Team Formation for Human-Artificial Intelligence Collaboration in the Workplace: A Goal Programming Model to Foster Organizational Change

Davide La Torre, Cinzia Colapinto, Ilaria Durosini, and Stefano Triberti

***Abstract*—The need for preparing for digital transformation is a recurrent theme in the recent public and academic debate. Artificial Intelligence (AI) has the potential to reduce operational costs, increase efficiency, and improve customer experience. Thus, it is crucial to forming project teams in an organization, in such a way that they will welcome AI in the decision-making process. The current technological revolution is demanding a rapid pace of change to companies and has increased the attention to the role of teams in fostering innovation adoption. We propose an innovative multicriteria model based on the goal programming approach for solving the optimal allocation of individuals to different groups. The model copes with human resources' cost and human–machine trust. Indeed, we propose an aggregated measure of the attitude towards AI tools to be employed to support tasks in an organization: more precisely our index is based on three dimensions: technology acceptance, technology self-efficacy, and source credibility. By incorporating this index in a team formation model, each team can be guaranteed to have less resistance to change in adopting machine-based decisions, a scenario that will characterize the years to come. The proposed index can also be integrated into more complex and comprehensive models to support business transformation.**

***Index Terms*—Artificial intelligence (AI), goal programming (GP), multiple criteria decision-making (MCDM), team formation, technology acceptance, organizational change, innovation drivers.**

I. Introduction

The so-called "fourth industrial revolution" based on a disruptive set of digital technologies is rapidly and radically altering industries, governments, people, markets, businesses, and definitely decision-making processes. Since 2000, the emergence of a diverse set of new powerful digital technologies and platforms has transformed both innovation and entrepreneurship in significant ways with broad organizational implications [1]. Previous researchers [2] have shown that Small and Medium-size Entreprise (SMEs) competitiveness rely on innovation and the human dimension. Team formation has strong effects on organizational performance; as a result, it has become a more and more critical issue: specific skills and attitudes have to be considered especially in the current digitization shift that is affecting business models. In this paper, we introduce a new aggregated criterion T which models the human–machine interaction and the trust of a certain individual to replace humans by machines in the decision-making process: it is a good proxy to support a diverse and technology-oriented team formation process. We then embed this criterion into a multiple criteria decision-making (MCDM) model for team formation which simultaneously takes into account two different criteria, T and the monthly salary, respectively.

The paper is organized as follows. Section II reviews the extant literature about team formation. In Section III, we recall the most important facts in multiple criteria decision analysis (MCDA) and goal programming (GP). Section IV introduces our approach based on a combination of three existing attitude theories; indeed, it presents a new index to measure human–machine interaction to be considered in the process of team formation. Section V is devoted to present the team formulation model and its general properties. Section VI illustrates how the model works in practical contexts, and Section VII concludes this article.

II. Role and Challenges of Team Formation

The importance of teams has been largely recognized in management and entrepreneurship research since the early 1980s [3]. Considering the extant literature, it is clear that the study of teams is crucial for different reasons: in primis team members constitute a newborn organization's most valuable asset and the members' personalities, skills, and social capital have a profound impact on the company performance [4], [5]. This element is reaffirmed by the fact that investment decisions depend heavily on the entrepreneurial team members' profiles [6]. Also,

Manuscript received 29 November 2020; revised 27 February 2021 and 10 April 2021; accepted 25 April 2021. Date of publication 26 May 2021; date of current version 17 March 2023. Review of this manuscript was arranged by Department Editor F. Ferreira. (*Corresponding author: Cinzia Colapinto*.)

Davide La Torre is with the SKEMA Business School, Université Côte d'Azur - Sophia Antipolis Campus, 06902 SOPHIA ANTIPOLIS CEDEX, France (e-mail: davide.latorre@skema.edu).

Cinzia Colapinto is with Department of Management, Ca' Foscari University, San Giobbe, Cannaregio 873, 30121 Venezia, Italy (e-mail: cinzia.colapinto@unive.it).

Ilaria Durosini is with the Applied Research Division for Cognitive and Psychological Science, IEO, European Institute of Oncology IRCCS, via Giuseppe Ripamonti 435, 20141 Milan, Italy (e-mail: ilaria.durosini@ieo.it).

Stefano Triberti is with the Applied Research Division for Cognitive and Psychological Science, IEO, European Institute of Oncology IRCCS, via Giuseppe Ripamonti 435, 20141 Milan, Italy, and also with the Department of Oncology and Hemato-Oncology, University of Milan, via Festa del Perdono 7, 20122 Milan, Italy (e-mail: stefano.triberti@unimi.it).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TEM.2021.3077195.

Digital Object Identifier 10.1109/TEM.2021.3077195

in mature organizations, many decisions are rarely made by individuals as employees spend significant time working in one or more teams [7], [8]. Company's members are organized in teams and/or departments, and whether such organized teams and departments function as intended, will impact on the performance of the entire organization [9]. It is well known that teams are special types of groups, as teams rely more on discussion, debate and decision, sharing information, and best practice.

The challenge in team formation resides in many factors, also because it is a process that occurs in a social space where political, cultural, and scientific interests interact, creating a dynamic series of tradeoffs. Moreover, some projects require high specialty in specific areas, whilst others will achieve good results only by maximizing workforce diversity. The evaluation of team members is conducted by defining their abilities and attitudes. In many studies [10], the abilities of the candidates are evaluated in the general aspect of Human Resource Management, thus they lack the evaluation for specific characteristics required for a specific project.

