A flexible machine learning model for optimizing organizational capital development strategies and resource allocation*

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Abstract

In this paper, we present a comprehensive approach to optimizing organizational capital development strategies through the application of a flexible machine learning model. We advance from initial conceptualization to the implementation stage, employing Q-leaning to enhance the selection process of the most effective organizational capital development strategies within the framework of intellectual capital. Our model aims to improve decision-making reliability by employing data-driven techniques. In the final phase of our study, we simulate various alternative strategies for organizational capital development using machine learning techniques. This simulation framework streamlines the process of exploring different strategic options, enabling more informed management decisions. To enhance the machine learning process, we introduce coefficients that influence decision-making, resulting in more accurate and effective outcomes. Our findings emphasize that innovative information potential is a key facet of successful organizational capital development strategies. Furthermore, our approach demonstrates the potency of integrating intellectual capital management mechanisms with other capital types.

Keywords

machine learning, organizational capital, strategy optimization, Q-leaning, intellectual capital management

1. Introduction

In the contemporary economy, the significance of intellectual capital as a potent driver of effectiveness is well substantiated. The notion of intellectual capital surpasses the confines of intellectual property and intangible assets, while closely aligning with the concept of intangible capital, a term explored in economic theory and econometrics since the 1970s [2].

The work by Daum [3] provided a definition of intangible capital rooted in the interconnectedness of structured knowledge and competencies, which bear the potential to foster development and value creation.

Leontiev [4] conceptualized intellectual capital as encompassing the value of an enterprise's

M3E2-MLPEED 2022: The 10th International Conference on Monitoring, Modeling & Management of Emergent Economy, November 17-18, 2022, Virtual, Online

*Extended and revised version of paper [1] presented at the 10th International Conference on Monitoring, Modeling & Management of Emergent Economy.

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collective intellectual assets, encompassing intellectual property, innate and acquired cognitive abilities of its personnel, as well as amassed knowledge repositories and beneficial collaborations with other entities.

In the perspective of Roos et al. [5], intellectual capital comprises all non-monetary, intangible resources contributing to an organization's value generation, which it possesses full or partial control over.

Intellectual capital, by nature, poses challenges in terms of assessment and quantification due to the intricacies of delineating its constituent elements. Yet, it can be deconstructed into various capitals: human capital, organizational capital, and customer or consumer capital.

Each facet of intellectual capital can be further delineated as follows:

1. Human capital, embodying the value contributed by employees through their skill sets, expertise, and knowledge. This form of capital resides within individuals and can be attributed to an organization.
2. Organizational capital comprises: technological capital; branding capital; business culture capital; economic value added (EVA) capital; information potential innovation strategy capital. The evaluation criteria encompass manufacturability, productivity, innovativeness, cooperativeness, adaptability, and efficiency.
3. Customer equity, encompassing elements such as customer relationships, supplier relationships, trademarks and trade names (whose value stems solely from customer relationships), licenses, and franchises.

This multi-faceted nature of intellectual capital engenders complexity in its assessment. Methods for measuring intellectual capital encompass four primary categories, as posited by Sveiby [6]: Direct Intellectual Capital Methods; Market Capitalization Methods; Return on Assets Methods; Scorecard Methods. However, each category has its limitations that necessitate integration with machine learning techniques. By adopting a unified machine learning algorithm, a comprehensive mathematical model can be formulated, enhancing the precision of estimates across all constituent elements of intellectual capital.

2. Results

If we consider the structure of Organizational Capital (OC) as a set of its qualities and properties, their ratios, which directly affect labor productivity, which increases the income for personnel, the company as a whole, society, and the nation, then there is an opportunity to cover all possible options for its evaluation.

1. Assessment of the level of manufacturability

Let's move on to the assessment of the properties of the components of manufacturability capital. We will use its structure, which consists in determining the share a_t^k of the t-th property in the formation of the k-th type of components of manufacturability capital (k_k^t), which allows us to establish the probable level of the k-th type of manufacturability capital:

$$KT_{t^k} = \sum_{k=1}^{n_{ip}} k_{k^t} * a_{k^t}, \tag{1}$$

where

KT_{t^k} – technological capital;

k_{k^t} – exploitation and repair manufacturability of the structure to k item for t-th indicator (materials, energy, labor, compatibility, etc.);

a_{k^t} – volatility of the injection of the t-th indicator for manufacturability of k item.

