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# MODELING THE COLLECTIVE INTELLIGENCE OF INNOVATIVELY INTEGRATED ENTERPRISES

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**Abstract**. The article addresses the challenges of modelling the collective intelligence of innovation-integrated enterprises in the context of digital transformation. An overview of mathematical models used to describe collective intelligence technologies is given. It is noted that collective intelligence technologies focus on the effective use of intellectual potential in working with an enterprise's organisational capital. The concept of IQ as a measure of intelligence has been confirmed as applicable to the enterprise. The paper proposes a new mathematical model for calculating the collective intelligence quotient IQ, which makes it possible to compare group capabilities with individual ones, and, in particular, allows demonstrating the possibility of increasing the efficiency of the intelligence quotient for each group member by dividing work according to the competencies of the participants. This mathematical model for calculating collective IQ can serve as a basis for assessing the efficiency of enterprises in using collective technologies. To address the most difficult modelling task – the synergy of the intelligence of different people in the course of joint work – a model is proposed that assesses synergy based on participants' analytical or creative abilities. A variant of such synergy is a joint solution to a problem using brainstorming technology. The proposed model enables assessing the effectiveness of collaboration and can also be used to select participants for collaboration. The scientific novelty of the study lies in the study of collective intelligence technologies in enterprise management, substantiation of the place of these technologies in the tasks of corporate informatization and calculation of the effectiveness of new technologies, which made it possible to prove the special role of collective intelligence technologies in the organization of work in the knowledge age. The results of scientific research and the authors' practical recommendations contribute to the effective use and development of collective intelligence in the design of knowledge management systems at enterprises and their network associations in promising knowledge-intensive technological areas.

**Keywords***:* business processes, collective intelligence, competencies, intellectual activity, brainstorming, collaboration tools, human intellectual potential.

**JEL Classification:** C6, D83, J24, M53, O15

## 1. INTRODUCTION

As traditional information technologies used in business free employees from routine tasks and provide self-service to customers and partners, enterprises will face challenges that increasingly require creative teamwork. The innovation competition, currently observed in the high-tech, finance, and telecommunications sectors, will become common across all large enterprises. Meanwhile, collective intelligence technologies are sporadically used to organise expert community groups or, in a simplified form, in organisational knowledge management systems that use CoP tools.

To develop specific methods of use in the economy, collective intelligence technologies require measuring the effectiveness of collective creative activity. It is necessary to investigate how such measurements can be linked to the assessment of human capital within the enterprise, so that the economic impact of introducing collective intelligence technologies can be calculated. Another necessary issue is the study of personality psychology in the organization of collective creative work systems. The professional community's ability to manage the psychology of relationships is difficult to overestimate.

Collective intelligence technologies increase the efficiency of creative activity by precisely matching participants' competencies and reducing the time and quality requirements of tasks (Jaiswal et al., 2023; Gabsi, 2024). At the same time, some creative tasks require a collective search for unique solutions that are beyond the expertise of the experts. In practice, brainstorming is used to generate such ideas, enabling groups to find solutions that are difficult to find individually. How to organise (and whether it is necessary) a networked brainstorming session in which remote experts can participate, and what the limits are on the number and competencies of participants – these questions remain open. Collective intelligence technologies are a new, still unexplored area of knowledge, but they have excellent prospects for use across a wide range of corporate practices. In this regard, the effective use of collective intelligence technologies is becoming increasingly important and relevant.

Collective intelligence technologies serve as a link between information systems that automate a company's business processes and employees with specific competencies (Schemmer et al., 2022). In conventional activities, employees are selected so that their competencies align with the business process, and in some cases, they receive appropriate training. In the case of intellectual activities, the required competencies increase significantly. At the same time, they are related not only to the professional sphere but also to organisational and creative abilities, which are complex and sometimes impossible to teach (Rastogi et al., 2022). In addition, solving creative tasks usually does not fit into a strict time frame and, when "assembled" into a single business process, can have unpredictable results. In this regard, competency models for effective problem solving should be tailored to the business process itself, enabling the distribution of problems within it to be tailored to specific employees (Ostrovska et al., 2023). The interaction between competencies and business processes represents the interconnection between explicit and implicit knowledge within companies. It is in this context that we should talk about the effective management of intellectual potential. The key objective of collective intelligence technologies is to effectively utilise an enterprise's intellectual capital to manage organisational capital.

## 2. LITERATURE REVIEW

Collective intelligence is a well-known postulate that when large human communities pool their knowledge, experience, and insights, they can outperform the average participant in a range of practical tasks. This "amplification effect" scales with group size, especially when participants have different knowledge, experience, perspectives, or situational awareness (Malone, 2019). The concept of collective intelligence was discovered by Sir Francis Galton in 1906. In the late nineteenth century, this concept was associated with the studies of G. Tarda, E. Durkheim, G. Le Bon, S. Siegel, and G. Simmel.

The relevance of collective intelligence technologies for managing corporate knowledge amid digital transformation is substantiated by a study (Ostrovska et al., 2021). In this context, the authors (Weng et al., 2018) propose that all social networks be considered as a knowledge infrastructure of collective intelligence. It is noteworthy to mention a study (Riedl et al., 2021) that proposes a methodology for quantitatively assessing collective intelligence.

In studying collective intelligence technologies, the authors (Garzón et al., 2025) emphasise the potential of collective intelligence structures as a promising direction in metaheuristic research. They demonstrate the interaction between individual members and a specific community, which contributes to the emergence of global solutions under unknown conditions, and illustrate similar emergent phenomena that manifest in social organisations. In this context, Naplyokov (2021) demonstrated that collective emotional intelligence contributes to the development of a "collective mind" and to the effective use of social capital, fostering a culture of trust and tolerance in which extensive networks of voluntary associations emerge.

