Equilibrium Means Equity? An E-CARGO Perspective on the Golden Mean Principle

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***Abstract*—In the team allocation problem (TAP), eliminating team disparities aims at keeping an equilibrium of the resource or ability among teams for equality. For this concern, existing literature merely utilized the golden mean principle to eliminate team disparities from a static perspective. Few of them reasonably investigate the pros and cons of this principle from a computational perspective. Moreover, maintaining equilibrium is a dynamic process and requires dynamic adjustment, especially after considering team members' self-efforts and adaptivity. With respect to the environments—classes, agents, roles, groups, and objects (E-CARGO) model and its role-based collaboration (RBC) methodology, this article formalizes and solves the TAP, i.e., revised group role assignment (GRA) problem, from both the individual and team's perspective. Based on the revised GRA, this article provides novel insight into the effectiveness of dynamically maintaining equilibrium, which may help decision-makers be proactive in building more sustainable teams. Relevant large-scale simulation experiments are conducted in this article to verify the proposed method. This article reveals a social paradox: even though considering all about the team members' self-efforts and adaptivity, equilibrium still seems inequitable. Conversely, pursuing equilibrium may bring the Matthew effect.**

***Index Terms*—Environments—classes, agents, roles, groups, and objects (E-CARGO), equilibrium, group role assignment (GRA), role-based collaboration (RBC), team allocation problem (TAP), team assignment (TA), golden mean principle.**

Nomenclature

$\mathcal{A}$	Set of agents.
$\mathcal{R}$	Set of roles.
m	Cardinality of agent set $\mathcal{A}$.
n	Cardinality of role set $\mathcal{R}$.
k	Value represents the percentage.
$0 \le i, i_0, i_1, \ldots, < m$	Indices of agents.
$0 \le j, j_0, j_1, \ldots, < n$	Indices of roles.
r_j	Element in $\mathcal{R}$.
a_i	Element in $\mathcal{A}$.
L	Role range vector.
Q	Qualification matrix.
T	Role assignment matrix.
ς	Role performance vector.
σ	Group performance, i.e., team disparities.
λ	Incentive value.
P^a	Agent personality vector.
C^a	Agent personality capacity vector.
$\mathcal{C}$	Cardinality of agents with different personalities.
Γ^a	Agent initial performance vector.
$\mathcal{Q}$	Overall qualification matrix.
ϱ	Overall team performance.

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I. Introduction

The golden mean principle [1], [2] states that the decision-makers should choose the mean and avoid the extremes on either side during an allocation process as far as possible, i.e., equilibrium. This principle is widely applied in team allocation problems (TAP), whereby TA means assigning people to different teams. For example, when an enterprise develops to a certain extent, it is necessary to establish balanced regional branches [3] for better service. Similarly, in a youth children's recreation league, parents often enroll their child in the league rather than in a specific team. The league must then assign the children to teams. If the league creates imbalanced teams, children on the weaker teams may be discouraged (and their parents may be offended) [4]. However, relevant research merely applies this principle to achieve static equilibrium between teams [4], [5]. Few of them investigate the pros and cons of utilizing this principle from a dynamic computational perspective. It is because simulating such a social computational problem is highly challenging and complex due to the lack of formalization tools [6], especially when considering the team members' personalities and self-efforts over a long-term period.

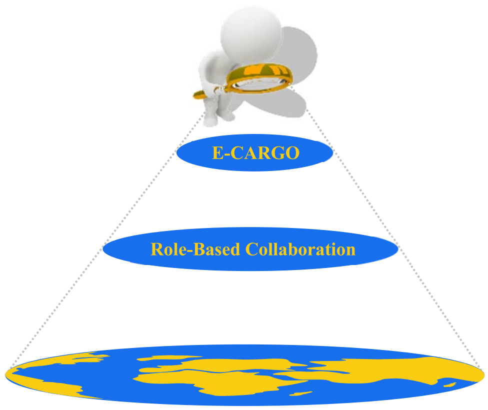

Fig. 1. E-CARGO is a tool to investigate the world [6].

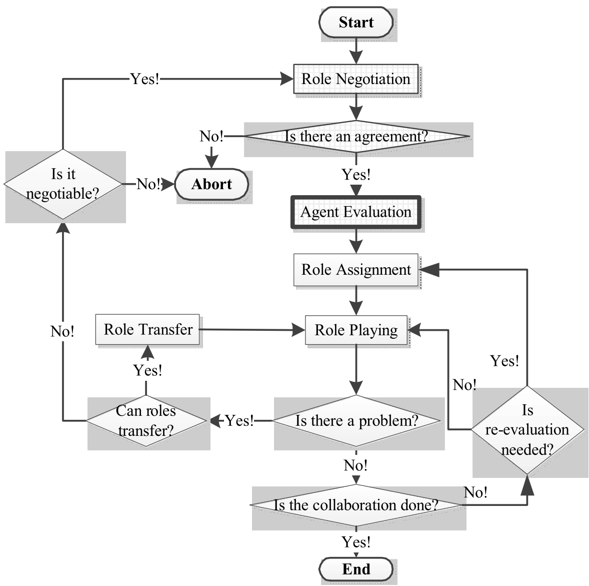

Fig. 2. Life cyle of the RBC process [11], [14].

With the booming of the environments—classes, agents, roles, groups, and objects (E-CARGO) fundamental model [7], [8], group role assignment (GRA) [9], [10] submodel, and their role-based collaboration (RBC) [11]–[13] methodology, they have been proposed as a well-specified tool to formalize and insight into the complex social computational problem [6] (see Fig. 1). In this article, the whole process of the TAP can be taken as an RBC process (Fig. 2). First, in the role negotiation part, we take teams as roles and people (i.e., team members) as agents. After role negotiation, the agent evaluation part can be conducted. It requires decision-makers to select proper evaluation criteria to quantify the suitability of an agent for a role (see Definition 4). After agent evaluation, role assignment is a process in that decision-makers leverage E-CARGO and GRA to assign agents to corresponding roles.

This article looks at the rationality for using the golden mean principle in TAPs from a long-term perspective through this methodology. We first demonstrate that using the golden mean principle can help eliminate the disparities and keep equilibrium in team performance among different teams. Then, since maintaining equilibrium is a dynamic process, we verify the pros and cons of dynamically utilizing this principle for maintaining equilibrium, from both individual and team's perspectives. Such pros and cons can be used to help decision-makers build sustainable teams (e.g., newly built branches, youth recreation leagues, or academic programs in universities).

Based on large-amount simulations, we reveal the following interesting findings.

1) The golden mean principle, i.e., equilibrium, can help properly eliminate the disparities in team performance between different teams.

2) Maintaining equilibrium is a dynamic process and requires dynamic adjustment, that is, team members are reallocated for equilibrium at a specific stage (e.g., year-end assessment) among teams, i.e., dynamic equilibrium strategy.

3) Whether a dynamic equilibrium strategy brings in a higher overall team performance depends on the proportions of the number of agents' personalities.