2. Capital assessment of business culture

$$CC_{k^t} = \sum_{k=1}^{n_{ip}} c_{k^t} * b_{k^t} \tag{2}$$

where

CC_{k^t} is the capital of business culture;

c_{k^t} – organizational and corporate culture of a certain business model of doing business according to the t-th indicator (liberty and democracy, monoactivity of the business culture type; polyactivity of the business culture type; reactivity of the business culture type, etc.);

b_{k^t} – the importance of the impact of the t-th indicator on the cultural capital of the k-th business model of doing business.

3. The efficiency capital of added economic value

The productivity of the production process has a significant range of properties, the characteristic features of which are formed and reflected by a significant network of indicators that have branched relationships of quantitative and qualitative capital assessment of performance. Among the important features of performance, the following should be noted:

- Activation of human heuristic abilities and structuring of discovered knowledge and verification according to the criterion of objectivity;
- Orderliness of the communication process for the exchange of information flows, emotions, social and individual values, economic interests;
- Formation and growth of the fundamental and market value of the enterprise as a criterion of performance.
- Identification and elimination of dysfunctions in enterprise management, which arise due to a malfunction.

Capital assessment of efficiency of added economic value. Performance is assessed as the level of intellectual leverage (LIL) and is calculated according to the formula:

$$LIL = \frac{\triangle EVA\%}{\triangle NOPLAT\%} \tag{3}$$

where:

$\triangle EVA\%$ is the rate of profit growth;

$\triangle NOPLAT\%$ is the growth rate of economic added value.

LIL – the degree of sensitivity of profit to changes in economic added value.

The level of intellectual leverage shows: how many times the growth rate of economic added value exceeds the growth rate of profit. This excess is provided with the help of the effect of intellectual leverage, one of the components of which is its differential (the ratio of the involved intellectual capital to its own).

4. The capital of the strategy of attracting innovations of the information potential

The information capital of the strategy or the capital of the strategy of attracting innovations of the information potential determines the trajectory of intellectual capital and the direction of the implementation of the proposed strategy within the framework of the implementation of innovations of the information potential, which is aimed at increasing the value of capital and depends on the speed of updating this strategy. Informational capital and its potential act as investment capital to maximize the value of intellectual capital:

$$\left(\frac{\sum_{i=1}^{k} EVA}{ROI_{opt} - WACC} - CAPITAL\right) \rightarrow max \tag{4}$$

where

ROI_{opt} is the economic profitability of intellectual capital;

$WACC$ – weighted average interest rate of the involved intellectual capital;

$CAPITAL$ – the capital of the strategy of attracting innovations of the information potential.

5. Capital of turning knowledge into a result

The capital of the transformation of knowledge into a result declares the path of transformations from an idea to the formalization of knowledge in official documents and its structuring for communicative use [7]. Therefore, its components are the following indicators that reflect the characteristic properties of transformations: an idea as a creative and spiritual message, and the level of formalization of knowledge in official documents.

An idea has its own depth of penetration into the macro or micro world [5]. Based on Einstein's thesis that the development of society requires the improvement of everyday thinking, it is appropriate to consider an idea-concept as a complex of properties and relationships that determine the characteristics of the image of the object of research. we can establish a connection between intellectual capital (figuratively speaking, the mass of intellectual substance that is at rest or in motion, that is, in its use) and the strategy of interaction of processes in an economic object and its results. The question arises, does the strategy have energy? It is known that the strategy has different value, that is, weight. Suppose that, like any economic potential, it has potential energy, and when the process of its realization takes place, it also has kinetic energy. That is, strategy is the energy of capital that goes to the realization of an idea-concept. Therefore, it can have its own dimension. Strategy, like any energy, consists of the energy of rest and the momentum of intellectual capital. As the speed of this impulse, we will take the speed of the generation of an idea-concept in the direction predetermined by the strategy. To measure images-properties, that is, the amount of intellectual substance, a unit is introduced, – image.

