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RESEARCH PAPER

A Hybrid Decision-Making Framework to Manage Human Assets in Project Teams Considering Competency Criteria Based on Industry 4.0 and Post-COVID-19 Era

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Abstract

The selection of human assets for teams significantly impacts the success and profitability of projects. Industrial Revolution 4.0 (4IR) and the post-COVID-19 conditions impose requirements on virtual collaboration, bots-human collaboration, and teleworking projects. The matrix-structured organization faces challenges in this process because it requires weighing various criteria from distinct perspectives. Accordingly, an inappropriate team selection process can result in high costs or failure. Team member competency criteria are identified based on 4IR, in this study. The study also evaluates the theory of generations based on the fact that project teams consist of members from different generations, each with unique characteristics. To this end, a multi-objective allocation model is presented that maximizes competency level while minimizing costs, considering the organizational structure, the 4IR, the post-COVID-19 era condition, and the generation theory. The study attempts to provide decision-makers in multiple-project organizations with a realistic picture to make a trade-off between the cost and competency level of teams. The linear best-worst method (BWM) is used to weigh the competency criteria. Regarding the developed bi-objective model, the Augmented ε- Constraint (AUGMECON) method is utilized to solve the problem. The model is also validated using the Iran Mall project. The findings indicate that younger generations have almost 1.3 more competence scores in virtual communication than older generations. Also, the organization should increase expenditures by 7.1% to reach the highest level of competency.

Keywords: Project Management, Theory of Generations, Best-Worst Method, The Covid-19, Virtual Collaboration, Multi-Objective Programming, Human Resource Management.

Introduction

Due to the critical role of Project Teams (PTs) in ensuring project success, selecting and assigning human resources to PTs is significantly pivotal and challenging [1], [2]. Besides, simultaneously taking competency profiles and human costs into account is one of the most challenging issues for Decision-Makers (DMs) in project-based organizations. In other words, the formation of productive PT is vital in reaching the organization's targets [3].

Following the 4IR, a combination of human factors and robots will comprise future PTs, cooperating to accomplish project objectives [2], [4]. The 4IR made new requirements for the

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PTs. It also has directly impacted how PT members interact [2]. Indeed, the digitalization of the industry through revolutionary innovations has been rising [5]. Thus, to increase PT resilience, the organizations should choose the competency criteria for candidates with an eye to the requirements of the 4IR.

The coronavirus, an emerging global health threat, has infected and killed millions worldwide [6], [7]. The global pandemic COVID-19 shook the world and changed work styles to teleworking [8], [9], [10]. According to preliminary statistics, 40% of European full-time jobs shifted to remote work due to the pandemic [11]. Also, since 2020, digital technologies have been increasingly used and invested in by the industry to prevent the extent of COVID-19 [9]. Further, by combining the physical and virtual worlds, cyber-physical systems (CPS) provide an opportunity for the actual smart industry [12]; therefore, as per the 4IR and the post-COVID-19 conditions, it appears that some new competencies, such as virtual collaboration, are required that are not adequately addressed in fundamental competency development frameworks [2], [9]. However, some researchers, such as [2], acknowledged that 4IR has led to a new evolution in projects and competency criteria for selecting human resources in the PT.

The PT's members, who collaborate to accomplish common goals, are usually from various generations based on the generation theory [2]. Indeed, each generation possesses distinct personal characteristics shaped by their era's conditions and events [13]. Likewise, the degree to which team members interact with technology is generational. Younger generations are more receptive to technology, whereas older generations, who think in processes, are less receptive [2]. Indeed, each person possesses unique strengths and weaknesses based on their generation type, and selecting a mix of different generations in PTs is essential.

Studies [2], [13], [14] have described three generations, labeled X, Y, and Z. The X generation was born between 1965 and 1979 and is known for being process thinkers and individuals who must work outside the home to make money. Also, they are less receptive to cutting-edge technology and seek a balance between work and life. The Y generation was born between 1980 and 2001 and developed a strong affinity for television and virtual social networks. Moreover, they are well-suited to use virtual business tools, are adept at multitasking and adapting to changing circumstances, and are less devoted to their employer than previous generations. Overall, they are already familiar with technology, as most have owned computers or mobile phones since childhood. The Z generation, known as the Internet generation, includes those born in the 1990s. Also, studies distinguished them from the previous generation, i.e., generation Y. Likewise, most of the members of Generation Z will be using digital communications and media for the rest of their lives. So, some people have named them digital citizens. Currently, this generation is entering the work market, and organizations are capable of directing their skills and attitudes.

Since the quality of project deliverables depends on the competency of human assets [15], [16], skilled people can lead to success [17][18], the selection process must effectively choose competent people considering what is required in each project [19], [20]. The formation of a PT is, therefore, an essential factor that, in turn, directly affects project achievement in Project-based organizations (PBOs) [1]. On the other hand, the human resource cost in a PT is also of considerable importance, which is influential in selecting team members considering the organization's budget [21]. By considering the points above and the 4IR requirement, the theory of generations, and the COVID-19 crisis, a comprehensive model is presented in this research work to increase PT resilience based on the industry requirements. This way, candidates are allocated to the PT considering the project requirements and individual limitations. The research is, therefore, among the first works in which all concepts above are quantitatively modeled to prevent subjective judgments and confirm the results of previous qualitative studies. The following challenges and questions will be answered in this research:

i. How can the most competent PT be selected, considering human resource costs?

ii. Considering 4IR and the COVID-19 crisis, what are the competency criteria?
iii. How can PT be formed in light of the theory of generations?
iv. What would be the performance of each generation in terms of competency criteria?
v. When a matrix organization is tasked with several projects, how can human resources be efficiently distributed among the various disciplines?

This study proposes a framework for addressing the above questions by considering the essential competency criteria in PBOs according to the 4IR requirements. After weighing the criteria by BWM, each candidate's score is evaluated in each criterion by an expert's opinion. Then, a bi-objective mathematical model is presented to determine the team combinations by maximizing the total competency score of PTs and minimizing the cost of human resources simultaneously. The concept of the theory of generations is also embedded in the developed model, which is why PT includes various ages with different characteristics. The multi-objective model is optimized by applying the AUGMECON approach. Finally, the proposed framework is analyzed and validated by a real case of Iran Mall Company. The research results give a proper perspective to the DMs in multi-project organizations to allocate human assets to PTs effectively.

This is how the research is organized: Section 2 overviews previous studies. Section 3 presents the methodology of the investigation. The approach to quantify competencies and the bi-objective allocation model are described in section 4. Section 5 explains the solution approach. The case study and numerical analysis are presented in section 6. A discussion of the obtained results is conducted in section 7. Sensitivity Analysis is presented in section 8. Also, Section 9 provides some managerial insights, and finally, section 10 concludes the research.

Literature Review

Two of the most related areas investigated on the member selection of PTs are as follows:

Trend Studies Considering 4IR and the post-COVID- 19 era to Configure Competency Frameworks

Bernat [22] investigates the impact of stakeholder engagement, knowledge management, and sustainable practices on project success within virtual work environments, amid the rising trend of virtual teams following the COVID-19 pandemic. Through quantitative analysis using structural equation modeling and surveying experienced Portuguese-speaking project management professionals, the study reveals that virtual teams do not diminish the influence of these factors on project success. This research offers valuable insights into optimizing project success in virtual work environments, particularly emphasizing sustainability, and fills a crucial gap in the project success theory. Mayer said that Virtual collaboration benefits team productivity. Shared task-oriented leadership enhances productivity and satisfaction in virtual teams [23]. Yavuz [24] explained that perceptions of leadership evolve with modernization, impacting Generation Z's expectations. Their desired leadership traits encompass foresight, digital skills, and emotional intelligence. Juras [25] analyzed the competency of the PT and its effects on project success. Also, they explained that PT plays an essential role in the comparative business [25]. By studying previous studies and considering 4IR, Marnewick [2] presented the requirements of the future PT. Indeed, they claimed that future teams would include human factors and robots; and investigated competencies related to 4IR. Also, he discussed the theory of generations' impacts in selecting the PT problem; and presented the X, Y, and Z Generation attributes. According to [2] and Weber et al [26], PT includes individuals from different generations cooperating to accomplish project goals. Indeed, they described that younger generations, contrary to older generations with process thinking, are affected by technology and virtual communication tools. Mathieu et al [27] explained that a new PT includes two or more people interacting in the present or virtual form. Also, he proposed that structure and the combination of the PT play an essential role in selecting members. Anantatmula and Shrivastav [13] suggested that using different generations is challenging for project managers. Also, they compared the characteristics of generations in qualitative form. Richert [4] defined future teams as human members or bots collaborating through digital communication tools. Bajer [28] explained that fixed roles and responsibilities of PT members would be replaced by dynamic roles and responsibilities, leading to the management of continuous changes.