Indeed, different authors focused on different criteria to be used in the team formation process, such as technical knowledge, teamwork experience, personal characteristics, communication skills, culture, leadership, and motivation in selecting the project team members [10]–[12]. For instance, according to Katzenbach and Smith [13], team members must have three different types of skills to achieve effectiveness, namely technical/functional expertise, problem-solving and managerial skills, and interpersonal skills. Chung and Guinan [14] expressed that experience increases team performance.

Great attention was also paid to the collaboration and synergy among team members, the existence of cohesion or conflict, or team climate: authors tried to indicate how to minimize incompatibilities [15] or maximizing synergy. On the latter, we can cite Yang and Tang [16] who tried to determine the index of cohesion in terms of the reciprocally positive (or negative) relationships among team members.

Other researchers tried to study knowledge as the main variable to support team formation. For instance, Wi *et al.* [17] presented a framework for analyzing the knowledge competencies of the candidates for team members for a new team and considered collaborative capabilities of the members: they proposed a genetic algorithm and social network measures for choosing a team manager and team members.

This article does not focus on skills or competencies but intends to consider the intention to use technology in a team. We look at the attitude to welcome the shift from human-based to machine-based decision-making process. Indeed, we integrate an index to measure the factors underlining this attitude in a weighted GP model.

III. Multi-Criteria Decision Making and GP

As stated by Meyer [18], multiple goals are the predominant reality of organizational life. Indeed, managers and entrepreneurs are frequently challenged with complex decision-making situations which involve several, and often conflicting, objectives and priorities. MCDA offers effective techniques that can be used to obtain candidate solutions among different criteria. The spurt in the growth of modeling and computational ease has made GP a popular MCDA technique to deal with challenges implying conflicting criteria. Several GP techniques have been used to study applications spanning from budget allocation to scheduling, and in many areas, from marketing and quality control to production and Human Resources (i.e., [19]). We refer the readers to extant reviews [20], [21] and books [22], [23] highlighting different GP model variants with several applications.

Let us consider a classical MCDA framework, where there are conflicting criteria $F_1, F_2, \ldots, F_p$ that have to be maximized or minimized simultaneously. One of the simplest models to deal with the complexity of this decision analysis context is the GP model, first introduced by Charnes and Cooper [24] and Charnes *et al.* [25]

$$\text{Min} \sum_{j=1}^{p} \alpha_j^+ D_j^+ + \alpha_j^- D_j^- .$$

Subject to:

$$F_j\left(X_1, X_2, \ldots, X_n\right) - D_j^+ + D_j^- = G_j \;\; j = 1 \ldots p$$

$$X = \left(X_1, X_2, \ldots, X_n\right) \in \Omega$$

$$D_j^-, D_j^+ \geq 0 \; j = 1 \ldots p$$

$$X_i \geq 0 \; i = 1 \ldots n$$

where X_i are the decision variables, and D_i^- and D_i^+ are the negative and positive deviations with associated negative and positive weights α_i^- and α_i^+, respectively. The letters G_i, $i = 1, \ldots, p$ describe the aspirational goal levels while Ω is the feasible set. Several different variants of this basic formulation have been introduced over the years (see i.e., [20]).

The GP model is preferable as a manager is often not interested only in minimizing or maximizing a specific criterium, but he/she looks for the best compromise among conflicting criteria. We present a weighted GP (WGP) that allows the manager to set weights in line with the needs and the strategic goals of the organization. If a firm is interested in transforming its decision-making process extensively by adopting black-box solutions generated by machines, the manager can increase the weight associated with the human–machine criterium and/or settle a different (much higher) goal in terms of the human–machine trust. A more sophisticated way to include the preferences and judgments of the decision maker (DM) is to refer to the concept of satisfaction function (SF) developed by Martel and Aouni [26]. In general, an SF satisfies the following property

1. SF takes values in [0,1];
2. SF(0) = 1, that is the satisfaction is maximum when a criterion is achieving its goal;
3. SF is monotonically decreasing according to the DM's appreciation of the achievement level of each objective;

4. SF is equal to zero for all deviation values greater than the veto threshold.

The GP model with SF takes the form

$$\text{Max} \sum_{j=1}^{p} \alpha_j^+ \text{SF}\left(D_j^+\right) + \alpha_j^- \text{SF}\left(D_j^-\right).$$

Subject to:

$$F_j\left(X_1, X_2, \ldots, X_n\right) - D_j^+ + D_j^- = G_j \;\; j = 1 \ldots p$$

$$X = \left(X_1, X_2, \ldots, X_n\right) \in \Omega$$

$$0 \leq D_j^- \leq \Delta_j^- \; j = 1 \ldots p$$

$$0 \leq D_j^+ \leq \Delta_j^+ \; j = 1 \ldots p$$

$$X_i \geq 0 \; i = 1 \ldots n$$

where Δ_j^+ and Δ_j^- are the positive and negative thresholds.

As mentioned above, GP models have been used in strategic planning and human resource management. There exists a wide literature presenting GP models to solve scheduling problems. For instance, Lee and Kwak [27] propose a GP model to support the planning functions of resource allocation in the healthcare organizations; and Cetin and Sarucan [28] introduce a binary fuzzy GP model for nurse scheduling problems. GP is also employed to assist human resource managers in identifying a promotion policy [29]. Additionally, a fuzzy GP model is introduced for allocating tasks to employees in teamwork [30]. In this article, we propose a WGP model to support the team formation process considering the attitude toward technology.