Any image of intellectual substance contains the same number of images-properties that reflect the properties of the object of the real world. For example, the number of images-properties that characterize a person is a constant value, a number that can be established experimentally, as Avogadro's number was established at one time (the principle of equivalence in nature). But each person has a different number of images-relationships characterizing his intellectual capital. This value of images-relationships, corresponding to intellectual capital, will be assigned the unit of measurement – intel. Intel measures the level (mass) of intellectual capital of a person, enterprise, state.

The definition of images-properties is a consequence of the same type of process properties during the realization of an idea-concept in time, which contain a certain number of these images in one unit. We denote the number of images-properties by N_{img}:

$$N_{img} = \frac{100}{image} - const \tag{5}$$

From here we can determine the amount of the level (mass) of the intellectual capital of the economic system, which corresponds to the capital of transforming knowledge into a result:

$$ic = \frac{N}{N_{img}} M_{ic} \tag{6}$$

where

N – the number of images-properties, respectively, ideas-concepts,

M_{ic} - the intellectual mass of image-properties per image-property for a specific phenomenon, intel / image.

The level of an idea-concept can be represented in four quantitative measurements with the introduction of a unit of measurement – *id*, which contains a certain integral number of images-objects that characterize the properties of this very idea-concept using established criteria:

- Elementary level (household, cognitive, which does not require the formation of new knowledge), where $id = 1$.
- The technological level associated with the emergence of new technologies, etc., where $id = 1000 = 1K$.
- Conceptual level containing new knowledge and discoveries, where $id = 1000000 = 1M = 1000K$.
- The planetary level is determined by the depth of penetration of human activity into the macro and micro world, where $id = 1000000000 = 1G = 1000M = 1000000K$.

$InfConvert_k^t$ – informativeness as a measure of usefulness. The level of structuring of knowledge of special and general scientific terms and its verification according to the criterion of objectivity of the k-th type of the indicator of capital transformations according to the t-th component of this indicator.

$InfCap_k^t = InfConvert_k^t / TotalExp$ – the level of orderliness of the communication process for the exchange of information flows, emotions, social and individual values, economic interests of the k-th type of the indicator of capital transformations according to the t-th component of this indicator.

Evaluation of the capital of the transformation of knowledge into a result

$$CP_k^t = \sum_{k=1}^{n_{ip}} (ic_k^t + InfConvert_k^t + InfCap_k^t) d_k^t \tag{7}$$

where

CP_k^t – the capital of transforming knowledge into a result;

ic_k^t – the capital level of the transformation of knowledge into the result of the k-th type of the indicator of capital transformations according to the t-th component of this indicator;

d_k^t – the weight of the influence of the k-th indicator of transformations on the capital of the transformation of knowledge into a result according to the t-th component of this indicator of transformations.

For a preliminary analysis of the capital criteria, their importance, influence on the choice of the best alternative for the development of the properties of organizational capital, we will use the method of hierarchical comparisons when evaluating the level of priorities of alternatives, the results of which are shown in the table 1.

Table 1
Influence of criteria on a choice of alternatives (properties) of improvement of the level of capital.

Criteria	Properties				
	Intellectual	Communicative	Strategic	Cognitive	Innovative
Branding capital	0.14	0.12	0.14	0.1	0.09
Technology capital	0.12	0.14	0.13	0.14	0.1
Capital efficiency of added economic value	0.11	0.12	0.11	0.13	0.12
Capital of business culture	0.11	0.12	0.13	0.11	0.12
The capital of the strategy of attracting innovations of the information potential	0.1	0.12	0.13	0.12	0.1
General approach	0.11	0.12	0.13	0.115	0.11

The structure of OK is primarily related to branding capital, which is the main relative indicator of the company's attractiveness on the market and to some extent attests to the fate of the firm's market capital, which is adjusted to its organizational, i.e., intellectual capital.

The relevance of the use of machine learning in the field of economics [8, 9, 10, 11] allows us to consider many aspects of the strategy for the development of organizational capital and ways to optimize the cost of resources for its development in different ways. Learning to find the most optimal and less resource-intensive way of developing organizational capital can be presented as a continuous cycle that will end only after the specified conditions are reached (figure 1).