Waizenegger [29] researched the collaboration of teams during the COVID-19 pandemic. He defined that COVID-19 has led to unpredictable challenges in the projects. Overall, this research dealt with practical virtual cooperation between team members and compared the pre- and post-pandemic collaboration. According to Zuofa [30], organizations must update their strategies based on remote control and virtual teams. Likewise, having interviewed project managers in Nigeria, he showed that achieving project deliverables in virtual teams requires more effort. Elrefaey [9] Undertook a study to define the status on three levels: pre-COVID, COVID, and post-COVID. He also showed that the advantages of digital technology would remain to be used in the industry. Also, Brown Sr et al [8] focused on teleworking during the pandemic and showed that the organization could enable PTs to accomplish the work as if they were at the workplace. Likewise, Amade [10] proposed a model to raise ICT adoption in construction projects.

Previous studies investigated qualitatively the differences between generations and competencies related to 4IR.

Fundamental studies in mathematical models to select HR in the project teams

Several types of research are taken into the mathematical programming to determine PT combinations. First, we present multi-objective; and subsequent single-objective studies. A multi-objective model to optimize team size and competency score of individuals was provided by Baykasoglu et al [31] by considering fuzzy variables and budget constraints. Wi et al [32] presented a multi-objective model to form a PT and solved it by a Genetic Algorithm (GA). In addition, the researchers proposed a framework to analyze the knowledge and skill of each candidate with the aim of collaboration increase among PT members. However, this research did not pay attention to the cost and the number of required human resources. An integer model was presented by Feng et al [33] to select PT members in a functional organization looking to maximize individual performance as well as member collaboration. A multi-objective PT formation model for new product development projects was proposed by Zhang [34]). Indeed, the capabilities of all members and the interaction between every two candidates were maximized. The number of PT requirements as a constraint was regarded with no attention paid to the human resource cost. The authors used a fuzzy hierarchical analysis based on fuzzy linguistic variables and the Multi-Objective Particle Swarm Optimization (MOPSO) method to search for Pareto solutions. Two-stage zero-one programming was presented by Cavdur et al [35] to solve a PT formation problem. A goal programming Approach was applied to meet different skills as objective functions. Rahmanniyay et al [1] presented a multi-objective model to form a PT by considering the costs and competency of HR as objective functions.

Regarding single-objective mathematical models, several research works that deal with human resource planning in project teams. A linear model to select individuals for a particular work was used by Karsak [36]. In order to describe people's skills, fuzzy quantities were applied. By applying fuzzy sets and gray theory, Tseng et al [37] proposed a model to form PTs. Chen and Lin [38] developed an AHP approach to select a multi-functional team. A fuzzy-genetic model for creating the PT was developed by Strnad and Guid [39]. Tavana et al [40] provided a two-stage framework to choose players in multi-player sports. First, they evaluated players through a fuzzy ranking technique. Second, a combination of players was proposed through a fuzzy interface system. Considering social structures, a mathematical framework was proposed by Farasat [40] to deal with the PT formation problem. They presented a model to optimize the average output of team members.

Although much research has been done on the optimal combination of PT members, some vital features such as the theory of generation, 4IR and post-COVID-19 conditions, and matrix organizational structures of PBOs are rarely incorporated into the problem. To deal with these research gaps and boost PT resilience, the present study deals with the following innovations:

i. Proposing a novel competency framework to assess human assets in light of 4IR and post-COVID-19 conditions;
ii. Previous studies presented each generation's competency qualitatively. This study is among the first ones that deal with human assets assessment based on the generation theory. This way, the BWM linear method is applied to evaluate each competency weight;
iii. In the proposed model, it is possible that a person's competence is assessed for different projects. Therefore, it can be helpful for DMs in matrix organizations;
iv. The model evaluates candidates' competency scores separately based on each project's requirements; therefore, it assigns people to the project in which they score the highest; in other words, candidate competence can vary from project to project.

To deal with the above contributions, in this paper a hybrid Multi Criteria Decision Making-Multi Objective Decision Making (MCDM-MODM) framework is proposed. The MODM model simultaneously maximizes competency and minimizes the costs in PBOs so that the DMs can trade the price and competency score. Table (1) shows what differentiates the present study from the previous one.

Contribution and Research Gaps

In this section, we outline the contributions of our study as follows:

i. Integration of Competency and Cost Considerations: We have expanded upon previous research by proposing a model that simultaneously optimizes competency levels and associated costs in project team formation in several projects. By addressing both dimensions within a unified framework, our study offers decision-makers a comprehensive tool for making informed choices in matrix-structured Project-Based Organizations (PBOs).
ii. Alignment with Industry 4.0, Generational Diversity, and Post-COVID-19 Dynamics: Recognizing the transformative impact of the Fourth Industrial Revolution (4IR) and the COVID-19 pandemic on project management practices, our study incorporates these contemporary dynamics into the team formation process. By considering the evolving nature of work and communication patterns, our framework provides insights into how organizations can adapt their project teams to thrive in a rapidly changing environment.
iii. Generational Analysis of Competency Profiles: An important aspect of our study is the examination of competency profiles across different generational cohorts in the workforce. Through an analysis of social, virtual collaboration, and personal competencies, we contribute to a deeper understanding of how generational differences may shape project team dynamics and effectiveness in matrix-structured PBOs. Also, we model generational diversity for the first time.
iv. Practical Implications for Decision-Makers: Beyond theoretical insights, our study offers practical implications for human resource managers and decision-makers in PBOs. By providing a structured approach to project team formation that accounts for both competency and cost considerations, our framework enables organizations to optimize their human resources allocation and enhance project outcomes sustainably.

In summary, our study advances the literature on project team formation by proposing a comprehensive framework that integrates competency, cost, and contemporary workforce dynamics within the context of matrix-structured PBOs. It is believed that these contributions address significant gaps in the literature and offer valuable insights for both researchers and practitioners in the field of project management.

Table 1. The summary of the Literature review

References	Assumptions		Objectives		Methods		4IR and the COVID-19 requirements	Theory of Generations	Multi projects	Matrix organization
	Deterministic	Stochastic	single	Multi	Fuzzy interface	Mathematical programming				
Our paper	√			√		√	√	√	√	√
Nihan Yavuz (2024) [24]								√		
Mayer (2023) [23]							√			
Bernat (2023) [22]							√			
Amade (2023)[10]							√			
Brown Sr (2022)[8]							√			
Elrefaey (2022)[9]							√			
Zuofa (2021)[30]							√			
Marnewick (2020)[2]							√	√		
Rahmanniyay (2019)[1]		√		√		√				
Cavdur (2019)[41]	√			√	√					
Farasat (2016)[42]	√		√			√				
Zhang (2013)[43]	√			√		√				
Strnad (2010)[44]	√		√			√				
Feng (2010)[33]	√			√		√				
Wi (2012)[32]	√			√		√				
Tavana (2013)	√		√		√					
Gutierrez (2016)[45]	√		√			√				
Baykasoglu (2007)[21]	√			√		√				
Karsak (2000)[46]	√		√			√				

Methodology

In this section, the 6-step methodology applied is described as shown in Figure 1.

