	0.039	0.048	0.042
	Work planning	0.039	0.044	0.041
	Measuring ability	0.039	0.041	0.039
	Material management	0.033	0.037	0.035
	Quality Control	0.036	0.034	0.035
	5R & cont. improvement	0.030	0.030	0.030
	ISO 9001:2015	0.030	0.026	0.029
	CCPPKRTB	0.033	0.023	0.029

Table 9. Subjective criteria weights for both experts

Criteria	**Sub-criteria**	**Sub-criteria weights**		
		Expert 1	**Expert 2**	**Final**
Software mastery	MS Office	0.025	0.017	0.020
	ERP	0.006	0.007	0.007
	SAP	0.014	0.005	0.009
	AutoCAD	0.033	0.046	0.040
Work skills	Communication	0.026	0.039	0.033
	Leadership	0.021	0.026	0.024
	Analytics	0.019	0.028	0.024
	Teamwork	0.024	0.036	0.031
	Individual skill	0.023	0.016	0.019
	Problem solving	0.019	0.031	0.026
	Creativity	0.016	0.018	0.017
	Fast learner	0.019	0.034	0.027
	Smart	0.025	0.013	0.015
	Highly motivated	0.006	0.023	0.019
	Systematic	0.014	0.021	0.019
Attitude	Assertive	0.033	0.043	0.043
	Disciplined	0.026	0.043	0.042
	Honest	0.021	0.186	0.167
	Responsible	0.019	0.049	0.075
Work flexibility	Work in shifts	0.024	0.321	0.343

Table 10. Subjective components of the ranking model

Criteria	**Sub-criteria**	**Weights**	**Value**	**Score**
Software mastery	MS Office	0.020	0-10	
	ERP	0.007	0-10	
	SAP	0.009	0-10	
	AutoCAD	0.040	0-10	
Work skills	Communication	0.033	0-10	
	Leadership	0.024	0-10	
	Analytics	0.024	0-10	
	Teamwork	0.031	0-10	
	Individual skill	0.019	0-10	
	Problem solving	0.026	0-10	
	Creativity	0.017	0-10	
	Fast learner	0.027	0-10	
	Smart	0.015	0-10	
	Highly motivated	0.019	0-10	
	Systematic	0.019	0-10	
Attitude	Assertive	0.043	0-10	
	Disciplined	0.042	0-10	
	Honest	0.167	0-10	
	Responsible	0.075	0-10	
Flexibility	Work in shifts	0.343	0-10	

Table 11. Objective components of the ranking model

Criteria	Sub-criteria	Weights	Categories	Value	Score
Education	-	0.147	Industrial Eng.	8	
			Machine Eng.	10	
			Chemical Eng.	4	
			Electrical Eng.	10	
			Pharmacy	0	
GPA	-	0.269	< 2.75	0	
			2.75–3.00	2	
			3.01–3.25	4	
			3.26–3.50	6	
			3.51–3.75	8	
			3.76–4.00	10	
Age	-	0.106	22–26 years	2	
			27–30 years	4	
			31–35 years	6	
			36–40 years	8	
			41–45 years	10	
Gender	-	0.095	Male	10	
			Female	8	
Assignment plan	-	0.103	Head office	8	
			Branch office	5	
Knowledge	Course grade in PPIC	0.042	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	Work planning course grade in APK	0.041	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	Engineering drawing (ED) course grade	0.039	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	Material management (MM) course grade	0.035	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	Quality control (QC) course grade	0.035	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	Lean enterprise system (Lean) course grade	0.030	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	ISO 9001:2015 Quality Management System (QMS) course grade	0.029	A	10	
			AB	8	
			B	7.2	
			BC	6.5	
			C	5.9	
	CCPPKRTB	0.029	Certified	10	
			Not	0	

4.6. Model Application

The ranking model was developed using Microsoft Excel. After interviewing and evaluating five candidates, the interviewer entered their values and obtained their scores. Table 12 compares the candidates' scores as well as the PROMETHEE parameter's type of criteria/sub-criteria, preference threshold (p), and indifference threshold (q). As can be seen from Table 12, all subjective criteria are Promethee type I (usual criterion) except SAP as Promethee type III (criterion with linear preference). In contrast, objective criteria are Promothee type V (criterion with linear preference and indifference area). The Preference index is presented in Table 13, along with the leaving flow $\Phi^{+}(A)$ and entering flow $\Phi^{-}(A)$, resulting in a net flow of candidate performance as shown in Table 14. The net flow value determines the candidate's ranking: the greater the net flow, the higher the candidate's ranking. The ordering of the candidates in Table 14 based on net flow is A1, A5, A3, A2, and A4.