In the reinforcement learning algorithm, the agent's actions are directed to the steps to achieve success with a reward estimate. After $\triangle t$ steps into the next step, the human capital will decide some next step. The weight for this step is calculated as $\gamma^{\triangle t}$, where γ is the discount factor, which can take a value from 0 and 1 ($0 \leq \gamma \leq 1$) and has the effect of evaluating actions that are aimed at achieving the human capital goal. γ can be called the level of success in achieving the desired state by human capital, when the investment data changes at the $\triangle t$ step.

Thus, we can conclude that a function is required that will determine the quality of combinations of the state of human capital and the action aimed at it:

$$Q \div S \times A \rightarrow R. \tag{8}$$

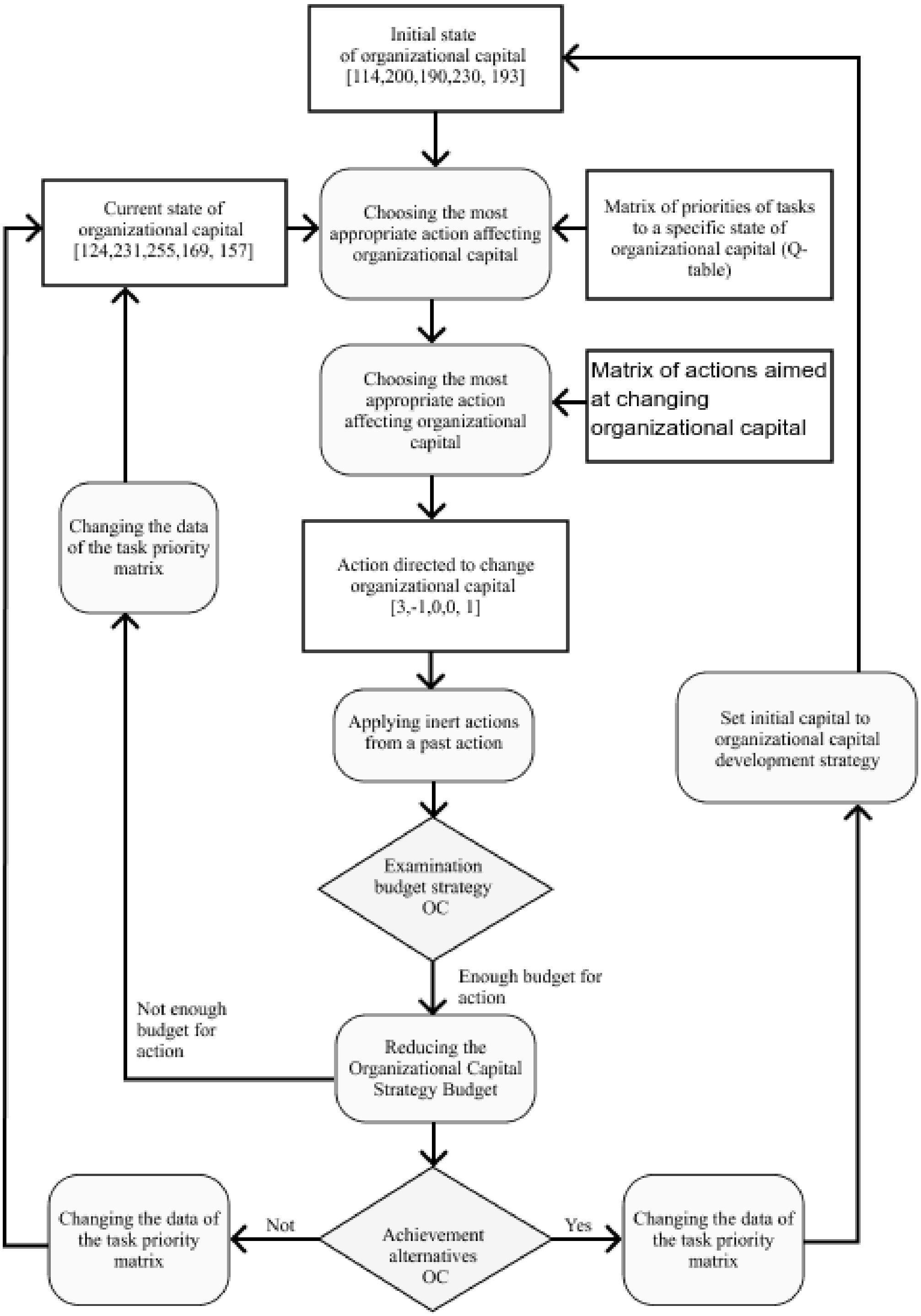

Figure 1: Machine learning of alternative development of human capital of the enterprise.