I. The competency criteria for PTs are specified by taking the 4IR and post-COVID-19 conditions into account via the related literature;

II. The weights of the competency criteria are evaluated by the BWM linear method [47], [48]. In our study, the Best-Worst Method (BWM) linear model was employed to evaluate the weights of competency criteria in the project team formation process. This method was selected due to its ability to handle complex decision scenarios effectively, particularly in multi-criteria decision-making (MCDM) problems. To implement the BWM linear model, a structured questionnaire based on the competency criteria was developed and administered to experts within the Iran Mall company. The questionnaire facilitated the collection of expert opinions and allowed for the systematic comparison of criteria based on their perceived importance. We conducted a survey where we asked 50 experts to rate each criterion on a 9-degree scale, capturing both the best and worst aspects of each criterion. Each criterion was evaluated in terms of its relative significance compared to others, with experts providing ratings on a scale that captured both the best and worst aspects of each criterion. The average scores obtained from the questionnaire responses were then used to determine the weight of each competency criterion. Pairwise comparisons were conducted to calculate both the best-to-others and others-to-worst scores, enabling the derivation of relative weights for each criterion. This approach provided a comprehensive and structured method for evaluating the importance of competency criteria in project team formation. Furthermore, the BWM linear model offers several advantages over traditional methods such as the best-worst method. It provides higher reliability and accuracy with less data, making it well-suited for decision-making in complex and dynamic environments. Additionally, the linear process of the BWM model allows for the faster calculation of inconsistency rates, ensuring the robustness of the decision-making process. By incorporating the BWM linear model into our methodology, we aimed to ensure the reliability and validity of our findings while providing a transparent and systematic approach to evaluating competency criteria in project team formation. This methodological extension enhances the rigor and credibility of our study's approach to decision-making in matrix-structured Project-Based Organizations (PBOs);

III. In the subsequent step of our methodology, we proceeded to assess the competency criteria for each individual within the project team. This involved senior experts employing a five-point Likert scale, as delineated in Table 2 of our methodology, to evaluate each person's competency criterion. The Likert scale spanned from 'Excellent' to 'Very poor,' denoting scores of 5 to 1, respectively. Through a meticulously designed survey, senior experts provided ratings for each criterion based on their informed observations and assessments. This utilization of the Likert scale facilitated a nuanced evaluation of competency, enabling the capture of diverse performance levels across different criteria. Post-survey, we computed the average of expert opinions for each competency criterion. This collective assessment approach ensured that competency evaluations were founded on a broad-based perspective, amalgamating the insights of multiple senior experts. Notably, our choice of linguistic terms within the Likert scale was deliberate, as prior research has indicated their efficacy in more accurately reflecting expert viewpoints compared to rigid numerical values [34], [49]. By embracing the Likert scale-based methodology, we aimed to furnish a comprehensive evaluation of individual competency criteria, thereby facilitating the identification of strengths and areas for improvement within the project team. This methodological refinement further bolstered the validity and reliability of our study's findings of competency assessment within matrix-structured Project-Based Organizations (PBOs). A survey focused on a contractor company involved in the Iran Mall project is conducted. Utilizing the data provided in Tables 6 and 8, we aimed to assess the competency level of each candidate.;

Table 2. 5-point Likert scale

Very poor	Poor	Average	Good	Excellent
1	2	3	4	5

IV. Using stages 2 and 3 and multiplying the weights by the scores, the final competency score of each candidate is calculated for each project. It is worth noting that a person may have different scores for various projects;

V. A bi-objective allocation mathematical model is developed by considering total cost and competency scores. At this stage, the Augmented-ε Constraint method is applied to obtain the Pareto solutions [1], [50], [51]; and,

VI. Management insight can be gained from analyses and verification of the obtained results.

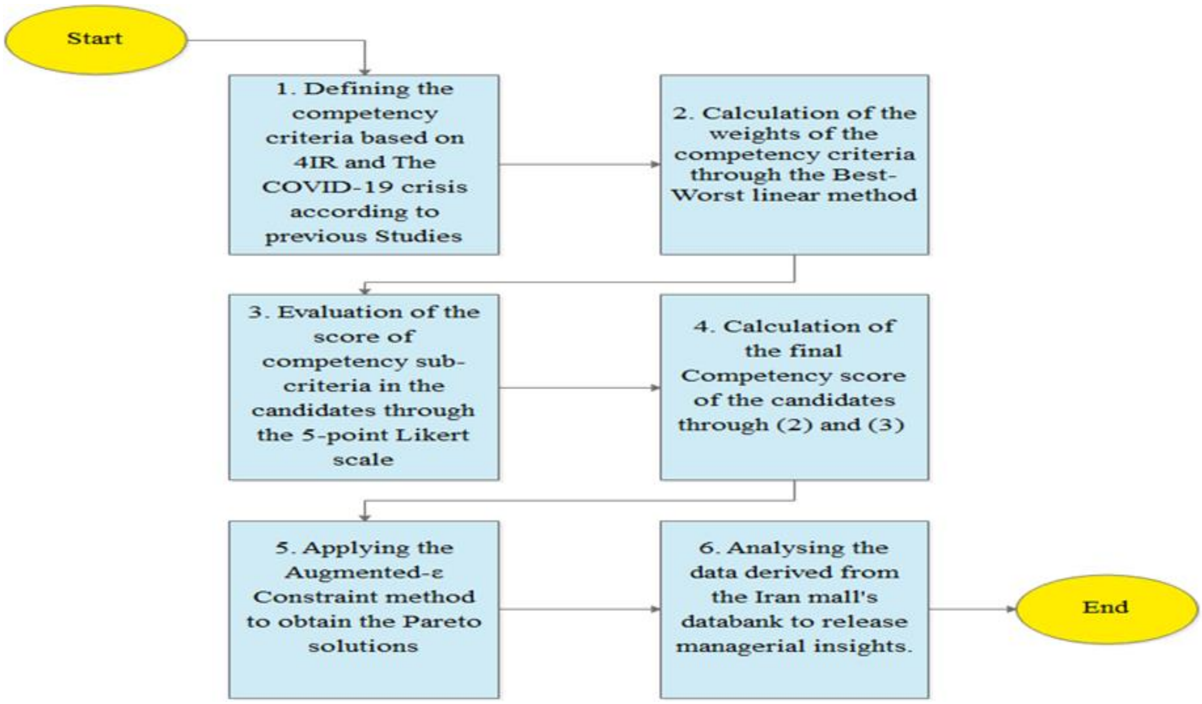

Figure 1. The methodology

Problem Definition

Assume a PBO with various projects done in a matrix organizational structure, as Figure 2 shows. As well, there are different employees from different generations that have to be assigned to PTs. Each employee has a different competency level for various projects. For example, consider a company with two projects, A and B. Project A requires high proficiency in Auto CAD, while Project B needs a high specialty in Revit software. Regarding "Familiarity with required software" competency, an employee may get a higher score for Project A than Project B. Obviously, it is expected to expend more for experts rather than non-experts. The main issue is assigning employees to PTs by balancing human costs and competency scores and combining different generations. To deal with the explained problem, a two-phase framework is proposed. The first phase presents a competency evaluation model considering 4IR conditions and the post-COVID-19 era. Then, a bi-objective model is developed to find the optimal combination of PTs in the second phase. This way, the following assumptions are taken into account:

