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Application of a Model Life Cycle Concept to Investments in Artificial Intelligence Evaluation on the Example of Large Language Models

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ABSTRACT

The life cycle of an artificial intelligence model is the **object** of research. The **purpose** of the study is to develop a model life-cycle methodology that describes the economic content of the investment process in artificial intelligence technology. During the study, both general scientific **methods** such as analysis, synthesis, comparison, abstraction, induction and deduction were used, as well as project methodologies of the life-cycle, employed as the basis for the value creation life-cycle of the model. The analysis was based on identifying the necessary stages of model development in terms of the CRISP-DM methodology and determining the features of each of them in terms of cash flows. Modified versions of the model life-cycle containing risk assessment, including model risk, were also taken into account. In the process of research, the proposed generalized model life-cycle methodology was specified for a specific AI technology — large language models. As a result of the study, the author proposed a three-stage model. The possible optionality between the stages and the characteristics of cash flows are described. It was **concluded** that an investment project for the development of AI contains several real options — abandonment, reduction, expansion and replacement. For large language models, the life cycle structure and possible optionalities are preserved. The peculiarity is that the value creation process involves cash flows from different areas of application of the model in business processes. The results of the study are of practical importance for medium and large businesses engaged in the independent development of AI models and/or applying them to their business processes. The proposed concept of the model life-cycle can also be used to develop a methodology for evaluating investments in AI using real options.

Keywords: model life-cycle; investment valuation; artificial intelligence; cash flows; large language models

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INTRODUCTION

Since the 2010s, artificial intelligence (further — AI) has undergone a new stage of development and close integration into social processes, including economic processes. According to Stanford University, corporate investment in AI technology increased from 17 billion dollars to 276 billion dollars between 2013 and 2021 [1]. Analytical agencies estimate AI's contribution to global GDP at 1.5% and predict that AI will be a new driver for economic growth over the next 30 years. Companies investing in this type of technology are interested in the most optimal use of resources, which is achieved through the organization of an efficient development and implementation process. This process of creating, implementing and commercializing artificial intelligence innovations is called the life-cycle model (further — LCM). Understanding the key stages of the life cycle of the model and their contribution to the creation of added value of the enterprise enables you to make the right investment decisions.

One of the most promising AI technologies — large language model (further — LLM) — is the most modern method of working with texts and solving the problems of natural language processing. Their key feature is the use of a large number of parameters for learning (for example, ChatGPT-4 uses more than 100 trillion parameters), which allows them to generate meaningful text. The most famous are models developed by American companies, such as OpenAI (models GPT-2, GPT-3, GPT-4), Google (model BERT-large). Russian companies have created their own versions of language models: for example, in 2023, Yandex introduced in its software products YandeXGPT, and Sberbank developed Gigachat. Combined with generative LLM models,[1] they solve a much larger range of problems compared to machine learning models that are aimed at solving a single specific problem.

Despite the closer approach to the concept of general artificial intelligence, which entails a machine performing a wide range of tasks at the human intelligence level, this type of technology still preserves the risk inherent in traditional machine learning models, — model risk. The essence of modular risk is the reduction of the predictive qualities of the model. Indicative is the study of the GPT-3.5 and GPT-4 work, which showed that in the four-month period of GPT 4,[2] the accuracy of the definition of simple numbers decreased from 97.6% to 2.4%, and the proportion of correct software codes written by the model decreased from 52% to 10% [2].

The lifecycle methodology can be used to assess investments in modern AI technologies, but this requires the analysis of existing concepts and the proposal of a model that takes into account both the design features of AI development and their economic content. Another task of the study is to test the life-cycle model by applying it to the latest AI technologies — large language models.

The scientific novelty of the study is the development of a life-cycle model concept in terms of value creation and its application to assess investments in artificial intelligence technology. The theoretical significance is due to the combination of the design approach to the life cycle of the model with the economic content of the investment process and the analysis of embedded options in it. The possibility of enterprises applying the proposed life cycle concept of the model in assessing investments in AI determines the practical relevance of the study.

EVOLUTION OF THE MODEL LIFE-CYCLE CONCEPT

In foreign scientific literature, the concept of a model's life-cycle emerged in the early 2000s as part of a design approach, in which the data process was organized as an independent project. The result of such a project was an intelligent system (model) for the analysis of data. This methodology was formulated by Colin Sherrer in 2000 and was called the CRoss-Industry Standard Process for Data Mining (CRISP-DM) [3]. This model includes six key stages in the development of data analysis models:

1. Business analysis. This phase involves the analysis of key business goals and ways to achieve them using data models. As a result of the analysis, business objectives are linked to specific data analysis problems.

2. Data processing. The second phase involves analyzing the data needed to achieve the project objectives. At this stage, the search for relationships, the verification of hypotheses, and the selection of the necessary parameters and data are carried out.

3. Data preparation. It represents the technical side of the data process and the most important step before choosing a model, as the final result will depend on the quality of the data and the level of processing.

4. Modeling. At this stage, different learning techniques and parameters are applied, and based on objective statistical indicators, they are calibrated to optimum solutions. The developer has the ability to determine the learning technique and the

[1] Author's note: generative AI, abbreviated from «generative artificial intelligence», is a type of AI system that can generate unique or original content such as text, audio, video, or images on demand.