4) Dynamically maintaining equilibrium may cause the Matthew effect, that is, the agents with excellent performance get more excellent and vice versa.

5) Whether the appropriate team disparities contribute to the overall team performance also depends on the proportions of the agents' personalities.

Based on these, this article reveals a social paradox. Even though considering all about the team members' self-efforts and adaptivity, equilibrium still seems inequitable. Conversely, pursuing equilibrium may bring the Matthew effect.

The remainder of this article is arranged as follows. It first formalizes the TAP with the golden mean principle via the revised GRA model in Section II. Then, in Section III, it illustrates the basic assumption and the primary considerations in the simulation design. Section IV represents the simulation experiments. In Section V, the social meanings reflected by the simulation experiments are discussed. The related research is described in Section VI. This article concludes and points out future work in Section VII.

II. Revised GRA Model

The E-CARGO fundamental model can be described as a nine-tuple $\Sigma ::= < \mathcal{C}, \mathcal{O}, \mathcal{A}, \mathcal{M}, \mathcal{R}, \mathcal{E}, \mathcal{G}, s_0, \mathcal{H} >$, where Σ is a system, $\mathcal{C}$ is a set of classes, $\mathcal{O}$ is a set of objects, $\mathcal{A}$ is a set of agents, $\mathcal{M}$ is a set of messages, $\mathcal{R}$ is a set of roles, $\mathcal{E}$ is a set of environments, $\mathcal{G}$ is a set of groups, s_0 is the initial state of the system, and $\mathcal{H}$ is a set of users. In such a system, $\mathcal{A}$ and $\mathcal{H}$ and $\mathcal{E}$ and $\mathcal{G}$ are tightly coupled sets. A human user and her/his agent perform a role together. Every group should work in an environment. An environment regulates a group.

In E-CARGO, GRA is an abstract model that optimizes the role assignment of a group of agents from the team's perspective [6]. With these bits of help [9], [15], the TAP can be formalized by the revised GRA model. In the following discussions, we call the revised GRA model the TA model if we do not expressly state it. In the following descriptions, we clearly put citations to the definitions presented in the previous work. Those definitions without citations are coined the first time.

The priority to formalize the TAP is determining the roles (i.e., tasks) and the agents (i.e., task executors). To facilitate the definition of the TA model, we use nonnegative integers m (= $|\mathcal{A}|$, where $|\mathcal{A}|$ is the cardinality of set $\mathcal{A}$) to express the size of the agent set A, n (= $|\mathcal{R}|$) the size of the role set R, $i \in A = \{0, 1, \ldots, m-1\}$ and $j \in R = \{0, 1, \ldots, n-1\}$ the indices of agents and roles, respectively.

Definition 1: A role [12], [14], [16] is defined as $r ::= <id$, Ⓡ $>$, where *id* is the identification of r, i.e., role j ($j \in R$); Ⓡ represents the set of requirements or properties for agents to act r.

Note: In the TA model, roles are teams (e.g., regional branches), and Ⓡ is the required quality for the team members. For example, for those newly built regional branches, Ⓡ is the required expertise for the team members.

Definition 2: An agent [17], [18] is defined as $a ::= <id$, Ⓠ$>$, where *id* is the identification of a, i.e., agent i ($i \in A$); Ⓠ is the set of a's values corresponding to the abilities required in the group.

Note: In the TA model, agents are team members, and Ⓠ expresses the agents' performances about Ⓡ. The specific definition of Ⓠ is illustrated in Definition 4.

Definition 3: A role range vector [7] L is an n-dimensional vector of the number of agents required for roles, i.e., $L[j] \in \mathbb{N}^+$ ($j \in R$).

Note: The value of the L vector is determined when m and n are determined. Without loss of generality, the number of agents in different roles to be the same as possible, we will quantify L in the following way. If we can deduce m mod n $= 0$, we will set $L[j] = m/n$ ($j \in R$); otherwise, we first initialize $L[j] = \lfloor m/n \rfloor$ and then randomly select $[n - (m$ mod $n)]$ roles to increase their corresponding L value by 1. Note that the term mod represents the modulo operation.

Definition 4: A qualification matrix [14] Q is an $m \times n$ matrix, where $Q[i, j] \in \mathbb{R}$ expresses the suitability of an agent i for a role j.

Note: In the TA model, the social meanings of the matrix Q represent the individual performance (e.g., the qualification or the contribution) of an agent on a role. $Q[i, j] \geq 0$ represents a positive qualification or contribution and the reverse negative one.

Definition 5: A role assignment matrix [14] T is defined as an $m \times n$ control variable matrix, where $T[i, j] \in \{0, 1\}$ indicates whether or not an agent i is assigned to a role j. $T[i, j] = 1$ means yes and 0 no.

Definition 6: A role performance vector ς is defined as a vector, where $\varsigma[j] = \sum_{i=0}^{m-1} Q[i, j] \times T[i, j]$ ($j \in R$ and $\varsigma[j] \in \mathbb{R}$) indicates the overall performance of the assigned agents to role j.

Note: The social meanings of the vector ς in the TA model represent the performances of the teams.

Definition 7: The group performance σ is defined as the sum of standard deviation of the roles, i.e., $\sigma = ((\sum_{j=0}^{n-1}((\varsigma[j]/L[j]) - \mu)^2/n))^{1/2}$, where the expected value $\mu = (\sum_{j=0}^{n-1}(\varsigma[j]/L[j])/n)$.

Note: In the TAP, the social meaning of the group performance σ represents the performance disparities among roles (i.e., team disparities), and $(\varsigma[j]/L[j])$ represents the average performance of the role j. Please note that here, we utilize the standard deviation of the roles as the criteria of the group performance σ instead of the variance because we limit the initial values of matrix Q from 0 to 1 for facilitating calculation.

Correspondingly, the TA model is to find a workable T to minimize $\sigma = ((\sum_{j=0}^{n-1}((\varsigma[j]/L[j]) - \mu)^2/n))^{1/2}$, which is essentially finding the minimize $\sum_{j=0}^{n-1}|\varsigma[j] - \mu \times L[j]|$ (see Theorem 1).

Theorem 1: The TAP obtains its optimal value iff $\forall j \in R$, $\varsigma[j] = \mu \times L[j]$.

Proof: Based on Definitions 3 and 7, we can deduce $\sigma \geq 0$, $L[j]>0$, and $((\varsigma[j]/L[j]) - \mu)^2 \geq 0$. Thereby, the TA model can obtain its minimum value (i.e., $\sigma = 0$) if and only if $\forall j \in R$, $(\varsigma[j]/L[j]) - \mu = 0$. Hence, we can conclude the proof. ■

Note: Theorem 1 also demonstrates that the golden mean principle can help eliminate the disparities between different teams, i.e., moderation is best [1].