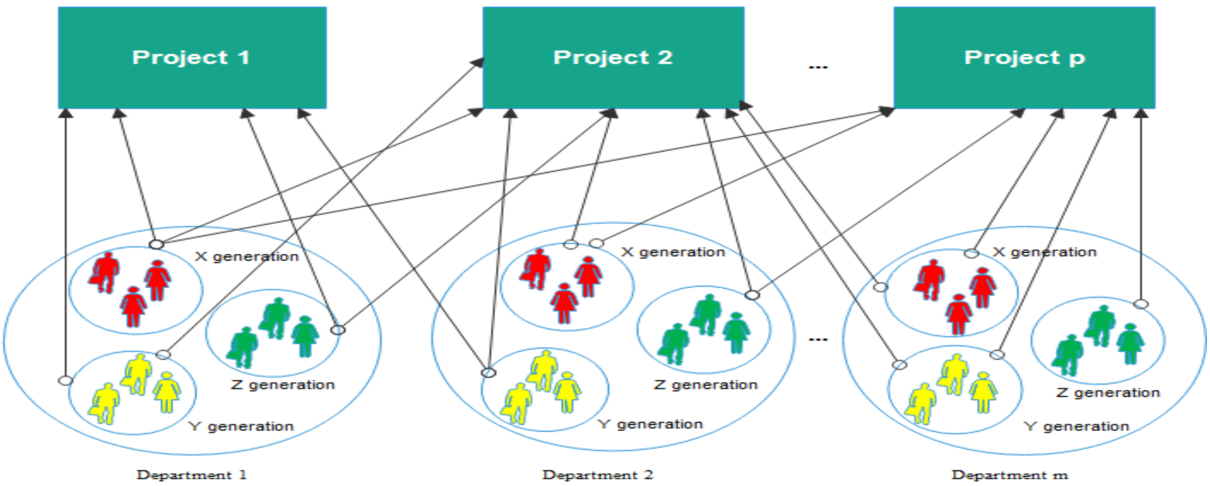

Figure 2. The conceptual model

- a deterministic condition is considered;
- a matrix organizational structure with multiple projects is considered;
- All employees have a full-time agreement. Each person should be allocated up to one project;
- It is aimed to determine the optimal combination of PTs by 1) Minimizing the cost of human assets and 2) maximizing the PTs' total competency scores.

How to Evaluate the Competency Score

In order to determine a competency model, three main classes of competencies, ie. Technical, social, and personal ones are considered based on the literature [2]. Technical competency is related to individuals' skills and knowledge in a specialized field, determined in each required discipline [2], [52]. These competencies should be completed by personal and social ones [2]. Emotional competency is related to individuals' personality traits, such as the ability to be creative [2], [26]. Social competency indicates how every person interacts and communicates with other members. For example, virtual communication tools are a social competency regarding 4IR [26], [53]. In brief, the criteria and sub-criteria are classified based on the literature [2], [4], [9], [28], [30], [53], [54], [55], [56] and experts' opinions as Table (3) shows. According to the studies, Table 3 shows that technical competencies are divided into three sub-criteria, personal ones are separated into four sub-criteria and social competencies are distributed into five sub-criteria. As the social competencies, the virtual collaboration competency allows the model to be executed for various types of projects, including IT, which can be performed transnationally by virtual collaborations.

Table 3. Competency criteria

Criteria	**Sub-criteria**
Technical	Familiar to software
	Job experience
	Process knowledge
Personal	Adaptive thinking
	Creativity
	Cognitive load management
	Problem-solving
Social	Social Intelligence
	Cross-cultural competency
	Virtual collaboration
	Team working
	Communication

Calculation of the Total Competency Scores

According to steps 2 and 3 of the methodology, this is how to calculate the total competency score for each candidate. Equation (1) implies the total competency score for candidate t. The notations applied in Equation (1) are defined in Table (4).

Table 4. Elements of the Competency Model

Set:	**Definition:**
$i \epsilon \{1, \ldots, 12\}$	Set of competency criteria
Parameters:	**Definition:**
C_i	The score of sub-competency criteria *i* of each candidate
W_i	Weight of sub-competency criteria *i*
Variable:	
C_t	The final competency score of each candidate

$$Ct = \sum_{i=1}^{12} Wi\, Ci \tag{1}$$

The Developed Bi-Objective Allocation Model

In this section, the developed bi-objective allocation model is presented in order to select the optimized combination of PTs with the aim of cost minimization and total competency level maximization considering the various generations. By showing the notations defined in Table (5), the model can be formulated as follows:

Table 5. Elements of the developed bi-objective allocation model

Set:	Definition:
$j\epsilon\{1,\ldots,J\}$	Generation j
$k\epsilon\{1,\ldots,K\}$	Department *k*
$z\epsilon\{1,\ldots,Z\}$	Project *z*
$i\epsilon\{1,\ldots,N_{jk}\}$	Candidate i from generation j and department k
Parameters:	**Definition:**
C_{ijkz}	Competency score of candidates *i* from generation *j* in department *k* for project *z*
L_{ijkz}	The HR cost of candidate *i* from generation *j* in department *k* for project *z*
P_{jkz}	Number of human assets required from department *k* and generation *j* for project *z*
N_{jk}	Number of employees available in department *k* from generation *j*
Variable:	**Definition:**
X_{ijkz}	1 if candidate i from generation *j* in department *k* is selected for project *z;* otherwise, 0

$$max\, z1 = \sum_{i=1}^{njk}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{z=1}^{Z} C_{ijkz}\, X_{ijkz} \tag{2}$$

$$min\, z2 = \sum_{i=1}^{njk}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{z=1}^{Z} L_{ijkz}\, X_{ijkz} \tag{3}$$

Subject to:

$$\sum_{z=1}^{Z} X_{ijkz} \leq 1 \quad \forall\ i, j, k \tag{4}$$

$$\sum_{i=1}^{N_{jk}} X_{ijkz} = P_{jkz} \quad \forall\, j, k, z \tag{5}$$

$$X_{ijkz} \in \{0, 1\} \quad \forall\, i, j, k, z \tag{6}$$

The conflict inherent in the goal functions arises from the trade-off between maximizing the total competency score and minimizing the total cost of human assets. This conflict necessitates finding an optimal balance between selecting highly competent candidates and minimizing associated costs, typical in multi-objective optimization problems.

Equation (2) maximizes the total competency score. In other words, this function selects candidates who obtain the highest competency score while considering the generation type in each department. The process determines C_{ijkz} explained in section 4.1.1. Equation (3) minimizes the total costs of human assets. L_{ijkz} indicates each candidate's total human resource cost, including wages, overheads, etc. The price of each individual is also determined by consideration of generation type, department, and project upon agreement and the approved base salary for each year. With attention to definitions and challenges related to each project and the effectiveness of the PT's human assets, Equation (4) ensures that each person can be allocated to at most one project. Equation (5) implies how many people of each generation are required for each project in every discipline. According to the project guidelines, the DMs also specify the number of individuals and the type of generation needed. Equation (6) determines the decision variables type. Indeed, if person i from generation j in department *k* is allocated to project *z*, X_{ijkz} is equal to 1; otherwise, it is 0.

Solution Approach

This study uses the AUGMECON method [1], [50], [57] to find the Pareto solutions of the developed bi-objective allocation model. Numerous ways have been developed to solve a multi-objective problem, like the weighted sum, ε- constraint, goal programming, and fuzzy programming approaches. The AUGMECON is an enhanced form of the ε -ε-constraint process, which was used by [58]. Besides the fact that it takes a short amount of time to solve, it guarantees that the solution will be efficient [59]. A primary objective is selected using this approach, while the other objectives, equations (4), (5), and (6) are transferred into constraints. It means we have constraints and objective functions that add surplus and slack variables, usually expressed as follows [1], [50]:

$$MAX(-f2(x) + \frac{eps.S1}{r1}) \tag{7}$$

$$f1(x) - s1 = e1 \tag{8}$$

$$x \epsilon s \tag{9}$$

Eps is a small number between 10^{-3} and 10^{-9}. Also, S1 is a positive auxiliary variable, and r_1 equals the difference between the best and worst answer to the first objective function in this research. e_1 is the right-hand side of the constrained objective function [59].

$$r1 = f1max - f1min \tag{10}$$

Next, dividing r_1 to h at equal intervals, h+1 points (Grid points) will be formed for e_1 based on the following Equation (11) [60] :

$$e^{w}_{1} = f1^{min} + (r1/h)\, w \quad for\ w = 0,1,\ldots,h-1 \tag{11}$$

$$e^{h}_{1} = f1^{max} \tag{12}$$

After solving the model for each e^w value, a set of Pareto solutions is built (element $w \in h$).