[2] Author's note: Correctness (accuracy) shows the proportion of correct answers from all outcome variants. Is the most primitive in the calculation, but does not show the ratio of critical errors of the first or second kind for a particular type of problems.

parameters used, depending on the type of task to be solved. Additional limitations are imposed on the quality and type of data.

5. Evaluation. According to the development results, both statistical and operational effectiveness must be monitored. The result of the model must always bring improvement to the business process, as well as meet all the key requirements and conditions of its existence.

6. Deployment. The final stage involves the introduction of the model into the business process and its full use by the client. It identifies such stages as the development of the implementation plan, monitoring and maintenance, and the final report on the results of the project (*Fig. 1*).

Significantly later, this CRISP-DM methodology was developed to simplify the interaction of process participants with each other. The result was the Team Data Science Process (TDSP) model, which identified four main activities: business analysis, data analysis, modeling, and deployment, so that teams can repeat them at any stage of the production cycle [4]. Similar models have been proposed by Microsoft and IBM.

In 2021, researchers based on surveys of fintech managers conclude that the life cycle model needs to detail the risk assessment and control rules for the impact of the model [5]. In 2022, the LCM concept was introduced, taking into account both operational risks and the social and ethical implications of the implementation of AI. [6]. The CDAC AI life cycle concept preserves the design approach, dividing it into three stages — design, development, deployment, but defines mandatory steps in each of the stages, taking into account the above-mentioned aspects. For example, the projecting phase requires not only the identification of the business problem, but also the ethical aspects of the use of the model, the development phase analyzes the correctness of the interpretation of the results of the work of a model, and the deployment phase requires analysis and risk assessment.

COST APPROACH TO DETERMINING THE MODEL LIFE CYCLE

Russian research literature does not distinguish the life cycle of the model as an independent object of innovation and investment activity in the enterprise. As a rule, AI technologies are considered part of an innovation lifecycle, which summarizes the main stages of their creation:

1. The period of inception of an innovative product;
2. The period of product creation;
3. The period of product placement on the market;
4. The period of product maturity formation [7].

Studies in the application of AI suggest directions for its application in different industries. For example, AI addresses efficiency challenges in retail, medicine, construction, transportation, and other industries [8]. Research aimed at evaluating the effectiveness of investments in AI technology itself is still not sufficiently represented in the national scientific literature. The innovation product cycle is applicable to artificial intelligence technologies, but does not take into account its key specificity — the presence of model risk. For example, in the financial technology industry, risks associated with the deployment and cost of AI development, as well as risks related to the quality of data, algorithms, and outcomes, pose a threat to both large and medium-sized market participants [9]. Furthermore, AI technologies do not always act as a product for an external customer: often, the development of models is focused on internal business needs in order to improve the operational processes of the enterprise [10].

In foreign literature, this problem has become relevant in connection with the transformation of business under the influence of AI. For example, researchers Orström and Raim examine different value-creation models by enterprises developing AI models and identify three phases of an innovative business model:

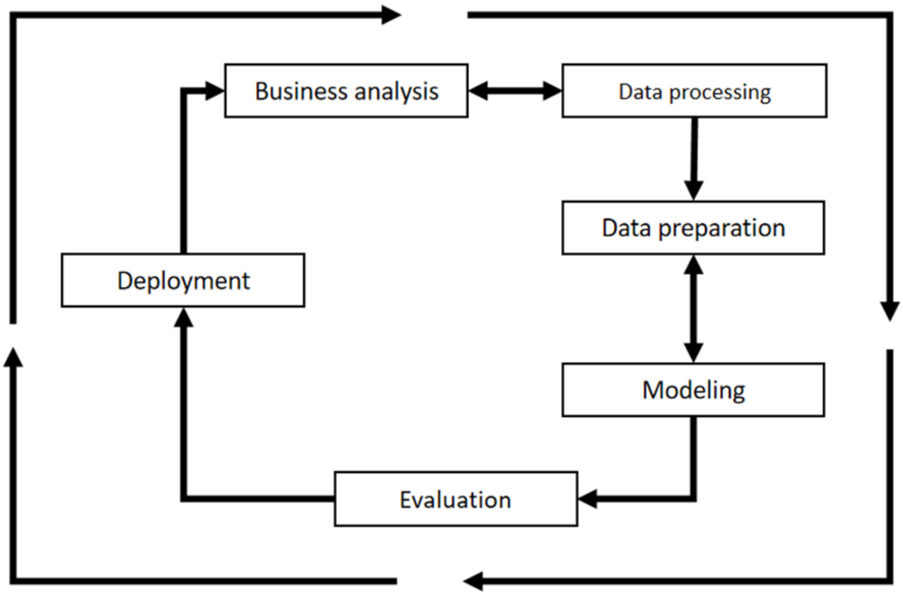

Fig. 1. **Cross-Industry Standard Process for Data Mining (CRISP-DM) Methodology Illustration**

Source: Compiled by the author based on [4].

