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A prescriptive analytics approach to employee selection

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Introduction

Hiring new talent is one of the most crucial steps for an organization and it can be challenging to fill an open position, regardless of how big or small, the post is. According to Abdul et al., (2020), recruitment is becoming more difficult for both recruiters and job seekers as more opportunities are created and a large number of candidates apply for various roles. The HR industry is aware of the difficulties the hiring teams face in some of the hiring functions, including sourcing, interviewing, providing offers, post-offer follow-ups, and finally joining and inducting (Gupta et al., 2018).

Even though hiring challenges exist in most industries, those in the software industry deserve special attention. For software companies, projecting the skills seems to be quite a difficulty given that the knowledge, skills, and abilities of this dynamic profession are continually evolving (Rao, 2010, p.34). Furthermore, hiring suitable candidates is critical in this industry due to the high attrition rate caused by the industry's rapid growth, a lack of career opportunities in new domains and technologies, greater work pressure, and leaders' reluctance to invest in the development of team members (Agrawal et al., 2012, p.161). Thus, in the growing Information Technology (IT) field, the hiring process is extensive with a huge number of applicants with multiple skill sets that are difficult to evaluate and select the right fit for a growing organization. This research focuses on this industry to address some of these challenges.

Aside from the typical challenges faced by the human resources (HR) team, such as resume screening and interview scheduling, one of the key challenges is final decision-making for candidate selection/rejection. Final decision-making can be influenced by bias, which occurs when undetected or unaddressed biases influence a hiring manager's evaluations of job candidates, causing them to deviate from purely merit-based assessment (Hardy III et al., 2022, p.658). Besides bias, final decision-making to select the best candidates takes time because it depends on factors such as candidate performance, budget, and strategic constraints. Murray (2019, p.20) states that the lengthy hiring process, which takes an average of 15 days to respond to a resume, weeks to schedule the first interview, and involves multiple rounds of interviews, is one of the main reasons employers struggle to find the right candidate. Thus, when the amount of time is taken into consideration in the standard hiring schedule, the chances of finding the perfect candidate as per the posted job requirement become infeasible.

To address these issues, this study employs Multi-Criteria Decision Making (MCDM) techniques in tandem with prescriptive analytics to assist HR in final decision-making and team formation. Analytical Hierarchy Process (AHP) is an MCDM technique used to organize a set of complicated problems into a hierarchy and then insert a numerical value as a substitute for human perception when making relative comparisons(Sari et al., 2017, p.1). TOPSIS is a ranking method developed by Hwang and Yoon in 1981 that attempts toselect alternatives that are both closest to the positive ideal solution and farthest away from the negative ideal solution (Behzadian et al., 2012, p.13052).

Existing studies (Kusumawardani and Agintiara, 2015, p.639 Samanlioglu et al., 2018,p. 1576) have combined these MCDM techniques for personnel selection, with AHP calculating the relative weightage of hiring criteria followed by TOPSIS, which then computes the candidate rank taking the criteria weightage into account. Before selecting/rejecting a candidate, the decision-making process should also consider budget and strategic constraints; this research aims to use prescriptive analytics for candidate selection within the overall budget constraints.

Currently, the vast majority of business analytics efforts are focused on descriptive and predictive analytics, in conjunction with common methodologies such as data mining, machine learning, artificial intelligence, and simulation (Lepenioti et al., 2020, p. 57). Prescriptive analytics is mentioned in the same study as the next step toward increasing data analytics maturity and leading to optimized decision-making ahead of time for business performance improvement. As per existing research (Lele, 2015, p.22; Saaty, Peniwati, and Shang, 2007, p.1041), prescriptive analytics can be used with AHP for decision-making purposes in personnel selection.

While prescriptive analytics has been used with AHP and TOPSIS in supplier selection and order allocation (Nazar et al. 2019, p. 030050-2), very limited research has been done on using the same in personnel selection in the software industry. The objective of this study is to use AHP and TOPSIS with prescriptive analytics in the final decision-making step of the hiring process in the software industry. Thus, this study asks the following research question (RQ):

RQ: How can prescriptive analytics in conjunction with the decision-making techniques (AHP & TOPSIS) aid in the removal of influential factors such as inherent biases and reduce time during the personnel selection in the hiring process?