Case Study

This section studied an organization with a matrix structure, i.e., Iran Mall Company to validate and apply the model to real-world challenges. Iran Mall is one of the primary civil projects throughout the Middle East. It includes administration and commercial projects. The scheme performed in an area of 270km2 is of 3.4B$ value. The project contains hotels, parking lots, restaurants, sports stadiums, shopping centers, and a musical lake [61], [62]. The Contractor understudy intends to allocate ten candidates to prepare engineering documents for two sub-projects of the Iran Mall, i.e., the hotel and the parking lot. Besides, the electricity and mechanic departments (two departments) are responsible for performing engineering design and documentation.

Table (6) shows the number of human assets available, and Table (7) implies the required number of human assets for each discipline in projects based on the generation type. Team members are considered full-time laborers who can perform remote work based on the requirements. Overall, figure (3) shows the conceptual model of the case study.

Table 6. Available Candidates

Department	Generation	Available Candidates
Electrical	X	3
	Y	2
	Z	2
Mechanical	X	2
	Y	3
	Z	2
Total	-	14

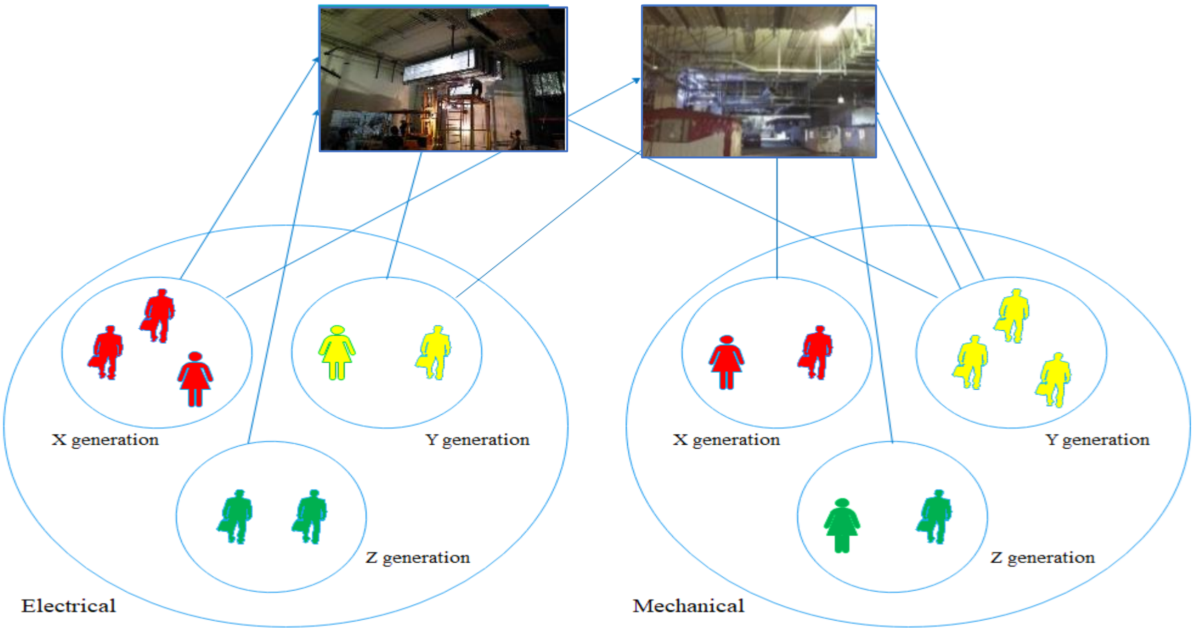

Figure 3. Conceptual Model of the case study

Table 7. Team requirements

Project	Department	Generation	Team requirement
Hotel	Electrical	X	1
		Y	1
		Z	1
	Mechanical	X	0
		Y	1
		Z	0
Parking	Electrical	X	1
		Y	1
		Z	0
	Mechanical	X	1
		Y	2
		Z	1
Total	-	-	10

In order to calculate the weights of criteria and sub-criteria through the best-worst linear method [48]and after preparing the questionnaire, four statistical groups of experts in the Iran Mall project provided their views in Table (8). Then, the average value of experts' views is used to evaluate the weights. The best and worst criteria are specified based on the opinions provided by superior DMs. Finally, the weighted employee's competency scores are determined.

Table 8. Statistical group for BWM survey

Group	Number
Project manager	10
Site Manager	10
Senior technical expert	20
Senior human resources expert	10
Total	50

The results calculated via the best-worst linear method based on expert views are shown in Table (9). Besides, Figure (4) shows a set of weight diagrams resulting from BWM. Based on this Figure, it can be derived that "job experience" and "process knowledge" are the essential criteria, respectively. However, "adaptive thinking" and "cross-cultural skills" have the lowest weight scores.

Table 9. Weight of criteria based on the BWM linear method

Criteria	Weight	Sub-criteria	Weight
Technical	0.625	Familiar to software	0.08
		Job experience	0.35
		Process knowledge	0.20
Personal	0.125	Adaptive thinking	0.01
		Creativity	0.04
		Cognitive load management	0.02
		Problem-solving	0.06
Social	0.250	Social Intelligence	0.03
		Cross-cultural competency	0.01
		Virtual collaboration	0.08
		Team working	0.09
		Communication	0.03

