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Research on Intelligence Evaluation Method for Crowd Collaboration System

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ABSTRACT

Crowd collaboration system, originating from cooperation among animals in nature, is composed of intelligent subjects, characterized by complex dynamic interactions, and has many applications in daily life. In the fields of psychology and computing, scientists have tried to quantify individual intelligence with performance on tasks. In this paper, we explore the main factors affecting group performance for small production factories from the perspective of intelligence. Based on the individual daily efficiency and the average process efficiency, we evaluate individual intelligence level and interaction intensity by integrating group size and efficiency difference, and thus propose crowd intelligence evaluation method. The rationality of the method is analyzed from overall group performance and change in the average individual performance. In the future, the intelligence evaluation method can be applied to more general production scenarios, and the impact of external uncertainty on the intelligence can be studied with simulation to achieve real-time and quantitative optimization of intelligence level of the crowd collaboration system.

KEYWORDS

crowd collaboration system; interaction intensity; individual intelligence; crowd intelligence; intelligence emergence

Crowd collaboration, as a pervasive association in nature and human society, can be traced back as far as cooperative behavior among animals. This cooperative behavior can be either within the same species, such as the highly structured group behavior presented by ant colonies in achieving complex tasks, or between different species, such as the cooperative symbiosis between sea anemones and anemone fish based on predation and defense[1,2]. Through social behavior observation of these animals, scientists have proposed several bionic optimization algorithms, such as the particle swarm algorithm that simulates the movement of a flock of birds[3] and the ant colony algorithm that simulates the movement of ant colonies[4].

Since the origin of species theory, scientists have continuously tried to explain the mechanism of the occurrence of collaborative behavior from the perspective of evolutionary psychology, and they argued that species select suitable characteristics for survival competition in groups[5]. From closely related primates to humans themselves, groups coordinate actions among individuals through intrinsic cognitive mechanisms to cooperate to achieve common group goals and tasks[6–8].

Furthermore, "crowd collaboration system" is a system composed of multiple subjects and characterized by complex dynamic interactions between subjects, carrying fixed or open tasks. With the development of technology and the Internet, crowd collaboration system presents a broader prospect of practice and application based on the breakthrough and innovation of participating subjects, collaboration methods, and spatial and temporal expansion, such as knowledge coconstruction[9], project crowdsourcing[10], public opinion management[11], and so on.

The current researches on intelligence evaluation form two major systems. In the field of psychology, scientists believed that intelligence evaluation needs to be based on individual cognitive mechanisms. They measured individual performance in this area by identifying key aspects of human or animal cognitive activity[12] and then establishing the corresponding tasks. They attempted to quantify individual intelligence[13] by examining the relevant variables such as Mental Speed or Efficiency of Process in a series of tasks, namely General Intelligence, also known as G factor.

Whereas, with the development and advancement of society, this evaluation method has become significantly inadequate. Some scientists have proposed the computational method of Universal Intelligence from the perspective of information theory, which is applicable to humans, animals, and even machines[14,15].

Both of these intelligence evaluation methods use the individual performance in some tasks to measure intelligence, and then infer the individual performance in other tasks, but it remains doubtful whether such inferences are reasonable[16], and with the increasing trend of specialization, such general intelligence evaluation methods blur the distinction between different kinds of professional intelligence.

As for crowd intelligence, on the other hand, group is currently more treated as a whole and the crowd intelligence is evaluated in the same way as individual intelligence[17].

Psychologists have conducted a series of experiments on groups to demonstrate the existence of crowd intelligence in terms of task performance[18]. Moreover, this experiment found no significant relationship between crowd intelligence and the average or maximum intelligence of group members. Thus, there are key factors other than individual intelligence that determine the intelligence emergence[18].

The basic principle of intelligence emergence can be summarized as follows. Under the stimulation of external

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environmental information, many differentiated intelligent subjects, guided by specific rules, interact non-linearly through organizational forms and dynamically evolve synergistic effects to emerge system intelligence. Among them, intelligent subjects[19], interaction networks[20,21], rules[22–25], and information are the key factors.

In addition, with the development of the economy and society, Small and Medium Enterprises (SMEs) have gradually become an important force in China in terms of economic growth, employment promotion, and technological innovation. However, due to the shortage of capital, talents, management, and technology, SMEs are often in an unfavorable position when facing market competition from large enterprises. Therefore, how to adjust the production and operation mode with limited resources, so that SMEs can create larger revenue with smaller cost, is the breakthrough strategy for the problem of industrial transformation and upgrading.

This paper is based on small manufacturing factories scheduled according to daily orders, with fixed processes and compensation. Employees work as "independent contract workers" to provide labor for the factories, choosing processes based on their abilities and working hours with high mobility. These are exactly "crowd collaboration systems" in which employees interact with each other because of differences in ability levels and work styles. This interaction can be either intra-process or inter-process; it can be either cooperative or competitive. With information transparency, interactions affect crowd intelligence in the form of intelligence emergence.

This paper aims to explore the evolution of production with production factors based on the actual scenario of small manufacturing factories and to propose a universal evaluation method of crowd collaboration system, including individual intelligence and crowd intelligence.

1 Model

1.1 Individual intelligence

1.1.1 Production data

The production data in this paper are taken from a footwear manufacturing factory in Shenzhen, which has introduced an information system in order to schedule the production and contract salary settlement. We obtained the original production data from the service provider, including the punching records and personal information of employees. And we extracted the main information as shown in Table 1.

Through the analysis, we divided the production links and subjects into three categories, namely production orders, processes, and employees, and outlined the basic characteristics: the characteristics of production orders include number and processes involved, the characteristics of processes include process name, unit wages, and employees involved, and the characteristics of employees include employee name, process name, work date, punching time, completed quantity, and actual wages.

Table 1 Punching records.