Problem Statement

Tedious and Time-Consuming Nature of Hiring

Digital transformation has had a remarkable impact on all the existing industries where the decision-making tasks are tedious and time-consuming. Like all aspects of business today, recruitment and selection depend on speed and accuracy. With an increasing number of qualified applicants chasing a shrinking pool of available jobs, human resource professionals must find ways to sort through applications quickly while accurately selecting the best candidates (Sołek-Borowska and Wilczewska, 2018). As a result, tools are required to conduct a successful selection process, but due to the complexity of the needs and job roles, this is a difficult task (Paoletti et al., 2015).

While there is complexity involved in the hiring process, HRM also faces the challenges of a structured and prohibitive process subject to various requirements in the private sector (Vineyard et al., 2020), moreover, they are also responsible for many tasks that are repetitive, time-consuming, and rely on manual processes to help employees complete their tasks (Nawaz, 2019). The number of employees working in the software industry has been increasing over the years– almost threefold; making staffing a very time-consuming process (Murthy and Abeysekera, 2007), with many HRM leaders spending almost 80 percent of their time on recruitment and selection (Grossman, 2006).

It has been also observed that personal interviews fail to assess candidates' true intentions, and the inner dynamics remain hidden, making the selection process difficult and time-consuming (Janetius et al., 2019). Another recurring observation is lethargy in manual processes and dependencies on other departments or agencies, as well as uncertainty about the candidate's decision to join or not which in turn affects an organization's overall performance (Gupta et al., 2018). Another time-consuming task is scheduling the candidate's interview. It is no longer effective to simply call the candidate because most of them do not answer unrecognized phone numbers (Nawaz and Gomes, 2019). Also, the same research shows that calling the candidate when they are working with their current company or requesting a time that is convenient for both parties may be inconvenient. This entire procedure becomes lengthy and complicated until the right candidate is identified.

Bias in hiring

Researchers have long acknowledged the significance of studying and enhancing employee views of fairness, especially the perceived fairness of decision-making systems (Newman, et al., 2020). People regard decision-making procedures as fairer when they are (1) consistent, (2) based on reliable information, and (3) free of influence from decision-makers' personal biases (Brockner, 2002). Cognitive biases are one of them which occur during the assessment of potential candidates where the inherent traits of the interviewee impact the decision-making element of hiring (Deniz, 2020). One of the best examples of cognitive bias is the Halo and Horns effect which are significantly contrasting to each other. One might decide to hire someone because they are uniquely skilled in one area and 'outperform' the other candidates, on the contrary, Horns effect i.e., if one notices a bad skill in the candidate, they will have limited visibility and will be unable to see beyond that particular skill. This is harmful because there is a loss of ability to see future potential, which should be an important factor in the hiring decision (Thomas and Reimann, 2022). Organizations are thus strongly incentivized to find ways not merely to make better human resource decisions, but also to ensure that those affected by such decisions regard the decision-making procedures as fair (Weaver & Trevino, 2001).

Unconscious or implicit bias refers to beliefs that unintentionally affect our judgments and have an influence on our conduct, conversations, and outcomes (Marcelin et al., 2019). The instinctive character of human survival leads to the evolution of unconscious biases. There is a particular synergy when we are around people who are most like us. Executives automatically seek to associate with people with whom they share a bond. People who are similar to one another and don't constitute a hidden threat are more likely to be hired, promoted, and relied upon (Prestia, 2019). All people have the innate tendency of unconscious bias and they frequently have their roots in the human brain, which is constantly inundated with data and influences from one's upbringing, values, societies, cultural surroundings, etc (Oberai & Anand, 2018). Since unconscious prejudice is unavoidable, equipping an organization with the correct tools and policies can drastically lessen its impact on the hiring process.

This research focuses on the influence of bias during the candidate evaluation phase, which refers to the selection process stage following recruitment and final hiring decisions. Hiring managers typically gather data during this phase by utilizing a variety of factual, intuitive, conventional, and casual methods to establish conclusive opinions regarding the skills and potential of different individuals within the candidate pool (Hardy III et al., 2022). More generally, accepting that there will almost certainly be some degree of bias in the hiring process when human judgment is involved emphasizes the need to minimize negative outcomes as soon as they begin to materialize and to look for potential sources of bias where we may not currently be looking (Klein et al.,2021).

To summarize, incorporating and employing prescriptive and MCDM in recruitment methods highlights the importance of justice in organizational decision-making. When implemented, enabling fairness with analytics might take a different shape than promised.

Data and Methodology

This research was carried out as part of the MSc Business Information and Analytical Systems course at University College Cork in Ireland. The following subsections discuss the detail of data collection and research methodology used in this research.