IV. Addressing the Black Box Problem: A New Measure for Users' Attitude

Employees often approach Artificial Intelligence (AI) initiatives with mixed feelings as the emergence of AI will transform the nature of work and the relationship between human beings and machines in all enterprises. The main issue at stake here is to optimize productivity and reliability of work processes featuring AI. Neural networks break large computation problems into millions or billions of pieces and then advance step by step. Deep learning uses calculations. A model can reach a correct conclusion via a path that has nothing to do with what would be, for us, a human-like view of the problem which includes expertise and intuition, emotions, and heuristics [31]. One may think this is not an issue given that a correct and viable solution to the problem is reached. Yet, this conception disregards the fact that work processes featuring AI solutions are grounded in real-life work contexts. Being AI used in medicine and healthcare, the military or business, problem solving, and especially implementation of the solutions holds consequences for people's real life and career. For example, if we focus on the health and care industry, doctors may incur controversies and legal actions because of their decisions, a phenomenon which has considerably risen in the last decades. Furthermore, while we are getting encouraging data about the utility of AI for diagnosis and identification of treatment, we still do not know how the inclusion of AI in the medical process may influence the doctor–patient relationship. Recent contributions have begun to hypothesize some possible influences of AI on the patient–doctor relationship, highlighting that

1) clinical decisions could be paralyzed or delayed when artificial entities' recommendations are difficult to explain or to understand to patients;
2) patients' symptomatology or diagnosis could be misinterpreted when adapted to AI classifications;
3) AI can cause confusion about roles and about "who really has authority" in patient's perception [32].

For this reason, AI users need certainty in order to make decisions based on AI's elaborations. Certainty is a psychological issue, which has an indefinite relation with a tool's functionality, while it is influenced by the user's *subjective perception* of the reliability and validity of the tool. For example, the huge research field of technology acceptance demonstrated that the best predictors of intention to use technology are perceived utility and perceived easiness of use, that in turn are determined by a number of individuals (e.g., expertise, personality, pre-existent intentions) and contextual factors (e.g., social norm and peer influence) [33]–[35].

It is possible to identify three main approaches to this issue across the literature. The first one is eXplainable AI (XAI), or the interdisciplinary effort to develop AIs able to present their computational outcomes in a transparent and understandable fashion [36], [37]. While the term exists since the 1970s, recently XAI became of particular interest regarding the rise of AI solutions in many professional contexts, and it has been associated with the social sciences more than with the technical capabilities of AI tools [36]. Future XAI will benefit more and more of cognitive science and philosophical research focused on understanding what is an effective explanation within human users' perception, in order to optimize AI implementation. Within this approach, future AI may benefit from user experience research to analyze and improve user-AI interface.

A second approach regards marketing [38]. Trust and transparency are issues that put at risk the effectiveness of AI on the market. It is well known that consumers often use tools they do not really know how they work, holding some mental representation of the tool's functioning which has little or nothing to do with the representation of the designer or engineer [39]. Marketing is able to build and influence consumers' trust in products and services by strategic use of communication techniques [40], [41], independent of their actual understanding of how the tool works. For this reason, it is possible that marketing will be used to convince people they could trust AI solutions and to reduce their concerns. This approach to the trust issue is probably the most controversial because it does not really address the problem but aims to just annihilate it in users' attitudes by strategic persuasion.

The third approach is the one employed in the present contribution. Without disregarding the importance of XAI, managers and DMs involved in AI implementation should be able to employ the best human resources combination possible to deal with AI-mediated work tasks, taking into consideration their attitudinal and cognitive predispositions to the job. Exactly like managers analyzing the ability to work in a team or manage diversity within job candidates [42], [43], they could be interested in having a glimpse about employers' attitude toward AI solutions they are supposed to use to make important decisions. However, an objective and synthetic measure of employers' ability to work productively with AI does not exist. For the sake of computation and GP, we propose a measure created by aggregating multiple factors that, according to literature, contribute to determine users' ability to positively approach the AI tool and to work productively with it. According to literature, attitudes toward technology are relevant to develop the intention to use it. Attitude is a broad construct in psychology that often refers to subjective and declared opinions on something that could be quantified [44]. It should be said that such aggregated measure does not aim to be a complete rendition of all possible individual and contextual factors that affect users' attitude and ultimately behavior, nor has it undergone a deep evaluation from a psychometric point of view. However, we propose it as a testing ground for the idea to "conflate" multiple factors in a single formula which at least partially represents relevant psychological factors. We identify three main groups of relevant attitudes:

1) **Technology acceptance:** Based on the theory of social psychology, the Technology Acceptance Model (TAM) [45] suggested the attitude– intention–behavior causal relationship for explaining and predicting technology acceptance among potential users. The TAM proposes that the individual's attitude toward technology is determined by its perceived usefulness and its perceived ease of use, which, in turn, determine the user's intention to use. Davis *et al*. [46] highlighted that the perceived usefulness of technologies is the degree to which people believe that using the technology will enhance their performance, while the perceived ease of use is the degree to which people believe that using technology will be free of effort. The TAM has been developed further in a number of studies [47], including additional predictors. One of them is peer influence, in that social pressure or influence also affects the intention to use the technology within the organization. Employees will be asked to rate their acceptance of technology they are supposed to use on the job through three items resembling the dimensions of TAM (e.g., I would find the technology useful in my job; I would find the technology easy to use; My colleagues encourage me to use the technology);
2) **Technology self-efficacy:** Technology self-efficacy can be defined as the individual's perception of their ability to apply new technologies for specific aims [48]. People with high technology-related self-efficacy are able to understand what technologies are capable of and, consequently, use them proficiently and make intelligent decisions about which technology to use and when to use it. Employees' technology self-efficacy could be explored through three items (e.g., I am quite an expert in new technologies; I consider myself proficient in the usage of this technology or very similar ones; I feel confident in my ability to use the technology on the job)
3) **Source credibility:** People can evaluate the credibility of artificial entities prior to or when interacting with them. This relates to the concept of source credibility, typical of marketing and advertising research. Source credibility is an antecedent of the persuasiveness of communication [49], [50] and can be based on how attractive, expert, and reliable AI appears to the users. Employees will be asked to rate the technology they are supposed to use on the job, after a presentation or first experiences of use, on three adjectives resembling the components of source credibility, e.g., how much do you think the technology is attractive/pleasant, trustworthy/reliable, expert/competent.

To reach an integrated measure of users' global attitude toward AI tools, we propose that the scores from the three variables (three questions each) are summed to obtain a single general index, which takes into consideration users' acceptance of the technology (perceived utility, perceived easiness of use, peer influence), users' attitude toward their own proficiency with the technology (technology self-efficacy), and source credibility attributed to the specific tool. Being the items rated on a 1–5 Likert scale, each individual variable could range between 3 and 15, while the total score of the "attitude index" could range between 9 and 45 (the attitudes and questions to analyze them are resumed in Fig. 1).

V. Model Formulation

We suppose to have $X_1, \ldots, X_N$ individuals, each of them has an associated cost (monthly salary) S_i, $i = 1, \ldots, N$, and an associated level of the index T_i, $i = 1, \ldots N,$. We want to form M groups and, for each group, we need to achieve a goal for the cost and the group level of T.

Let x_{ij} be the input variables, $i = 1, \ldots, N$, $j = 1, .., M$. In the sequel $x_{ij} = 1$ is the individual i assigned to the group j, and 0 otherwise.

The first model we consider is a weighted GP model that simultaneously considers the two different criteria as follows:

$$\text{(O) Min} \sum_{j=1}^{M} \alpha^+ CD^+ + \alpha^- CD^- + \beta^+ TD^+ + \beta^- TD^-.$$

Subject to:

$$\text{(C1)}\ \frac{\sum_{i=1}^{N} C_i \cdot x_{ij}}{\sum_{i=1}^{N} x_{ij}} - CD^+ + CD^- = g^C$$

$$\text{(C2)}\ \frac{\sum_{i=1}^{N} T_i \cdot x_{ij}}{\sum_{i=1}^{N} x_{ij}} - TD^+ + TD^- = g^T$$

$$\text{(C3)}\ \sum_{i=1}^{N} x_{ij} = g_j\ j = 1 \ldots M$$

Fig. 1. Trust index components with possible questions to use to analyze relevant attitudes.

$$\text{(C4)}\ \sum_{j=1}^{M} x_{ij} = 1\ i = 1, \ldots, N$$

$$\text{(C5)}\ CD^{+}, CD^{-},\ TD^{+}, TD^{-} \geq 0\ j = 1, \ldots, M$$

$$\text{(C6)}\ x_{\text{ij}} \geq 0 \text{ and integer } i = 1, \ldots, N,\ j = 1, \ldots, M$$

where

1) the objective function in (O) takes into consideration the weighted sum of all criteria with respect to their goals. The DM aims at minimizing the difference between each achievement level and the corresponding goal.
2) the constraint (C1) measures, for each group, the distance between the average level of salary and the corresponding group goal;
3) the constraint (C2) describes, for each group, the distance between the average level of index T and the corresponding group goal;
4) the constraint (C3) defines, instead, the group capacity in terms of team members;
5) the expression (C4) models the fact that each person is assigned to only one group (exclusivity);
6) inequalities (C5) and (C6) are sign constraints, which state that each variable in the model must be positive.

The second model, instead, utilizes the notion of SF. The model reads as

$$\text{(SO)}\ \text{Max}\ \sum_{j=1}^{M} \alpha_j^{+} \text{SF}\left(CD_j^{+}\right) + \alpha_j^{-} \text{SF}\left(CD_j^{-}\right) + \beta_j^{+} SFF\left(TD_j^{+}\right) + \beta_j^{-} SFF\left(TD_j^{-}\right).$$

Subject to

$$\text{(SC1)}\ \frac{\sum_{i=1}^{N} C_i \cdot x_{ij}}{\sum_{i=1}^{N} x_{ij}} - CD_j^{+} + CD_j^{-} = g_j^{C}\ j = 1 \ldots M$$

$$\text{(SC2)}\ \frac{\sum_{i=1}^{N} T_i \cdot x_{ij}}{\sum_{i=1}^{N} x_{ij}} - TD_j^{+} + TD_j^{-} = g_j^{T}\ j = 1 \ldots M$$

$$\text{(SC3)}\ \sum_{i=1}^{N} x_{ij} = g_j\ j = 1 \ldots M$$

$$\text{(SC4)}\ \sum_{j=1}^{M} x_{ij} = 1\ i = 1 \ldots N$$

$$\text{(SC5)}\ CD_j^{+}, CD_j^{-},\ TD_j^{+}, TD_j^{-} \geq 0\ j = 1 \ldots M$$

$$\text{(SC6)}\ x_{ij} \geq 0 \text{ and integer } i = 1 \ldots N,\ j = 1 \ldots M$$

$$\text{(SC7)}\ CD_j^{+}, CD_j^{-} \leq \Delta_F\ j = 1 \ldots M$$

$$\text{(SC8)}\ TD_j^{+}, TD_j^{-} \leq \Delta_{FF}\ j = 1 \ldots M$$

where SF and SFF are the SFs related to the first and second criterion, respectively and Δ_F and Δ_{FF} are the corresponding veto thresholds.