Attribute	Description
Employee name	N1–N263
Time span	2019-08-02 13:45–2020-11-19 11:28
No.	#1–#8033
Process name	Type 1–Type 13
Quantity	0–4740

1.1.2 Individual daily efficiency

We define the statistical period as 475 days between 2019-08-02 and 2020-11-19, and use day as the time unit for individual efficiency. Based on the punching records, we can know the number of pieces Q_i and the daily working hours t for each production order, so the individual daily efficiency E_{Staff} is calculated as Eq. (1).

$$E_{\text{Staff}} = \frac{\sum Q_i}{t} \tag{1}$$

The total number of records is 255 734, and we calculate the sum of the daily quantity of each employee in each process $\sum Q_i$, and the total number of records after merging is 19 193.

We found that some employees performed multiple processes in a single day. Since we want to measure the distribution of individual intelligence levels within a single process, we need to remove records that involve multiple processes. The daily number of processes performed by employees are shown in Table 2.

As above, about 5.87% records involve multi-process work, after removal, the number of records is 17 031 in total. According to Eq. (1), the individual daily efficiency E_{Staff} is calculated.

1.1.3 Average individual efficiency

To measure the average performance of each employee in each process, we averaged the individual daily efficiency E_{Staff} and obtained the average individual efficiency $\bar{E}_{\text{Staff}}$ with a total of 252 entries.

1.1.4 Average process efficiency

Also, to measure the average performance of all employees in each process, we averaged the average individual efficiency $\bar{E}_{\text{Staff}}$ and obtained the average process efficiency $\bar{E}_{\text{Type}}$ in Table 3.

Table 2 Daily number of processes performed by employees.

Number of processes	Number of records involving multiple processes
1	17 031
2	1027
3	34
6	1

Table 3 Average process efficiency.

Process name	Average process efficiency
Type 1	431.491
Type 2	142.594
Type 3	263.110
Type 4	56.563
Type 5	78.628
Type 6	830.839
Type 7	110.500
Type 8	91.915
Type 9	90.317
Type 10	219.100
Type 11	90.837
Type 13	444.575

1.1.5 Individual intelligence level

We define intelligence as the ability of an intelligent subject to solve a certain type of problem, and that ability is the effective value created by the intelligent subject in this task. Since there are individual differences between different intelligent subjects, we need to calculate the individual relative intelligence of intelligent subjects in the social average dimension, so a certain type of intelligence I of intelligent subjects is shown in Eq. (2).

$$I = \frac{V_\eta}{\bar{V}} \tag{2}$$

where V_η is the effective value of an intelligent subject, and $\bar{V}$ is the effective value of the social average solving that type of problem.

In this paper, we take independent contract workers as the intelligent subjects. For the effective value created in the process, we use the individual daily efficiency to measure; for the social average effective value, we use the average process efficiency to measure. Therefore, the ratio of individual daily efficiency to average process efficiency is individual intelligence I shown in Eq. (3).

$$I = \frac{E_{\text{Staff}}}{\bar{E}_{\text{Type}}} \tag{3}$$

We calculate the individual intelligence I of each employee in each process.

Considering that there are certain fluctuations and uncertainties in the individual intelligence I, we further proposed the individual intelligence level IL, as shown in Eq. (4).

$$\text{IL} = (\mu(I), \sigma^2(I)) \tag{4}$$

The individual intelligence level IL consists of the mean $\mu(I)$ and the variance $\sigma^2(I)$, with the mean $\mu(I)$ reflecting the average level and the variance $\sigma^2(I)$ reflecting the fluctuation, and the individual intelligence level IL is calculated.

We counted the number of employees who had worked on each process, as shown in Table 4.

The distribution of the number of employees in different processes varies widely and can be divided into two main categories.

Types 1–5, 8, 9, and 11: High number of employees, presumably with high mobility in this type of process, low technical barriers, and high demand for personnel.

Table 4 Number of process employees.

Process name	Number of employees
Type 1	8
Type 2	30
Type 3	10
Type 4	72
Type 5	42
Type 6	2
Type 7	2
Type 8	33
Type 9	22
Type 10	2
Type 11	26
Type 13	3

Types 6, 7, 10, and 13: Small number of employees, presumably this type of process is more specialized, with higher technical barriers, relatively fixed personnel, and fewer orders.

In order to present the distribution characteristics and production features of each process, we mapped the distribution of individual intelligence level for each process, as shown in Fig. 1. The horizontal axis represents the mean of individual professional intelligence, and the vertical axis represents the variance.

The points on the graph represent employees. Above the main graph is the histogram of the mean distribution and to the right is the histogram of the variance distribution. We divided the distribution into three main categories.

Types 2, 4, and 9: The mean value shows a good normal distribution, and the mean and variance are obviously concentrated in the distribution, and we presume that the intelligence level of the employees in this process is relatively close.

Types 8, 9, and 11: The range of variance distribution is extremely small, and we speculate that the processes in this category may be more mechanized and the employees' intelligence level is more stable.

Types 1, 3, and 5: The distribution of mean and variance is more dispersed, and we speculate that this type of process may be more specialized, and the skill level of employees reflects the differences in individual intelligence level.

1.2 Crowd intelligence

1.2.1 Interaction intensity evaluation index

Motivated by the external environment, employees working in the same process at the same time, under the rule of high information transparency, have certain interactions with each other, showing synergistic effects, and crowd intelligence emerges in the process.

Therefore, we introduce the concept of group interaction intensity e to quantify the degree of interaction between intelligent subjects. However, the interaction within a group is not a simple linear relationship, and we need to integrate several evaluation indicators. Based on the relevant assumptions, we propose two major indicators, the difference in efficiency and the number of people in the group.

To portray the dispersion of the efficiency, we introduce the coefficient of variation, which is calculated as Eq. (5).

$$c_v = \frac{\sigma}{\mu} \tag{5}$$

Based on the individual daily efficiency of each group, the standard deviation σ and the mean value μ were calculated to obtain the ratio c_v of the two as the difference in efficiency of the group. Using the ratio of the standard deviation and the mean, rather than the standard deviation itself, to portray the degree of dispersion can effectively eliminate the influence of the measurement scale on the results.

In order to analyze the relationship between employees' performance and the difference in efficiency of the rest of the group, we fitted the number of individual completions with the difference in efficiency using a linear regression algorithm, and the estimated coefficients are shown in Table 5. The fitted curves and distributions are shown in Fig. 2. The horizontal axis represents the coefficient of variation of the number of completions by the rest of the group, and the vertical axis represents the number of individual completions.