Definition 8: Based on Theorem 1, Given $\mathcal{A}$ ($|\mathcal{A}| = m$), $\mathcal{R}$ ($|\mathcal{R}| = n$), Q, and L, the TA model is to find a workable T to obtain

$$\min \sigma = \sum_{j=0}^{n-1}|\varsigma[j] - \mu \times L[j]| \tag{1}$$

$$\text{s.t. } \varsigma[j] = \sum_{i=0}^{m-1} Q[i, j] \times T[i, j] \quad (i \in A, j \in R) \tag{2}$$

$$\mu = \frac{\sum_{j=0}^{n-1}\frac{\varsigma[j]}{L[j]}}{n} \quad (j \in R) \tag{3}$$

$$T[i, j] \in \{0, 1\} (i \in A, j \in R) \tag{4}$$

$$\sum_{i=0}^{m-1} T[i, j] = L[j] \quad (j \in R) \tag{5}$$

$$\sum_{j=0}^{n-1} T[i, j] \leq 1 \quad (i \in A). \tag{6}$$

Note that Expression (1) involves absolute values, and an alternative method to deal with absolute values is to introduce new variables $\bar{\varsigma}[j]$ ($j \in R$ and $\bar{\varsigma}[j] \in \mathbb{N}^*$). Thereby, we can equivalently transform the TAP as follows [19]:

$$\min \sigma = \left(\sum_{j=0}^{n-1} \bar{\varsigma}[j]\right) \tag{7}$$

such that Expressions (2)–(6) and

$$\varsigma[j] \leq \bar{\varsigma}[j] + (\mu + \lambda) \times L[j] (j \in R, \lambda \in \mathbb{R}) \tag{8}$$

$$\varsigma[j] \geq \bar{\varsigma}[j] - (\mu + \lambda) \times L[j] (j \in R, \lambda \in \mathbb{R}) \tag{9}$$

where λ represents an expert experience incentive value. Here, we introduce the incentive value λ in Expressions (8) and (9) because the TAP may not achieve equilibrium (i.e., $\sigma = 0$) and $\varsigma[j] = \mu \times L[j]$) due to the not divisible individual performance. The social meaning of λ is that appropriate team disparity may contribute to the overall performance of the teams to a certain extent. We will discuss the impact on the TA model when the value λ changes in Section IV.

Through the above conversion, the TA model has become a mixed-integer linear programming (MILP) problem, which can be properly solved by a commercial solver, e.g., IBM ILOG CPLEX optimization package (CPLEX) [20].

III. Simulation Assumptions and Design

A. Assumptions

Based on the proposed TA model in Section II, we can formally conduct the simulation experiments to verify the pros and cons of utilizing the golden mean principle in the TAP. Since newly formed roles (i.e., teams) usually exist for a specific period, most of the simulations are focused on the long-term operation of the TAP. Moreover, agents (i.e., team members) are emotional and different [21], [22], and their individual performances (i.e., qualification (Q) value) may continuously change because of their adaptive ability to the surroundings or their self-efforts. Thereby, maintaining equilibrium is a dynamic process that requires dynamic adjustment. Through the above analysis, we propose the following assumptions for the following simulations.

1) To better describe the simulations in Section IV, we utilize the formation of balanced regional branches (regarded as teams) as a scenario, where an enterprise invests in forming a few regional branches with the same budget for each branch to hire a similar number of people.
2) The number of agents in roles keeps the same for a long-term period unless the reallocation process or accidence. This is reasonable because, for many teams, it takes a long time to operate, and changes will only occur after the multiquarter assessment.
3) Agents are different. The differences may be the self-efforts and their personalities [23]. Note that the differences in the personalities of agents may cause them to be periodically affected by other team members (e.g., competitive relationships) to different degrees.
4) The qualification (Q) values of agents are changing based on individual differences [6].
5) As agents' qualification value changes may cause the inequality of the team to be broken, the decision-makers may need to reallocate the teams in a specific milestone for equilibrium (e.g., the year-end assessment).
6) In the following discussions, we call one-time initial allocation utilizing the TA model/reallocation at each specific milestone utilizing the TA model the static equilibrium strategy/dynamic equilibrium strategy if we do not specifically state it.

The above assumptions are rational because each has corresponding social facts. Thus, we can confirm that the simulations based on these assumptions are acceptable.

B. Design

To better understand the changes in the qualification (Q) values, we supplement the following definitions.

Definition 9: The agent personality vector P^a is an m-dimensional vector, where $P^a[i] \in \{0, 1, 2\}$ ($i \in A$).

Note: Based on analyzing the relevant research [23], we can intuitively partition the personalities of agents into three categories: "philosophical," "vulnerable," and "involuntary." These three categories correspond to $P^a[i] = 0$, 1, or 2, respectively. It is easy to access agents' personalities because many companies can conduct mental health surveys when recruiting.

Definition 10: The agent personality capacity vector C^a is an vector, where $C^a[w] = \{a_i | a_i \in \mathcal{A}$ and $P^a[i] = w\}$ ($i \in A$ and $w \in \{0, 1, 2\}$).

Note: The social meaning of C^a is the series set of agents of each personality in $\mathcal{A}$. For example, $C^a[1] = \{a_i | \ a_i \in \mathcal{A}$, and $P^a[i] = 1\}$ represents the set of agents of vulnerable personality in $\mathcal{A}$.

Definition 11: The team personality tuple $\mathcal{C}$ is a three-tuples, where $\mathcal{C} = <|C^a[0]|, |C^a[1]|, |C^a[2]|>$.

Note: The social meaning of $\mathcal{C}$ consists of teams' personalities. For example, $\mathcal{C} = <192, 10, 0>$ means that the numbers of the three types of agents are $\mathcal{C}[0] = 192$, $\mathcal{C}[1] = 10$, and $\mathcal{C}[2] = 0$, respectively.

Definition 12: The agent initial performance vector Γ^a is an m-dimensional vector, where $\Gamma^a[i] \in [0, 1]$ ($i \in A$).

Note: The social meaning of Γ^a is the self-efforts of the agents. It also represents the initial performances of agents. For facilitating calculation, we limit its value to 0–1.

With Definitions 9–12, the qualification values of agents on roles will be initialized and updated by the following equation:

$$
\begin{aligned}
&Q[i, j](t)\\
&= \begin{cases} \Gamma^a[i], & P^a[i] = 0\\ \alpha_1[i] sin(\omega_1[i]t + \theta_1[i]) + \beta_1[i] + \Gamma^a[i], & P^a[i] = 1\\ \alpha_2[i] sin(\omega_2[i]t + \theta_2[i]) + \beta_2[i] + \Gamma^a[i], & P^a[i] = 2 \end{cases}\\
&\quad -1 \le \alpha_1[i] + \beta_1[i] \le 0, 0 \le \alpha_2[i] + \beta_2[i] \le 1 \quad (i \in A)\\
&\quad \alpha_1[i] = \beta_1[i], \alpha_2[i] = \beta_2[i] \quad (i \in A)\\
&\quad \omega_1[i], \omega_2[i] \in (0, \tau] \quad (i \in A, \tau \in \mathbb{R}^+)\\
&\quad \theta_1[i] = \theta_2[i] = \frac{-\pi}{2} + 2c\pi \quad (i \in A, c \in \mathbb{N}).
\end{aligned} \tag{10}
$$

In Expression (10), $t \in \mathbb{N}^*$ represents the time, $\alpha_1[i]/\alpha_2[i]$ represents the amplitude, $\omega_1[i]/\omega_2[i]$ represents the period, $\theta_1[i]/\theta_2[i]$ represents the initial phase, $\beta_1[i]/\beta_2[i]$ represents the vertical shift, and τ represents the end time of the TAP. The meanings of this setting include the following.