Table 12. Comparison of candidates' scores, PROMETHEE's parameter type

Criteria/Sub	Weights	A1	A2	A3	A4	A5	Type	P	Q
Subjective Components									
MS Office	0.020	8	10	10	8	8	I	5	3
ERP	0.007	6	6	6	8	10	I	5	3
SAP	0.009	4	8	6	2	4	III	5	-
AutoCAD	0.040	4	4	6	2	2	I	5	3
Communication	0.033	10	10	6	8	8	I	5	3
Leadership	0.024	10	10	8	8	8	I	5	2
Analytics	0.024	8	8	8	6	6	I	5	3
Team work	0.031	8	10	8	10	10	I	5	3
Individual skill	0.019	10	10	10	10	8	I	5	3
Problem solving	0.026	8	8	10	6	6	I	5	2
Creativity	0.017	8	10	10	6	6	I	5	2
Fast learner	0.027	10	8	10	6	4	I	5	3
Smart	0.015	8	8	8	8	10	I	5	2
Highly motivated	0.019	10	8	8	8	8	I	5	3
Systematic	0.019	10	8	8	6	4	I	5	2
Assertive	0.043	10	8	8	10	6	I	5	2
Disciplined	0.042	10	8	8	8	8	I	5	3
Honest	0.167	10	10	10	10	8	I	5	3
Responsible	0.075	10	10	10	10	8	I	5	3
Work in shifts	0.343	8	10	10	10	10	I	5	3
Objective Components									
Education	0.147	8	8	8	8	8	V		
GPA	0.269	10	4	6	2	10	V		
Age	0.106	10	10	10	10	10	V		
Gender	0.095	8	10	10	8	8	V		
Grade in PPIC	0.103	5	5	5	5	5	V		
Grade in APK	0.042	10	8	10	8	10	V		
Grade in ED	0.041	10	7.2	7.2	5.9	10	V		
Grade in MM	0.039	6.5	6.5	8	6.5	8	V		
Grade in QC	0.035	10	8	8	8	8	V		
Grade in Lean	0.030	8	10	10	8	10	V		
Grade in QMS	0.029	10	10	8	10	10	V		
CCPPKRTB	0.029	0	10	10	0	10	V		

Company XYZ used this assessment model and assigned subjective and objective weights of 0.30 and 0.70, respectively. A1 was the most qualified candidate for company XYZ, since she had the highest net flow. If the weights of the objective and subjective criteria were modified, the candidates would have been ranked differently, as illustrated in Table 15. However, according to Table 15, A1 was still the best candidate even after shifting the emphasis from subjective to objective criteria. The overall ranking is unaltered if the weight of the subjective criteria is increased from 0% to 61.2%, although when the weight of the subjective criteria reaches 61.3%, there will be an exchange between the second and third positions. Smaller weights for the subjective criteria are insensitive to changes, but become extremely sensitive above a certain level.

Table 13. Preference index

	A-1	A-2	A-3	A-4	A-5	$\Phi^+(A)$
A-1		0.4010	0.3680	0.4100	0.1557	1.3346
A-2	0.1100		0.0262	0.3296	0.0799	0.5458
A-3	0.1332	0.2704		0.4267	0.0982	0.9286
A-4	0	0	0.0201		0.0086	0.0287
A--5 -	0.0667	0.2990	0.2366	0.3406		0.9430
$\Phi^-(A)$	0.3099	0.9704	0.6509	1.5069	0.3424	

Table 14. Net flow of the candidates' performance

	A-1	A-2	A-3	A-4	A-5
$\Phi^+(A)$	1.3346	0.5458	0.9286	0.0287	0.9430
$\Phi^-(A)$	0.3099	0.9704	0.6510	1.5069	0.3424
$\Phi(A)$	1.0247	−0.4246	0.2776	−1.4782	0.6006

Table 15. Candidate rankings for various weights

	Candidate rankings				
	A-1	A-2	A-3	A-4	A-5
S = 0.000; O = 1.000	1	4	3	5	2
S = 0.3 ; O = 0.7	**1**	**4**	**3**	**5**	**2**
S = 0.613; O = 0.387	1	4	2	5	3
S = 0.789; O = 0.211	1	3	2	5	3
S = 0.92 ; O = 0.08	1	3	2	4	4
S = 0.928; O = 0.072	1	2	2	4	4
S = 0.949; O = 0.051	1	2	2	4	5
S = 1.0 ; O = 0.0	1	2	2	4	5

5. Conclusion

In this study, a multi-criteria Assessment Model was established which would allow a company to reduce the possibility of a mismatch between a job applicant's skills and the company's needs. Twelve manufacturing organisations were surveyed to obtain their acceptance criteria for the role of production supervisor; this resulted in a list of requirements for a production supervisor, which were classified into four objective and six subjective criteria.

Company XYZ applied these acceptance criteria to fill the position of production supervisor. The criteria weights were determined based on the preferences of the relevant experts at the firm, and expertise-based weights were used to construct the criteria weights.