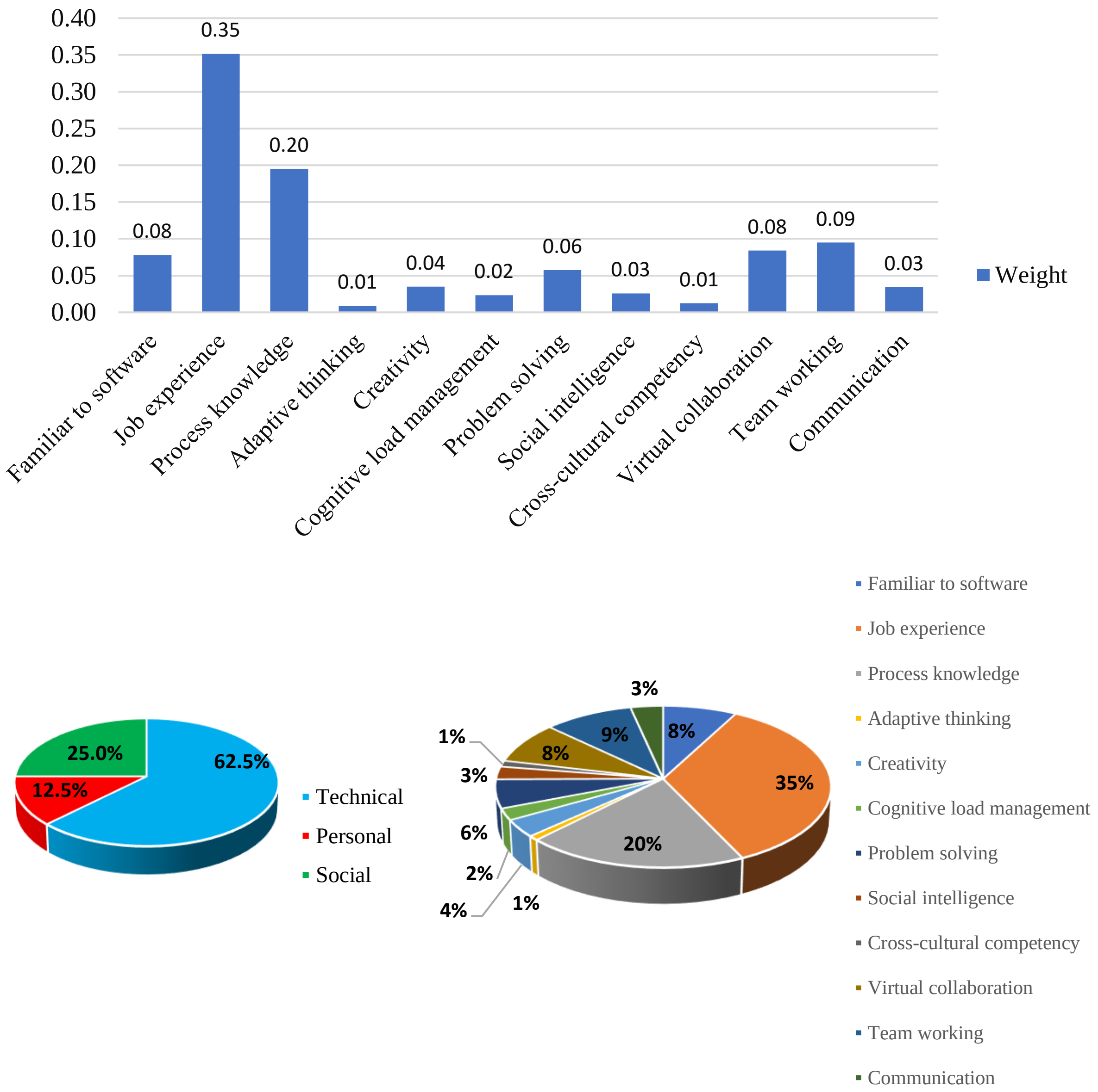

Figure 4. Set of weights diagrams based on BWM linear

Table (10) shows the inconsistency rate calculation of weights based on the BWM linear with acceptable results referring to [47], [48]. On a scale of [0,1], if this rate is near 0, it is more accurate.

Table 10 The inconsistency rate of the BWM linear method

Competency criteria	inconsistency rate
Sub-criteria of technical competency	0.06
Sub-criteria of personal competency	0.1
Sub-criteria of social competency	0.07
Main competency criteria	0.1

Finally, using Equation (1), the final competency score of each individual is calculated according to the features of each project. In the second phase, after calculating and collecting model parameters and running the multi-objective allocation model via GAMS software, a set of optimal Pareto solutions is calculated. Accordingly, and based on the experts' opinions, the total cost is taken as the primary objective function in this research. At this stage, it is determined by the DMs that each person with generation j from department k should be allocated to which project, considering the importance level of competencies and total cost functions via grid points (Figure 5). As Figure 5 shows, the cost of human assets directly correlates with their competency level. A collection of Pareto solutions gives DMs a macro image to select the best combination of PTs considering the organization's strategy. Table (11) shows Pareto solutions determined by applying the augmented ε- Constraint method. This way, it shows 4 points on which DMs can make a trade-off between cost and competency based on policies set by the organization board. Regarding Table 11, the lowest amount of cost as well as the lowest level of competence is achieved in grid point 1, where the importance of cost for the decision maker is the highest. On the contrary, point 4 is obtained when the importance of the competence level is at its highest importance weight.

Table 11. The result of each objective function

Grid	Competency score	Cost ($/day)	Percentage of cost increase
1	31.8	47.9	-
2	32.76	49.9	4.2
3	33.71	50.7	1.6
4	34.67	51.3	1.2

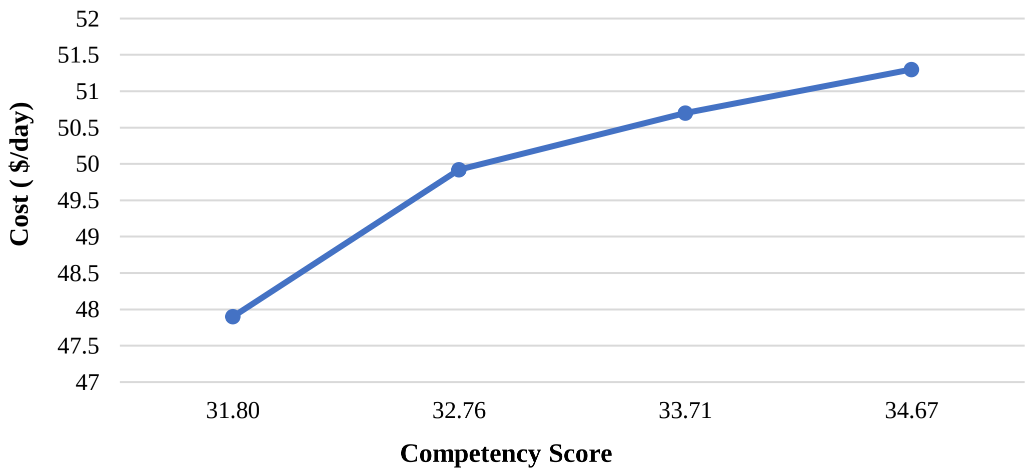

Figure 5. The Pareto solutions

Result Analysis and Discussion

In order to analyze the obtained results, first, the relationship between competency and the cost of human assets is investigated. Second, according to the Iran Mall database, the competency criteria scores in different generations are quantitatively analyzed to prevent personal judgments. The set of Pareto solutions implies that the higher the competency level, the more the cost of human assets. In other words, the more an organization requires competency, the more it has to pay for HR. Table (11) shows that to increase the competency level from 31.8 to 34.67, 7.1% more cost must be paid according to the set of optimal Pareto solutions. This way, those DMs to whom cost is more essential than competency will choose grid points 1 or 2. On the other hand, DMs who expect work to be performed quickly and with high quality will choose high competency points, including grid points 3 or 4; as a result, it should expend 5.8% or 7.1% more in comparison with grid point 1. Finally, assume that the minimum competency score and maximum budget required for human assets are equal to 32.6 and 51 $ per day by considering the HR and financial strategies of the organization under study. It implies that grid points 2 and 3 are feasible under the defined condition. If the DM prefers saving costs, he will select grid 2 rather than 3. Indeed, DM chooses to expense 4.2% more than grid 1. Assuming E as the electrical department, M as mechanical, and X Y Z as generations. Regarding grid point 2, (E, X_1), (E, Y_1), (E, Z_2), and (M, Y_2) are chosen for the hotel. Where (E, X_3), (E, Y_2), (M, X_2), (M, Y_1), (M, Y_3), and (M, Z_1) are selected for the parking lot.

Now, we are going to analyze competency values based on the mean score of every generation, considering experts' views. Table (12) and Figure (6) show various generations' technical competency assessment results. The results imply that Generation X had the highest level of technical competency due to work experience and procedural knowledge. If the DMs determine technical competency as the most important one, it is expected to choose more people with X generation. This result is also acknowledged by [63], [64], [65].