According to the coefficients, we classify the processes into two major categories.

Types 3 and 11: Individual efficiency shows a negative

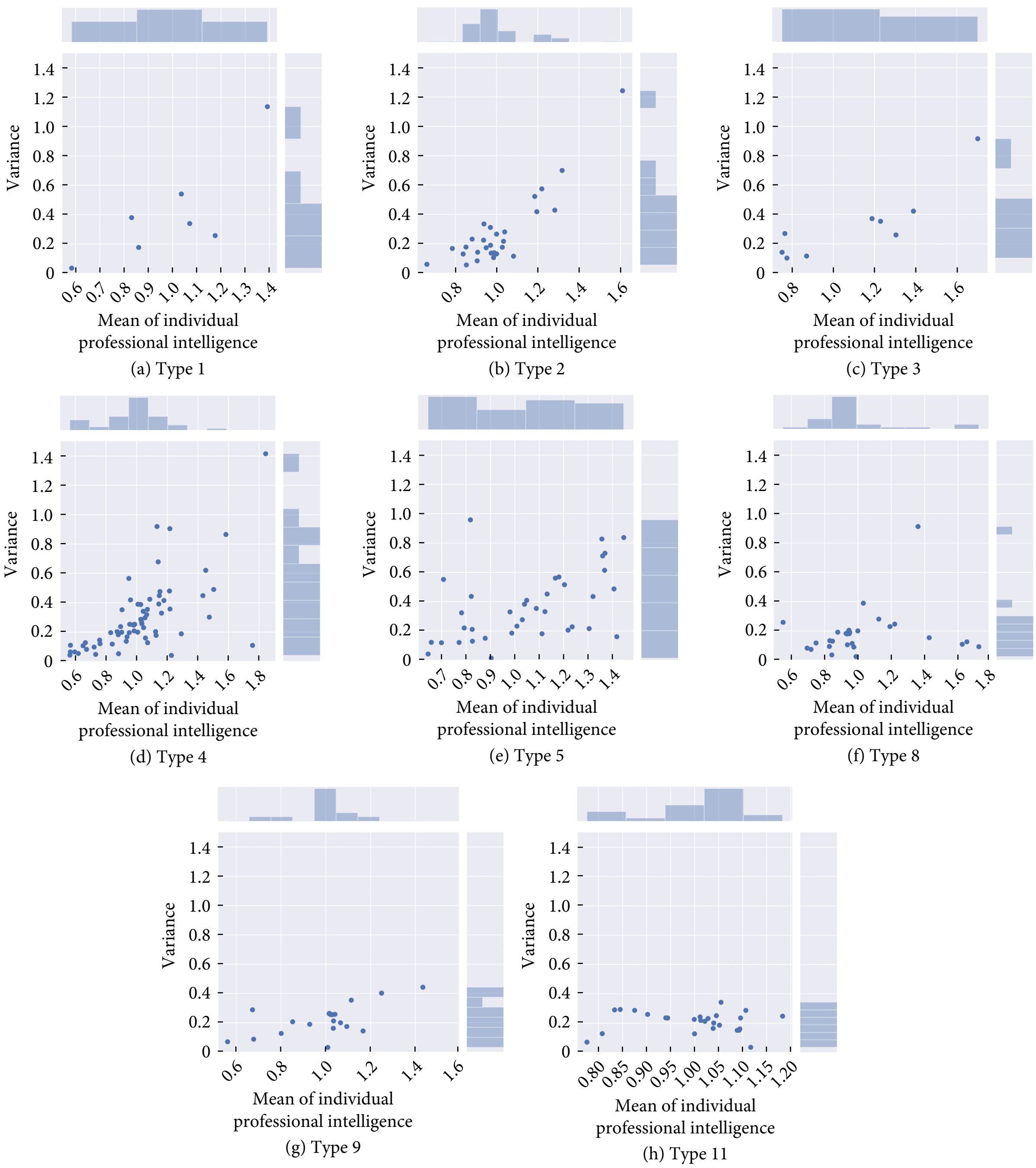

Fig. 1 Process individual intelligence level.

Table 5 Estimated coefficient of individual completions with efficiency difference.

Process name	Estimated coefficient
Type 1	434.74
Type 2	9.01
Type 3	−63.97
Type 4	21.62
Type 5	11.05
Type 8	31.42
Type 9	18.19
Type 11	−103.79

correlation link with the efficiency difference. It can be inferred that this type of process is more specialized, and when the efficiency difference increases, those with low efficiency believe that they cannot catch up with those with high efficiency even if they work hard, and the intensity of crowd interaction gradually decreases.

Others: Individual efficiency is positively related to the efficiency difference. It can be speculated that this type of process is more learnable, and when there is certain efficiency difference in the group, employees will work harder and acquire skills and experience from those with high efficiency due to the sense of competition, and the crowd interaction intensity will gradually increase.

Therefore, we propose the efficiency difference index Z_1 for crowd interaction intensity.