1. Determining the prerequisites for value creation from the use of AI;
2. Identification of technologies needed to create value;
3. Development of the business model of the proposal of the results of the work of AI [11].

The proposed stages include both business analysis, technology analysis, the needs of economic sectors and consumers, and the assessment of potential risks. At the same time, the work of AI is treated exclusively as an external product. This model may describe the value chain of the commercialization of AI technologies, but it is not always their commercialization that has an effect on the enterprise. The authors note that AI can influence revenue from non-AI-related business areas directly, as well as increase operational efficiency by reducing enterprise costs.

The Moro-Visconti study on the value assessment of firms investing in AI notes that their assessment must be based on real options, as successful development and implementation can significantly improve the cash flow of the firm. At the same time, it is necessary to distinguish between firms that develop AI and those that use AI technologies to improve existing operational processes. Analysis of the latter should imply the definition of incremental value as the difference between the values "using AI in processes" and "without AI in the processes" [12]. The life-cycle methodologies described above do not assess the effect of optionality, the benefits of which the entity can evaluate and utilize at all stages of development.

The CRISP-DM model will be used as a framework for the development of the lifecycle cost model, as it describes the necessary stages of the data process. However, we see a need to reduce their number to three: the development phase, the hypothesis testing phase and the operational phase (*Fig. 2*).

The development phase includes business analysis, data analysis and modeling. At this stage, the entity shall carry out the following actions:

1. Formation of the initial design, definition of the business problem and relationship between it and the machine learning task.
2. Assessment of human, technological and financial resource needs.
3. Development of a technical requirement for an artificial intelligence model, including data.

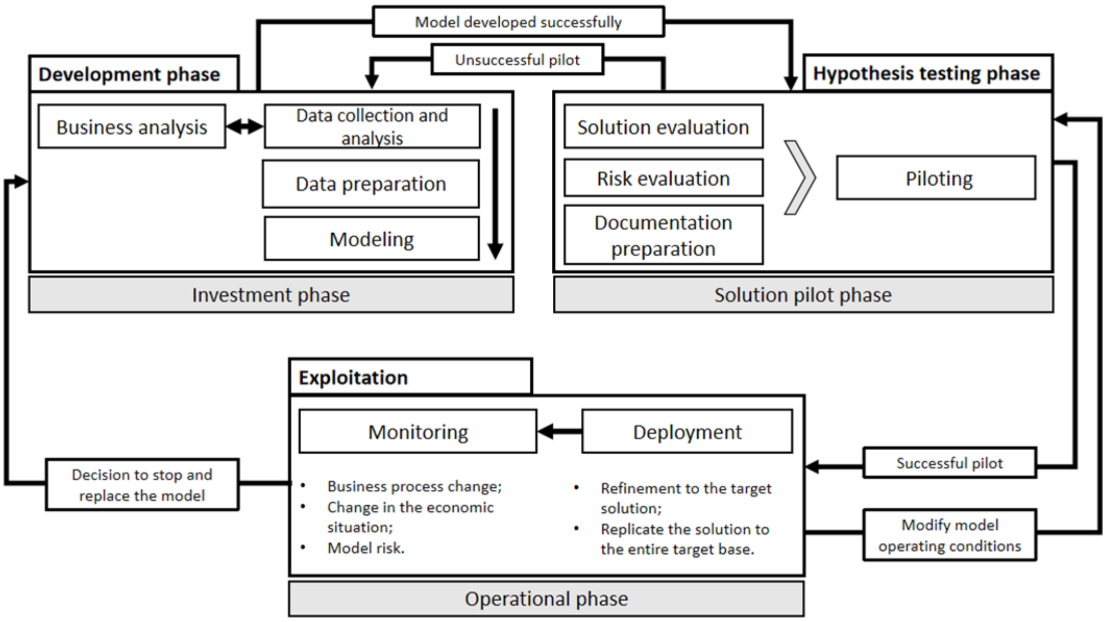

Fig. 2. **The Life Cycle of an AI Model in Terms of Value Creation**

Source: Compiled by the author.

4. Development of a system of project success indicators, including assessment of the statistical effectiveness of the model, operational and financial metrics.
5. Direct work with data related to its acquisition, storage, analysis and processing.
6. Training of the model of artificial intelligence, preliminary evaluation of the quality of its work.

After the development of the model/grip of the models and the preliminary evaluation of their quality, there is an option to abandon: if the model does not meet the technical requirements of the process, the enterprise has the option to stop its development. In this case, the company will avoid the potential losses that could arise from the operation of the model. In addition, pre-modeling quality control will prevent process quality deterioration. Since the development phase involves a significant amount of investments in data, software and hardware and the remuneration of the work of specialists, in the event of a decision to withdraw from the project, the company will be able to reorient part of the resources or implement them on the market (for example, the sale of hardware at the residual cost).

The phase of hypothesis testing is itself an option to expand. It includes the following actions:

1. Assessment of the solution in terms of optimization and maximization of the target relative to other modelling methods, including without the use of artificial intelligence.
2. Assessment of the risks to both the company itself and to external actors of economic relationships leading to potential reputational and financial costs.
3. Preparation of validation documentation with detailed description of model performance, required data, risk assessments and model quality.
4. Model launch on a limited part of the process (pilot team) to obtain objective factual data on the process performance to decide whether to extend the use of the model to the entire process.