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References

[1] D. Ulrich, HR at a crossroads. Asia Pac J of Hum Resou. 54, 2, pp. 148–164, **(2016)**

[2] A. Hambleton, T. Kalliath, and P. Taylor, Criterion-related validity of a measure of person-job and person organization fit. J Psychol. 29, 2, pp. 80–85 **(2000)**

[3] J. H. Michael, Z. G. Guo, J. K. Wiedenbec, and C. D. Ray, Production supervisor impacts on sub ordinates safety outcomes: An investigation of leader-member exchange and safety communication. J Safety Res. 37, pp. 469–477 **(2006)**

[4] D.J. Therkelsen and C.L. Fiebich, The supervisor: The linchpin of employee relations, J Commun. Manag. 8, 2, pp. 120−129, **(2003)**

[5] A. Camuffo and F. Gerli, The competent production supervisor: A model for effective performance Industrial Performance Centre Working Paper Series. Massachusetts Institute of Technology **(2005)**

[6] R. Martin, G.Yves, G. Thomas, L.Allan, and E. Olga, Leader–member exchange (LMX) and performance: A meta-analytic review. Pers Psychol. 69, pp. 67–121 **(2016)**

[7] J. Volmer, C. Niessen, D. Spurk, A. Linz, and A. E. Abele, Reciprocal relationships between leader–member exchange (LMX) and job satisfaction: A cross-lagged analysis. Appl Psychol. 60, 4, pp. 522–545, **(2011)**

[8] R. Desjardins and K. Rubenson, An analysis of skill mismatch using direct measures of skills. OECD Publishing **(2011)**

[9] J. Allen and R. van der Velden, Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search. Oxf. Econ. Pap. 53, 3, pp. 434–452 **(2001)**

[10] R. van der Velden and I. Bijlsma, Effective skill: A new theoretical perspective on the relation between skills, skill use, mismatches, and wages. Oxf. Econ. Pap. 71, 1, pp. 145–165 **(2019)**

[11] E. Herowati, J. Parung, S. Limantara, R. D. Wahyudi, and I. M. Ronyastra, A self-assessment model for measuring the fitness level of industrial engineering graduates competence to a quality control job position. Proceeding of the 4th International Conference on Engineering and Technology for Sustainable Development, **(2021)** December 13; Jogjakarta, Indonesia

[12] C. H. Setiawan, E. Herowati, R. D. Wahyudi, and I. M. Ronyastra, MCDM-based instrument for fresh graduate's competencies conformity in banking service field. Proceeding of the 17th International Conference on Quality in Research, Indonesia, **(2021)** October 13-15; Jakarta, Indonesia

[13] I. M. Ronyastra, E. Herowati, R. D. Wahyudi, J. Parung, and C. Henadi, Assessing individual fitness for research and development position using fuzzy AHP and Pareto: Case study in manufacturing industry. Proceeding of the 4th International Conference on Applied Science and Technology, **(2021)** October 23-24; Samarinda, Indonesia

[14] N. Banaeian, I. W. Nielsen, H. Mobli, and M. Omid, Criteria definition and approaches in green supplier selection—A case study for raw material and packaging of food industry. Prod. Manuf. Res. 3, 1, pp. 149–168, **(2015)**

[15] J. Rezaei, Best-worst multi-criteria decision-making method. Omega. 53, pp. 49–57 **(2015)**

[16] F. Chiclana, E. Herrera-Viedma, F. Herrera, and S. Alonso, Induced ordered weighted geometric operators and their use in the aggregation of multiplicative preference relations. Int J of Intell Syst. 19, pp. 233–255 **(2004)**

[17] T. L. Saaty and L. G. Vargas, Model, Method, Concepts, and Applications of The Analytical Hierarchy Process, Springer Science Business Media, New York **(2012)**

[18] E. Herowati, U. Ciptomulyono, and J. Parung, Expertise-based ranking of experts: An assessment level approach. Fuzzy Set Syst. 315, pp. 44–56, **(2017)**

[19] D. J. Weiss and J. Shanteau, Who's the best? A relativistic view of expertise. Appl Cognitive Psych, 28, pp. 447–457 **(2014)**

[20] E. Herrera-Viedma, F. Chiclana, F. Herrera, and S. Alonso, Group decision-making model with incomplete fuzzy preference relations based on additive consistency. IEEE T Syst Man Cyb, Part B (Cybernetics). 37, 1, pp. 176–189 **(2007)**

[21] E. Herowati, U. Ciptomulyono, J. Parung, and J. Suparno, Expertise-based Experts ranking at multiplicative preference relations on alternatives. Proceeding of Int. Conf. Asia Pacific Industrial Engineering & Management Society, **(2014)** October 12-15; Jeju Island, South Korea

[22] E. Herowati, Expertise-based decision makers' importance weights for solving gup decision making problems under fuzzy preference relations. IOP Conference Series: Materials Science and Engineering. 703, 1, pp. 012028. IOP Publishing **(2019)**

[23] F. Chiclana, F. Herrera, and E. Herrera-Viedma, Integrating multiplicative preference relations in a multipurpose decision-making model based on fuzzy preference relations. Fuzzy Set Syst. 122, 2, pp. 277–291 **(2001)**

[24] H. K. Alfares and S. O. Duffuaa, Assigning cardinal weights in multi-criteria decision making based on ordinal ranking. J. Multi-Criteria Decis. Anal. 5, 5–6, pp. 125–133 **(2008)**

[25] J. P. Brans, P. Vincke, and B. Mareschal, How to select and how to rank projects: The Promethee method. Eur. J. Oper. Res. 24, 2, pp. 228–238 **(1986)**