VI. Illustrative Examples

In this section, we present a numerical illustrative example implemented in LINGO. We suppose to have the following data (Table I) collected from a group of $N = 10$ persons. In the first model below, Model I, we propose a GP model in which we aim at forming a group of 5 people (out of 10) with a specified level of group cost and trust. In the second model, Model II, we propose a GP model to allocate all 10 people to two different groups of five people each.

A. Model 1

In the first numerical example, we are interested in the case in which we form only one group of five people, that is $M = 1$ and $g_1 = 5$. In this context, the DM aims at forming a group of level of trust in the human–machine interaction equals $g_1^T = 30$, which means a goal in the upper part of the (9–45) scale. This value implies a propensity to welcome innovation and change in the decision-making process. Regarding the cost, it is assumed an average monthly salary of 6000 euros. We also suppose that

TABLE I
MODEL DATA

ID Number	Acceptance (3-15)	Self-Efficacy (3-15)	Source Credibility (3-15)	T Index (9- 45)	Gross Monthly Salary (Euros)
P1	15	12	11	38	15,000
P2	10	9	12	31	15,000
P3	7	10	9	26	12,000
P4	11	10	9	30	9,000
P5	8	9	10	27	9,000
P6	7	13	8	28	6,000
P7	9	8	9	27	5,000
P8	11	5	5	21	4,000
P9	10	5	5	20	3,000
P10	6	7	7	20	1,000

all weights α^+, $\alpha^-\beta^+$ β^- are normalized to 1. In other words, we do not include preferences in this model, each criterion has the same relevance for the DM.

The model we are interested in solving is listed below. The objective function takes a simple form as it is just the linear combination of the positive and negative deviations. The first two constraints model the gap minimization between the achievement levels of team cost and team trust, respectively. The third constraint, instead, limits the number in the team to five. Finally, the last one states that all variables must take boolean values. A decision variable is flagged to 1 if the corresponding person belongs to the group, 0 otherwise.

The model reads as follows:

$$\mathrm{Min} \cdot CD^+ + CD^- + TD^+ + TD^-.$$

Subject to:

Group cost: 0.2∗(15000∗X1+15000∗X2+12000∗X3 +9000∗X4+9000∗X5+6000∗X6+*5000*∗X7+4000∗X8+3000 ∗X9+1000∗X10) $- CD^+ + CD^- = 6000$;

Group trust: 0.2∗(38∗X1+31∗X2+26∗X3+30∗X4+27∗X5 +28∗X6+27∗X7+21∗X8+20∗X9+20∗X10)$-TD^+ + TD^- = 30$;

Maximum team members: X1+X2+X3+X4+X5+X6 +X7+X8+X9+X10 = 5;

Integer constraints: X1, X2, X3, X4, X5, X6, X7, X8, X9, X10 ϵ {01}.

The model has been solved using LINGO 18 and it provides the following optimal solution X1 = 1, X6 = 1, X7 = 1, X9 = 1, X10 = 1 while all other variables are set to zero (these individuals have not be selected to be included in the group). In terms of the deviations, we have $C\ D^+ = C\ D^- = T\ D^+ = 0$ and $T\ D^- = 3.4$. This means that the achieved average group attitude is equal to 26.6, that is, 3.4 levels below the goal that has been set to be equal to 30. One of the reasons for this result has to be found in the goal for the average group salary that is equal to 6000 euros: the salary is a proxy of educational background and skills of an individual. In order to get a better result for the group attitude, let us set a greater value for the average group salary, for instance, equal to 8000 euros. The model we are going to solve reads as

$$\mathrm{Min} \cdot CD^+ + CD^- + TD^+ + TD^-.$$

Subject to:

Group cost: 0.2∗(15000∗X1+150005∗X2+12000∗X3+ 9000∗X4+9000∗X5+6000∗X6+5000∗X7 +4000∗X8+3000∗X9+1000∗X10) $- CD^+ + CD^- = 8000$;

Group trust: 0.2∗(38∗X1+31∗X2+26∗X3+30∗X4+27∗ X5+28∗X6+27 ∗X7+21∗X8+20∗X9+20∗X10)$-TD^+ + TD^- = 30$;

Maximum team members: X1+X2+X3+X4+X5+X6+ X7+X8+X9+X10 = 5;

Integer constraints: X1, X2, X3, X4, X5, X6, X7, X8, X9, X10 ϵ {01}.

In this case, LINGO 18 shows the following optimal solution X1 = 1, X4 = 1, X5 = 1, X6 = 1, X10 = 1 while all other variables are set to zero (not selected). In terms of the deviations, we have $C\ D^+ = C\ D^- = TD^+ = 0$ and $T\ D^- = 1.4$. As expected, an increment in the salary goal provides a different allocation of people in the team and, therefore, a better human–machine collaboration attitude result.