When conducting AI piloting, solutions form a control and test group. The first involves the use of solutions without AI, and its results are compared with the work of the process with the application of AI. Statistical tests are used to assess performance to verify the significance of the indicators that have been selected as indicators of success [13]. Operational or financial performance does not always improve after improved statistical metrics. For example, an article describing the use of AI in the practice of X-rays concludes that even precise models, when applied in the real process, do not always improve the quality of diagnosis, especially in interaction with the human employee [14].

This phase may be absent if the company has not created a data-based decision-making environment or if there is no process of validating machine learning models on its own. Furthermore, piloting helps to identify the relationship between model risk and financial impact.

From the point of view of value creation, this step increases the significance of management decisions, as the built-in option allows low costs to level the risk of uncertainty of the incremental cash flows of investments after the model is introduced into the business process as a whole. In the assessment of AI projects, the presence of the hypothesis testing determines the accuracy of the economic assessment. Thus, the incremental cash flow of the pilot from AI at time t will be measured by *formula 1*:

$$CF_t = CF_t^{TG} - CF_t^{CG} \qquad (1)$$

where CF_t^{TG} — cash flow from the AI process in the target group, CF_t^{CG} — cash flow from the process without AI in the control group.

On the evaluation of pilot values, cash flows can be predicted after the model is implemented by extrapolating the cash flow per unit of the pilot driver to the volume of the driver in general. The pilot's success criterion may be positive net value (NPV) [15]. In the event of a pilot failure, either an option for replacement arises, resulting in the project returning to the investment phase, or an option to withdraw investment in the model and resource realization at the residual cost.

The operating phase follows a positive management decision to distribute the model throughout the entire business process. Since its introduction, the model monitoring process has become a mandatory precondition for operational risk control. Due to the existence of a model risk, changes in the economic environment or the business process itself in which the model operates, regular validation of its effectiveness is required. From the point of view of the value chain, this stage represents the revenue part of the project. One condition is the need to take risks into account. For example, coefficients that reduce cash flows by the probability of this type of risk can be used as a solution. The formula (2) presents the concept of accounting for cash flows at the operating stage from time $t + 1$ and lasting n periods::

$$\sum CF_{exploitation} = CF_{t+1} * k_t + \ldots + CF_{t+n} * k_{t+n}, \quad (2)$$

where CF_{t+n} — the cash flow of the drawing in the post-pilot period at the time t; k_t — this is the adjustment coefficient that takes into account the model risk.

The value of the adjustment factor varies from 0 (model risk equalizes the incremental cash flow from the implementation of AI) to 1 (no model risk). Its use is due to the need to take into account the imperfection of AI technologies, which do not always realize their function in proportion to the results of human activity [16].

Fig. 3 shows comparative results of different models in relation to the outcomes of human activity for different types of tasks: text, speech and image recognition, language and reading comprehension. Despite the fact that modern models such as SQuAD and Glue developed their accuracy quickly enough, it took developers at least a year to improve the model. And in the example of ImageNet, we can see a comparative deterioration of the results of work, which is an example of model risk.

In accordance with the model risk accounting methodology, each time moment in the period from $t + 1$ to $t + n$ has a built-in option to reduce the operation of the model to verify the hypothesis. Since there is not

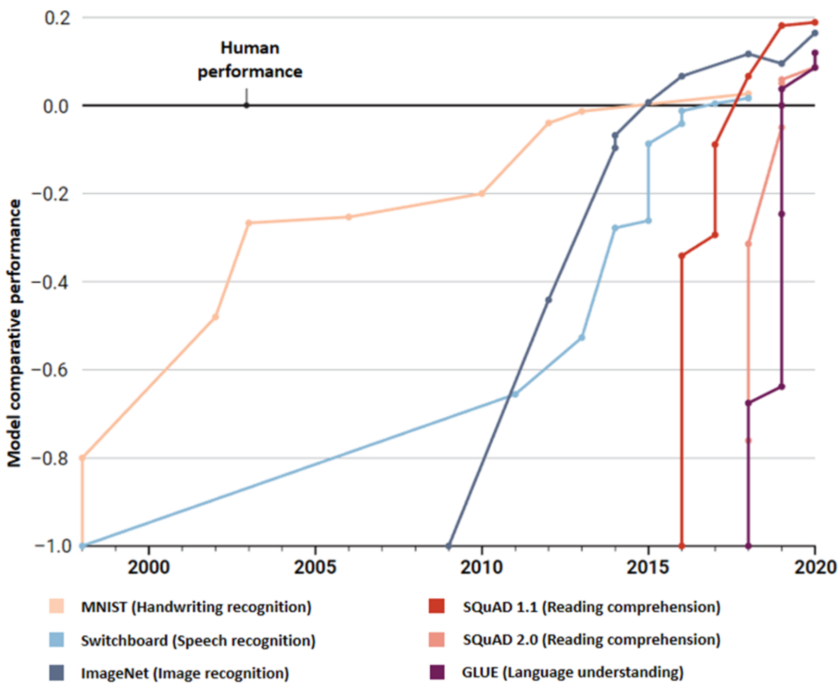

Fig. 3. **Development of the Effectiveness of Models that Solve Various Machine Learning Problems**
Source: Compiled by the author based on [17].

always a direct relationship between an objectively observable statistical quality metric and the incremental economic effect of the introduction of AI, a return to the hypothesis testing stage is the best management solution.