Several scientists (Willcox et al., 2023) present a new collective intelligence technology, hyper swarm ranking and demonstrate that it allows online communities to generate group ratings much faster than traditional methods. Another noteworthy paper (Rosenberg, 2025) explores the pursuit of collective superintelligence through a new technology called conversational swarm intelligence, which enables real-time conversational discussions among networked human groups of potentially unlimited size and rapid decision-making through significantly enhanced collective intelligence.

The authors (Wu et al., 2024) analyse collective intelligence technologies in the context of their application in industrial settings to create intelligent perception-cognition-decision-action processing cycles that support a platform economy with distributed intelligence and reshape the ecosystems of industrial development and the digital economy.

Currently, there is no consensus on precisely what collective intelligence technologies should include. Collective intelligence technologies are understood to be tools and systems that bring together the necessary number of people with their own individual goals into groups, but organised in such a way that the collective intelligence and effectiveness of the group increase.

Despite the extensive bibliography on the issue under consideration, a full-fledged collective intelligence combining people, networks, and computers has not yet been created. The literature primarily consists of theoretical works based on a multi-agent approach. In addition to recognising the holistic and adaptive nature of collective intelligence, the issues of integrating collective intelligence with computer systems and technologies that frame it, the interaction of collective intelligence and individual intelligence, and the scope of collective intelligence remain relevant.

## 3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

The purpose of the article is to develop and study models and mathematical methods for analyzing microeconomic processes and systems using collective intelligence technologies. The object of research is the process of modelling and analysing the characteristics of collective intelligence to improve the efficiency of the management of innovation-integrated enterprises. The study examines the theoretical and applied roles of developing mathematical models using collective intelligence technologies in the context of the digital transformation of innovation-oriented enterprises.

The development of the theoretical and methodological approach should be based on the theory of the phenomenon of collective intelligence of the individual and its development in activity; the theory of organisation and competitive advantage; and motivation, creativity, and innovation.

General and special research methods: dialectical cognition; deduction and induction; generalisation and scientific abstraction; synergetics; integrated use of systemic, expert, and comparative analysis; economic and mathematical modelling; method of verification of conceptual models; formal and logical development and justification; competence; dialectical and synergistic approaches.

## 4. RESULTS AND DISCUSSION

### 4.1. Modeling collective intelligence

Even though collective intelligence technologies are widely studied, and D. Engelbart coined the term collective IQ in the mid-1990s, there are few mathematical models for calculating collective IQ in the literature. Obviously, the first work on calculating CIQ (collective IQ) is Szuba's (2001) research. The author developed a quasi-chaotic numerical model that could simulate the collective solution of tasks that cannot be solved by individuals, only through interaction between participants. The model is built at the macro level, and, in this sense, the author even calls it simplified. Wolpert (2003), modelling the intellectual activity of groups, used game-theoretic methods to model the connections between group members that must satisfy the various private interests of participants in the collective work. Wolpert called the methods he and his colleagues used COllective Intelligence – COIN. Another researcher in the field of collective IQ modeling was Schut (2010), who proposed a general model that takes into account various characteristics of collective intelligence proposed in the works of other researchers, in particular, Eben, Tom, Butz, Stanley, Bryant, Mikkulainen, and A. Engelbrecht.

Some field studies have attempted to calculate collective IQ in social networks (Kosinski et al., 2012). In these circumstances, the results were close to those of traditional IQ tests, allowing comparisons between the effects of group work and individual work. It has been demonstrated that, with an increase in the number of participants (especially with the introduction of a system for selecting the most competent), group IQ increases. However, when the group IQ is applied to the participants, it is lower than the participants' individual IQs. Thus, crowdsourcing technologies are not effective for intellectual work and are appropriate only for solving research problems.

Numerous studies on the efficiency of collective intelligence have also marked recent years. For example, the work of Swiss scientists R. Mann and Helbing (2017) investigates the impact of incentives on the efficiency of collective intellectual work. The authors built a simulation model in which a collective forecast is formed by aggregating individual forecasts based on simple voting. In this context, agents were "motivated" by rewards for accurate predictions. These studies confirm that collective intelligence produces more accurate results (and converges to them faster) when agents are rewarded not only for correct results, but also for correct predictions in the face of minority ("opposition"). A similar study was presented by a group of scientists led by MIT professor Prelec et al. (2017). In the survey, Bayesian methods were used to improve the accuracy of collective decision-making, and the authors propose using hypothetical-scenario assessments as additional conditional probabilities.

Taiwanese researchers (Weng et al., 2018) conducted a large-scale study of the UPVoCI (user-perceived values of collective intelligence). Out of 26 factors that influence the value of collective intelligence, including strengthening interpersonal relationships, enhancing personal reputation, etc., they selected the 17 most influential ones. According to the authors, the new structural scale for measuring UPVoCI will help determine companies' perceived values and the benefits of participating in joint intellectual activities. This measurement scale also allows online social networking service providers to assess potential limitations in users' perceptions of their services, thereby improving and developing popular social networking features and platforms.

Collective intelligence refers to the collective behaviour of decentralised, self-organising systems that can quickly coordinate their actions.

The effect of properly organised teamwork, taking into account participants' competencies, can be seen through a simple mathematical model for calculating the collective intelligence quotient. Such a model can also be used to automate group activities, as it allows estimating the distribution of work among experts so that their time is minimised and quality is maximised. Since the collective IQ for a group of 1 person should equal the individual IQ, the CIQ formula must be coordinated with the individual IQ calculation.