Data Collection

Data was gathered based on a sample recruitment criteria used within an organization that our project mentor is familiar with. The company wanted to grow its engineering team by hiring a project manager, a product owner, and two software developers. The table below summarizes the hiring requirement. The overall budget allotted for hiring was €250,000. The research aims to assist the firm in identifying the best candidate for various open positions.

Role	**Description**	**Number of Employees Required**	**Salary (In Euros)**
Project Manager	Responsible for all the key aspects of the project's delivery lifecycle, including business analysis and process re-engineering, testing, and rollout.	1	80,000
Product Owner	Lead the Platform Squad, shaping and guiding the evolution of the e-commerce system from an existing monolith solution to a microservices-based solution.	1	70,000
Software Developer	Develop object-oriented models, design data structures for new software projects, and implement business logic and data models in suitable class design.	2	50,000

Table 1: Hiring requirement received by HR

The organization had to make a lot of trade-offs when evaluating candidates based on a wide range of evaluation criteria. The hiring managers worked with the organization's experts to finalize the evaluation parameters for these three job roles which can be found in Table 2. Since all applicants for a specific job role will be rated and evaluated based on the same set of criteria, establishing these criteria ensured uniformity in the hiring process. Establishing the critical evaluation criteria and the respective weightings (relative significance) can occur well in advance of the decision to proceed with hiring further talent.

Role	Criteria	Description
Project Manager	Experience	10-12 years
	Communication	Strong written and verbal communication skills.
	Risk Assessment	Identify and manage any risks to the project. Assess and manage risk within, and across, multiple projects
	Leadership	Build and develop the project team to ensure maximum performance, providing purpose, direction, and motivation
Product Owner	Experience	8-10 years
	Negotiation	Work together with people to focus on problems. Understand what underlying interests matter most to both parties. Generate creative options for solving the problem.
	UML Modelling	Have hands-on experience in developing UML diagrams (Class, Sequence, Component, Deployment, etc.)
	Agile Methodology	Act as a consultant, allocating the right personnel, processes, and resources to bolster team effectiveness and efficiency.
Software Developer	Experience	5-6 years
	Problem Solving	Excellent debugging skills of application. A team player with a keen eye for detail and problem-solving skills.
	Dot Net	Must have worked in .Net MVC 5.0 with exposure to .Net MVC 6.0. Extensive experience in using the Microsoft development toolset (e.g., Visual Studio 2022). Exposure to performance tuning of an application.
	SQL	Proficiency in any one database like SQL Server. Ability to write queries with complex joins. TSQL Skills are preferred.

Table 2: Role criteria and description

Finalization of decision-making techniques

Even though there are numerous MCDM methods available, such as AHP, OWA (Order Weighted Average), TOPSIS, ELECTRE (Elimination and Choice Translation algorithm), and others, a combination of AHP and TOPSIS methods was identified as suitable MCDM techniques for this use case. AHP is a popular and powerful method that uses a hierarchical structure (goals, criteria, and alternatives) for the decision-making process, and it is widely used for allocating resources during any strategic planning process (Jolayemi, 2012). As personnel selection is an MCDM process, AHP assists the decision-makers in selecting the best fit applicant from the available alternatives (Jabri, 1990). Since the hiring process involves both qualitative and quantitative parameters, and the other MCDM techniques do not account for the impact of internal and external business environment constraints (Dwivedi et al., 2020), we chose AHP as one of the MCDM techniques for this study. In this research, AHP is used to obtain the weightage of job roles and their criteria by performing a pair-wise comparison.

Due to the multiple mathematical calculations required by the numerous pairwise comparisons, using AHP has some drawbacks (Zaidan and Zaidan, 2018). This method cannot be used to rank candidates because multiple pairwise comparisons must be performed against each evaluation criterion, which would be a time-consuming and tedious process for interviewers, and the number of pairwise comparisons increases as evaluation criteria are added. To overcome this limitation, this research uses another MCDM technique, i.e., TOPSIS to compute the final score of each candidate and rank them. Since TOPSIS requires an efficientand effective technique for determining the relative importance of various criteria in relation to the objective and AHP provides such a procedure, it is recommended to combine AHP and TOPSIS to compensate for the weakness that exists in AHP (Zaidan et al., 2020). Existing research (Nabeeh et al., 2019; Nilsson et al., 2016) supports the idea of combining these two techniques to help decision-makers choose the best option among several alternatives. Hence, this research uses AHP along with TOPIS to obtain the final score and rank of the applicants.