1) The changes of the agents' qualification (Q) values consist of two equally important parts: the initial performance $\Gamma^a[i]$ and the adaptive ability of the surroundings $\alpha_1[i] \sin(\omega_1[i]t + \theta_1[i]) + \beta_1[i]/\alpha_2[i] \sin(\omega_2[i]t + \theta_2[i]) + \beta_2[i] + \Gamma^a[i]$. Here, we use the weighted sum (WS) method to quantify Q because WS is well accepted to combine many numerical factors to form one numerical indicator [24].

2) We utilize Fig. 3 to illustrate the changes in agents' qualification values. For those agents with philosophical personalities (i.e., $P^a[i] = 0$), since they are hardly affected by their surroundings [see Expression (10)], their performance merely depends on their initial performance $\Gamma^a[i]$. As for those agents with vulnerable personalities (i.e., $P^a[i] = 1$), their performance may get worse until they become familiar with the new circumstance. Conversely, for those agents with

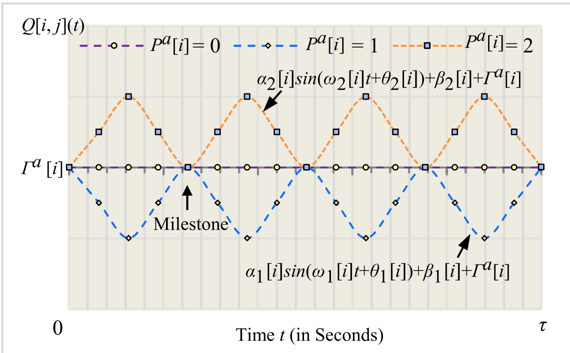

Fig. 3. Changes in qualification values of agents ($Q[i, j](t)$). Note: for display purposes, we set $\alpha_1[i] = \alpha_2[i]$ and $\omega_1[i] = \omega_2[i]$ ($i \in A$, $j \in R$, and $t \in [0, \tau]$). The milestone represents the reallocation time point (e.g., the year-end assessment).

involuntary personalities (i.e., $P^a[i] = 2$), they may perform better in the new environment until the environment becomes familiar and then return to their normal performances.

3) Note that we leverage trigonometric functions to simulate the adaptability of the agent because trigonometric functions can synthesize any periodic function through the Fourier transform (FT) [25]. Moreover, the milestone in Fig. 3 represents the reallocation time point.

Since the contribution of team members to the team is a continuous process, we introduce the following definitions for better evaluating the pros and cons of utilizing the golden mean principle in the TAP.

Definition 15: The overall qualification matrix $\mathcal{Q}$ ($\mathcal{Q} \in \mathbb{R}$) in the interval $[0, \tau]$ (e.g., $\tau = 4\pi$) is defined as

$$\mathcal{Q}[i, j](t) = \int_0^{\tau} Q[i, j](t)dt \quad (i \in A, j \in R). \tag{11}$$

Note: $\mathcal{Q}[i, j](t) < 0$ represents that agent i may be fired in the end of the assessment (i.e., $t = \tau$) because it has a negative contribution to role j. Note that when agent i is negative at a certain milestone, it will not be fired immediately. This is because agent i's contribution may become positive due to its self-effort in a long-term perspective.

Definition 16: The overall team performance ϱ is defined as the sum of roles' performance, i.e., $\varrho = \sum_{j=0}^{n-1} \varsigma[j]$ ($j \in R$).

Note: $\varsigma[j]$ in Definition 16 represents the overall role performance of role j, that is, $\varsigma[j] = \sum_{i=0}^{m-1} \mathcal{Q}[i, j] \times T[i, j]$. Moreover, ϱ_1 represents the overall team performance in the dynamic equilibrium strategy, while ϱ_2 is that of the static equilibrium strategy.

Definition 17: Equity is measured by comparing the individual performance of each agent.

Note: Equity theory points out that equity is measured by comparing the ratio of contributions (or costs) and benefits (or rewards) for each person [26]. In the TA model, the contribution of each agent (i.e., team member) is quantified by its individual performance, i.e., $\mathcal{Q}$.

TABLE I
CONFIGURATION OF THE EXPERIMENTAL PLATFORM

Hardware	
CPU	2.6GHz Intel Core i7
Memory	16GB 2400MHz DDR4
Software	
OS	macOS Monterey Version 12.1
Editor	Visual Studio Code Version 1.63.2
Python	Python 3.8.5

IV. SIMULATION DESIGN AND EXPERIMENTS

A. Experimental Setup

To demonstrate the viability and efficiency of our proposed method, we perform large-scale random simulation experiments on a laptop configured, as shown in Table I.

Here, we first determine the scale and scope of the TAP, i.e., quantifying the L, m, and n, since human communities/teams have a distinctive layered structure with successive cumulative layer sizes of 15, 50, 150, 500, and 1500 [27]. Meanwhile, the newly built regional branches are usually small- and medium-sized teams, which are from 30 to 100 people [28]. Thereby, we set regional branch's capacity as 50, i.e., $L[j] = 50$ ($j \in R$). Moreover, due to limited funding for newly built regional branches, the number of its roles is also limited. For display purposes, we empirically set the number of roles $n = 4$. Note that the number of roles n does not affect the conclusion of the simulations. Once $L = [50, 50, 50, 50]$ and $n = 4$ are determined, $m = \sum_{j=0}^{n-1} L[j] = 200$ is also determined.

For a better description, we will fix L, n, and m in the simulation part if we do not expressly state it. As for the incentive value λ in Expressions (8) and (9), we first set $\lambda = 0$ for achieving equilibrium among teams in Simulations 1–4. Then, in Simulation 5, we investigate the influence of λ on the overall team performance. Please note that we will obtain a near-optimal value obtained by terminating the CPLEX with setting solution time as 5 s (an empirical value) in advance. It is because the TA model may not achieve equilibrium due to the indivisible individual performance. This solution will be verified by Simulation 1 in Section IV. Please note that the results of all simulation experiments in this article are the average of hundreds of random experiments.

B. Simulation Overview

This section introduces the relationships among the following simulations in this article (see Fig. 4). First, Simulation 1 has demonstrated the effectiveness of the golden mean principle in eliminating the disparities among teams, which, combined with Theorem 1, serves as a theoretical basis for other simulations. Then, in Simulations 2–4, we investigate the impact of the static and dynamic equilibrium strategies from both team's and individual perspectives in the case where the incentive value λ is 0. Finally, Simulation 5 investigates the impact of the appropriate team disparity, i.e., incentive value $\lambda \neq 0$, on the TAP.