At the beginning of training, Q is initialized, possibly with an arbitrary fixed value – 0. After initialization, at each moment of time t, the agent selects an action, observes a reward, enters a new state (that may depend on both the previous state and the selected action), and Q is updated. The core of the algorithm is a Bellman [12] equation as a simple value iteration update, using the weighted average of the old value and the new information [13]:

$$Q^{new}(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \times (r_t + \gamma \times maxQ(s_{t+1}, a) - Q(s_t, a_t)), \tag{9}$$

where r_t is the reward received when moving from the state S_t to the state S_{t+1}, and $0 < \alpha \leq 1$;

Note that $S^{new}(s_t, \alpha_t)$ is the sum of three factors:

$(1 - \alpha)Q(s_t, \alpha_t)$: the current value weighted by the learning rate. Values of the learning rate near to 1 made faster the changes in Q;

αr_t: the reward $r_t = r(s_t, a_t)$ to obtain if action a_t is taken when in state s_t (weighted by learning rate);

$\alpha\gamma \max Q(s_{t+1}, \alpha)$: the maximum reward that can be obtained from state s_{t+1} (weighted by learning rate and discount factor).

Each action has its own parameters, and system changes can be limited by parameters that can be correlated with the required resource costs to apply the action chosen by machine learning. Thus, each iteration of training implies two possible effects:

1. Changes in the coefficient of effectiveness of the action, depending on the state that the system acquires as a result of the application of the action.
2. Return of the iteration to the initial state due to non-compliance with the specified restrictions for machine learning.

For the application of Q-Learning, the following parameters were selected:

- Impact on the Intellectual Capital criteria
- Time spent in days
- Resource costs equivalent to monetary units
- The coefficient of the complexity of the action
- Risk ratio of failure to take action
- Inert influence on the system
- Coefficient of possibility of inert influence on the system

Each action parameter is used in the calculation of the effectiveness of the action taken at each training step. Applied properties of actions can be represented as a table of actions, which is presented in figure 2.

Thus, at each iteration, the system calculates a promising system that has already been acted upon and recalculates the result of intellectual capital with new parameters.

Thus, we can say that the calculation of the effectiveness of the action is carried out according to the following formula:

$$AE = IK_{t+n}, \tag{10}$$

where

AE – action efficiency;

			IK									PIK			
Action	Branding Capital	Technology Capital	Value Added Efficiency Capital	Business Culture Capital	Implementation capital innovation information capacity	T	RE	WI	RoD	Branding Capital	Technology Capital	Value Added Efficiency Capital	Business Culture Capital	Implementation capital innovation information capacity	PP
1	1	3	0	1	2	24	40	0.3	0.3	0	0	0	0	1	0.3
2	0	0	1	2	0	12	120	0.1	0.4	0	1	1	1	0	0.1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
23	T	T	T	T	T	40	240	0.3	0.12	1	1	1	1	0	0.5

Figure 2: Action properties used in machine learning with resource cost parameters.

IK – the cost of intellectual capital;

IK_{t+n} — the cost of intellectual capital after applying the action.

So the value of AE will be rewards for moving to the next machine learning state.

$$Q^{new}(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \times (AE + \gamma \times maxQ(s_{t+1}, a) - Q(s_t, a_t)), \tag{11}$$

However, each action additionally has a time cost parameter for performing this action, which can optionally be included in the formula. For greater accuracy of calculations, you can use hours, days, months or quarters. In this case, integer values of days were used.

Thus, the new formula for calculating efficiency can be represented as follows:

$$AE = IK_{t+n} * T, \tag{12}$$

where AE – action efficiency, T is the time spent on applying the action

Also, an optional parameter can be resource costs, which are presented in monetary terms. To simplify the loads and quick calculations, all action parameters can be divided by a certain coefficient Mk. In this case, $Mk = 1000$.