Individual IQ tests are sets of tasks that assess different competencies (logical, spatial, permutation, etc.) and vary in complexity, to be solved in a limited time. The solution to any problem involves a probabilistic process that can be represented by a probability density function, such as (1).

$$p(t, a_i, \sigma_i) = d_i e^{-\left(\frac{t-a_i}{2\sigma_i^2}\right)^2} \tag{1}$$

where $p$ is the probability that the task will be solved at time $t$, the value of $a_i$ can be interpreted as the complexity of the task, and the value $1/\sigma_i$ can be interpreted as the analytical ability of the test subject (at small values of $\sigma i$ or high analytical ability, the function degenerates into a $\delta$-function). The task will be solved at some point, i.e., there is a reliable event with probability 1.

$$d\int_0^\infty p\left(t,a_i,\sigma_i\right)dt=1 \tag{2}$$

Calculating the integral, we find the normalizing multiplier $d_i$.

$$d_i=\frac{1}{\sqrt{\pi\cdot 2}\sigma_i\left(\frac{1}{2}+\Phi\left(\frac{a_i}{\sigma_i}\right)\right)},$$

Here, $\Phi(x)$ is a Laplace function.

$$\Phi\left(x\right)=\frac{1}{\sqrt{2\pi}}\int_0^x e^{-\frac{t^2}{2}}dt \tag{3}$$

From a practical point of view, only the integral values of the probability density function make sense: the value is the probability that the task will be solved at time t, and the value is the average time to solve the task. If two tasks (1) and (2) of different complexity and with different analytical capabilities are solved sequentially, the probability density that the first task will be solved in time $t'$ and the second in time ($t$-$t'$) for all values of $t'$ before time t is (4):

$$p\left(t,a_{1,2},\sigma_{1,2}\right)=\int_0^t p\left(x,a_1,\sigma_1\right)\cdot p\left(t-x,a_2,\sigma_2\right)dx \tag{4}$$

Fig. 1 shows the probability densities of the form (1) for solving problems of different degrees of complexity and analytical capabilities separately (curves 1 and 2), as well as the probability of solving two problems simultaneously (curve 3). It is easy to see that the "total" probability density is close in shape to the distribution with less analytical ability, and the maximum corresponds approximately (exactly, if one of the distributions is a $\delta$-function) to the sum of the complexity of solving individual problems.

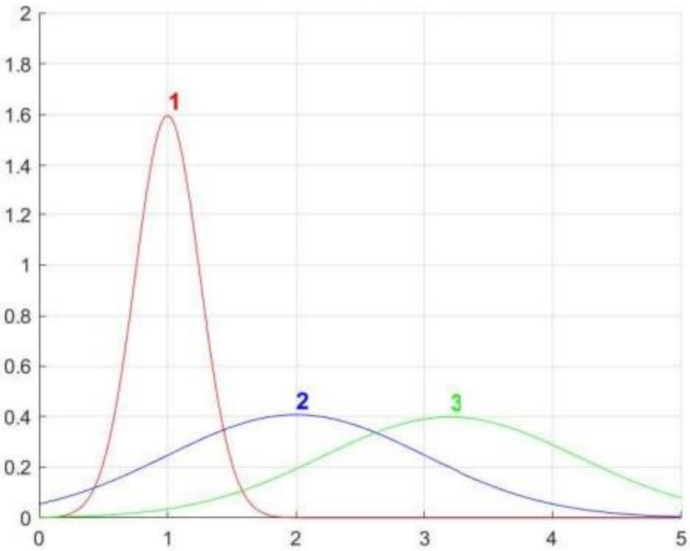


*Fig. 1. Probability density of problem-solving dynamics*

*Curve 1 –* $a_i=1, \sigma_a=4$. *Curve 2 –* $a_1=2, \sigma_a=1$. *Curve 3 – corresponds to the probability density of solving two problems*

*Source: compiled by the authors*

The most important property of the probability density function from the point of view of building a model for calculating IQ is that the average time to solve two tasks is precisely equal to the sum of the average time to solve each task separately, regardless of the task complexity and analytical capabilities of those who solve them, according to equation (5):

$$T_{1,2} = \int_0^{\infty} t dt \int_0^{t} p(x, a_1, \sigma_1) \cdot p(t - x, a_2, \sigma_2) dx =$$
$$= \int_0^{\infty} x \cdot p(x, a_1, \sigma_1) dx + \int_0^{\infty} x p(x, a_2, \sigma_2) dx = T_1 + T_2 \quad (5)$$

The additivity of the average time value means that any task can be decomposed into a set of simpler tasks, whose total time will not change. Thus, the average time required to solve a task can serve as a universal indicator of both its complexity and a person's analytical capabilities. As a rule, in the management of an organization, business processes are structured in such a way that the time to solve a task is longer than the average time to solve a task, taking into account the time of possible delay in solving it, proportional to $\sigma_i$, the inverse of which determines the analytical capabilities of the employee. At the same time, it is implicitly assumed that $\sigma_i$ is much smaller $T_i$ (the probability density distribution is close to the $\delta$-function), meaning that employees have all the necessary competencies (sufficient analytical capabilities) to solve tasks within the specified time frame. For complex intellectual tasks, the probability density of their solution may differ significantly from a δ-function. Given this, it is not the average time to solve a problem that makes sense, but the probability of solving it in a given time interval $\Delta t$, as determined by formula (6):

$$P(\Delta t, a_i, \sigma_i) = \int_0^{\Delta t} p(x, a_i, \sigma_i) dx. \quad (6)$$

In real life (including during testing), the time available to solve a problem is always limited. Therefore, it is the value of the probability of solving a problem ($\Delta t$) that should be correlated with a person's intellectual abilities.

Let's assume that in IQ tests, a certain amount of time is allocated to each task (usually, the test allocates time for each task, but the test subject allocates time for solving complex tasks). Then, if the test taker is asked to solve several tasks, the time for each task is allocated proportionally. With this approach, the number of tasks solved by the test subject equals the probability of solving one task multiplied by the number of functions (each of which is allocated time). Such a testing algorithm allows us to build a simple mathematical model for calculating the intelligence quotient, which will be valid for both individual and collective IQ.