Table 12. Technical competency score of each generation

Generation	**Score**
Z	2.02
Y	3.74
X	4.52

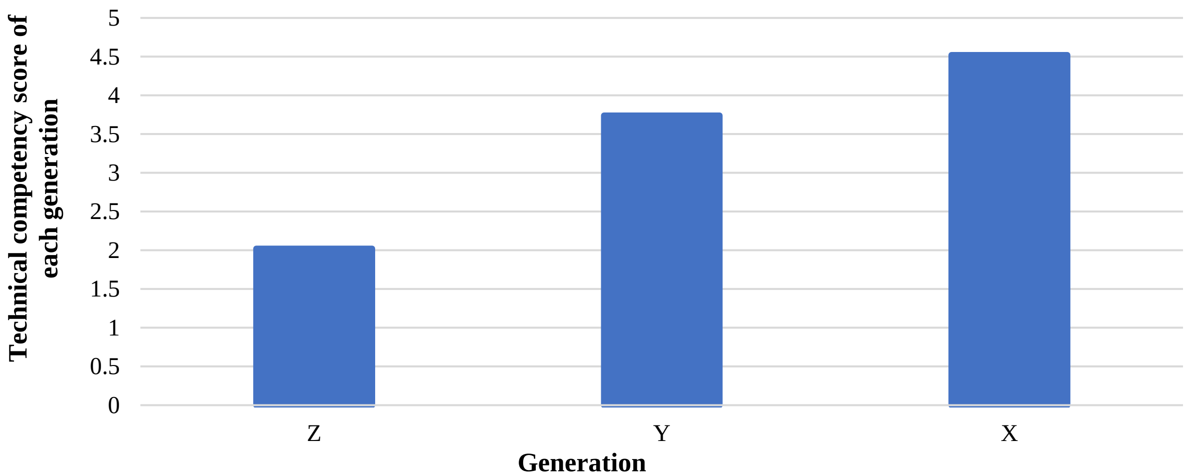

Figure 6. Technical competency score of each generation chart

Table (13) and Figure (7) describe each generation's mean assessed value of social competency score. Considering the results and the social competency sub-criteria such as virtual collaboration, generation Y has the highest mean value. Also, the score of Generation Z is slightly lower than the score of Y Generation due to less experience. In addition, generation X is located in the last position due to the age range and technological effects imposed at the time of their maturity. This result is qualitatively pointed out by [63], [64], [65], [66].

Table 13. Social competency score of each generation

Generation	**Score**
Z	3.82
Y	4.1
X	3.01

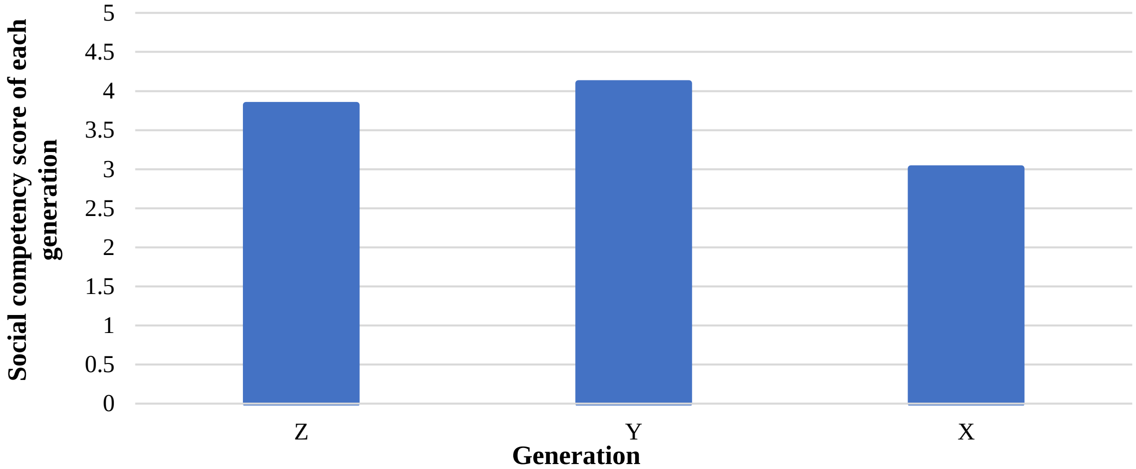

Figure 7. Social competency score of each generation chart

The research investigates virtual collaboration as one of the most crucial factors in new PTs. Table (14) and Figure (8) compare each generation's mean virtual collaboration assessment value. According to the results, generation Y has the highest virtual collaboration competency score, and Generation Z is close to it. The results imply that the new generations have almost 1.3 more competence scores. Although younger people are more involved with virtual tools [63], [64], generation Y makes optimum virtual tools to perform work due to more experience in teamwork and communication. Furthermore, generation X has the lowest score due to the age range and low level of virtual technological effects they experienced during their working lives [63], [64], [65], [66]. In the study, the parking can be performed remotely, so more new generations are selected than the hotel project.

In addition, Table (15) and Figure (9) display the average score of personal competencies in each generation. Considering the results and the related sub-criteria such as problem-solving, generation X, with more experience, scored higher. Also, older people are more loyal and compatible with the work environment, which means they have procedural thinking. However, younger people seek more freedom in the workplace and have less loyalty [63], [64], [65], [66]

Regarding Table (16), which represents the average cost of each generation, the average salary of older generations is higher than other ones due to their work experience as expected. Figure 10 also shows the average cost as well as a share of each generation from the company's human resources budget.

In comparison with Rahmanniyay and Yu (2019), our study expands upon the existing literature by incorporating several novel features, including an innovative competency framework aligned with Industry 4.0 and post-COVID-19 dynamics, a generational analysis of competency profiles, and a practical MCDM-MODM framework for decision-makers in PBOs. Unlike previous studies that primarily focused on either competency or cost optimization, our approach simultaneously optimizes both dimensions, offering decision-makers a comprehensive tool for project team formation. Furthermore, our study's integration of contemporary workforce dynamics and consideration of generational diversity contribute to a deeper understanding of project team dynamics in matrix-structured PBOs. Overall, by comparing our findings with Rahmanniyay and Yu (2019) and other relevant literature, we aim to provide valuable insights into the effectiveness and applicability of different modeling approaches in project team formation.