B. Model 2

In this second numerical simulation, we allocate all 10 people in two groups. The model again can be formulated by means of GP and by specifying the trust and cost criteria for each group. We identify two different groups, namely a group characterized by greater openness toward change and the use of machine in decision-making. Indeed, Group 1 has been designed with a higher trust index (30) and with an average salary of 9000 Euros; whilst Group 2 will require a lower trust index (23) and an average salary equal to 4000 Euros.

The model reads as

$$\mathrm{Min} \cdot CD_1^+ + CD_1^- + TD_1^+ + TD_1^- + CD_2^+ + CD_2^- + TD_2^+ + TD_2^-.$$

Subject to:

Group 1 cost: 0.2∗(15000∗X11+15000∗X21+ +2000∗X31+9000∗X41+ 9000∗X51+6000∗X61+ 5000∗X71+4000∗X81+3000∗X91+1000∗X101) $- CD_1^+ + CD_1^- = 9000$;

Group 1 trust: 0.2∗(38∗X11+31∗X21+26∗X31+30∗X41 +27∗X51+28∗X61 +27∗X71+ 21∗X81+20∗X91+20∗X101)$-TD_1^+ + TD_1^- = 30$;

Group 2 cost: 0.2∗(15000∗X12+15000∗X22+ +2000∗X32+9000∗X42+ 9000∗X52+6000∗X62+ 5000∗X72+4000∗X82+3000∗X92+1000∗X102) $- CD_2^+ + CD_2^- = 4000$;

Group 2 trust: 0.2∗(38∗X12+31∗X22+26∗X32+30∗X42 +27∗X52+28∗X62+27∗X72+ 21∗X82+20∗X92+20∗X102) $-TD_1^+ + TD_1^- = 23$;

Maxi group 1 members: X11+X21+X31+X41+X51 +X61+X71+X81+X91+X101 = 5;

Maxi group 2 members: X12+X22+X32+X42+X52 +X62+X72+X82+X92+X102 = 5.

Mutual exclusivity constraints:

$$\mathrm{X11} + \mathrm{X12} = 1$$

$$\mathrm{X21} + \mathrm{X22} = 1;$$

$$\mathrm{X31} + \mathrm{X32} = 1;$$

$$\mathrm{X41} + \mathrm{X42} = 1;$$

$$\mathrm{X51} + \mathrm{X52} = 1;$$

$$\mathrm{X61} + \mathrm{X62} = 1;$$

$$\mathrm{X71} + \mathrm{X72} = 1;$$

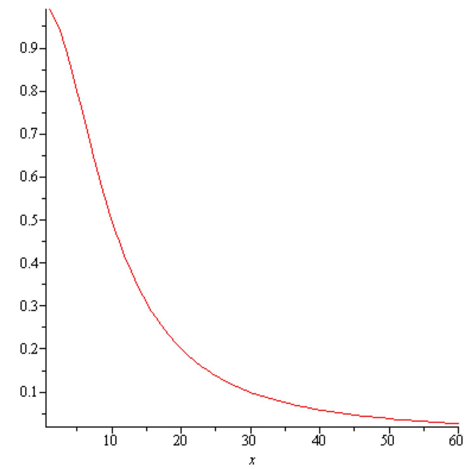

Fig. 2. SF shape.

$$\mathrm{X81} + \mathrm{X82} = 1;$$

$$\mathrm{X91} + \mathrm{X92} = 1;$$

$$\mathrm{X101} + \mathrm{X102} = 1.$$

Integer constraint: X11, X21, X31, X41, X51, X61, X71, X81, X91, X101, X12, X22, X32, X42, X52, X62, X72, X82, X92, X102 ϵ {01};

The solution provided by LINGO 18 shows that X11 = X21 = X31 = X41 = X61 = 1 and X52 = X72 = X82 = X92 = X102 = 1 which then implies that group 1 will be formed by P1, P2, P3, P4, P6, while group 2 by P5, P7, P8, P9, P10. The deviations are all zero except $C\ D_1^+ = 400$, $T\ D_1^+ = 6$, $C\ D_2^+ = 400$. All goals are almost achieved with the formation of two different groups. More precisely Group 1 will show a higher trust (equal to 36) with an increase in cost (average salary equals to 9400 Euros), which again reflects the positive impact of educational background and skills on the trust level; while Group 2 matches the trust goal but requires a higher average salary (4400 Euros).

C. Model 3

In this third numerical simulation, we still allocate all 10 people in two groups, and we introduce the notion of SF. Also this model can be formulated by means of GP and by specifying the trust and cost criteria for each group adding the DM preferences through the notion of SF. As SF, let us consider the following expression:

$$\mathrm{SF}\ (x) = \frac{1}{1+\rho^2 x^2}\ .$$

This function satisfies all properties identifying an SF (see Fig. 2) and it is trivial to verify that $\mathrm{SF}\ (0) = 1$, $\mathrm{SF}\ (+\infty) = 0$, $\mathrm{SF}''\ (x) = 0$ iff $x = \frac{1}{2\rho}$. This function shows a level of satisfaction between 90% and 100% when $0 \leq x \leq \frac{1}{3\rho}$ and a level of satisfaction between 0% and 10% when $x \geq \frac{3}{\rho}$. A natural candidate for the dissatisfaction threshold is $\Delta = \frac{3}{\rho}$

As in the previous example, we identify two different groups. Again Group 1 has been designed with a higher trust index (30) and with an average salary of 9000 Euros; whilst Group 2 will require a lower trust index (23) and an average salary equal to 4000 Euros.