Here is our concept of a group competency matrix $A$.

$$A = \begin{pmatrix} p_{11} & p_{12} \cdots & p_{1k} \\ p_{21} & p_{22} \cdots & p_{2k} \\ \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} \cdots & p_{nk} \end{pmatrix}$$

$P_{ij}$ is the probability of solving the problem in a given time, where $i$ is the ordinal number of the group member. And $j$ is the ordinal number of the competence $\left( j = \overline{1, k} \right)$.

Let us also set the group test matrix $B$:

$$B = \begin{pmatrix} b_{11} & b_{12} \cdots & b_{1k} \\ b_{21} & b_{22} \cdots & b_{2k} \\ \cdots & \cdots & \cdots \\ b_{n1} & b_{n_2} \cdots & b_{nk} \end{pmatrix}$$

*Bij* is the number of tasks (tests) corresponding to competence $j$ that must be solved by a group member with the sequence number $i$.

Then the probable number of tasks solved by the group is equal to $\sum_{i=1}^{n} \sum_{j=1}^{k} a_{ij} b_{ij}$, and the group intelligence coefficient is equal to expression (7):

$$IQ_{\text{групи}} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k} a_{ij}\cdot b_{ij} \tag{7}$$

As can be seen, when the number of group members ($n$) is 1, we get the usual model for calculating IQ for one person, which summarizes the probabilities of solving tasks multiplied by their number in the text:

$$IQ_1 = \sum_{j=1}^{k} a_{1j} b_{1j}$$

If the values of $b_{ij}$ of the group matrix do not depend on $i$, i.e., the task sets are the same for all group members, the group IQ calculated by (7) will be equal to the average of the individual IQs of the group members (8):

$$IQ\,\text{групи} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{\text{к}} a_{ij}\cdot b_{ij} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{\text{к}} a_{ij}\cdot b_{1j} = \frac{1}{n}\sum_{i=1}^{n} IQ_i \tag{8}$$

It's another matter if the group members cooperate, exchanging tasks so that their competencies are used most effectively. Of course, such collaboration should not violate the rules for solving a common task, as outlined in the group test matrix. This means that the redistribution of tests should not change the total number of functions within a particular competence, and cannot exceed the number of tasks (workload or time) for each group member $\sum_{j=1}^{k} b_{ij} = const = C_i$.

Let's introduce the concept of a collaborative group test matrix $K$:

$$K = \begin{pmatrix} x_{11} & x_{12}\dots & x_{1k} \\ x_{21} & x_{22}\dots & x_{2k} \\ \dots & \dots & \dots \\ x_{n_1} & x_{n2}\dots & x_{nk} \end{pmatrix}$$

Conditions must be met:

$$\sum_{i=1}^{n} x_{ij} = B_j, \quad \sum_{j=1}^{k} b_{ik} = C_i \tag{9}$$

Taking into account the definition of the collaboration matrix, the collective intelligence coefficient will be determined as:

$$CIQ = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k} a_{ij}\cdot x_{ij} \tag{10}$$

This is the formula for the collective intelligence quotient (CIQ), which, in general, does not coincide with the definition of group IQ (8), but is related to it by the ratio (9). For now, let's use a simple example to show that using a collaboration matrix to organise a group's work can increase the group's IQ, even when the number of tasks and the time allocated to their solution remain constant. Let's assume that we have a group of 4 test subjects, and the tasks can be grouped into six competencies. Let's also assume, for simplicity, that the probabilities of the test subjects solving the tasks are either 1 (they will definitely solve them) or 0 (they will definitely not solve them). A possible competency matrix for group A is shown in Fig. 2 (left).

| | | | |
|---|---|---|---|
| 1 | 0 | 1 | 0 |
| 1 | 0 | 1 | 1 |
| 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 1 |

| | | | |
|---|---|---|---|
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |

| | | | |
|---|---|---|---|
| 1 | 0 | 1 | 0 |
| 1 | 0 | 1 | 1 |
| 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 1 |

**3 3 4 2**

*Fig. 2. Competency matrix, group IQ matrix and test results*

*Source: compiled by the authors*

Let's assume that the group matrix of tests is also simple: each group of competencies is allocated the same number of tests, equal to 1. The view of matrix B is shown in the centre of Fig. 2. Then it is easy to see that multiplying the matrices (one by one) will give a matrix that coincides with the competency matrix, the sum of which by columns shows the IQ of each participant, as shown in Fig. 2 on the right. In this case, the group IQ equals the average IQ of the group's participants (3).

Now we'll consider the case of using a collaboration matrix, as shown in Fig. 3.

| | | | |
|---|---|---|---|
| 1 | 0 | 1 | 0 |
| 1 | 0 | 1 | 1 |
| 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 1 |

| | | | |
|---|---|---|---|
| 2 | 0 | 2 | 0 |
| 0 | 0 | 0 | 4 |
| 0 | 4 | 0 | 0 |
| 4 | 0 | 0 | 0 |
| 0 | 2 | 2 | 0 |
| 0 | 0 | 2 | 2 |

| | | | |
|---|---|---|---|
| 2 | 0 | 2 | 0 |
| 0 | 0 | 0 | 4 |
| 0 | 4 | 0 | 0 |
| 4 | 0 | 0 | 0 |
| 0 | 2 | 2 | 0 |
| 0 | 0 | 2 | 2 |
| **6** | **6** | **6** | **6** |

*Fig. 3. Competency matrix, collaboration matrix, and test results*

*Source: compiled by the authors*

The collaboration matrix shown in the centre of the figure is consistent with the group test matrix because the sums of the cells in each column (six in this example) and in each row (four) are equal. Each test taker will have the same number of items to solve, and the total number of items per competency will match those in the group test matrix. However, if the competency matrix and the collaboration matrix are multiplied (i.e., the test items are redistributed among the participants), the results shown by the group members - in the figure on the right - will be different, with each subject showing the maximum possible result (six), and, therefore, the collective CIQ will be twice as high as in the previous case, when the participants did not exchange tasks. When organizing work within collective intelligence technology framework, it is essential to define a collaboration matrix. No tests are needed in the real world of organisations. However, as shown, any task can be divided into subtasks, and the average time to solve them equals the average time to solve the overall task. If the division into functions is carried out in such a way that each task requires separate competencies and approximately the same time, then the collaboration matrix will allow you to distribute these tasks in a group in such a way as to maximize the probability (or quality) of their solution.