Furthermore, employee selection necessitates taking into account various organizational constraints (e.g., budget) as well as optimizing team efficiency and cost, so linear programming in conjunction with the decision-making techniques is recommended (Dwivedi et al., 2020). As a result, in addition to AHP and TOPSIS, linear programming is used in this research for optimization and constraint consideration.

Artifact

As a part of this research, a web-based application was created which could be used by both HR and interviewers. HR can use it to set up the job roles and criteria and prioritize them using AHP. Interviewers will rate the candidates (on a scale of 1-5) against each criterion using this application. After the ratings are captured, the system uses TOPSIS to compute the candidate ranking and then uses linear programming to recommend the best candidate while taking into consideration financial and strategic constraints.

Analytical Hierarchy Process

AHP was created in the 1970s by Thomas L. Saaty and consists of several steps, which are listed below. These steps demonstrate how AHP is used to calculate the weightage of job roles.

Step 1: Creating a hierarchal structure

Since hierarchal structure plays a crucial part in AHP, the following diagram summarizes the hierarchy of job roles and their criteria which are derived from tables 1 and 2.

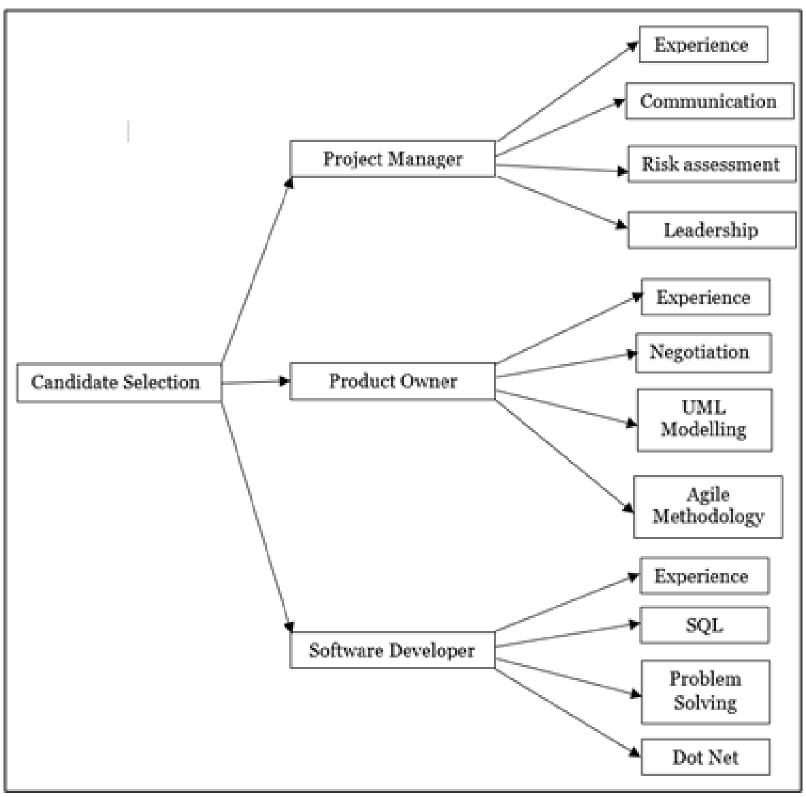

Figure 1: AHP hierarchy

Step 2: Perform the comparisons and create a matrix

Using the web application, HR prioritizes the three job roles by doing pairwise comparisons between them and assigning a weight on a scale from 1 to 9, as shown below.

Figure 2: Job Roles Comparison

The figure clearly shows that the HR of that company had a slightly higher preference for the role of project manager over the role of product owner and the role of product owner over the role of software developer, whereas they had a much higher preference for the role of project manager over the software developer. The following figure summarizes the pair-wise comparison scale.

Based on the priorities entered by HR, a comparison matrix is generated as follows.

	Project Manager	**Product Owner**	**Software Developer**
Project Manager	1	3.00	9.00
Product Owner	1/3.00 = 0.33	1	3.00
Software Developer	1/9 =0.11	1/3.00 = 0.33	1
Sum	1.44	4.33	13.00

Table 3: Comparison matrix

Step 3: Normalization of comparison matrix

According to Saaty (1987), each component of the comparison matrix must be divided by the sum of the numerical columns before being normalized. The final weight (W) is then calculated by averaging the results of normalization, as illustrated below.