Thus, if Action 1 has a resource cost (FE) of 1300000, then the resources spent can be represented as RE and calculated by the formula:

$$RE = \frac{FE}{Mk} * T. \tag{13}$$

Taking into account resource costs, the action efficiency formula will look like this:

$$AE = \frac{IK_{t+n}}{RE} * T. \tag{14}$$

The calculation of resource costs can also include the coefficient of complexity of performing an action (WI), which can be represented by a value in the range from 0.1 to 1.0. Thus, now the resource costs can be represented as:

$$RE = \frac{FE}{Mk} * T * WI. \tag{15}$$

Also, given the individuality of the systems to which actions can be applied, it is worth considering the risks of not performing an action (RoD) or its success in execution.

The risk of investing in organizational capital is the possibility that the accumulated organizational capital will not bring the expected return, will not be in demand in the market, or will not bring the expected return. This value can be represented as a range from 0 to 1. A low value of this coefficient means a low level of success of the action and its high risks. Given the risk ratio, the formula for the effectiveness of action can be represented as follows:

$$RE = RoD\frac{IK_{t+n}}{RE}. \tag{16}$$

The relationship of all parameters of intellectual capital does not exclude the influence of the development of some parameters on the possibility of developing other parameters as a result of these actions.

Thus, each action has the values of the inert development of intellectual capital and the coefficient of the possibility of this development.

Given these parameters, the formula for the effectiveness of actions can be represented as follows:

$$RE = ROD\frac{IK_{t+n}}{RE} + PIK * PP * RoD, \tag{17}$$

where PIK is the value of the possible inert development of intellectual capital, PP is the probability coefficient of the development of intellectual capital.

Thus, each iteration of training affects the value of intellectual capital by changing the values of its parameters. However, it is the efficiency values of the action that are written to the state table, not the cost of capital. Having an unlimited resource of investments, achieving the desired value of the cost of intellectual capital had a large set of action algorithms, but given the parameters of each of the actions, machine learning will find the most optimal algorithm for this system.

The development of Intellectual capital occurs with the choice of an alternative to which the capital must approach as a result of learning.

For more effective training and achievement of the most favorable conditions for achieving the desired alternative, development alternatives were introduced. Development alternatives are coefficients for each of the parameters of actions that affect the state of capital. Using the hierarchy analysis method, the following coefficients were introduced (table 2).

Table 2
Alternatives of the development method for managing the choice of effective action.

	Accelerated	Safe	Risky	Budgetary	Effective
IK	0.21	0.26	0.31	0.2	0.32
T	0.23	0.12	0.2	0.08	0.13
FE	0.12	0.12	0.12	0.09	0.12
WI	0.12	0.16	0.13	0.32	0.1
RoD	0.1	0.07	0.08	0.09	0.13
PIK	0.1	0.19	0.1	0.08	0.08
PP	0.12	0.07	0.06	0.14	0.12

For this study, a risky alternative of the method of developing capital for machine learning was chosen.

Thus, each iteration of learning and applying actions to the system will affect the state table and calculate its new values according to the following formula:

$$AE = (RoD\ a_5)\frac{IK_{t+n}\ a_1}{(FE\ a_3)\ (T\ a_2)} + (RoD\ a_5)\ (PIK\ a_6)\ (PP\ a_7) \tag{18}$$

After carrying out the calculations with the initial data, the results describing the strategy for investing in organizational capital shown in table 3.

Table 3
Factor of importance of action properties for learning.

IK	T	FE	WI	RoD	PIK	PP
a_1	a_2	a_3	a_4	a_5	a_6	a_7
0.31	0.2	0.12	0.13	0.08	0.1	0.06

It should be noted that the coefficients of capital alternatives and development alternatives affect value preferences and spending.

The first stages of training provide impressive indicators of cost optimization for investment in organizational capital. With an increase in training cycles, obtaining a better result becomes more rare.

The data in the table 4 and in the figure 3 show optimization costs of developing organizational capital to achieve the cost of organizational capital, taking into account the chosen alternative. It can be concluded that in order to achieve the best results, it is necessary to conduct a sufficient number of training cycles.

Thus, after each stage of learning new indicators, alternatives should be identified and calculations should be made that determine subsequent investments in human capital. It should also be borne in mind that each the alternative has its own characteristic features and characteristics, behavioral connections and influence on the choice of options capital investment.

Table 4
Initialized data affecting machine learning training in the search for optimal investments in organizational capital.