Let's take a closer look at the algorithm for calculating the collaboration matrix. The collaboration group matrix of tests *K* depends both on the group IQ matrix of tests *B* (whose elements are greater than zero and determine the number of tasks with the time allotted for their solution), with which it is connected by the relations (9), and on the competence matrix *A*, since it must satisfy the requirement of maximum value (10).

To obtain the maximum value of CIQ, it is necessary to find the maximum of the linear function of the variables xij subject to the constraints (9).

$$u = \sum_{i=1}^{n}\sum_{j=1}^{k} a_{ij} \cdot x_{ij} = a_{11}x_{11} + a_{12}x_{12} + \ldots a_{1k} \cdot x_{1k} + a_{21} \cdot x_{21} + a_{22} \cdot x_{22} + .. + a_{2k} \cdot x_{2k} +$$

$$+ \ldots + a_{n_1} \cdot x_{n1} + a_{n2} \cdot x_{n2} + \ldots + a_{nk}x_{nk} \qquad (11)$$

This is an integer linear programming problem for which methods have been developed, and programs are available (e.g., Excel).

Suppose there is a group of eight experts, and 20 different competencies can be distinguished in the tasks. The probability of experts solving the tasks, depending on their competencies, is unevenly distributed.

Table 1 shows the competency matrix.

*Tab. 1*

*Competency matrix*

| Competencies / Participants | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | 0,06 | 0,00 | 0,01 | 1,00 | 0,08 | 0,00 | 0,03 | 0,00 |
| 2 | 0,12 | 0,00 | 0,03 | 0,95 | 0,16 | 0,00 | 0,06 | 0,00 |
| 3 | 0,20 | 0,00 | 0,08 | 0,82 | 0,27 | 0,00 | 0,10 | 0,00 |
| 4 | 0,28 | 0,00 | 0,16 | 0,64 | 0,36 | 0,00 | 0,15 | 0,00 |
| 5 | 0,32 | 0,02 | 0,27 | 0,45 | 0,40 | 0,00 | 0,22 | 0,00 |
| 6 | 0,33 | 0,07 | 0,36 | 0,29 | 0,36 | 0,00 | 0,29 | 0,00 |
| 7 | 0,32 | 0,22 | 0,41 | 0,17 | 0,27 | 0,00 | 0,37 | 0,00 |
| 8 | 0,33 | 0,51 | 0,39 | 0,09 | 0,17 | 0,00 | 0,44 | 0,00 |
| 9 | 0,34 | 0,85 | 0,35 | 0,04 | 0,09 | 0,00 | 0,48 | 0,00 |
| 10 | 0,35 | 1,00 | 0,33 | 0,02 | 0,07 | 0,02 | 0,50 | 0,01 |
| 11 | 0,34 | 0,85 | 0,35 | 0,01 | 0,09 | 0,07 | 0,48 | 0,02 |
| 12 | 0,33 | 0,51 | 0,39 | 0,00 | 0,17 | 0,22 | 0,44 | 0,04 |
| 13 | 0,32 | 0,22 | 0,41 | 0,00 | 0,27 | 0,51 | 0,37 | 0,09 |
| 14 | 0,33 | 0,07 | 0,36 | 0,00 | 0,36 | 0,85 | 0,29 | 0,17 |
| 15 | 0,32 | 0,02 | 0,27 | 0,00 | 0,40 | 1,00 | 0,22 | 0,29 |
| 16 | 0,28 | 0,00 | 0,16 | 0,00 | 0,36 | 0,85 | 0,15 | 0,45 |
| 17 | 0,20 | 0,00 | 0,08 | 0,00 | 0,27 | 0,51 | 0,10 | 0,64 |
| 18 | 0,12 | 0,00 | 0,03 | 0,00 | 0,16 | 0,22 | 0,06 | 0,82 |
| 19 | 0,06 | 0,00 | 0,01 | 0,00 | 0,08 | 0,07 | 0,03 | 0,95 |
| 20 | 0,02 | 0,00 | 0,00 | 0,00 | 0,03 | 0,02 | 0,02 | 1,00 |

All elements of the group test matrix $b_{ij} = 1$

*Source: compiled by the authors*

The average indicator of the work of such a group without collaboration is 4.54. If collaboration is used in this group's work, its efficiency can increase almost threefold (2.84, to be exact), up to 12.87. The collaboration matrix calculated by the described algorithm is shown in Table 2.

*Tab. 2*

*Collaboration matrix*

| Competencies / Participants | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 |
| 3 | 3 | 0 | 0 | 4 | 1 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 |
| 6 | 4 | 0 | 4 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 |
| 9 | 0 | 7 | 0 | 0 | 0 | 0 | 1 | 0 |
| 10 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 0 | 5 | 0 | 0 | 0 | 0 | 3 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 |
| 13 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 |
| 14 | 4 | 0 | 0 | 0 | 0 | 4 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 |
| 16 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 |
| 17 | 5 | 0 | 0 | 0 | 3 | 0 | 0 | 0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 18 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 4 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 |

*Source: compiled by the authors*

Interestingly, in collaborative settings, individual participants may be less effective than when working alone. Thus, in the calculations, the first participant, who is the most effective in individual tests and solves an average of 5 problems out of 20, will show lower efficiency in collaboration, solving an average of 4.77 issues out of 20. Instead, some of the group members will achieve performance several times higher than their own and the group's highest performance. In the above case, the average performance of the four participants will be even higher than 18 out of 20 (the second, fourth, sixth, and eighth). In practice, organisations can still improve efficiency because, unlike testing, in real life, there is no strict requirement for an even distribution of all group members - free participants can be used to handle other tasks within the enterprise.

