Психологическая наука и образование
2026. *31*(3), 35–49.
https://doi.org/10.17759/pse.2026310303
ISSN: 1814-2052
ISSN: 2311-7273 (online)

Psychological Science and Education
2026. *31*(3), 35–49.
https://doi.org/10.17759/pse.2026310303
ISSN: 1814-2052
ISSN: 2311-7273 (online)

Научная статья | Original paper

Artificial intelligence use motives: adaptation of the diagnostic tool

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Abstract

Context and relevance. Artificial intelligence is a technology with the potential to fundamentally transform all spheres of human life. Its rapid integration into everyday reality intensifies research dedicated to the psychology of using neural networks. However, the development of empirical research in the Russian scientific field is limited by the lack of validated psychodiagnostic tools that allow assessing users' attitudes toward neural networks and the specific features of their motivation for using them. **Objective.** To adapt a questionnaire for diagnosing the motives of using artificial intelligence (AI) for the Russian population and to validate it. **Hypothesis.** It was assumed that the two-factor structure of the "Artificial Intelligence Use Motives" questionnaire would make it possible to create a Russian-language version of the tool with satisfactory psychometric properties, and that the composition of its factors would replicate the original model. **Methods and materials.** The study involved 368 university and secondary vocational education students (mean age 19 years old, 75% of the sample were women). Convergent validity was tested using the Adolescent and Parent Technology Use Attitude Questionnaire and the Career Engagement Scale. For data processing and analysis, exploratory and confirmatory factor analyses and Spearman correlations were used. **Results.** The two-factor structure of the "Artificial Intelligence Use Motives" questionnaire was confirmed as "Expectancy related to AI use" and "Subjective task value". The second factor contains four subscales. All scales are characterized by high internal consistency, and the overall psychometric indicators of the questionnaire confirm its reliability and validity. **Conclusions.** The Russian-language version of the AI use motives questionnaire retains the factor structure of the original version and possesses sufficient psychometric properties for its use in psychological science and practice.

Keywords: artificial intelligence (AI), artificial intelligence use motives, attitudes towards technology, psychodiagnostics, expectancy, subjective task value

Funding. The study was implemented in the framework of the Basic Research Program at HSE University (HSE-BR-2025-077).

Supplemental data. Dataset is available: https://doi.org/10.48612/MSUPE/v73m-ba1n-5at1.

For citation: Volkova, N.V., Kochetkov, N.V., Chiker, V.A. (2026). Artificial intelligence use motives: adaptation of the diagnostic tool. *Psychological Science and Education, 31*(3), 35–49. https://doi.org/10.17759/pse.2026310303

Мотивация использования искусственного интеллекта: адаптация диагностического инструментария

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Резюме

Контекст и актуальность. Искусственный интеллект является технологией, потенциально способной кардинально изменить все сферы жизни человека. Его быстрая интеграция в повседневную реальность интенсифицирует исследования, посвященные психологии использования нейросетей. Однако развитие эмпирических исследований в отечественном научном поле ограничено недостатком валидизированного психодиагностического инструментария, позволяющего оценивать отношение пользователей к нейросетям и особенности мотивации их использования. **Цель**. Адаптировать для российской популяции методику диагностики мотивов использования искусственного интеллекта и провести ее валидизацию. **Гипотеза**. Предполагалось, что двухфакторная структура опросника «Мотивы использования искусственного интеллекта» позволяет создать русскоязычную версию методики с удовлетворительными психометрическими свойствами, а состав ее факторов будет воспроизводить оригинальную модель. **Методы и материалы**. В исследовании приняли участие 368 студентов вузов и учреждений среднего профессионального образования (средний возраст — 19 лет, 75% выборки — женщины). Конвергентная валидность проверялась с помощью опросника отношения к технологиям для подростков и родителей и диагностики карьерной вовлеченности. Для обработки и анализа данных были использованы эксплораторный и конфирматорный факторный анализ, корреляции Спирмена. **Результаты.** Подтвердилась двухфакторная структура опросника «Мотивы использования искусственного интеллекта»: «Самоэффективность», связанная с использованием ИИ, и «Субъективная ценность» задачи (деятельности), второй фактор содержит четыре субшкалы. Все шкалы характеризуются высокой внутренней согласованностью, общие психометрические показатели опросника подтверждают его надежность и валидность. **Выводы**. Русскоязычная версия методики диагностики мотивов использования искусственного интеллекта сохраняет факторную структуру оригинальной методики и обладает высокими психометрическими свойствами для ее использования в психологической науке и практике.

Ключевые слова: искусственный интеллект (ИИ), мотивы использования ИИ, отношение к технологиям, психодиагностика, самоэффективность, субъективная ценность

Финансирование. Исследование осуществлено в рамках Программы фундаментальных исследований НИУ ВШЭ (HSE-BR-2025-077).

Дополнительные данные. Наборы данных доступны: https://doi.org/10.48612/MSUPE/v73m-ba1n-5at1.