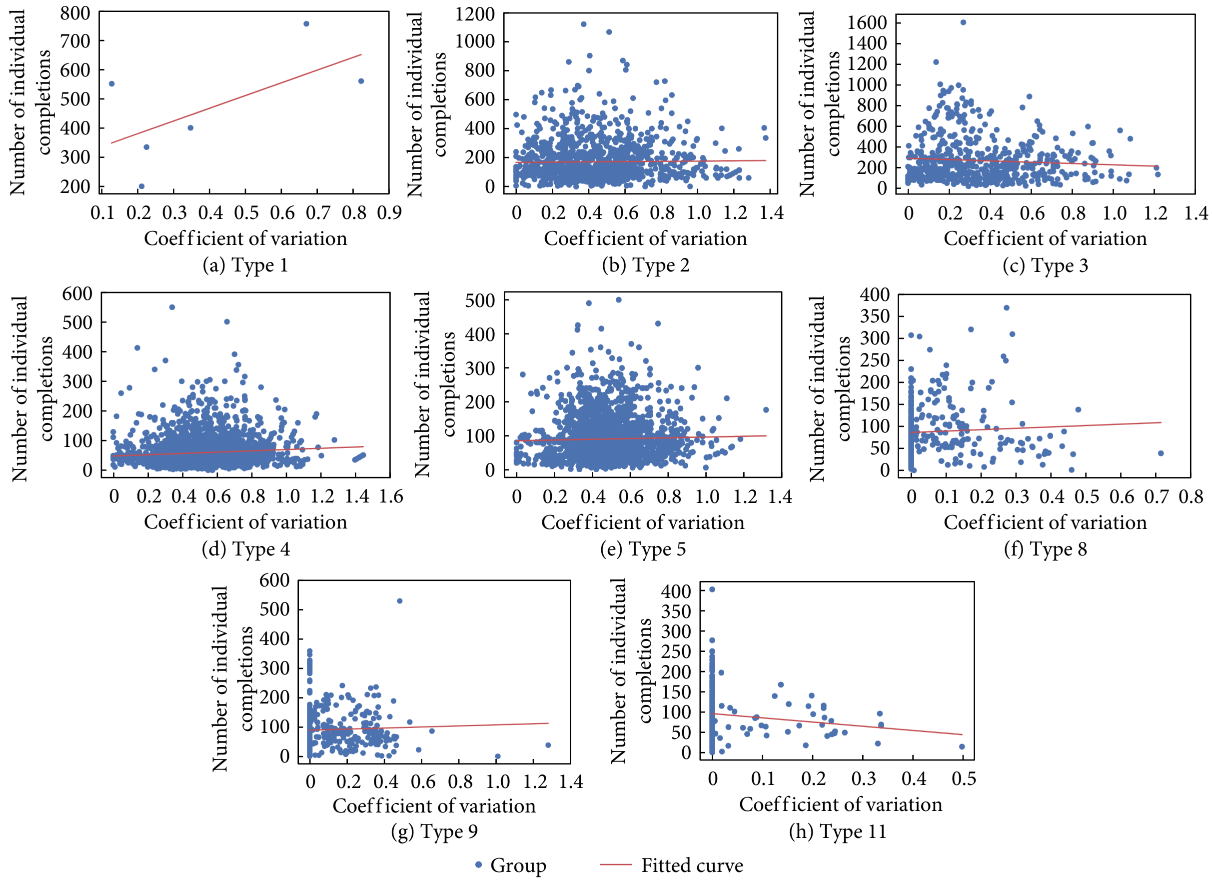

Fig. 2 Relationship between employees' performance and efficiency difference of the rest.

$$Z_{1,i} = \begin{cases} 1 - \dfrac{c_i - C_{\min}}{C_{\max} - C_{\min}}, & \text{if } i \text{ is 3 or 11;} \\ \dfrac{c_i - C_{\min}}{C_{\max} - C_{\min}}, & \text{others} \end{cases} \tag{6}$$

where c_i is the efficiency difference of process i, $C_{\min}$ is the minimum value of the efficiency difference, and $C_{\max}$ is the maximum value of the efficiency difference.

We conducted a linear regression of the relationship between the mean of group completions and the efficiency difference index Z_1, and the estimated coefficients of the fitted curves for each process are shown in Table 6, all of which are positively correlated.

Subsequently, we performed a linear regression of the relationship between the mean number of group completions and the number of people in the group, and the estimated coefficients of the fitted curves for each process are shown in Table 7. The fitted curves and distributions are shown in Fig. 3. The horizontal axis represents the group size and the vertical axis represents the mean of completions in the group.

According to the coefficients, we classify the processes into two major categories.

Type 3: The mean value of efficiency in the group shows a negative correlation with group size. It can be inferred that this type of process is more specialized, and when the group size increases, the influx of low efficiency workers disrupts the normal work of high efficiency workers, and the interaction intensity gradually decreases.

Others: The mean value of efficiency in the group shows a positive correlation with group size. It can be inferred that when the total tasks in this process are small, each can receive a limited

Table 6 Estimated coefficient of mean of group completions with the efficiency difference index Z_1.

Process name	Estimated coefficient
Type 1	17.79
Type 2	1.69
Type 3	182.60
Type 4	51.62
Type 5	5.14
Type 8	2.20
Type 9	51.52
Type 11	54.52

Table 7 Estimated coefficient of mean of group completions with the group size.

Process name	Estimated coefficient
Type 1	67.92
Type 2	7.19
Type 3	−2.34
Type 4	0.96
Type 5	2.36
Type 8	10.36
Type 9	0.88
Type 11	3.60