	Project Manager	**Product Owner**	**Software Developer**	**Final Weight (W)**
Project Manager	0.692308	0.692841	0.692308	0.692485
Product Owner	0.230769	0.230947	0.230769	0.230828
Software Developer	0.076923	0.076212	0.076923	0.076686

Table 4: Normalized matrix and final weight

Step 4: Calculating Consistency Ratio (CR)

The CR is calculated to determine whether the results are consistent. If the CR is not at its optimal value of 0.10 or less, the prioritizing must be redone (Saaty, 1987). For this example, the value of CR is less than the ideal value.

Hence, based on the priority values entered by HR, the final weightage of the job roles can be represented as follows.

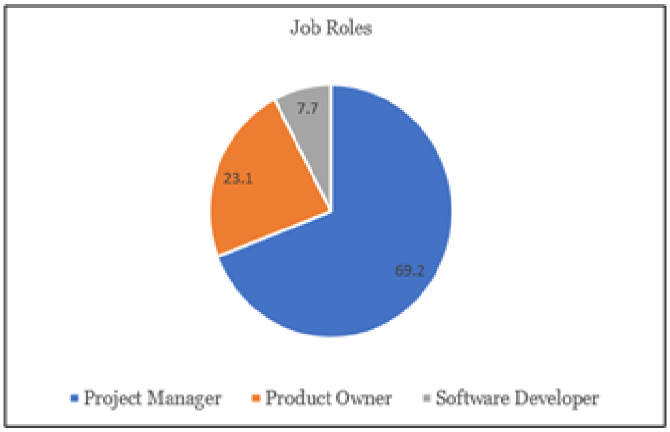

Figure 3: Job role AHP weights

Steps 1-4 are repeated for each job criterion to obtain their final AHP weights, as shown in Table 4.

Theory Order Preference by Similarity to Ideal Solution

After calculating AHP weights for the job roles and criteria, the interviewer rates the candidates on a scale of 1-5 for each criterion using the candidate evaluation screen in the web application. Once the interviewer ratings are captured in the system, the TOPSIS MCDM technique is used to rank the candidates. As discussed previously, this technique is based on the assumption that the selected alternative must be the closest to the ideal solution.

TOPSIS consists of the following steps (Ishizaka and Nemery, 2013; Yadav and Sharma, 2016). The steps explain the calculations considering the ratings provided to the candidates who applied for the project manager's position.

Step 1: Perform Normalization

Table 4 summarizes the rating provided by the interviewer to the candidates who applied for the position of project manager.

	Experience	**Communication**	**Risk Assessment**	**Leadership**
Edwin Donnely	4	4	2	4
Timothy Patrick	2	3	3	2
Ulisses Franca	2	3	4	3
SRSQ	4.8989	5.8309	5.3851	5.3851

Table 5: Interviewer ratings

To perform normalization, each element in the matrix is divided by the square root of the sum of the square (SRSQ) of each column as shown below.

Candidate	**Experience**	**Communication**	**Risk Assessment**	**Leadership**
Edwin Donnely	0.81649	0.6859	0.37139	0.74278
Timothy Patrick	0.40824	0.5145	0.5570	0.37139
Ulisses Franca	0.40824	0.5145	0.74278	0.55708

Table 6: Normalized data

Step 2: Consider the weightage of the criteria obtained using AHP

In this step, the criteria weightage which was obtained by AHP (refer to Fig. 4 for AHP weightage) is multiplied by the normalized data to obtain a weighted normalized matrix.

Step 3: Determine the positive and negative ideal solution

The positive ideal solution (Vj+) is the highest value in each column, while the negative ideal solution (Vj-) is the lowest value in each column.

Step 4: Determine the Euclidean distance

The Euclidean distance of each alternative from the positive (Si+) and negative ideal solution (Si-) is calculated by taking the square root sum of squares of the alternative value from the positive (Vj) and negative ideal solutions (Vj-).

Step 5: Calculate the final performance score

The final performance score (Pi) is calculated by using the following formula.

$$Pi = Si- / (Si- + Si +)$$

The table below displays the performance score (local weight) of the candidates who applied for the position of project manager. After that, the global weightage (Gi) is calculated by multiplying the AHP weightage for the job role by the local weightage.

	Pi	**Gi**
Edwin Donnely	0.76864	0.52387
Ulisses Franca	0.32111	0.21886
Timothy Patrick	0.12955	0.08829

Table 7: Local and global scores for PM candidates

Similarly, by following steps 1-5, the global weights can be obtained for candidates who applied for the position of product owner and software developer. Table 10 summarizes the global score obtained by all the candidates.