Thus, the investment project for the implementation of the AI solution is a complex option, that contains different types of options. *Fig. 4* shows a simplified scheme of the relationship between cash flows, model lifecycle stages, and built-in options. Unlike the point-to-point approach used previously to determine the life-cycle of the AI model, the value-creation approach allows for the identification of the discretion of the cash flows from the AI project as well as taking into account their optional nature. Elements of the life-cycle presented by us depend on the organizational practice of developing and implementing AI models. For example, the absence of a validation process will not allow us to take account of the opt-out option, as the enterprise will not be able to determine when the performance of the model has become negative, and the lack of practice of verifying hypotheses does not allow the option of expansion to be taken into account.

APPLICATION OF THE LIFE CYCLE CONCEPT FOR LARGE LANGUAGE MODELS

The characteristics of large language models in the context of the life cycle described above modify its phases. This is because classical machine learning models solve one specific problem. For example, a regression task is aimed at predicting a specific value of the indicator, whereas LLMs can solve a wide range of tasks. Contemporary English-language articles investigating the work of GPT-4 note that large language models are a step towards general artificial intelligence, because in addition to the high quality of working with the text and its contents are able to solve the following tasks: image generation, writing music, solving simple mathematical problems, writing software code, understanding the context of medical, legal and psychological problems. GPT-4 does some of these tasks no worse than a human [18].

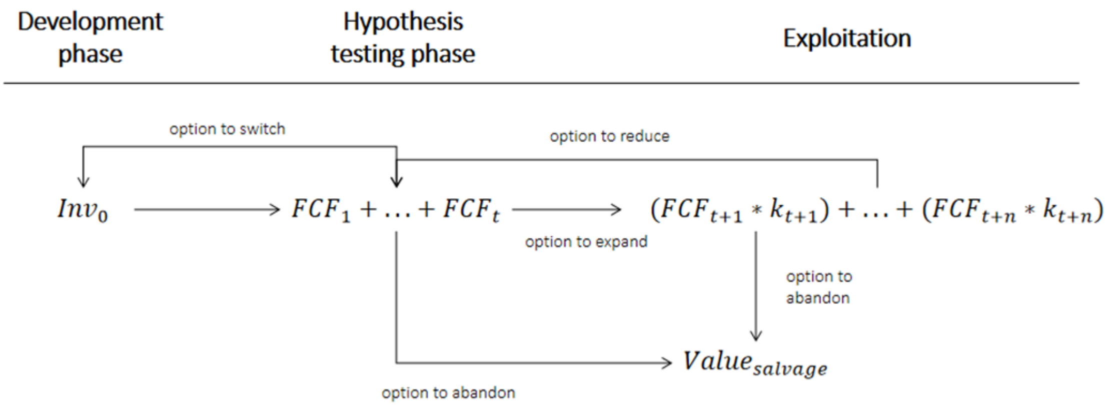

Fig. 4. **Scheme of Built-In Options in the Life Cycle of an AI Model from a Value Creation Perspective**
Source: Compiled by the author.

LLMs represent a set of neural networks for learning sequential data without a teacher on unannotated text. In addition, large language models have long- and short-term memory, which allows them to construct a response to a query based on previously received inputs, as well as forecast the next sentence. The unit of text on which a model is taught and which it issues as a result is called a token. Obviously, a LLM requires a considerable amount of data, and hardware is required to process it. *Fig. 5* shows the quantity of conditional data units required to train different AI models. A conditional data unit is a unit that does not take into account a data type: for example, an image and a word can be equal to one unit of conditional information. The figure shows that a significant increase in data usage occurred in the 1990s and reached 3 trillion data units in 2023 for the Palm2 language model. This is due to three main factors:

1. Data acquisition in digital form;
2. Development of data storage technologies;
3. Development of big data processing technologies.

From the point of view of application in business processes, the following directions can be identified:

1. Alternative to traditional search.

Companies are actively implementing LLM as an alternative to the search engine, which allows users to find the information they need faster or aggregate it from multiple sources, without turning directly to sites. The key change is not to provide a set of links, but a ready-made response to the user. Examples of applications: search engines Yandex, Google, Bing.

2. Copilots.

It is a tool for increasing the productivity of employees and represents an LLM, trained on a specific set of data required by a specialist. A well-known example is JARVIS, developed by the Russian company Sber on the basis of GPT-3. It allows programmers without additional requests on the Internet to write the simplest code and find errors in the current.

3. Smart assistant.

Unlike copilots, which are aimed at increasing the productivity of employees by interacting with them, smart assistants allow for direct communication between client and employee. Smart assistants can be built into recommendation systems to quickly get information about a product or service, and sometimes get that service. For example, in medicine, LLMs can be used to conduct a primary examination and collect a patient's history. The multi-modality of the LLM, i.e., the ability to work with both text and image, allows them to be used as copilots for doctors [20].