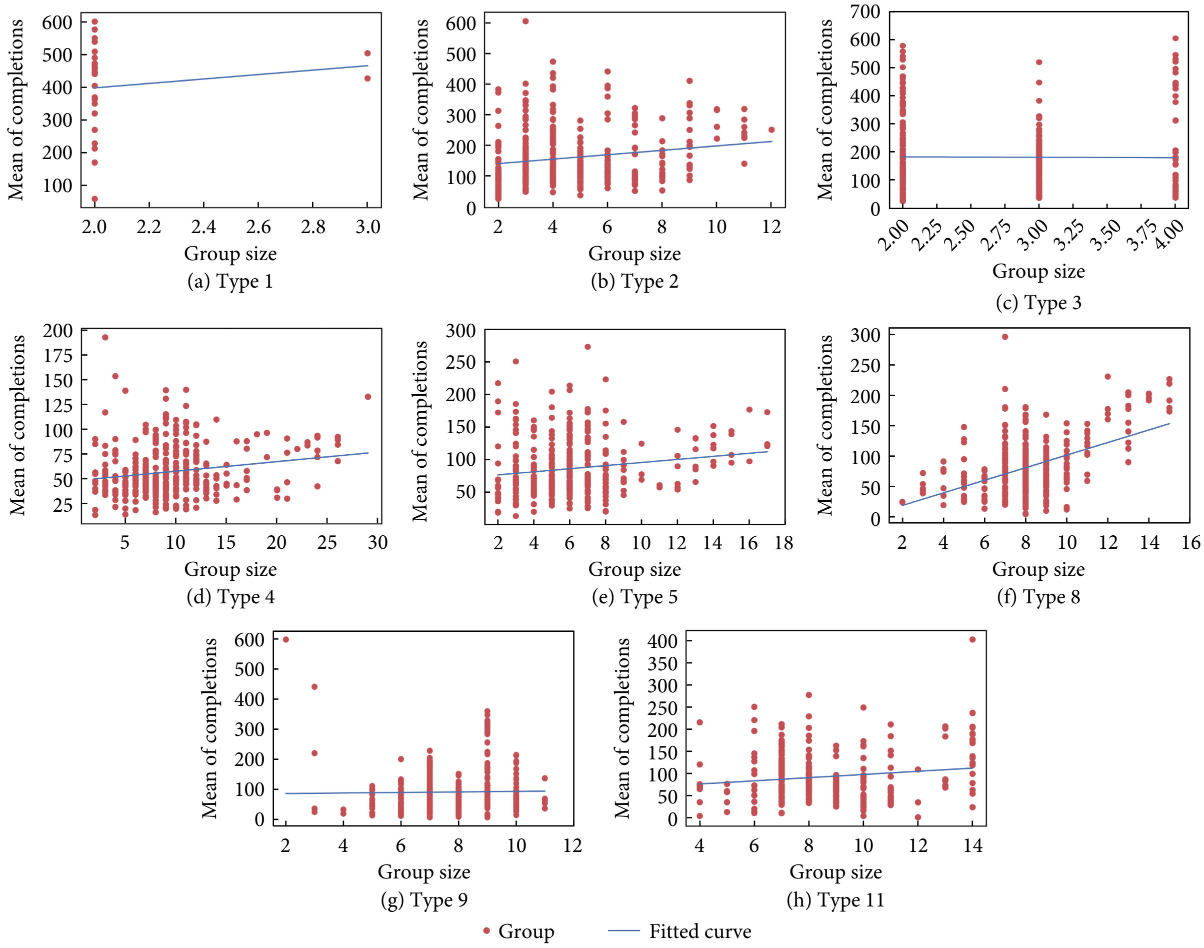

Fig. 3 Relationship between mean of group completions and group size.

number of tasks, and the efficiency is low. It is known that the information transparency is 100%, and as the group size increases, due to the scale effect, individual gets more information, thus improving individual efficiency, and the mean value of group efficiency also increases, and the interaction intensity gradually increases.

In addition, depending on the degree of data volatility, we classify the processes into two major categories.

The degree of fluctuation gradually decreases with the increase in group size: the process may contain employees with different levels, and colleagues have different influence on the employee, so when the group size is small, the efficiency is susceptible to deeper unilateral influence, so there is large difference between different groups; as the group size increases, employees are more comprehensively influenced and have more information, and the difference gradually becomes smaller.

The degree of fluctuation increases and then decreases with the increase in group size: initially, there may be few employees who master the process, and most of them have low skill level, so when group size is small, the average group efficiency is low; as group size increases, people with high efficiency enter some groups, so the partners in the same group can get information to improve their skill level, so the difference between groups is large; when the group size is larger, the probability of including high-level individuals in the group increases, and due to the scale effect, individual gets more information and the average group efficiency increases.

Therefore, we propose the group size index Z_2 for crowd interaction intensity.

$$Z_{2,i}=\begin{cases}1-\dfrac{n_i-N_{\min}}{N_{\max}-N_{\min}}, & \text{if } i \text{ is } 3;\\[2ex] \dfrac{n_i-N_{\min}}{N_{\max}-N_{\min}}, & \text{others}\end{cases} \tag{7}$$

where n_i is the group size of process i, $N_{\min}$ is the minimum value of group size, and $N_{\max}$ is the maximum value of group size.

We also conducted a linear regression of the relationship between the mean of group completions and the group size index Z_2, and the estimated coefficients of the fitted curves for each process are shown in Table 8, all of which are positively correlated.

1.2.2 Crowd interaction intensity

Combining the efficiency difference index Z_1 and the group size index Z_2, we obtained the crowd interaction intensity e, as shown

Table 8 Estimated coefficient of mean of group completions with the group size index Z_2.

Process name	Estimated coefficient
Type 1	135.85
Type 2	79.12
Type 3	7.01
Type 4	26.99
Type 5	37.81
Type 8	134.73
Type 9	7.92
Type 11	35.99

in Eq. (8).

$$e = \omega_1 \cdot Z_1 + \omega_2 \cdot Z_2 \tag{8}$$

where ω_1 and ω_2 are the weights of the efficiency difference index Z_1 and the group size index Z_2 in the crowd interaction intensity e, respectively, which are calculated using the statistical method of Principal Component Analysis (PCA).

We performed principal component analysis on the two indices and retained all the principal components to obtain the variance contribution as shown in Table 9.

We divide the individual loadings in the component matrix by the square root of the characteristic roots to obtain the component score coefficient matrix, i.e., the coefficients of the two indices in the linear combination of the two principal components, as shown in Eq. (9).

$$\begin{aligned} F_1 &= 2.9949Z_1 - 0.3338Z_2, \\ F_2 &= 0.4998Z_1 + 4.4835Z_2 \end{aligned} \tag{9}$$

We use the variance contribution rate as the weight, the weighted average of the coefficients of the two indices in the linear combination, and then normalize the coefficients of the indices to obtain the weights ω_1 and ω_2 of the two in the crowd interaction intensity e, and the formula for the crowd interaction intensity e_i of process i is shown in Eq. (10).

$$e_i = 53.23\% \cdot Z_{1,i} + 46.77\% \cdot Z_{2,i} \tag{10}$$

1.2.3 Crowd intelligence evaluation

We consider the simple scenario of two employees i and j as a group and assume that the individual intelligence of these two employees is I_i and I_j, respectively, and when these two employees do not have any interaction, we define the crowd intelligence I_{ij} of both as a linear sum of individual intelligence, as shown in Eq. (11).

$$I_{i,j} = I_i + I_j \tag{11}$$

When there is an interaction between employees i and j, we define the crowd intelligence $I_{i,j}$ of the two as shown in Eq. (12).

$$I_{i,j} = I_i + I_j + e_{i,j}\sqrt{I_i I_j} \tag{12}$$

where $e_{i,j}$ is the crowd interaction intensity between employees i and j, and $e_{i,j}\sqrt{I_i I_j}$ is the intelligence that emerges through the interaction.