Для цитирования: Волкова, Н.В., Кочетков, Н.В., Чикер, В.А. (2026). Мотивация использования искусственного интеллекта: адаптация диагностического инструментария. *Психологическая наука и образование, 31*(3), 35–49. https://doi.org/10.17759/pse.2026310303

Introduction

According to statistics, 81% of people under 34 years old use neural networks to work with information, and 14% of users have turned to neural networks for communication[1]. People's attitudes toward artificial intelligence (AI) are mixed: some feel uneasy about the development of this technology, while others are motivated to study neural networks, work with them, and delegate some of their tasks to technology. At the same time, people tend to regard AI products as their own. (Mayer, 2025).

How is the use of neural networks changing our lives? This is most clearly evident in the education system, which is made up of active users of AI thanks to students. It is argued that the learning process will soon change due to the fact that AI enables effective self-learning. Consequently, teachers will increasingly act as mentors who prevent mindless acquisition of information (Gocen, Aydemir, 2020). Perhaps this concern is one of the most serious — there is a risk of a decline in critical thinking among representatives of the digital generation who actively use AI tools, which is explained by the theory of cognitive unloading (Gerlich, 2025). In addition to critical thinking, creative thinking is also at risk, as neural networks are beginning to outperform the average person in this area (Bellemare-Pepin et al., 2026), which, in turn, creates the potential threat of their displacement from the arts, as is already happening, for example, in cinema.

Despite the benefits of AI, such as personalized learning (Yu, Guo, 2023) and increased student motivation (Yuan, Liu, 2025), it can be assumed that a significant change will occur in the near future, as the use of neural networks entails a new form of academic dishonesty. Students resort to their help to write various assignments (Subbotina, 2024), and teachers — to check them (Kuzmenko, 2025), which leads to a kind of confrontation between both sides of the educational process. In the context of social anomie (Meshcheryakova, 2012), an easy way to achieve success (including academic) will most likely lead to a sharp decline in academic motivation and a restructuring

[1] Demina, K. (2025) Neural Networks: A Tool, Not Magic. VTsIOM News. URL: https://wciom.ru/analytical-reviews/analiticheskii-obzor/neiroseti-instrument-a-ne-magija (date of access: 21.01.2026).

of the education system: "New technologies will create even greater differentiation between students. Smart students will use them with a degree of intelligence, that is, approaching the issue creatively. Those who were unsuccessful will widen this gap, since they will not test models for the task, but will use them head-on, without the ability to verify the quality of the answer or use the answer in practice" (Kazakova, Kuzminov, 2025, p. 23). A solution to this problem is possible through the joint efforts of society (Yu, Guo, 2023) — only then will AI become an assistant to humans, taking their development to a qualitatively new level.

The impact of AI on humans is a rapidly developing field of psychological science, but it can be stated that this development is still primarily theoretical. Empirical research is complicated by the lack of methodological tools.

The following methodological tools can be found in the field of psychological research:

— The General Attitudes towards Artificial Intelligence Scale. The scale has a two-factor structure: positive attitude and negative attitude (Schepman, Rodway, 2022).

— The Artificial Intelligence Assessment Scale, which "allows educators to choose the appropriate level of use of GenAI in assessment depending on the learning outcomes they want to achieve" (Perkins et al., 2024).

— The AI-Anxiety Scale, which includes anxiety regarding: AI training; AI similarity to humans; replacing humans with artificial intelligence; the possibility that technology could get out of control (Wang, Wang, 2019).

— The Trust in Automation Scale. Although this scale measures trust in automation, it is also applicable to working with AI (McGrath et al., 2025).

However, only one methodology dedicated to assessing attitudes toward technology can be found in Russian (Soldatova et al., 2021), which measures aspects such as technophilia, techno-rationalism, technophobia, and technopessimism.

It can be seen that research focuses on assessing attitudes toward AI as a new technology, while neglecting the area related to the motivations for its use. This fact, as well as the lack of methodological tools for studying the psychological aspects of AI use, determines the relevance and purpose of this study: to adapt a methodology for assessing motives for using artificial intelligence for the Russian population.

Research hypothesis: The Russian-language version of the methodology for diagnosing motives for using AI has satisfactory psychometric properties, and its factor structure coincides with the original methodology and expected value theory.

Theoretical framework

Selecting a theoretical framework to describe changes in human motivation in the AI era is a challenging task for researchers, given the large number of motivational theories in psychology. One of the turning points in the history of motivational development was the expectancy-value theory (EVT), which was formulated by J.W. Atkinson in 1964 and finalized in 2002 by J. Eccles and A. Wigfield (Eccles, Wigfield, 2002). The predecessor of EVT can be considered K. Lewin's field theory, which held that objects have a valence that can be revealed as subjective value for a person. Similarly, in modern EVT (see figure), motivation depends on **the subjective value of the task or activity being performed** and

expectancy. In this context, expectancy is a person's belief that they can effectively solve a task; in other words, it is the expected success, which depends on a subjective assessment of their capabilities, previous experience, and social comparison.