4. Generative content.

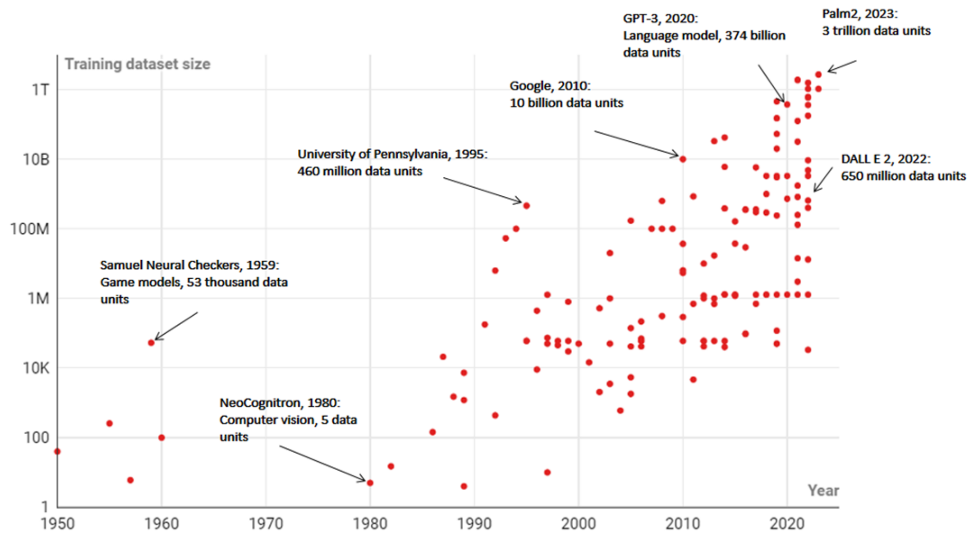

Fig. 5. **The Volume of Conventional Data Units Needed to Train Different AI Models**

Source: Compiled by the author based on [19].

LLMs, especially multimodal ones, allow you to replace a number of routines on-demand content creation operations. For example, LLMs are able to write a related text on a particular topic or generate an image. This direction is widely used in marketing and advertising and allows for increased productivity among employees when creating content [21].

5. Implementation of the results of the subscription model.

This approach can be used by companies that develop the LLM model themselves and have a patent for the development, which allows users to sell a subscription to use the model. This is implemented, for example, by OpenAI, which provides a limited amount of tokens for ChatGPT requests for a certain fee.

We illustrate the valuation of cash flows from one of the directions of implementation of the LLM. Suppose an IT company implements an LLM in the process of developing software products in copilot format. The average labour cost of one developer per year is 1.5 million rubles per year. The company employs 1 000 developers. Excluding indirect costs, the annual cash flow amounts to 1 500 million rubles per year.

In order to confirm the hypotheses about the effectiveness of the model implementation and the positive impact on productivity, the enterprise conducts a pilot and assigns 100 employees in a target group and a control group. The result is a 56% increase in labor productivity, which reduces costs (by reducing staff) by a multiplier.[3] Annual cash flow of the pilot in the control group is 150 million rubles, and in the target group — 84 million rubles. In this case, according to *formula 1*, the company receives the value of incremental cash flow equal to 66 million rubles.

To estimate operational cash flows, the company uses the assumption that the quality of the model results is reduced by half. The adjustment factor in the first year is $k_1 = 0.5$, a and in the second year of the model $k_2 = 0.25$. After two years, the operation is discontinued. Annual incremental cash flow at the stage of operation without taking into account the deterioration of the quality of the model is 660 million rubles, as it extends to all 1000 employees. For the entire operating phase, the cash flow will be:

$$\sum CF_{exploitation} = 660\,mln\,rubles\ *0.5 + + 660\,mln\,rubles * 0.25 = 495\,mln\,rubles. \quad (3)$$

[3] Author’s note: the real productivity growth recorded in the study on the assessment of productivity growth of software developers using the GitHub Copilot model is used [22].