In the process of interaction and emergence of intelligence by intelligent subjects, the two are inseparable as a whole, so we use the product to describe the interaction. In order to make the emergence of intelligence more comparable with the summation of individual intelligence, we improve the direct product to a geometric mean. In addition, during the individual intelligence evaluation, we calculate the individual relative intelligence in the dimension of social average, eliminating the magnitude influence.

Further, we extend the scenario for the interaction of two employees i and j. For an interaction group consisting of n employees, the crowd intelligence I_{group} can be obtained using the above computational law as shown in Eq. (13).

Table 9 Variance contribution.

Principal component	Variance contribution (%)
First	69.15
Second	30.85

$$I_{\text{group}} = \sum_{i=1}^{n} I_i + e\sqrt[n]{I_1 I_2 \cdots I_n} \tag{13}$$

2 Result and Dissussion

We introduced the concept of crowd interaction intensity to portray the degree of intelligence emergence during crowd interaction, and thus calculated the crowd intelligence for each process. Then, does crowd intelligence, which includes the emergence of crowd intelligence, better reflect the actual group production performance than the simple sum of individual intelligence? In this regard, we conducted a deeper study and comparison.

2.1 No interaction

In order to compare with the crowd intelligence that takes into account the emergence of intelligence, we need to calculate the crowd intelligence in the absence of any interaction, when the crowd intelligence is the sum of individual intelligence, as is shown in Eq. (14).

$$I_{\text{group}} = \sum_{i=1}^{n} I_i \tag{14}$$

We selected the records with group size of 1. At this time, the employees are working individually in production, so there is no interaction and no emergence of intelligence. We obtained the individual intelligence in the absence of interaction and averaged it by process, and the average individual intelligence in the absence of interaction for each process is shown in Table 10.

We calculated the sum of individual intelligence for each group in each process, i.e., crowd intelligence I_{group} in the absence of any interaction. We fitted the variation law of the sum of the number of group completions with the sum of individual intelligence for each process using a linear regression algorithm, as shown in Fig. 4. The horizontal axis represents the sum of individual intelligence and the vertical axis represents the total number of group completions.

To measure the degree to which the sum of individual intelligence portrays the group performance without interaction, we introduced two statistical measures, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), respectively.

MAE is the mean of the absolute error between the predicted and actual values and is calculated as shown in Eq. (15).

$$\text{MAE} = \frac{1}{m}\sum_{i=1}^{m} |y_i - \hat{y}_i| \tag{15}$$

where m is the total number, $\hat{y}_i$ is the predicted value, and y_i is the actual value.

RMSE is the arithmetic square root of the squared expectation of the deviation between the predicted and actual values and is calculated as shown in Eq. (16).

Table 10 Average individual intelligence without interaction.

Process name	Average individual intelligence
Type 1	1.3676
Type 2	0.6259
Type 3	0.7712
Type 4	0.7418
Type 5	0.7102

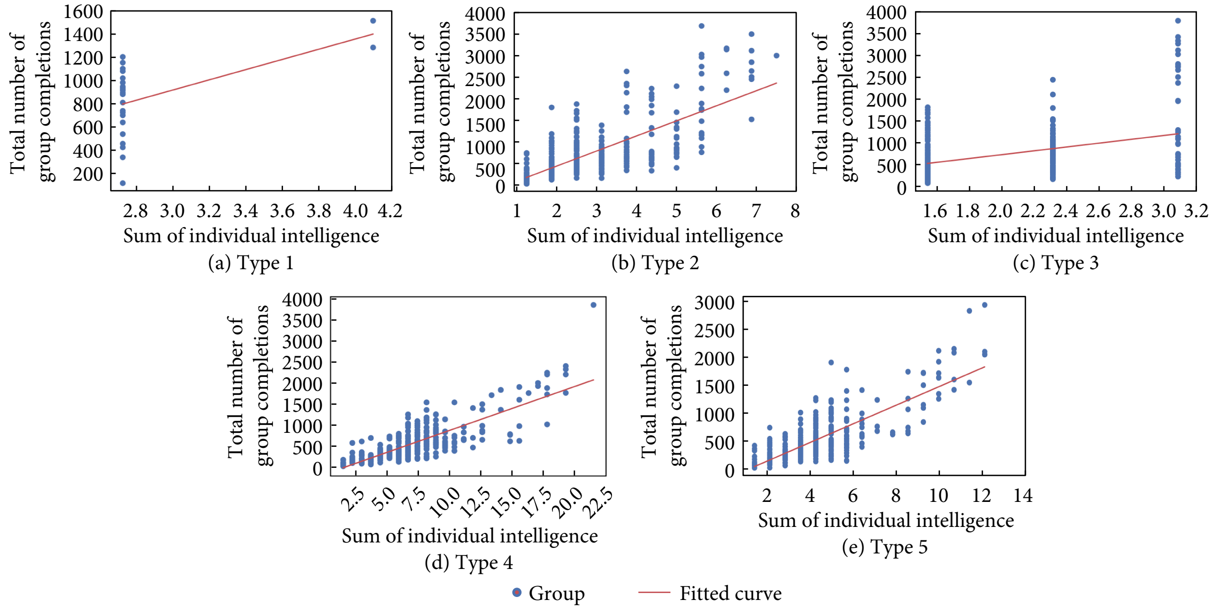

Fig. 4 Relationship between the sum of the number of completions within a group and the sum of individual intelligence.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{16}$$

We measured the degree to which the sum of individual intelligence of each process portrayed the group performance, and the results of the calculation are shown in Table 11.

Table 11 Portrayal of the sum of individual intelligence on group performance.