Mixed Integer Programming

Once the candidate's global score is determined, the application recommends the ideal candidates (in the final results screen) to be selected considering the strategic constraints (number of positions) and the budget constraints. Mixed Integer Programming (MIP) is used for recommending the best candidates. MIP is a subset of linear programming in which the decision variables can only take integer values (Richards and How, 2005, p.2676).

The MIP decision variables and objective function used for this use case are as follows:

Decision Variable	**Candidate**
X1	Edwin Donnely
X2	Ulisses Franca
X3	Timothy Patrick
X4	Paul Desmond
X5	Shane Mahony
X6	Cathy Sierra

X7	Sandy Orton
X8	Cathryn Fernandes
X9	Mark Obrien

Table 8: Decision variable representing candidates

The objective function used to maximize the score of the candidates is:

Maximize z = 0.532X1 + 0.21886X2 + 0.08829X3 + 0.23645X4 + 0.16389X5 + 0.12286X6 + 0.06066X7 + 0.04897X8 + 0.00635X9

Constraint 1: Since the max budget allocated the recruitment is 250,000 the salary constraint can be represented as:

80,000X1 + 80,000X2 + 80,000X3 + 70,000X4 + 70,000X5 + 70,000X6 + 50,000X7 + 50,000X8 + 50,000X9 <= 250,000

Constraint 2: Since the number of project managers, product owners, and software developers required are 1, 1, and 2 respectively, they can be represented as:

X1 + X2 + X3 = 1 (Project Manager)

X4 + X5 + X6 = 1 (Product Owner)

X7 + X8+ x9 = 2 (Software Developer)

A candidate is either hired or rejected. As a result, the decision variables in the model can only have two possible values i.e., 1 for selection and 0 for rejection which is represented as follows:

X1 + X2 + X3 + X4 + X5 + X6 + X7 + X8 + X9 ∈ {0, 1}

After solving this MIP equation, the candidates recommended by the tool are:

Role	**Candidate**	**Compensation (In Euros)**
Project Manager	Edwin Donnely	80,000
Product Owner	Paul Desmond	70,000
Software Developer	Cathy Fernandes	50,000
	Sandy Orton	50,000

Table 9: Candidates Recommended by System

Findings and discussions

The purpose of this research is to propose a framework for selecting the best candidate among several positions and applicants. The proposed framework selects suitable candidates based on their interview performance and evaluates their soft skills. The findings of this research can be summarized in three stages as depicted below: HR Inputs, Interview Schedules, and Ratings followed by decision-making and optimization.