The model reads as

$$\mathrm{Min} \cdot \mathrm{SF}(CD_1^+) + \mathrm{SF}(CD_1^-) + \mathrm{SF}(CD_2^+) + \mathrm{SF}(CD_2^-) + SFF(TD_1^+) + SFF(TD_1^-)$$

$$+SFF\left(TD_2^+\right) + SDF\left(TD_2^-\right).$$

Subject to:

Group 1 cost: 0.2∗(15000∗X11+15000∗X21+ +2000∗X31+9000∗X41+ 9000∗X51+6000∗X61+ 5000∗X71+4000∗X81+3000∗X91+1000∗X101) $- CD_1^+ + CD_1^- = 9000$;

Group 1 trust: 0.2∗(38∗X11+31∗X21+26∗X31+30∗X41 +27∗X51+28∗X61+27∗X71+ 21∗X81+20∗X91+20∗X101) $-TD_1^+ + TD_1^- = 30$;

Group 2 cost: 0.2∗(15000∗X12+15000∗X22+ +2000∗X32+9000∗X42+ 9000∗X52+6000∗X62+ 5000∗X72+4000∗X82+3000∗X92+1000∗X102) $- CD_2^+ + CD_2^- = 4000$;

Group 2 trust: 0.2∗(38∗X12+31∗X22+26∗X32+30∗X42 +27∗X52+28∗X62+27∗X72+ 21∗X82+20∗*X92*+20∗X102) $-TD_1^+ + TD_1^- = 23$;

Maxi group 1 members: X11+X21+X31+X41+X51+X61 +X71+X81+X91+X101 = 5;

Maxi group 2 members: X12+X22+X32+X42+X52+X62 +X72+X82+X92+X102 = 5.

Mutual exclusivity constraints:

$$\mathrm{X11} + \mathrm{X12} = 1$$

$$\mathrm{X21} + \mathrm{X22} = 1;$$

$$\mathrm{X31} + \mathrm{X32} = 1;$$

$$\mathrm{X41} + \mathrm{X42} = 1;$$

$$\mathrm{X51} + \mathrm{X52} = 1;$$

$$\mathrm{X61} + \mathrm{X62} = 1;$$

$$\mathrm{X71} + \mathrm{X72} = 1;$$

$$\mathrm{X81} + \mathrm{X82} = 1;$$

$$\mathrm{X91} + \mathrm{X92} = 1;$$

$$\mathrm{X101} + \mathrm{X102} = 1.$$

Integer constraint: X11, X21, X31, X41, X51, X61, X71, X81, X91, X101, X12, X22, X32, X42, X52, X62, X72, X82, X92, X102 ϵ {01}.

Veto constraints:

$$0 \leq CD_1^+,\ CD_1^-, CD_2^+,\ CD_2^- \leq \Delta_F$$

$$0 \leq TD_1^+, TD_1^-, TD_2^+, TD_2^- \leq \Delta_{FF}.$$

The DM expresses his/her own preferences by means of two SFs, namely SFF and SF. The first one is characterized by having set $\rho = 0.5$ which implies a veto threshold of $\Delta_{\mathrm{F}} = 600$ Euros: In this case, the DM has flexibility in achieving the goals related to the average group cost. We set $\rho = 1$ in the expression of the second SF which implies $\Delta_{\mathrm{FF}} = 3$ units. In this case, instead, the DM has no flexibility in achieving the goals related to the trust index and the DM gives more priority to the achievement of this goal by setting a small veto threshold. LINGO provides the following results: P1, P2, P5, P7, and P8 are assigned to group 1 while P3, P4, P6, P9, and P10 to group 2. The corresponding nonzero deviations are $CD_1^+ = 600$, $T\,D_1^+ = 0.4$, $C\,D_2^+ = 200$, $TD_2^+ = 3$. This optimal solution shows that almost all goals have been achieved. By introducing a system of preferences through the notion of SF, it is possible to differentiate between different goals and to assign different priorities to them. Indeed, we can observe that the DM can obtain a better compromise in terms of technology acceptance by achieving an optimal value much closer to the trust goal than in model 2 (total deviation in model 3 is 3.4 rather than 6 as in model 2).

VII. Discussion and Conclusion

Businesses decide to invest in technology for many reasons, among these we find: pressures to cut costs, to increase efficiency, and/or simply to improve the quality of services or products. What is evident is that digitalization is the inevitable end of any company in today's business world. Other specific contexts have a notable interest in developing high-level use of technology such as AI, for example, medicine: health professionals have to take complex decisions taking into account evidence, value, patient preferences, and personal attitudes [51]–[54]. Therefore, across multiple contexts, it is important to form teams able to realize this change process with the least cost and resistance.