Process name	MAE	RMSE
Type 1	217.24	266.40
Type 2	349.42	474.04
Type 3	429.22	591.34
Type 4	191.14	264.51
Type 5	205.97	274.62

2.2 Intelligence emergence

2.2.1 Group performance

After considering the interaction, the crowd intelligence is the sum of the individual intelligence and the sum of the interaction intelligence emergence, which is calculated as shown in Eq. (13).

We calculated the crowd intelligence in the presence of interactions and fitted the variation pattern of the sum of the number of group completions for each process with the crowd intelligence using a linear regression algorithm, as shown in Fig. 5. The horizontal axis represents the crowd intelligence and the vertical axis represents the total group completions.

We also used MAE and RMSE to measure the degree to which crowd intelligence under the inclusion of intelligence emergence portrayed group performance, as shown in Table 12.

As can be seen from Table 12, compared the portrayal of group

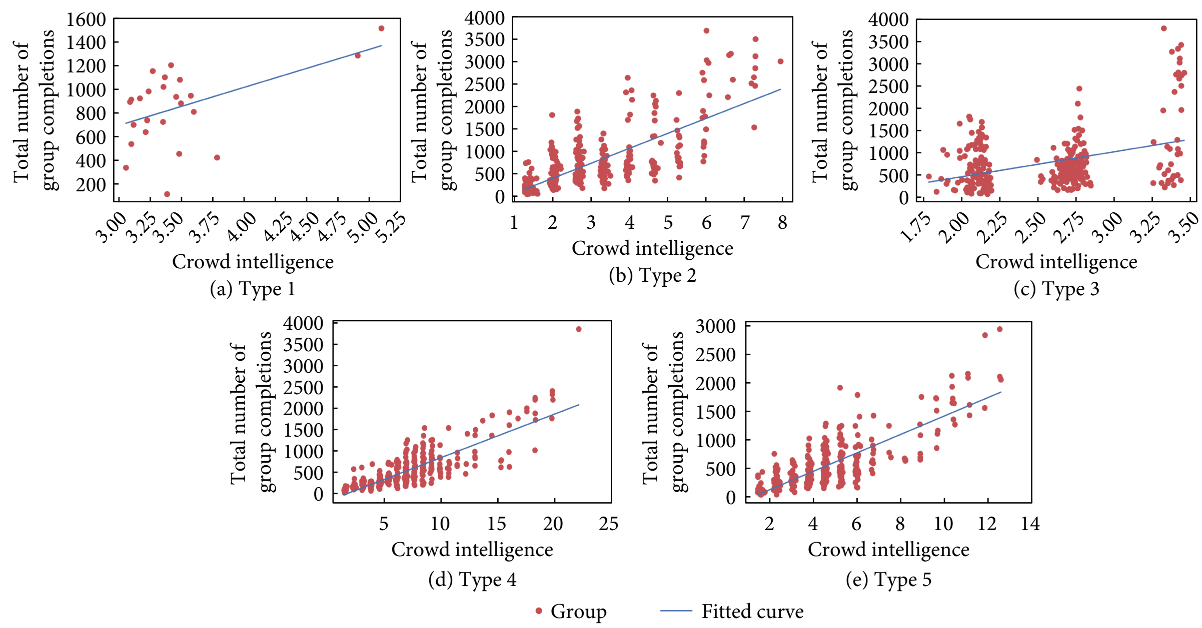

Fig. 5 Relationship between the sum of group completions and crowd intelligence.

Table 12 Portrayal of group performance by crowd intelligence.

Process name	MAE	RMSE
Type 1	212.65	270.93
Type 2	348.35	473.10
Type 3	426.05	585.05
Type 4	189.66	263.06
Type 5	205.92	274.69

performance with the sum of individual intelligence without interaction in Table 11, the crowd intelligence with the emergent intelligence shows a smaller MAE in the portrayal of group performance for all five existing processes, reflecting a better prediction of the actual situation. In addition, the crowd intelligence also outperforms the sum of the individual intelligence on most processes in terms of the RMSE metric, reflecting a smaller RMSE, i.e., a more accurate reflection of the prediction curve for the actual situation.

In addition, compared the distribution of the sum of group completions with the sum of individual intelligence in Fig. 4, the crowd intelligence portrayed the group performance with a combination of discrete data, and the overall data tended to be more concentrated, showing a more similar trend, and the prediction bias was significantly reduced.

In summary, we investigated the trend of the sum of group completions with crowd intelligence at the level of group performance as a whole and reflected the better portrayal of crowd intelligence on production performance in MAE and RMSE indices.

2.2.2 Change in individual average performance

We analyzed the group performance portrayal under the intelligence emergence from the perspective of the average individual performance in the dimension of the amount of variation. For each group of each process, the actual average performance of the individuals can be described by the average group completions. For crowd intelligence, we obtained the mean value of the emergent intelligence, i.e., the average emergent intelligence per person in the group.

Using a linear regression algorithm, we fitted the variation of the mean of group completions for each process with the variation of the mean of crowd intelligence emergence, as shown in Fig. 6. The horizontal axis represents the change in the mean of intelligence emergence, and the vertical axis represents the change in the mean of group completions.

We found that change in the mean of group completions and change in the mean of intelligence emergence in all eight processes of Fig. 6 showed a positive correlation.

Since the two groups of data for each process do not necessarily satisfy the condition of normal distribution, we used Spearman correlation analysis, which does not have any requirement on the distribution of the original variables, to analyze the statistical dependence of the two groups of data. As shown in Table 13, the