The algorithm for teamwork organisation, based on collective IQ calculation, resembles the division of labour, except that it applies to intellectual rather than physical labour. The appropriate breakdown of the overall task into subtasks, along with personnel recruitment, contributes to the effective use of scholarly potential.

However, in intellectual activities, collaboration can lead to increased efficiency not only through competent distribution of responsibilities, but also through joint activities. It is not easy to model such processes, but it is possible to evaluate their effects to understand how to use them in collective intelligence technologies.

**4.2. Modeling the effect of expert collaboration**

The distribution of tasks based on competencies is not the only condition for increasing the efficiency of collective intellectual activity. The proper organisation of joint work on a single task is essential. Let us consider a mathematical model of expert collaboration to assess the effects of joint work and determine which experts should be combined. The collaboration model will concern the joint work of an analyst and an "idea generator".

The division of experts into analysts and "idea generators" is an essential component of the brainstorming method. To understand how synergy is achieved in the interaction between an idea "generator" and an analyst, we will utilise the probability density functions mentioned above to solve the problem by choosing model distributions that can be integrated analytically. In particular, for an expert with creative abilities to "generate" ideas, we will select the following form of the probability density function (12):

$$P_k(t) = \begin{cases} \gamma_k\left(-\frac{\alpha^2}{t_0^2}t^2 + \frac{2\alpha}{t_0}\right), & 0 \le t \le \frac{t_0}{\alpha}; \\ \gamma_{k,} & \frac{t_0}{\alpha} \le t \le \frac{2\alpha-1}{\alpha}t_0; \\ \gamma_k\left[-\frac{\alpha^2}{t_0^2}\left(t - \frac{2\alpha-1}{\alpha}t_0\right)^2 + 1\right], & \frac{2\alpha-1}{\alpha}t_0 \le t \le 2t_0, \end{cases} \tag{12}$$

where $2t_0$ is the time for solving the problem, and is a coefficient that characterizes the uniformity of the problem.

$\gamma_K$ - is determined from the following equation:

$$\gamma_k \int_0^{2t_0} P_k(x)dx = 1, \quad \gamma_k = \frac{3\alpha}{(6\alpha - 2)t_0} \tag{13}$$

For an expert with analytical skills, it is possible to take:

$$p_a(t)=\gamma_a e^{-\frac{(t-t_0)^2}{2\sigma_a^2}}, \qquad (14)$$

$$\gamma_a=\frac{1}{\sqrt{2\pi}\sigma_a\left(0,5+\Phi\left(\frac{t_0}{\sigma_a}\right)\right)} \qquad (15)$$

In this case, $\sigma_a$ is a coefficient that determines the uniformity of the solution. When $\alpha$ and $\sigma_a$ is sufficiently large, both distribution density functions will be approximately the same. For small $\sigma_a$ and $P_a(t)$, the point will be located near $t = t_0$ (Fig. 4).

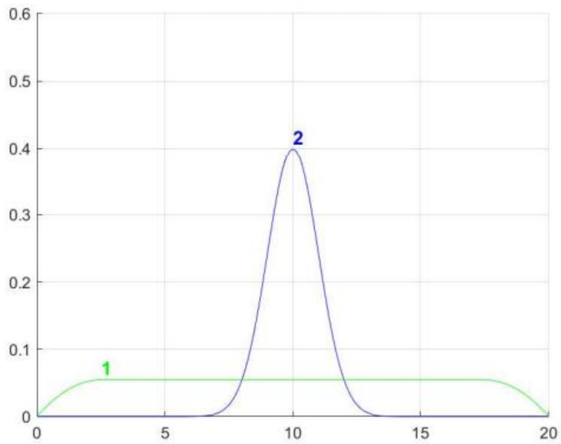


*Fig. 4. Probability density distribution*

*Curve 1 –* $p_k(t)$*. Curve 2–* $p_a(t)$

*Source: compiled by the authors*

The probability densities are chosen so that, in both cases, the average time to solve the problem is $t_0$. This can be interpreted as the analyst solving problems strictly according to the algorithm, exhaustively considering all possible solutions. At the same time, the idea "generator" intuitively guesses the solution quickly, and sometimes, on the contrary, spends more time searching for it.

Let's find the probability distribution functions that determine the probability of solving the problem

$$F(t)=\int_0^t p(x)dx$$

depending on $t$:

$$F_k(t)=\begin{cases}\gamma_k\left[-\frac{\alpha^2}{3t_0^2}t^3+\frac{\alpha}{t_0}t^2\right], & 0\le t\le\frac{t_0}{\alpha};\\ \gamma_k\left(t-\frac{t_0}{3\alpha}\right), & \frac{t_0}{\alpha}\le t\le\frac{2\alpha-1}{\alpha}t_0;\\ \gamma_k\left[-\frac{\alpha^2}{3t_0^2}\left(t-\frac{2\alpha-1}{\alpha}t_0\right)^3+t-\frac{t_0}{3\alpha}, \right. & \frac{2\alpha-1}{\alpha}t_0\le t\le 2t_0.\end{cases} \qquad (16)$$

$$F_a(t)=\frac{1}{0,5+\Phi\left(\frac{t_0}{\sigma_a}\right)}\cdot\left[\Phi\left(\frac{t_0}{\sigma_a}\right)+\Phi\left(\frac{t-t_0}{\sigma_a}\right)\right]. \qquad (17)$$

Fig. 5 shows the probabilities of solving problems for relatively large values of $t_0=10,\ \sigma=1$.