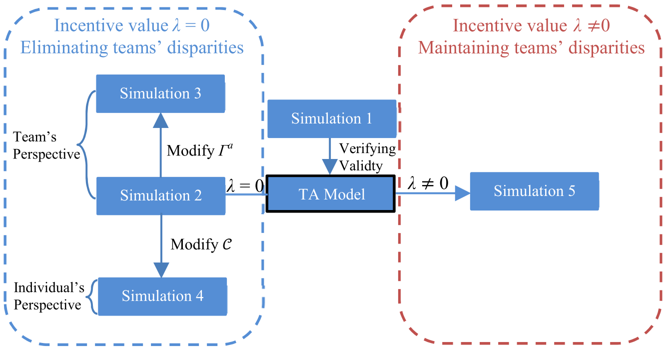

Fig. 4. Relationships among the following simulations in Section IV.

Fig. 5. Example to illustrate the SAA algorithm. Note: blue dashed rounded rectangle represents roles, and the red one represents agents that are ranked and numbered by individual performance.

C. Simulation 1: The Golden Mean Principle Can Achieve Equilibrium

In this simulation, we analyze the practicability of the proposed TA model to eliminate teams' disparities, i.e., $\lambda = 0$. Based on the analysis in Section IV-A, here, we set $L = [50, 50, 50, 50]$, $n = 4$, and $m = \sum_{j=0}^{n-1} L[j] = 200$. For an intuitive comparison, here, we set $Q[i, j](0) = \int_0^0 Q[i, j](0)dt = Q[i, j](0) = \Gamma^a[i] \in (0, 1)$ $(i \in A, j \in R)$, and it follows the uniform distribution, i.e., $U(0, 1)$. We also compare the TA model with an algorithm named serpentine arrangement algorithm (SAA) [29] (see Fig. 5), which is widely used in some universities in China [30], [31] to solve the equal division problem of students' classes. This is a typical TAP because the vast majority of universities in China divide groups of students into different balanced classes as the formal smallest unit of management, study, or competition.

Fig. 6 shows the solution results of the TA model and the SAA solution. It demonstrates that our proposed TA model in Section II can almost achieve equilibrium in performance among roles (i.e., teams), while the SAA cannot. It is because the latter only guarantees the equilibrium of the overall ranking of the agents in each role instead of the average performance of roles.

The following simulations will discuss the long-term effects of two different allocation strategies, that is, the static equi-

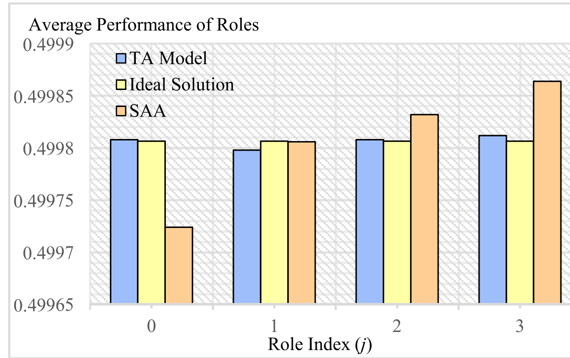

Fig. 6. Average performance of roles in the TAP under hundreds of random experiments.

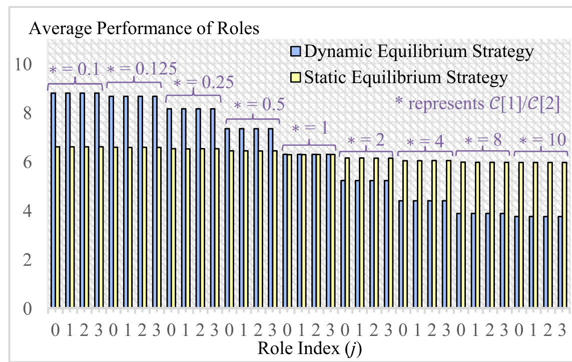

Fig. 7. Comparison of the average performance of roles under two allocation strategies when $\Gamma^a[i] \sim U(0, 1)$.

librium strategy and the dynamic equilibrium strategy, on the TAP.

D. Simulation 2: Static Equilibrium Is Easily Broken

Simulation 2 investigates whether the static equilibrium strategy can be maintained among teams. Here, we keep all the settings in Simulation 1 (i.e., $L = [50, 50, 50, 50]$, $n = 4$, and $m = \sum_{j=0}^{n-1} L[j] = 200$), but only change ratios of the number of agents with involuntary and vulnerable personalities, i.e., $\mathcal{C}[1]/\mathcal{C}[2]$ ($\mathcal{C}[1]/\mathcal{C}[2] \in \mathbb{N}^+$). Since the cardinality of agents is limited (i.e., $m = 200$), we empirically set the range of $\mathcal{C}[1]/\mathcal{C}[2]$ as $(0, 10]$. Without lose of generality, we also set the initial agents' performance vector $\Gamma^a[i] \sim U(0, 1)$. Moreover, for a better description, here, we empirically set the time period τ in Expression (15) as 4π, $(\alpha_1[i]+\beta_1[i]) \sim U(-1, 0)$, $(\alpha_2[i] + \beta_2[i]) \sim U(0, 1)$ $(i \in A)$, and $\omega_1[i] = \omega_2[i] = \tau/\pi$. $\omega_1[i] = \omega_2[i] = \tau/\pi$ indicates that the reallocation interval is $(2\pi/\omega_1[i]) = (2\pi/\omega_2[i]) = 0.5\pi$.

Fig. 7 shows the comparison of the average performance of roles under two allocation strategies when $\Gamma^a[i] \sim U(0, 1)$. It illustrates that the static equilibrium strategy can also maintain equilibrium among roles (i.e., teams). This may be caused by the small gap in the initial individual performance Γ^a among agents. Thus, we change $\Gamma^a[i] = \{b^x | b \in (0, 1)$ and $x \in \{(1/m), \frac{2}{m}, \ldots, (m-1/m), 1\}\}$, which can properly reflect different performance gaps between different agents. For a better illustration, here, we set b as a small value, i.e.,

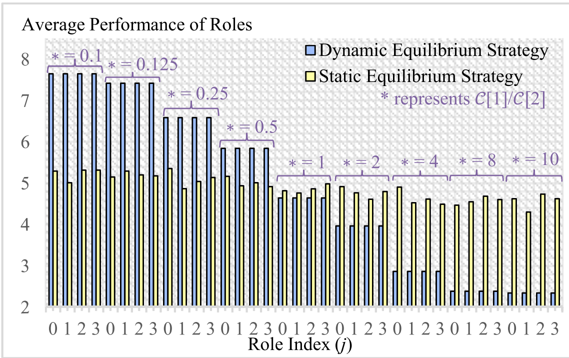

Fig. 8. Comparison of the average performance of roles under two allocation strategies when the initial individual performance gap b is 0.1.