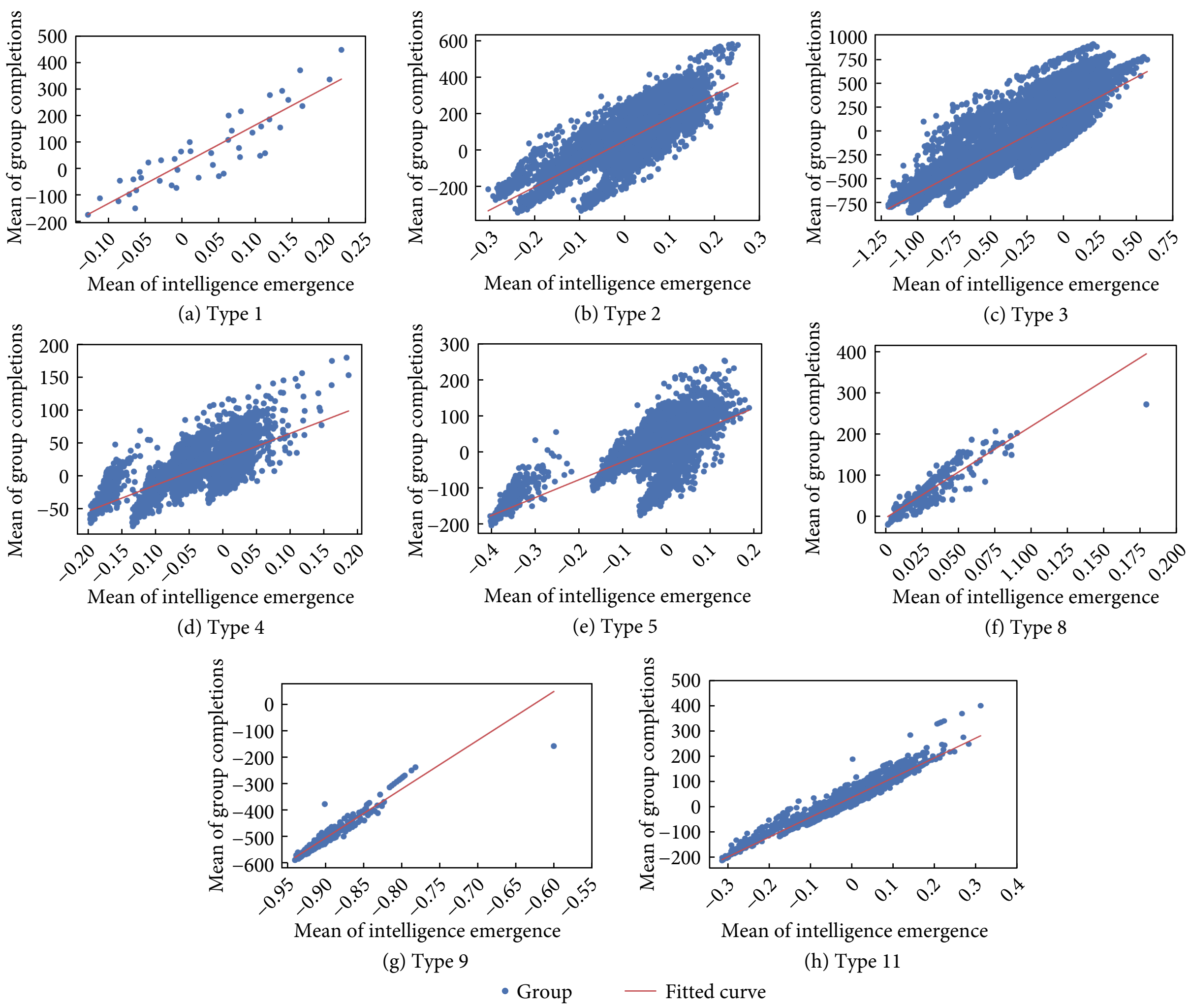

Fig. 6 Relationship between change in the mean of group completions and change in the mean of intelligence emergence.

Table 13 Portrayal of group performance by crowd intelligence.

Process name	Regression coefficient	p-value
Type 1	1481.59	<0.001
Type 2	1265.06	<0.001
Type 3	809.96	<0.001
Type 4	392.31	<0.001
Type 5	497.64	<0.001
Type 8	2226.40	<0.001
Type 9	1859.86	<0.001
Type 11	783.93	<0.001

p-value for all processes was much less than 0.01, showing significant correlations.

3 Conclusion

Based on the actual scenario of a small production manufacturing factory, this paper explores the change pattern of group production performance within a crowd collaboration system with the difference in efficiency and group size from the perspective of intelligence, proposes a crowd collaboration system evaluation method of individual intelligence and crowd intelligence, and analyzes the improvement of the correlation between crowd intelligence and actual production performance.

Quantification of individual intelligence: Based on the actual production data of the factory and the preliminary research on the production mode, production factors such as employees, processes, and orders are abstracted, and the basic characteristics of each production factor are analyzed and organized. From there, the individual daily efficiency and the average efficiency of the process are measured in turn, and the individual intelligence is finally obtained. By analyzing the mean and variance distributions of individual intelligence of each process, we observe the similarities and differences in the mean and variance of the number of people engaged and intelligence of each process and summarize the characteristics of each process in terms of personnel mobility, process requirements, and order demand.

Evaluation of crowd intelligence: We explore the correlation between production performance and efficiency differences and group size in each process, analyze the internal production characteristics of processes with different correlations, and then define interaction intensity evaluation indexes, both of which show positive correlation with the average performance of the group. Subsequently, we obtained the group interaction intensity based on the principal component analysis method to obtain the weight of the indexes and define the evaluation method of crowd intelligence based on the interaction intensity, and calculated the crowd intelligence.

The rationality of the evaluation method: From two aspects of the overall group performance and the change in the average individual performance, we use mean absolute error and root mean square error to reflect that the crowd intelligence considering the emergence of intelligence has a better correlation with group completions. And the Spearman correlation analysis concludes that there is a significant positive correlation between the change in the mean of crowd intelligence emergence and the change in the mean of group completions.

Based on the existing evaluation methods, in the future we can build a set of crowd collaboration system simulation model with actual scenario data, study the effect of environmental uncertainty on the intelligence level in crowd collaboration system, adjust and optimize the existing rules in crowd collaboration system, and realize the real-time and quantitative optimization of the intelligence level of crowd collaboration system.

In addition, the evaluation method of crowd collaboration system has a broad application prospect. We can move from the scenario of small manufacturing factories, which is the basis of this paper, to more common production and processing scenarios, and even from the production scenario to broader political, economic, and cultural fields. Furthermore, based on the existing traditional manufacturing scenario, we can expand to the field of smart manufacturing which is more closely related to individual intelligence and crowd intelligence, use the intelligence evaluation method to achieve a more general measurement of the effective value of things, and use it to guide our production and life.

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