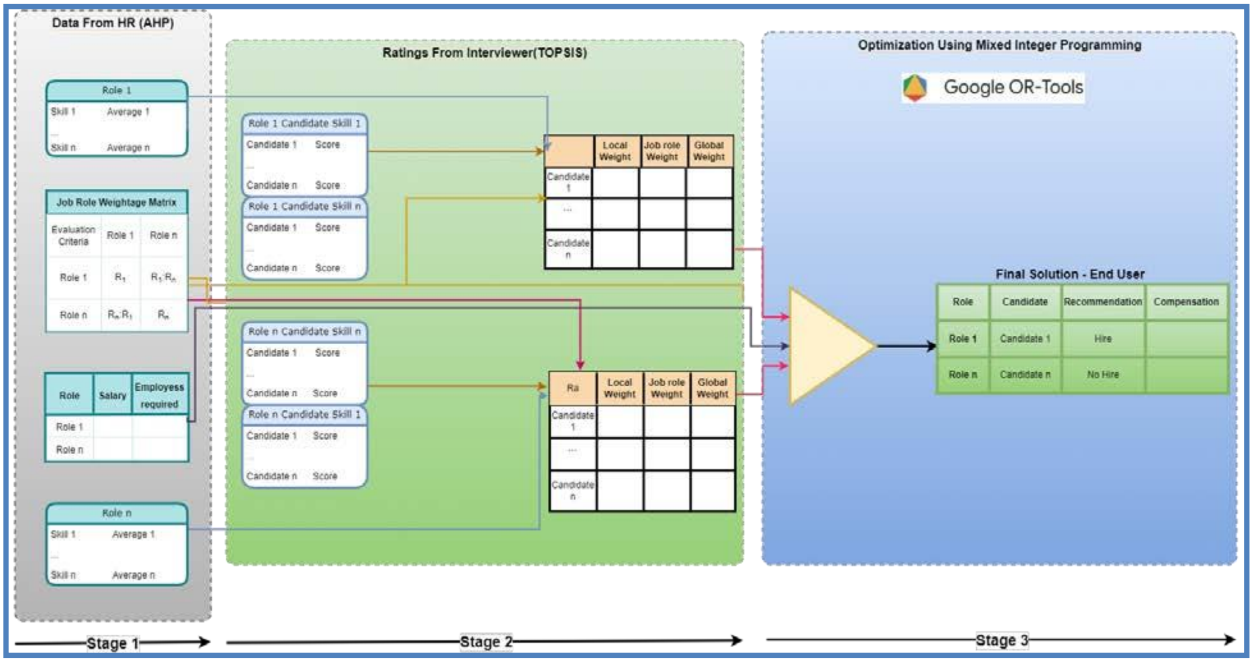

Figure 4: Stages of application

Stage 1: HR Inputs

In the first stage, defining the roles and their corresponding criteria for a particular quarter is a significant step that allows HR to gain visibility of the prioritization of a particular role over the other in a team that is to be formed before the potential candidates are identified. In addition to this, the number of roles to be hired and the budget constraints for each role are also entered into the system which will be used in stage three. This stage eventually helps in reducing the overall time of the final decision-making process, where the focus during the interview process will be purely on providing ratings on these criterias. This makes the whole process standardized and in turn, prevents back-and-forth discussion between the different parties during the decision-making process.

Fig 5 depicts that the Project Manager has the highest priority in the team to be hired as per the priority entered into the system by the HR executive and its weightage calculated by the AHP algorithm by the system is 69.2%. This is followed by the Product Owner at 23.1% and then the Software Developer at 7.1%. Subsequently, individual criteria have been prioritized as well using the same algorithm for each role based on HR inputs, for instance for the Project Manager role, communication has the highest importance (63.2%) as a criterion as compared to Leadership (20.1%), Risk Assessment (10.7%), and Experience (7.9%). The prioritization of the individual role criteria will eventually help in the next computation algorithm (TOPSIS) for the ranking of the best candidate once the interviewer provides their ratings on these criteria for a particular candidate.

While cognitive biases may certainly influence our judgments when comparing model elements, the visibility and transparency of the decision-making process allow us to detect potential biases much more easily, especially during the calculation of the consistency ratio as described earlier. Moreover, since the evaluation criteria and their respective weightage are established well in advance of the role-hiring process, there is an inherent level of separation between the interviewer bias and the level of influence of that bias.

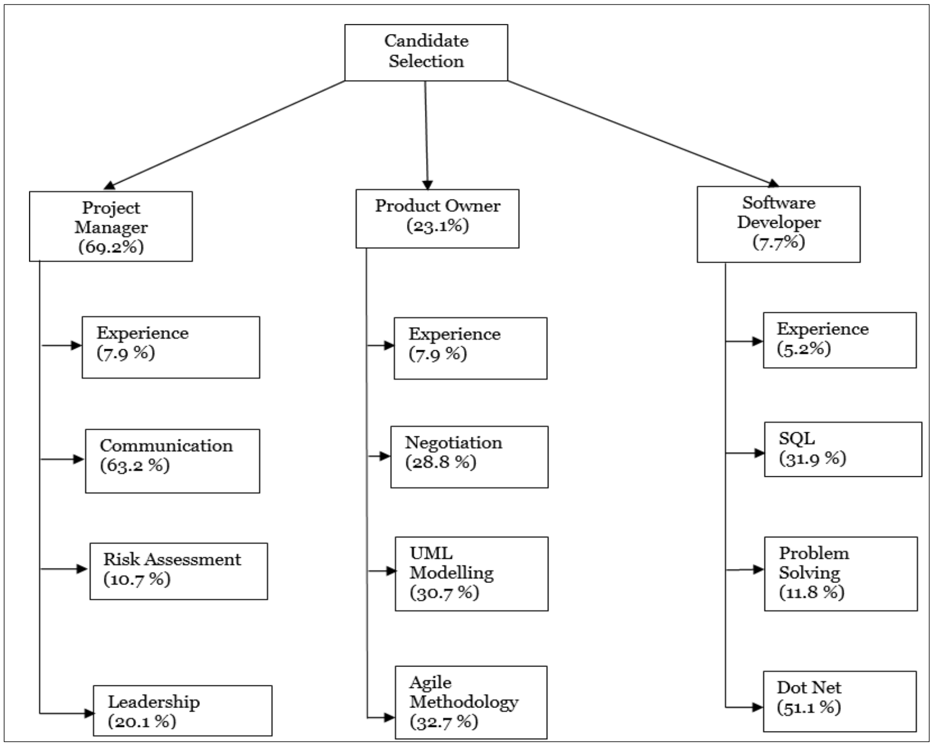

Figure 5: AHP Weightage

The prioritization of the individual role criteria will eventually help in the next computation algorithm (TOPSIS) for the ranking of the best candidate once the interviewer provides their ratings on these criteria for a particular candidate. The system makes sure that this weightage calculation and prioritization data is only available to HR and is not shared with the interviewer, avoiding any exposure of the criteria weightage and preventing any inherent bias.