Action number	Impact values on organizational capital					
	Salary	Branding Capital	Technology Capital	Value Added Efficiency Capital	Business Culture Capital	Implementation capital innovation information capacity
16637	2219	52	286	313	45	333
25352	1431	155	121	95	128	318
74521	725	157	151	54	138	340
168348	684	184	115	74	123	286
2236341	485	133	87	33	142	118
14330450	336	197	90	51	165	114
17735547	294	127	44	201	153	134

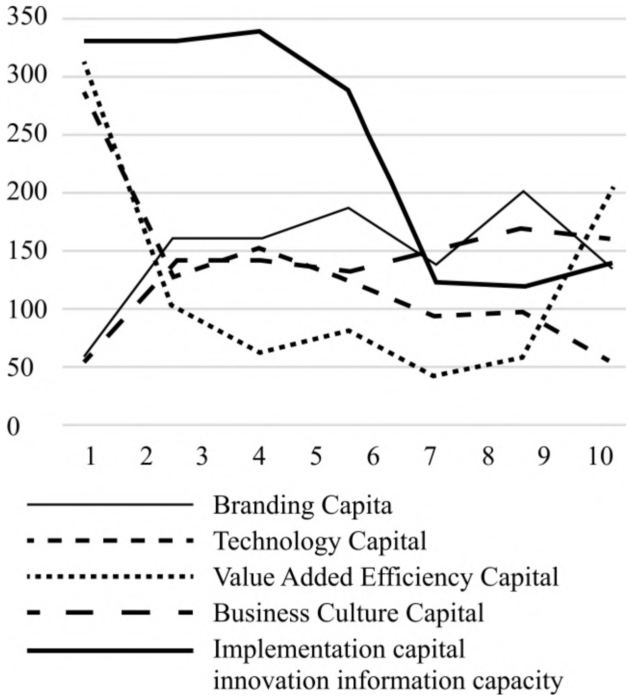

Figure 3: Machine learning of alternative development of organizational capital of the enterprise.

Taking into account the dynamics of changes in results, it can be concluded that subsequent training cycles can bring more optimized costs. Figure 4 shows the optimization of the costs of organizational capital development, taking into account the same level of organizational capital development.

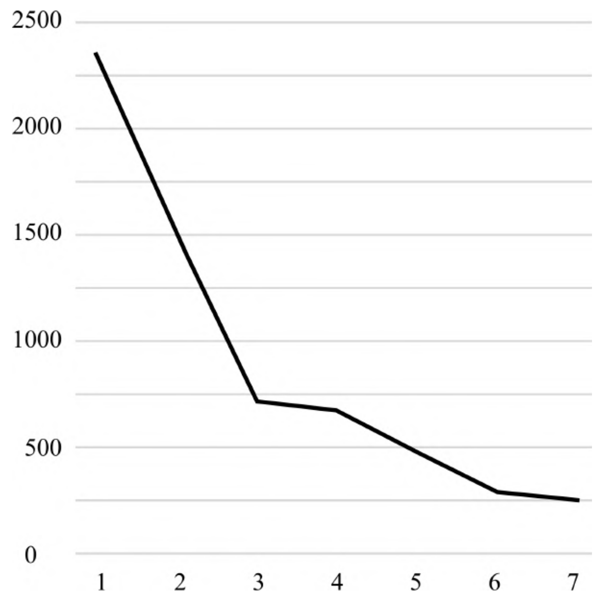

Figure 4: Machine learning of alternative development of organizational capital of the enterprise.

It is also worth noting that when the input data changes, machine learning will be able to rebuild and generate calculations and optimize the result better and faster than a person.

3. Conclusions

The study presents a conceptual framework for the application of Q-leaning to ascertain the most effective developmental strategy for organizational capital within the context of intellectual capital. This approach aims to bolster the reliability of the outcomes achieved.

As a result, the strategy's capital for fostering information potential innovations and the capital of alternatives independently undertake pivotal roles in shaping and implementing mechanisms for managing intellectual capital, both in conjunction with and separately from other capital types.

The crux of this approach lies in the judicious selection of significance indicators (returns) for contributions to various organizational capital facets, driving iterative learning cycles. Such an approach streamlines the exploration and formulation of organizational capital development strategies, opening pathways to genuine alternatives and simplifying decision-making processes.