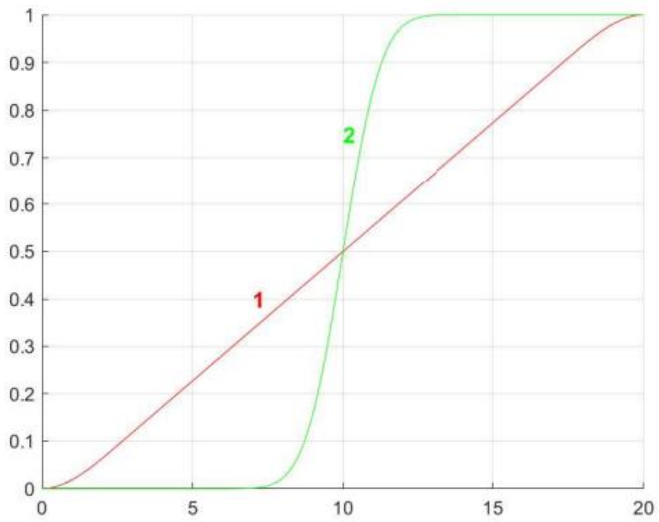


*Fig. 5. Probability distribution functions*

*Curve 1 –* $F_k(t)$ *in case of* $t_0 = 10, \alpha = 4$*. Curve 2 –* $F_a(t)$ *in case of* $t_0 = 10, \sigma = 1$

*Source: compiled by the authors*

The graph shows that an analytical expert is unlikely to solve the problem before time $t$ = 7 and is almost sure to solve it at time $t$ = 14. In contrast, an expert with creative competencies will definitely solve the problem only at t = 20, but is quite likely to solve it at smaller values of $t$. The probability function defined above can be interpreted not only as a probability, but also as a percentage of task completion. Of course, a particular task can either be solved entirely or not. But in some cases, partial completion of a task makes absolute sense, for example, when performing a research project, when one scientist can conduct only part of the research, while another can finish it.

This interpretation of the probability function allows us to understand how the probability of solving a problem changes when two experts work on it simultaneously, one an analyst and the other an "idea generator." The same interpretation allows modelling the joint work of experts on the same task: the probability value (i.e., the volume of functions) should not change during the transfer of the solution. Mathematically, this means that the probability function of a joint solution to a problem (when transferring a problem from one to another) must be continuous.

The continuity of the probability function for joint problem-solving is quite apparent. Still, this property alone does not allow us to determine when the task can be transferred to another participant. It is possible to formulate a hypothesis *that when a task is transferred from one participant to another, it is necessary to ensure that not only the volume of the solved task, but also the dynamics of its solution are equal*. There is no evidence for this hypothesis yet, but there is empirical evidence that partially supports it. For example, the paper (Alterman & Harsch, 2017) studied students' collaboration, conducted remotely using network tools (blogs, wikis, etc.). It showed that students are more successful in collaborative work when the task-solving style (skills, knowledge, goals, and plans) of their partners is more similar to and easier for them to understand. This hypothesis implies that the collaborative probability function of a joint solution should not only be continuous, but also smooth (with the first derivative continuous or the probability density function constant).

Fig. 4 shows the probability density functions for solving the problem for such experts as a function of the value. $\alpha = 4$, $\sigma_a$ = 1. The figure shows that at the time interval $\tau_1$, determined by the relation $P_K(\tau_1)$ = $P_a(T_1)$, when $\tau_1 \le t_0$, an expert with creative thinking will be more effective than an analyst. But this is true if each of them solves the problem separately. If they solve the same problem together and the analyst can use his colleague's ideas, then he will become more effective much earlier than after time $\tau_1$. Only now should the probability densities for solving the problem be compared, not their integrals.

Fig. 5 shows that in time $\tau_2$, an expert who "generates" ideas is equally likely to solve the same part of the problem as an analyst would solve in time $\tau_1$. Here, $\tau_2$ is determined from the equation $F_k(\tau_2) = F_a(\tau_1)$. This means that after time $\tau_2$, it is advisable to transfer the solution of the problem from the "generator" of ideas to the analyst. In Fig. 6, the composite curve describing the collaboration activities of experts is shown as curve 3. In fact, collaboration reduces the time required to solve the problem by an amount equal to the difference ($\tau1$ - $\tau_2$). According to the task parameters shown in the figure, the time values are as follows: $\tau1$ ~ 8,0 and $\tau2$ ~ 1,22; therefore, the time required to solve the task can be reduced by 6.78. It should be noted that a creative expert who "generates" ideas takes less time to solve the problem than an expert analyst (in the above case, more than 4 times). This suggests that, to use collaboration in creative activities effectively, it is advisable to assign one idea "generator" to work with several analysts. Management practice, which usually assigns the role of creative specialist to the head of a department, confirms this: employees, who are always few in number, bring the manager's ideas to fruition.

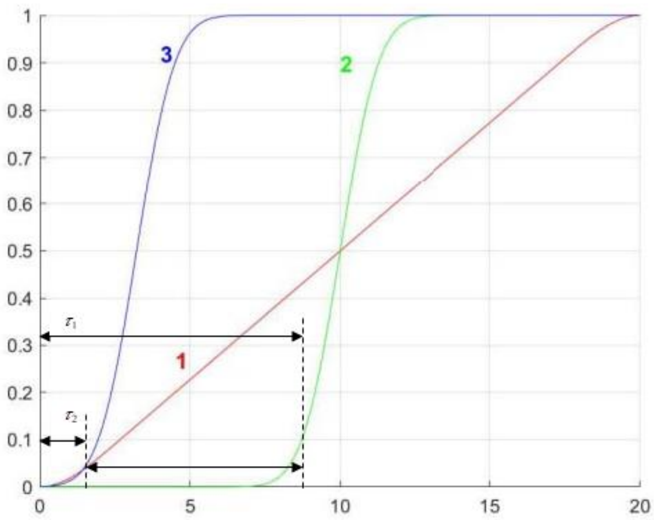


*Fig. 6. Probability distribution functions*

*Curve 1 –* $F_k(t)$ *in case of* $t_0 = 10,\ \alpha = 4$. *Curve 2 –* $F_a(t)$ *in case of* $t_0 = 10,\ \sigma = 1$. *Curve 3 describes the collaborative activities of experts*