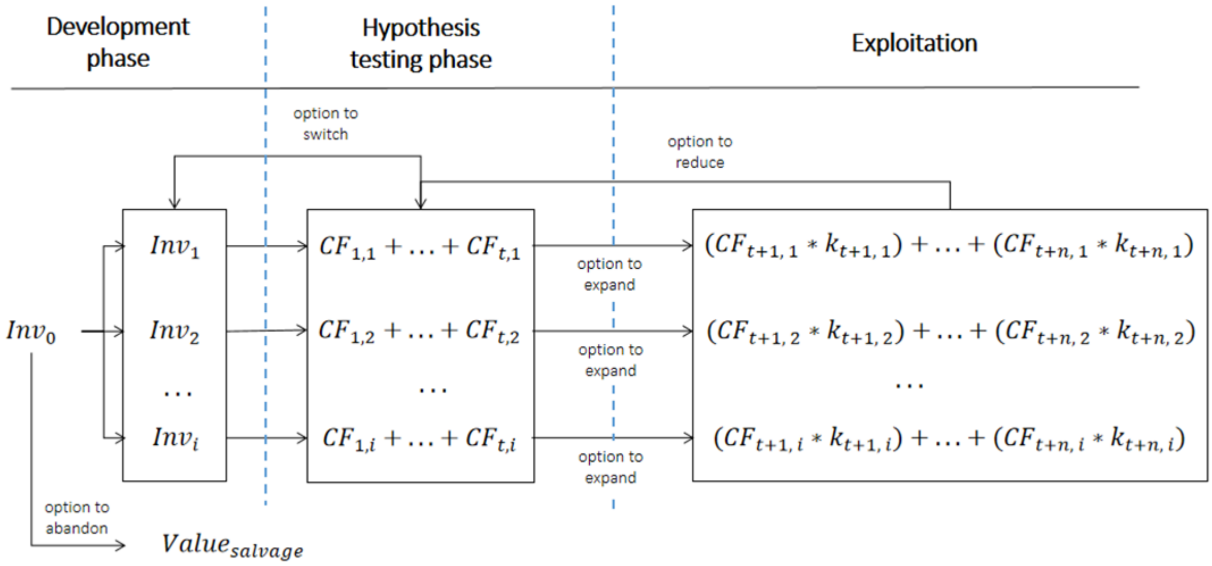

Fig. 6. **Life Cycle of Large Language Models in Terms of Value Creation**

Source: Compiled by the author.

Thus, the implementation decision is based on incremental cash flows from all potential implementation areas of the instrument. *Fig. 6* shows the LLM lifecycle scheme for a company that develops and implements it in its own operational processes and sells it as a product.

The development phase involves two areas of investment: the development of a common language model (Inv_0) and the investments related to the training of a model for a specific task that requires certain data that is not available in the public domain (Inv_i). This stage in AI development is called "fine-tuning" [23]. For example, a company trains an LLM to work with an internal legal documentation or a client's documentation. The fine-tuning procedure increases the efficiency of the model to solve specific tasks. The volume of such investments is determined on the basis of each implementation area requiring further training.

The hypothesis testing phase is similar to the machine learning process, with the feature that piloting is carried out for each direction and the decision is made on the basis of completion or commissioning. Accordingly, in the assessment of cash flows, the increment from each direction is taken into account ($CF_{t,i}$).

At the operational stage, the monitoring procedure is complicated, as it requires an assessment of the performance of the task model of each direction. Earlier, we gave an example of a GPT study, showing a significant change in the correctness of performing a number of tasks — writing code, understanding images. To reassess cash flows in the light of model risk, use your adjustment coefficient ($k_{t,i}$) depending on the problem solved by the model.

CONCLUSION

The existing life-cycle concepts of the model (CRISP-DM, TDSP and others) allow us to define the content of the AI development process as a project, but they do not reveal the economic content of investments in AI. The life-cycle methodology proposed by us does not contradict the design approach and allows us to explain its economic content in terms of value creation. The stages we described and the transitions between them allow us to identify the existing options — expansion, reduction, change, or abandonment of investments — whose use affects the final valuation of the investments. The use of this methodology expands the potential of evaluation tools and further research. An investment project in AI technology can be viewed as a system of embedded real options.

Another innovation of the methodology is the identification of the hypothesis testing procedure as a stand-alone stage. Previously, model performance assessment was limited to testing the statistical quality of model performance. We proposed a common practice in the evaluation of innovations — conducting piloting. Applying this approach to the verification of hypotheses allows low-cost methods to obtain actual knowledge not only of statistical quality, but also of the operational process and its economy. The specificity of conducting pilots to evaluate investment in AI technology could also be the subject of future research.

The LCM methodology has been tested on a specific type of model — large language models. Since, unlike a subset of AI models relating to machine learning, the LLM is a significant step towards general artificial intelligence in terms of the variety of tasks to be solved, the following adjustments have been proposed: Dividing the development phase into two investment phases — investment in the development of a common language model and investment in model adjustment.

Divide the life cycle into *i*-number of implementation directions with the allocation of separate incremental flows for each of them.

The model risk accounting factor is unique for each LLM implementation area.

The proposed methodology can be used in assessing the feasibility of investment in the development of LLM by large enterprises.