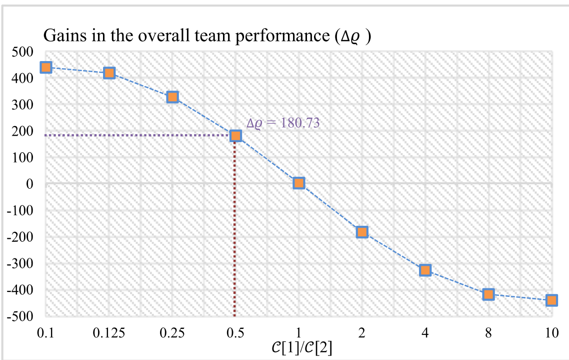

Fig. 9. Performance gains at different hierarchical levels of the team.

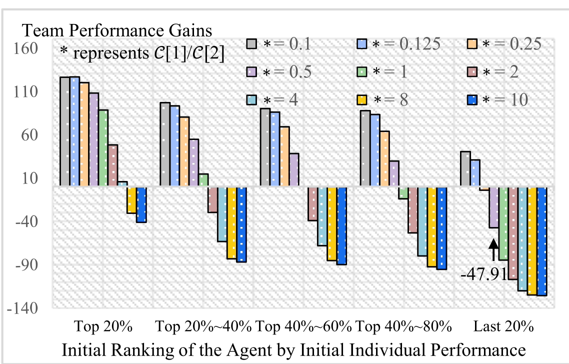

Fig. 10. Gains in the overall team performance ($\Delta\varrho$). Note: $\Delta\varrho = \varrho_1 - \varrho_2$.

0.1, which can reflect the phenomenon that the static/initial equilibrium is easily broken.

Fig. 8 elaborates that when the initial performance gap gets larger, the static equilibrium is easily broken. Thus, equilibrium is dynamic and requires dynamic adjustment at every milestone to eliminate team disparities, i.e., dynamic equilibrium strategy.

E. Simulation 3: Dynamic Equilibrium Still Seems Inequitable

Following Simulation 2, in this simulation, we investigate the impact of the abovementioned two allocation strategies on the team's perspective after considering agents' adaptivity and self-efforts. Here, we keep all the settings in Simulation 2 (i.e., $L = [50, 50, 50, 50]$, $n = 4$, and $m = \sum_{j=0}^{n-1} L[j] = 200$) and set $\Gamma^a[i] \sim U(0, 1)$ for not lose to generality.

Figs. 9 and 10, respectively, show the changes in the overall team performance and the hierarchical level of team

TABLE II

INDIVIDUAL PERFORMANCE CHANGES OF THE VULNERABLE AGENTS UNDER THE DYNAMIC EQUILIBRIUM STRATEGY*

Initial Ranking	Individual Performance Changes ΔQ		
	Increased Numbers	Unchanged Numbers	Decreased Numbers
Top 20%	3	0	7 (-7)
Top 20%~40%	0	0	10 (-10)
Top 40%~60%	0	0	10 (-10)
Top 60%~80%	0	0	10 (-10)
Last 20%	0	0	10 (-10)*

*Note: 10 (-10) represents the number of vulnerable agents that have decreased in individual performance is 10, and all of them have a negative performance in the end.

performance under different ratios of the number of agents with vulnerable and involuntary personalities (i.e., $\mathcal{C}[1]/\mathcal{C}[2]$).

As shown in Fig. 9, when $\mathcal{C}[1]/\mathcal{C}[2] < 1$, dynamically maintaining equilibrium brings a higher overall team performance; otherwise, it leads to lower overall team performance. However, Fig. 10 shows a contradiction that the dynamic equilibrium strategy seems not equitable [6], [32]. For example, when $\mathcal{C}[1]/\mathcal{C}[2]$ is 1/2, the dynamic equilibrium strategy brings a higher overall team performance (i.e., $\Delta\varrho = 180.73$), but the total performances for those agents ranking last 20% decrease by 47.91. Note that $\Delta\varrho = 180.73$ in Fig. 7 represents that the overall team performance of the dynamic equilibrium strategy is 180.73 higher than that of the static one when $\mathcal{C}[1]/\mathcal{C}[2] = 0.5$.

In Fig. 10, for those agents in the bottom 20% of initial performance rank, at $\mathcal{C}[1]/\mathcal{C}[2] = 0.5$, the dynamic equilibrium strategy achieves an overall performance of 47.91 lower than the static one.

F. Simulation 4: More Extreme Cases—Matthew Effect

Simulations 1–3 analyze the impact of the static and dynamic equilibrium strategies from the team's perspective. In this simulation, we investigate the effect of different allocation strategies from the individual agent's perspective. More pertinently, here, we investigate the changes in those vulnerable agents' performances under a dynamic equilibrium strategy since their performances may become negative because of their poor adaptivity (see Fig. 3). Fig. 10 in Simulation 3 shows that agents at different performance levels are affected differently by the allocation strategies. Thereby, we consider the changes in performance and corresponding rankings of vulnerable agents at different performance levels under the dynamic equilibrium strategy. For display purposes, we keep all the settings in Simulation 2, but only change $\mathcal{C} = \langle |C^a[0]|, |C^a[1]|, |C^a[2]| \rangle = \langle 190, 10, 0 \rangle$, that is, the agents' personalities are as follows: 190 agents with philosophical personalities, 10 agents with vulnerable personalities, and 0 agents with involuntary personalities.

Table II shows the changes in the individual performances of the agents with vulnerable personalities under the dynamic equilibrium strategy. Interestingly, some vulnerable agents with the highest initial performance (e.g., some agents with individual performance ranking top 20%) keep their individual performances increased under the dynamic equilibrium

TABLE III

INDIVIDUAL PERFORMANCE OF THE VULNERABLE AGENTS UNDER THE DYNAMIC EQUILIBRIUM STRATEGY

Agent-ID	Individual Performance Q			
	Initial Performance	Initial Ranking	Final Performance	Final Ranking
26	0.96	2	12.06	2
48	0.96	2	11.81	7
49	0.41	115	-1.13	196
72	0.06	188	-10.58	201
88	0.35	129	-3.24	198
151	0.94	9	11.56	12
155	0.41	115	-1.13	196
159	0.95	7	11.20	16
183	0.06	188	-10.56	200
194	0.17	163	-9.17	199

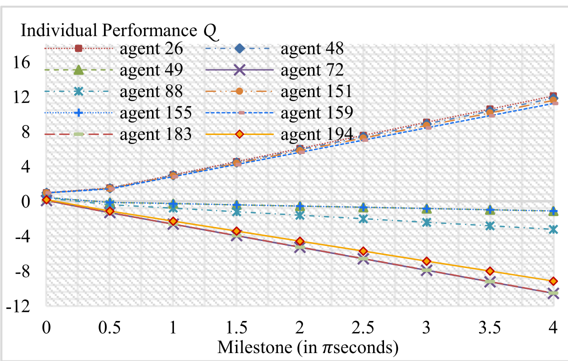

Fig. 11. Changes in the individual performance of the agents with vulnerable personalities under the dynamic equilibrium strategy.

strategy. It might be because their high individual performance may offset the impact of the surroundings. Here, we utilize Fig. 11 and Table III to illustrate this point.