Stage 2: Interview Schedule and Ratings

In the second stage, HR enters the list of candidates who must be interviewed for the positions into the system, assigns an interviewer to each candidate, and initiates the scheduling process, which sends an email notification with the candidate details to the respective interviewer. This helps the HR executive to strategize/pre-plan the upcoming elements of the hiring process, saving the hassle of manually initiating the scheduling of interviews. Once the interviewer receives the email notification, he or she can rate the candidates based on their technical and soft skills defined in the previous stage. These ratings are consumed by the system and then subsequently used in the TOPSIS algorithm which also calculates the global weightage (ranges from 0 to 1) of the candidates. For example, Table 10 shows that the candidate Edwin Donnely has the highest global weightage as far as the role of Project Manager is concerned. Global weightage is one of the important aspects of the constraints that will be used in the MIP in the next stage.

Role	**Candidate**	**Global Score**
Project Manager	Edwin Donnely	0.52387
	Ulisses Franca	0.21886
	Timothy Patrick	0.08829
Product Owner	Paul Desmond	0.23645
	Shane Mahony	0.16389
	Cathy Sierra	0.12286

Software Developer	Sandy Orton	0.06066
	Cathryn Fernandes	0.04897
	Mark Obrien	0.00635

Table 10: Candidate global score computed using TOPSIS

Since the interviewers have followed a standardized approach for assessing the candidates, the impact of Halo and Horns effect is considerably minimised.

Stage 3: Decision-making and optimization using prescriptive analytics

In the third stage, using the strategic constraints (number of positions) and the budget constraints from stage one, the HR executive gets the final results from the system stating the candidates that need to be hired or not. When the HRs are looking for candidates to be placed in certain positions, they can leverage the candidate rankings obtained from the AHP and TOPSIS calculations. They can ensure that all relevant data used by the algorithm is gathered and analyzed for all candidates. Then, they can apply the obtained results that were discovered by the algorithm to improve the recruitment and placement processes.

Thus, the first stage determines the roles to be hired and their corresponding criteria for hire. The second phase discusses the proposed decision-making based on the crossover between criteria and alternatives. In the third phase, the decision-making solution for selecting the best applicant for a job position is specifically and mathematically described based on the integrated AHP–TOPSIS method in conjunction with MIP. Thus, the tool reduces the time-to-hire by standardizing the hiring process, recommending the ideal candidates by decision optimization, and creating a talent pipeline.

Future Scope

Currently, the research is being conducted on a small dataset that focuses on specific roles within an engineering firm. As a student group, we were limited to access to one organisation. A larger dataset could be obtained from multiple organizations in order to generalize this study. This would also facilitate more comprehensive testing of the hypotheses.

Conclusion

Analytics in the HR domain is currently being used in the software industry in various complex stages of the recruitment process like resume screening through ATS, AI-based interview screening, etc. However, incorporating data analytics in the decision-making step is one of the areas which requires further research. Even though data is becoming more powerful and being accepted in the organisations, hiring managers will find it difficult to relinquish behaviours learned over a lifetime for running an automated system that might bring out the value in the current recruitment space. From a strategic HR point of view, there is a need for a framework that would primarily keep HR as the backbone of the hiring system. While a parallel approach would be the soft introduction of analytics in the hiring process that would give trust and confidence in analytics. In the proposed approach, the evaluation criteria for each role will be created by the HR and based on those criteria candidates will be evaluated and ranked. Also, there is the incorporation of the AHP and TOPSIS ranking criteria in the interview process based on the scores given by the interviewers and evaluation criteria provided by HR. Additionally, with the use of the AHP ranking criteria in conjunction with the TOPSIS system that uses multiple evaluation parameters, there could be a reduction in the blind spots or the inaccuracy of the decision-making process to find the perfect fit for the organisation.

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Appendix

Candidate Evaluation Screen

Figure 4: Candidate Evaluation Screen used by the interviewer

Result Screen