REFERENCES

1. Clark J., Perrault R., and others Artificial Intelligence Index Report 2023. Stanford University Human-centered Artificial Intellegence. 2023. URL: https://aiindex.stanford.edu/report/ (дата обращения: 01.08.2023)
2. Lingjiao C., Matei Z., James Z. How is ChatGPT's behavior changing over time? Cornell University. arXiv:2307.09009. 2023. DOI: https://doi.org/10.48550/arXiv.2307.09009 URL: https://arxiv.org/abs/2307.09009 (дата обращения: 01.08.2023)
3. Shearer C. The CRISP-DM model: the new blueprint for data mining. *J. DataWarehous*. 2000. (5): 13–22
4. Ericson G., Rohm W.A., Martens J., Sharkey K., Casey C., Harvey B., Schonning N. Team data science process documentation. 2017. URL: https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/ (дата обращения: 01.08.2023)
5. Haakman M., Cruz L., Huijgens H. et al. AI lifecycle models need to be revised. *Empirical Software Engineering*. 2021. (95): 1–29 https://doi.org/10.1007/s10664–021–09993–1
6. Daswin De Silva, Damminda Alahakoon, An artificial intelligence life cycle: From conception to production. *Patterns*. 2022. (3–6): 1–14 DOI: https://doi.org/10.1016/j.patter.2022.100489
7. Golubev A.A. The life cycle of innovation and resource support innovation. Modern problems of science and education. 2015. (2–2) URL: https://science-education.ru/ru/article/view?id=22026 (accessed on: 05.08.2023).
8. Gorodnova N.V. Primenenie iskusstvennogo intellekta v biznes-sfere: sovremennoe sostoyanie i perspektivy // *Voprosy innovatsionnoy ekonomiki*. 2021.11(4): 1473–1492 DOI: 10.18334/vinec.11.4.112249
9. Kashevarova N.A., Panova D.A. Analysis of the current practice of applying artificial intelligence in the financial sector and its impact on the transformation of the financial ecosystem. *Kreativnaya ekonomika*. 2020. (8): 1565–1580
10. Ustinova, O.E. Artificial intelligence in company management. *Kreativnaya ekonomika*. 2020. (5): 886–904 DOI: 10.18334/ce.14.5.102145
11. Åström J., Reim W., Parida V. Value creation and value capture for AI business model innovation: a three-phase process framework. *Review of Managerial Science*. 2022. (16): 2111–2133 DOI: https://doi.org/10.1007/s11846–022–00521-z

12. Moro-Visconti R. The Valuation of Digital Intangibles: Technology, Marketing, and the Metaverse. Palgrave Macmillan; 2022. pp. 265–282 URL: https://link.springer.com/book/10.1007/978–3–031–09237–4?page=1#toc (дата обращения: 09.08.2023)
13. Nikitin N.A. Financial evaluation of projects with artificial intelligence in the banking sector. *Financial Business*. 2022. (5–227): 122–125
14. Agarwal N., Moehring A., Rajpurkar P., Salz T. Combining human expertise with artificial intelligence: Experimental evidence from radiology. *NBER WORKING PAPER SERIES*. 2023. (31422): 1–54. — DOI 10.3386/w31422 URL: https://www.nber.org/papers/w31422 (дата обращения: 09.08.2023)
15. Pomulev A.A. Artificial intelligence as an object of valuation. *Imushhestvenny`e otnosheniya v Rossijskoj Federacii*. 2022. (6–249): 42–56
16. Nikitin N.A. Probabilistic methods for accounting model risks in assessing investments in artificial intelligence technologies. Innovative *Development of Economy Journal*. 2023. (2–74): 123–134. DOI 10.51832/2223798420232123
17. Douwe K., Bartolo M., Yixin Nie, Divyansh Kaushik, Atticus Geiger, Zhengxuan Wu, et al. Dynabench: Rethinking Benchmarking in NLP. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 2021. pp. 4110–4124. URL: https://aclanthology.org/2021.naacl-main.324/ (дата обращения: 11.08.2023)
18. Bubeck S., Chandrasekaran V., Eldan R., Gehrke J., Horvitz E., Kamar E., Lee P. et al. Sparks of Artificial General Intelligence: Early experiments with GPT-4. Cornell University. arXiv:2303.12712 [cs.CL]. 2023. DOI: https://doi.org/10.48550/arXiv.2303.12712 URL: https://arxiv.org/abs/2303.12712 (дата обращения: 11.08.2023)
19. Jaime Sevilla, Lennart Heim, Anson Ho, Tamay Besiroglu, Marius Hobbhahn, and Pablo Villalobos. 'Compute Trends Across Three Eras of Machine Learning'. Cornell University. arXiv:2202.05924 [cs.LG], 2022: 1–25. DOI: 10.48550/arXiv.2202.05924 URL: https://arxiv.org/abs/2202.05924
20. Waisberg E, Ong J, Masalkhi M, Kamran SA, Zaman N, Sarker P, Lee AG, Tavakkoli A. GPT-4: a new era of artificial intelligence in medicine. *Irish Journal of Medical Science*. 2023. https://doi.org/10.1007/s11845–023–03377–8
21. Rivas P, Zhao L. Marketing with ChatGPT: Navigating the Ethical Terrain of GPT-Based Chatbot Technology. *AI*. 2023; 4(2):375–384. https://doi.org/10.3390/ai4020019
22. Dohmke T., Iansiti M., Richards, G. Sea Change in Software Development: Economic and Productivity Analysis of the AI-Powered Developer Lifecycle. Cornell University. arXiv:2306.15033 [econ.GN], 2023: 1–30. DOI: 10.48550/arXiv.2306.15033
23. Chung H.W., Hou L., Longpre S., Zoph B., Tay Y., Fedus W. et al. Scaling Instruction-Finetuned Language Models. Cornell University. arXiv:2210.11416 [cs.LG]. 2022. DOI: 10.48550/arXiv.2210.11416 URL: https://arxiv.org/abs/2210.11416 (дата обращения: 11.08.2023)

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