Table 14. Virtual collaboration score of each generation

Generation	Score
Z	4.34
Y	4.43
X	3.11

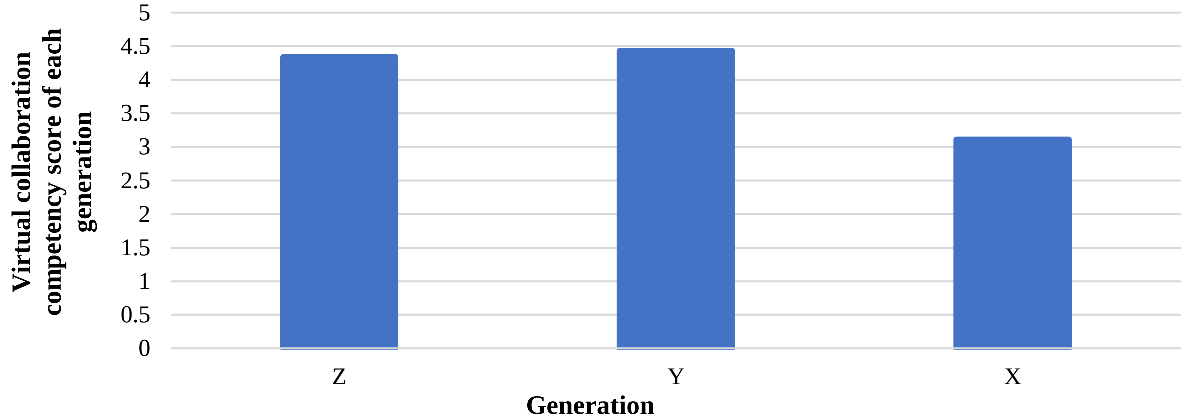

Figure 8. Virtual collaboration score of each generation chart

Table 15. Personal competency score of each generation

Generation	Score
Z	2.94
Y	3.65
X	3.78

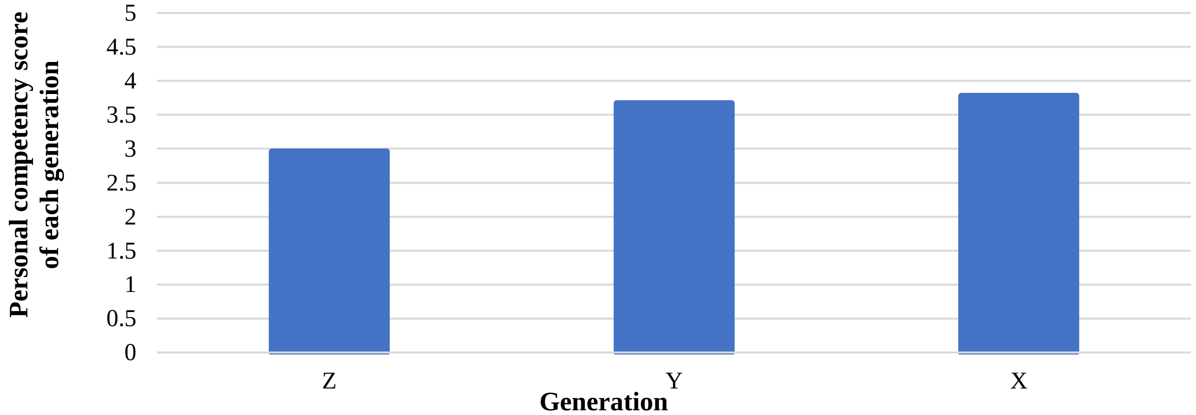

Figure 9. Personal competency score of each generation chart

Table 16. The average cost of each generation

Generation	Average cost ($/day)
Z	3.23
Y	4.46
X	6.78

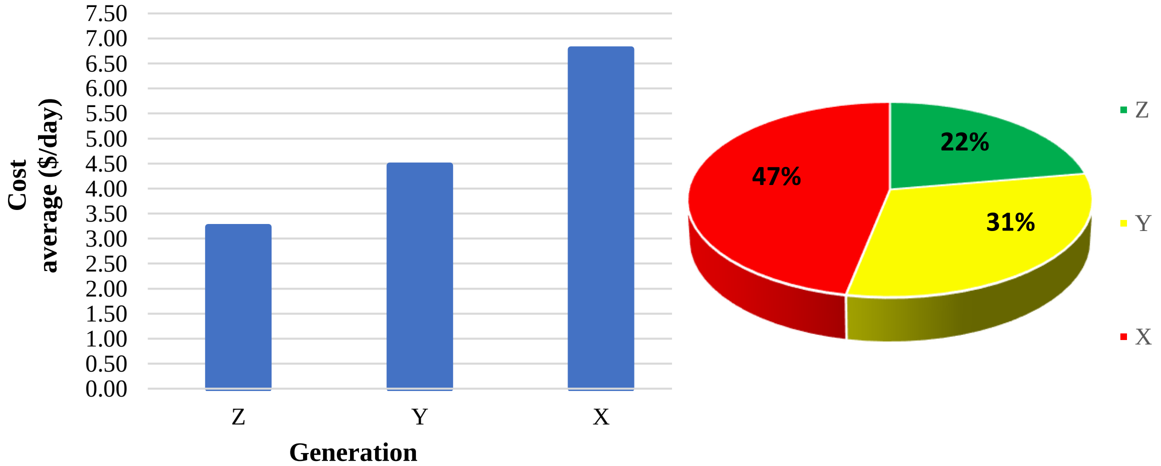

Figure 10. The average cost of each generation

Sensitivity Analysis

In this section, we perform a sensitivity analysis to assess the robustness of our bi-objective allocation model and investigate the impact of variations in key parameters on the optimization outcomes.

We systematically vary selected parameters within realistic ranges based on empirical data and model assumptions. The parameters considered for sensitivity analysis include:

i. Competency scores of candidates
ii. HR costs associated with candidates
iii. Number of human assets required for projects

Table 17. Sensitivity Analysis Results

Parameter	Base Value	Lower Bound	Upper Bound	Sensitivity Analysis Results
Competency Scores	3	1	5	Higher competency scores lead to increased total competency levels. However, overly stringent requirements may limit candidate selection.
HR Costs/ day	$5	$3	$7	Lower HR costs reduce project expenses but may compromise candidate quality and project outcomes.
Number of Human Assets	10	8	12	Adjustments in required human assets affect team composition and resource allocation, influencing project performance.

The sensitivity analysis underscores the trade-offs inherent in project team selection. Variations in competency scores highlight the balance between achieving higher competency levels and maintaining a diverse candidate pool. Similarly, adjustments in HR costs demonstrate the impact of financial considerations on project outcomes.

Furthermore, changes in the number of human assets required for projects emphasize the importance of resource allocation in project management. By optimizing team composition based on resource availability, organizations can enhance project performance while controlling costs.

Overall, integrating insights from the sensitivity analysis into decision-making processes enables organizations to make informed choices that align with their strategic objectives and resource constraints.

Managerial Insight

Assigning human resources to the PTs remains an ongoing challenge for human resource managers after investigating matrix-structured PBOs. The current research provides a comprehensive picture for DMs to assign employees to PTs optimally, taking into account costs and competencies simultaneously. The budget for human resources and the number of available individuals is factored into the decision-making process. Additionally, candidates may be skilled in one project but not proficient in another. As a result, a practical framework is proposed for DMs in project-based organizations. Regarding the numerical results, the DMs whose strategy is to progress the project with a high level of quality can select the people with more competency scores; therefore, 7.1% more expenditure should be spent.

4IR and the post-COVID-19 conditions have created new requirements for PTs, as previously mentioned. Alternatives were explored by the research to help DMs choose the best PT members. The PT's resilience can be enhanced by considering new necessities. The results provide a comprehensive picture of how to choose the best combination among different generations. If procedural thinking and job experience are more important than new skills related to technology, the older generation could be the best choice. In organizations that rely on virtual collaboration, the younger generation may be the ideal choice. Overall, a combination of different age groups is the most appropriate alternative for DMs, which is why the strengths of each generation could cover others' weaknesses according to the project's requirements.

Conclusion

The combination of PTs is crucial in achieving project goals. Allocating human assets to the project teams depends on the competency and cost of human assets. Additionally, 4IR has made significant improvements to projects. In the future, PTs will comprise a mixture of human and robot members interacting with each other. For this reason, this research updated the competency criteria based on 4IR. Furthermore, due to the severity of the post-COVID-19 conditions and forcing people to remain at home by governments, a wide range of evolution has been made in peoples' methods of communication. In this research, a six-step methodology is proposed to address these issues. To allocate candidates and balance cost and competency levels, a two-objective model was developed.

This study's results, which are approved by the literature, indicate that there is a direct link between competence and cost. The more the organization demands to perform its project with higher quality, the more competent personnel it will need. In this manner, it is required to pay more. According to the understudied case, if the organization requires the highest level of competency, it should expect to increase expenses by 7.1%. 4IR states that PTs are made up of different generations who can complete their competencies. Competency profile and generation type determine the strengths and weaknesses of each individual. Older people have more experience and procedural thinking than new generations; However, the results imply that the new generation's competence score is more than the older generation's score, by almost 1.3 in terms of virtual communication, which means they can be selected for remote work.

Overall, the research assists DMs in PBO in selecting an effective combination of human assets to make a trade-off between the competency and cost of human resources by considering 4IR and post-COVID-19 conditions.

In conclusion, our study employed a model-driven approach to investigate the relationship between age and virtual communication competence within project teams. While initial assumptions suggested higher competence scores among younger individuals, our analysis revealed nuanced findings, with older individuals also demonstrating proficiency in certain aspects of virtual communication. These contradictory results underscored the complexity of the relationship between age and competency in virtual communication, highlighting the importance of empirical validation. By contributing empirical evidence to inform discussions on this topic, our study enriches the scholarly discourse and underscores the value of model-driven analysis in uncovering nuanced insights.

As part of future studies, parameters such as the cost of human resources and the number of available individuals could be considered uncertain. The competency framework could incorporate other criteria that are based on agile HRM. Additionally, alternative decision-making methods, such as the Flexible and Optimized Criteria in Use of Methods (FOCUM), could be explored to enhance the robustness of the decision-making process. In the end, the proposed framework can be examined in complicated cases that have a vast array of data for competency criteria, candidates, and projects. By using metaheuristics, we can find near-optimal solutions in a reasonable time.

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