Fig. 11 and Table III elaborate on one of the random cases for the vulnerable agents (see Definition 9) under the dynamic equilibrium strategy in Simulation 4. They show the Matthew effect [33] that those vulnerable agents with high initial performances (i.e., self-efforts) maintain high final performances and rankings at the end of the reallocation process, while those vulnerable agents with lower initial individual performances eventually will be eliminated by teams because of their poor adaptability. This phenomenon also demonstrates a social paradox that dynamically maintaining equilibrium still seems inequitable after considering agents' adaptive ability for the surroundings.

G. Simulation 5: How to Properly Maintain Team Disparities

Simulations 1–4 devote to eliminating disparities among roles, i.e., incentive value $\lambda = 0$. Then, in this simulation, we investigate whether the appropriate team disparities may contribute to the overall team performance to a certain extent, i.e., $\lambda \neq 0$. Similarly, we keep all the settings in Simulation 2, but only change λ. Because of the initial individual performance $Q[i, j](0) = \Gamma^a[i] \in (0, 1)$, $m = \sum_{j=0}^{n-1} L[j] = 200$, and $n = 4$, the range of λ is $[-50, 50]$, i.e., $200/4 = 50$.

Figs. 12 and 13 show the changes in the overall team performance ϱ and the team disparities σ under different

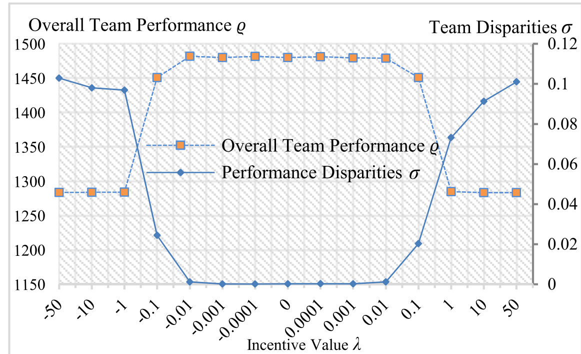

Fig. 12. Changes in the overall team performance ϱ and the team disparities σ under different incentive values λ when $\mathcal{C}[1]/\mathcal{C}[2] < 1$.

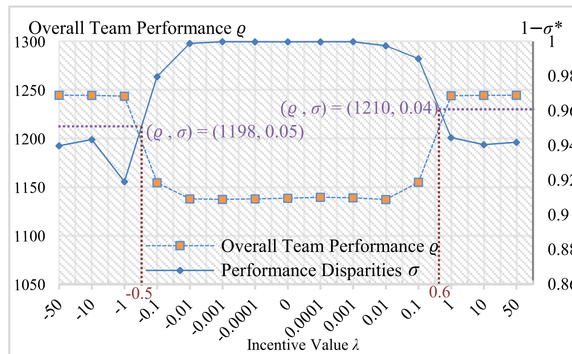

Fig. 13. Changes in the overall team performance ϱ and the team disparities σ under different incentive values λ when $\mathcal{C}[1]/\mathcal{C}[2] \geq 1$*. *Note: here, we use $1-\sigma$ instead of σ for a better comparison.

values of the incentive value λ. Fig. 12 shows that when involuntary agents are in the majority (i.e., $\mathcal{C}[1]/\mathcal{C}[2] < 1$), the increasing or decreasing incentive value λ brings a lower overall team performance, that is to say, the dynamic equilibrium strategy (i.e., $\lambda = 0$) can achieve higher overall team performance and eliminate team disparities. Conversely, when vulnerable agents are in the majority (i.e., $\mathcal{C}[1]/\mathcal{C}[2] \geq 1$), appropriate team disparities (i.e., $\lambda \neq 0$) lead to higher overall team performance, as shown in Fig. 13. Interestingly, when the incentive value $\lambda \geq 1$ or $\lambda \leq -1$, the dynamic equilibrium strategy degenerates into a static one because of the high tolerance of the team disparities.

V. DISCUSSION AND APPLICATION

A. Discussion

This section discusses the simulations conducted in Section IV and summarizes some social meanings. First, Simulation 1 has demonstrated the effectiveness of the golden mean principle in eliminating the disparities among teams, which, combined with Theorem 1, serves as a theoretical basis for other simulations. Then, in Simulations 2–4, we investigate the impact of the static and dynamic equilibrium strategies from both team's and individual perspectives in the case where the incentive value λ is 0.

Simulation 2 helps to demonstrate that the static equilibrium is easily broken when the initial individual performance gap gets more prominent (see Fig. 8). This means that equilibrium is a dynamic process and requires dynamic adjustment. Based on Simulation 2, Simulation 3 illustrates that after considering agents' adaptivity and self-efforts, whether the dynamic equilibrium strategy brings a higher overall team performance than the static one depends on the ratios of the number of agents with vulnerable and involuntary personalities, i.e., $\mathcal{C}[1]/\mathcal{C}[2]$. Meanwhile, Simulation 3 also illustrates a contradiction that the dynamic equilibrium strategy seems not equitable [6], [32] because it may scarify the benefits of those agents with a low ranking (see Fig. 10).

Simulation 4 utilizes extreme cases to investigate the effect of maintaining equilibrium from the individual agent's perspective. It shows the Matthew effect [33], i.e., the agents with excellent performance get more excellent and vice versa, that is, it demonstrates a social paradox that the dynamic equilibrium strategy seems inequitable even though considering agents' self-efforts and their adaptivity to the surroundings. Since the TA model aims at minimizing team disparities, it is necessary to continuously adjust the composition of the team. For members with higher performance values, they will basically remain unchanged in a certain team. Conversely, for those vulnerable agents with lower initial performance values, they are often used to reallocate teams to make up for team disparities. For example, as elaborated in Fig. 11 and Table III, vulnerable agents 26, 48, 151, and 159 with a higher initial performance ultimately maintain a higher final performance during the reallocation process, while vulnerable agents 49, 72, 88, 155, 183, and 194 are finally eliminated for their poor initial performances.

The interesting findings in Simulations 2–4 also reflect the importance of presenting the computational perspectives of the golden mean principle.

Simulation 5 investigates the impact of the appropriate team disparity, i.e., incentive value $\lambda \neq 0$, for the TAP. It illustrates that whether the appropriate team disparities contribute to the overall team performance also depends on the proportions of the agents' personalities. As shown in Fig. 12, when involuntary agents are in the majority, proper team disparities have a negative impact on the overall team performance. This means that the dynamic equilibrium strategy (i.e., $\lambda = 0$) is the best choice for keeping a higher overall team performance and lower team disparities. On the contrary, when vulnerable agents are in the majority, appropriate team disparities (i.e., $\lambda \neq 0$) lead to higher overall team performance, as shown in Fig. 13. In this case, decision-makers can proactively build more sustainable teams by making tradeoffs between the overall performance and the team disparities. As an example, if the decision-maker considers both to be equally important, setting the incentive value $\lambda = 0.6$ is an optimal choice because it ensures a high overall team performance and minimizes team disparities as much as possible (i.e., $\varrho = 1210$ and $\sigma = 0.04$).