In this contribution, we have proposed an index able to measure users' attitudes toward technology as the main component (or prerequisite) for optimal interaction within a team: the synergy or collaboration to achieve the organization's goals relying on AI to make decisions is explained at the light of three main components that create the index *T*. This should be considered the first step toward a more complex and systematic integration of psychological factors within team formation for human–AI collaboration. The index outlined here is not exempt from limitations: first, it is conceived as a mere sum of attitudes toward technology in general, one's own proficiency with it, and the specific tool to be employed. While the importance of these attitudes is widely demonstrated across the literature, and the sum of three different constructs has been adopted for the sake of computational simplification, further research is needed within the field of human-AI interaction to better identify their specific value and, therefore, attribute different weights to each criterium for effective team formation. Second, many psychological factors could of course influence team effectiveness as well as interaction with technology. It could be interesting for future models to integrate other relevant factors besides explicit attitudes, such as personality traits or thinking styles. For example, AI interfaces could be extremely various and in the future, they may become more or less human-like in their interaction capabilities (e.g., simulating conversation): as a result, it might become relevant to consider traits such as social anxiety and communication apprehension. Indeed, people tend to experience artificial entities (e.g., AI, robots) as social actors [55], [56]. This is not a form of delusion, meaning that people perfectly know that a machine is not sentient, does not feel emotions or thinks on its own, etc.; yet, humans have a natural tendency to attribute intentions to entities that show a form of organized behavior [57], and to develop so-called para-social interactions with them [58]. Consistently, research shows that individuals socially anxious or high in communication apprehension may feel uneasy in the company of artificial entities as much as they do with other human beings [59], [60]. It should be said that social anxiety and communication apprehension, although strictly related, are two different constructs, the first being more related to anxiety for encountering others (e.g., feeling evaluated, judged by them) and the second to the act of communication itself [59], [61]. These constructs have been investigated mainly in the field of robots, which are characterized by some kind of bodily representation and could engage in primitive forms of communication. While research is needed to understand whether personality dispositions could influence the perception of AI tools, which also may vary in their interface/appearance, social anxiety and communication apprehension may be taken into consideration as a mediating factor for the quality of human–AI interaction.

As pointed out by Kolbjørnsrud *et al*. [62], attitudes, readiness, and enthusiasm for AI vary extensively across organizational levels and geographies and this implies challenges about how organizations can best adopt AI and get the most entrepreneurial value from it. As a main message of the present contribution, it is possible to say that AI can be regarded as a driver for innovation and entrepreneurship insofar, as the same amount of effort is put in developing AI solutions, and in creating effective teams to work with it, which guarantees not only the implementation of advanced technology but also that it is used in the best way to achieve organizational objectives. MCDM and GP could be used to guide team formation, taking into account both functional criteria and the optimization/integration of individual differences across the working groups.

Future models could focus on more elaborated algorithms to account both for attitudes, demographics, and individual differences for team formation in the field.

Another aspect that could be investigated in future models dealing with team formation is the addition of further observable criteria such as gender, family composition, education, and others. For instance, including gender will consider risk-taking propensity and computer anxiety. Indeed, multiple criteria are often used in team formation or selection process and they imply different attitudes, and it is fundamental to build effective, inter-professional working systems to improve information management and collaboration [63], [64].

Another research avenue that could be further explored in future works is related to the specific GP model. The proposed model is based on a weighted GP model but other GP variants, which include the DM's preference or uncertainty control using stochastic or fuzzy approaches, could also be utilized in future research papers.

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Davide La Torre received the Habilitation à Diriger des Recherches degree in applied mathematics from the Université Côte d'Azur, Nice, France, in 2021, the Ph.D. degree in computational mathematics and operations research from the University of Milan, Milan, Italy, in 2002, and the professional certificates in big data and analytics from the Massachusetts Institute of Technology, Cambridge, MA, USA, in 2017.

He is a Mathematician, Researcher, and University Professor. He currently holds the position of Full Professor and Director of the Artificial Intelligence Institute with SKEMA Business School, Université Côte d'Azur. In the past, he held Permanent and Visiting University Professor positions in Europe, Canada, Middle East, Central Asia, and Australia. He was the Departmental Chair and Program Head at several universities. He has authored or coauthored more than 160 publications in Scopus, most of them published in high IF journals ranging from engineering to business. His research and teaching interests include artificial intelligence and machine learning for business, business and industrial analytics, economic dynamics, mathematical and statistical modeling, operations management, operations research, and portfolio management.

Cinzia Colapinto received the Ph.D. degree in business and corporate finance from the University of Milan, Milan, Italy, in 2006.

She is currently a Senior Researcher in strategy and entrepreneurship with the Department of Management, Ca'Foscari University of Venice, Venice, Italy. She is also an Adjunct Professor of management with SKEMA Business School, Lille, France and Abu Dhabi School of Management, Abu Dhabi, UAE. Her main publications are in *Management International Review, Management Decision, European Journal of Operational Research, Energy Policy, Annals of Operations Research*. She is the author of several monographs, including Adaptive Decision Making and Intellectual Styles (Springer). Her research interests include entrepreneurship, innovation, and strategy. In particular, she is interested in the role played by digital technologies on business model transformations and on their impact on the achievement of sustainable development goals by SMEs.

Ilaria Durosini received the Ph.D. degree in psychology from the Università Cattolica del Sacro Cuore, Milan, Italy, 2019.

She is currently a Psychologist with the Applied Research Division for Cognitive and Psychological Science, IEO European Institute of Oncology IRCCS, Milan, Italy. She has authored or coauthored around 30 scientific contributions on the topics of her research interests, which include psychological assessment, health psychology, and decision-making processes, with a recent focus on new technologies and innovations in the healthcare context.

Stefano Triberti received the Ph.D. degree in psychology from the Università Cattolica del Sacro Cuore, Milan, Italy, 2016.

He is currently a Psychologist with the Department of Oncology and Hemato-Oncology, University of Milan, Italy. He teaches artificial intelligence within the same university, cognitive sciences degree. He also collaborates with the Applied Research Division for Cognitive and Psychological Science, IEO European Institute of Oncology IRCCS, Milan, Italy. He has authored or coauthored around 100 scientific contributions on the topics of his research interests, which include the usage of new technologies to promote health and well-being (eHealth and Positive Technologies), ergonomics and user experience, and the interface issue and implementation of artificial intelligence.