*Source: compiled by the authors*

The values $\tau_1$ and $\tau_2$ can be determined graphically or analytically from the functional equations:

$$\frac{1}{\sigma_a\left(0,5+\Phi\left(\frac{t_0}{\sigma_a}\right)\right)}\varphi\left(\frac{\tau_1-t_0}{\sigma_a}\right)=\gamma_k$$

$$\gamma_k\left[-\frac{\alpha^2}{3t_0^2}\tau_2^3+\frac{\alpha}{t_0}\tau_2^2\right]=\frac{1}{0,5+\Phi\left(\frac{t_0}{\sigma_a}\right)}\left(\Phi\left(\frac{t_0}{\sigma_a}\right)+\Phi\left(\frac{\tau_1-t_0}{\sigma_a}\right)\right) \qquad (18)$$

Collective intelligence technologies, in addition to the expert's competencies, must also take into account their ability to serve as an "idea generator" or an analyst, and these capacities can vary across fields of knowledge. Therefore, when organising research or scientific activities, it is highly essential to consider how a participant solves problems — as an analyst or as a "generator" of ideas — to more effectively include them in teamwork.

Note that the variant of brainstorming technology described in this study is limited. At the same time, the possibility of effectively organising group brainstorming via network communication remains in question. World practice shows the following about network brainstorming: within the framework of group work on the network, you can interact well with each other and work constructively with documents, but this is not the same as working and collaborating with the entire group present.

However, collective intelligence technologies do not limit collaboration to networking; networked communications do not cancel out personal communications, but rather facilitate them.

The proposed models demonstrate a high degree of universality and can be applied across different types of economic activity without strict sectoral limitations. Their mathematical foundation, based on probabilistic functions and competency distribution matrices, is not tied to any specific industry, enabling the formalisation of virtually any business process in terms of tasks and competencies. In this respect, the models preserve their validity regardless of the scale of the enterprise or the sectoral context, since the differences concern only the configuration of the input parameters rather than the methodological principles. Such adaptability ensures the models' applicability in both knowledge-intensive industries and more traditional economic sectors, requiring only minor adjustments to reflect organisational specificities. Consequently, in practical application, the models have virtually no strict limitations, which confirms their broad relevance in the context of innovation-driven economic development.

## 5. CONCLUSIONS

One of the most critical tasks of an innovation-oriented enterprise is the efficient use of human intellectual capital. This is possible only if there is a competence management system and a selection of specialists for group problem-solving, both of which significantly increase the productivity of scholarly work. In this regard, it is necessary to understand and evaluate the characteristics of such productivity. One of these characteristics may be the collective (group) intelligence quotient (IQ). It is shown that the collective intelligence quotient can be calculated by analogy with the calculation of individual IQ, as the number of tasks solved by a group of experts in a given time. The concept is introduced, and an algorithm for constructing a collaboration matrix that accounts for group members' competencies is described, thereby increasing each group member's IQ above the maximum IQ of an individual expert.

In addition to effective task distribution based on specialists' competencies in group work, collective participation synergy is also essential. In this paper, based on the probability function for solving a task, which formally corresponds to the scope of solving a complex task, a model is proposed to show the effect of collaboration synergy. It has been proven that if the possibility of solving a problem by a specialist with analytical skills is localised in a limited area, and by a specialist with creative skills in a wide area, then their joint participation in solving the problem can reduce the time required to solve it several times.

Managing business processes based on collective intelligence technologies will require implementing a competency-based approach, with competencies continuously measured as part of the feedback process. Measuring competencies will enable the business process management system to adapt to changing conditions and to change or retrain employees. Enterprises that are the first to establish such business process management systems will have a competitive advantage in the field of innovative development.

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Стаття присвячена проблемам моделювання колективного інтелекту інноваційно інтегрованих підприємств в умовах цифрової трансформації. Дано огляд математичних моделей, що використовуються для опису технологій колективного інтелекту. Зазначено, що технології колективного інтелекту орієнтовані на ефективне використання інтелектуального потенціалу в процесі роботи з організаційним капіталом підприємства. Підтверджено, що поняття коефіцієнта інтелектуальності IQ може бути застосовним до підприємства. Запропонована нова математична модель розрахунку колективного коефіцієнта інтелектуальності IQ, що дає змогу зрівняти групові можливості з індивідуальними, і, зокрема, дозволяє продемонструвати можливість підвищення ефективності коефіцієнта інтелектуальності для кожного члена групи за рахунок розподілу робіт відповідно до компетенцій учасників. Ця математична модель розрахунку колективного IQ може стати основою оцінки ефективності підприємств з погляду використання колективних технологій. Для вирішення найбільш складного для моделювання завдання – синергії інтелекту різних людей під час спільної роботи, – запропоновано модель, що дає змогу оцінювати синергію залежно від аналітичних чи креативних здібностей учасників колаборації. Варіантом такої синергії є спільне вирішення завдання за технологією брейнстормінг. Запропонована модель дає змогу оцінити ефективність колаборації, а також може бути використана і як інструмент відбору учасників для колаборації. Наукова новизна дослідження полягає у дослідженні технологій колективного інтелекту в управлінні підприємством, обґрунтуванні місця цих технологій у завданнях корпоративної інформатизації та розрахунку ефективності нових технологій, що дало змогу довести особливу роль технологій колективного інтелекту в організації праці в епоху знань. Результати наукових розробок і практичні рекомендації авторів сприяють ефективному використанню та розвитку колективного інтелекту в процесі проектування системи менеджменту знань на підприємствах, їх мережевих об'єднаннях у перспективних наукоємних технологічних напрямах.

**Ключові слова:** бізнес-процеси, колективний інтелект, компетенції, інтелектуальна діяльність, брейнстормінг, колабораційні інструменти, людський інтелектуальний потенціал.