In summary, the abovementioned simulation results illustrate the following interesting findings.

1) The golden mean principle, i.e., equilibrium, can help properly eliminate the differences in team performance between different teams.

2) Maintaining equilibrium is a dynamic process and requires dynamic adjustment, that is, team members are reallocated for equilibrium at a specific stage (e.g., year-end assessment) among teams, i.e., dynamic equilibrium strategy.

3) Whether a dynamic equilibrium strategy brings in a higher overall team performance depends on the proportions of the number of agents' personalities.

4) Dynamically maintaining equilibrium may cause the Matthew effect [33], that is, the agents with excellent performance get more excellent and vice versa.

5) Whether the appropriate team disparities contribute to the overall team performance also depends on the proportions of the agents' personalities.

Based on these, it seems to reveal a social paradox: Even though considering all about the team members' self-efforts and adaptivity, equilibrium still seems inequitable. Conversely, pursuing equilibrium may bring the Matthew effect.

B. Applications

This section summarizes the scope of the TAP that the proposed TA model is applicable and helps apply this model. The proposed TA model aims to construct balanced teams by utilizing the golden mean principle from a long-term perspective. Thereby, the number of team members in teams keeps the same for a long-term period unless the reallocation process or accidence. This is reasonable because, for many teams, it takes a long time to operate, and changes will only occur after the multiquarter assessment. Moreover, team members between teams are fairly interchangeable in terms of skillset, and they can be reallocated between teams to eliminate team disparities.

VI. Related Work

A. Team Allocation Problem

TAP is a typical social computing problem that has been discussed from different perspectives for many years [14], [34]–[38]. For example, Jiang *et al.* [35] explored a novel crowdsourcing paradigm with a concept of contextual crowdsourcing value, which can build crowdsourcing teams with better synergy performance while reducing costs. Yu *et al.* [37] employed the definition of familiarity and then proposed faMiliarity-based cOllaborative Team recOgnition (MOTO) algorithm to recognize collaborative academic teams. Moreover, Zhu [14] proposed a practical solution, GRA with constraints (GRA$^+$) model, to avoid conflicts among team members when establishing new teams.

The aforementioned specific studies on the TAP have achieved substantial social results in the corresponding perspectives. Still, this article focuses on achieving equal allocation among teams by utilizing the golden mean principle and rationally analyzing its pros and cons in the long term.

B. Golden Mean Principle and TAP

Utilizing the golden mean principle in the TAP is aimed to build teams with equality since a larger performance gap will affect the cooperation between team members, thereby reducing team performance [5], [39]–[42]. For example, Bupaji *et al.* [40] reviewed the negative impact of income inequality on teams or society from the perspective of economics. In essence, the uneven distribution of team performances is a vital cause for uneven income between teams.

Downes and Choi [41] summarized that equality theory helps build more sustainable teams. More pertinently, Syed-Abdullah *et al.* [5] applied the golden mean principle to eliminate the inequality between teams with the help of a fuzzy rule-based technique, and Valentine [42] conducted an inductive study of temporary teams in four hospital emergency departments (EDs), which revealed that equal distribution could facilitate coordination between team members.

The aforementioned research has a proper explanation or application of the golden mean principle. Still, analyzing teams' performance at the individual level is a "black box" [40], especially in a long-term period, and there is a shortage of research efforts on it. Due to the RBC methodology and its relevant E-CARGO model, this article can rationally investigate the reason why utilizing the golden mean principle in the TAP and the pros and cons of it from a long-term perspective.

C. E-CARGO and TAP

The RBC [6], [7], [10], [18], [38] methodology, E-CARGO general model [11], [13], [43], and its GRA/GMRA submodel [8], [24], [34] have been proposed as a well-specified tool to formalize and insight into the complex social computing problem [44].

For example, Zhu [6] applied the RBC and E-CARGO model to analyze the Pareto 80/20 principle and revealed a social paradox that emphasizes individual differences inevitably leading to rapid social wealth accumulation and polarization, and ignoring such disparities certainly causes slow social wealth accumulation. Moreover, Jiang *et al.* [24] utilized the RBC and E-CARGO model to design a feasible refugee resettling scheme, which can swiftly resettle refugees from multiple suffering countries while appropriately ensuring host countries' benefit. However, the objective functions of the abovementioned methods are merely maximizing the team performance σ, instead of considering the equilibrium among roles. Moreover, the abovementioned methods focus on the assignment of a certain milestone, rather than considering a long-term period.

Based on the above analysis, this article first proposed the TA model, dynamically utilizing the golden mean principle, to eliminate the inequality between teams to maintain dynamic equilibrium. Then, with the help of the TA model, we can rationally investigate the pros and cons of using the golden mean principle from a long-term perspective. This investigation may help decision-makers be proactive in building more sustainable teams.

VII. Conclusion

The contribution of this article is providing a creative way, i.e., the TA model, to rationally analyze the pros and cons of dynamically utilizing the golden mean principle for equilibrium in the TAP from the long-term viewpoint of GRA. With this model, this article provides novel insight into the effectiveness of maintaining equilibrium, which may help decision-makers be proactive in building more sustainable teams. Large-scale simulation experiments reveal a social paradox: Even though considering all about the team members' self-efforts and adaptivity, equilibrium still seems inequitable yet. Conversely, pursuing equilibrium may bring the Matthew effect.

We may conduct more comprehensive investigations in the future.

1) Ensuring a balance between teams seems inequitable to individuals. Achieving equitable and balanced win–win teams is a multiobjective problem, and it is complex because of the interdependence between objectives. We may do further research to help decision-makers build equitable and balanced win–win teams.
2) The cooperative [45], [46] and conflicting factors among agents [28] should be considered for building a more sustainable team.
3) We may consider elimination mechanisms and iterations of teams and compare the TA model with the machine learning algorithms based on the evaluation metrics (e.g., precision, recall, and F-measure).
4) We may consider agents that are not interchangeable in terms of skillset.
5) The changes in the individual performance $Q[i, j](t)$ [see Expression (11)] should be fit through a large number of field survey questionnaires for better application.
6) Agents may cause their own periodic changes of individual performance $Q[i, j](t)$ to produce local nonperiodic changes due to major setbacks until it transforms into another periodic status.
7) We may consider the influence of herd psychology on the agents.
8) The losses caused by the reallocation process should be considered.
9) For those agents with vulnerable personalities (i.e., $P^a[i] = 1$), their adaptive abilities may be influenced by the individual performance ranking.

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