Notably, tuning training by altering parameters such as reward magnitude, data optimization value, and training constraints can yield superior outcomes by accelerating training processes and furnishing a more proficient AI capable of delivering enhanced results.

Leveraging machine learning to optimize costs linked with organizational capital development stands as the most effective method. The advantages of swiftness, objectivity, and adaptability to external shifts distinguish this approach from human-centric alternatives.

To bolster outcomes, fine-tuning of these actions and precise selection of alternatives for action-based choices are deemed essential.

References

[1] V. Porokhnya, V. Penev, R. Ivanov, V. Kravchenko, Flexible Evolutionary Model of Machine Learning of Organizational Capital Development Strategies with Optimization of Spent Resources, in: S. Semerikov, V. Soloviev, A. Matviychuk, V. Kobets, L. Kibalnyk, H. Danylchuk, A. Kiv (Eds.), Proceedings of 10th International Conference on Monitoring, Modeling & Management of Emergent Economy - M3E2, INSTICC, SciTePress, 2023, pp. 71–79. doi:10.5220/0011931400003432.

[2] A. Brooking, Intellectual Capital: Core Assets for the Third Millenium, International Thompson Business Press, 1996.

[3] J. H. Daum, Intangible Assets, Wiley, 2002, pp. 152–154.

[4] B. B. Leontiev, Tcena intellekta. Intellektualnyi kapital v rossiiskom biznese [The price of intelligence. Intellectual capital in Russian business], Moscow, 2002.

[5] G. Roos, S. Pike, L. Fernstrom, Managing Intellectual Capital in Practice, Butterworth-Heinemann, 2005. URL: https://www.researchgate.net/publication/274392498.

[6] K.-E. Sveiby, Methods for Measuring Intangible Assets, 2010. URL: https://www.sveiby.com/article/Methods-for-Measuring-Intangible-Assets.

[7] V. Porokhnya, The general theory of relativity of economic growth, State and regions. Economy and entrepreneurship series (2009) 153–160.

[8] V. Kobets, O. Novak, EU countries clustering for the state of food security using machine learning techniques, Neiro-Nechitki Tekhnolohii Modelyuvannya v Ekonomitsi 2021 (2021) 86–118. doi:10.33111/nfmte.2021.086.

[9] V. Derbentsev, A. Matviychuk, V. N. Soloviev, Forecasting of cryptocurrency prices using machine learning, in: L. Pichl, C. Eom, E. Scalas, T. Kaizoji (Eds.), Advanced Studies of Financial Technologies and Cryptocurrency Markets, Springer, Singapore, 2020, pp. 211–231. doi:10.1007/978-981-15-4498-9_12.

[10] A. Kiv, S. Semerikov, V. N. Soloviev, L. Kibalnyk, H. Danylchuk, A. Matviychuk, Experimental Economics and Machine Learning for Prediction of Emergent Economy Dynamics, in: A. Kiv, S. Semerikov, V. N. Soloviev, L. Kibalnyk, H. Danylchuk, A. Matviychuk (Eds.), Proceedings of the Selected Papers of the 8th International Conference on Monitoring, Modeling & Management of Emergent Economy, M3E2-EEMLPEED 2019, Odessa, Ukraine, May 22-24, 2019, volume 2422 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2019, pp. 1–4. URL: https://ceur-ws.org/Vol-2422/paper00.pdf.

[11] A. Kiv, P. Hryhoruk, I. Khvostina, V. Solovieva, V. N. Soloviev, S. Semerikov, Machine learning of emerging markets in pandemic times, in: A. Kiv (Ed.), Proceedings of the Selected Papers of the Special Edition of International Conference on Monitoring, Modeling & Management of Emergent Economy (M3E2-MLPEED 2020), Odessa, Ukraine, July 13-18,

2020, volume 2713 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2020, pp. 1–20. URL: https://ceur-ws.org/Vol-2713/paper00.pdf.

[12] R. Bellman, Dynamic Programming, Princeton University Press, New York, 1957. URL: https://www.gwern.net/docs/statistics/decision/1957-bellman-dynamicprogramming.pdf.

[13] C. J. C. H. Watkins, P. Dayan, Q-learning, Machine Learning 8 (1992) 279–292. doi:10.1007/BF00992698.