The theory distinguishes four types of subjective value of a task (activity):

1. *Attainment value*. This relates to a person's value system, determining the importance of achieving a goal or solving a problem.
2. *Utility value*. This is determined by how useful what they are currently achieving will be to them in the future.
3. *Intrinsic/interest value*. This is internal motivation, an interest in what they are doing.
4. *Expected resource expenditure (costs)*. Since any activity requires a resource, motivation for it depends on its size. A high "cost" of an activity can demotivate a person.

The "Artificial Intelligence Use Motives" questionnaire, validated in 2024 by Turkish scientists Yurt and Kasarci (2024), is based on EVT. The authors selected the questionnaire to adapt it for the Russian population.

Materials and methods

The study consisted of three sequential stages. During *the first stage* (August 2025), cross-cultural adaptation of the scale was conducted, including translation, back-translation, and expert evaluation, as well as pilot testing to verify the clarity and unambiguity of statement wording. During *the second stage* (September 2025), the translated version of the questionnaire was piloted on a sample of students from Moscow higher education institutions. During *the third stage* (October–December 2025), a representative sample was selected in compliance with ethical standards, including the voluntary informed consent of respondents.

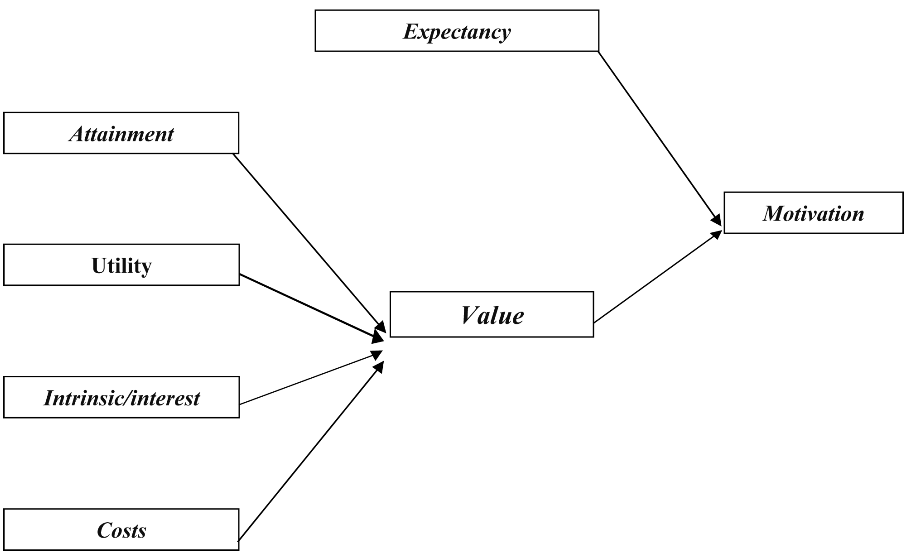

Fig. The motivation model (Eccles, Wigfield, 2002)

Stage 1. The procedure of scale translation

To ensure cultural and linguistic equivalence of the instrument, the scale was adapted using a standardized forward and back translation procedure (Brislin, 1970). An expert forward translation, conducted by three specialists in psychology and management, and subsequent consensus evaluation resulted in an intermediate Russian-language version. Its back translation by an independent bilingual expert and comparison with the original confirmed the semantic consistency of the statements, which is a prerequisite for further psychometric validation.

Stage 2. Pilot testing of the scale

The pilot testing of the questionnaire was conducted on a sample of 20 students enrolled in psychology programs at a university located in Moscow. Based on feedback from pilot participants, the wording of individual statements was adjusted. The final version of the scale for data collection consisted of 20 statements.

Stage 3. Data collection

Previous studies have demonstrated that expectancy and activity value, which form the basis of J. Eccles and A. Wigfield's theory (Wigfield, Eccles, 2000), are decisive factors in career choice and trajectories (Eccles, Wigfield, 2002). Accordingly, the sample was drawn from students, who are active participants in the labor market and, due to their socialization during the development of digital technologies, are confident users of these resources.

A total of 368 students from secondary vocational education institutions (20,1%) and higher education institutions (79,9%) in Moscow and St. Petersburg participated in the anonymous online survey. The average age of respondents was 18,8 years (SD = 2,05). Women predominated in the sample — 75% (n = 276), while men accounted for 25% (n = 92).

Questionnaires

The original version of the “Artificial Intelligence Use Motives” scale included 20 items designed to assess self-efficacy related to AI use and the subjective value of the activity or task (Yurt, Kasarci, 2024).

The following questionnaires were used to assess the convergent validity of the scale:

1. *The Career Engagement Scale*, developed by A. Hirschi et al. (2014) and adapted for the Russian context by N.V. Volkova et al. (2026), consists of 10 items. It was used to assess three dimensions of this indicator: career planning (4 statements; Cronbach's alpha coefficient (α) = 0,87), career networking (3 statements; α = 0,84), and career self-development (3 statements; α = 0,73).

2. *The Technology Attitudes Questionnaire for Adolescents and Parents* (Soldatova et al., 2021), which was developed taking into account the cognitive and emotional aspects of attitudes toward technology in adolescents and parents of adolescents aged 14–17, was used to assess technophobia (4 statements; α = 0,8), technophilia (8 statements; α = 0,82), technorationalism (4 statements; α = 0,64), and technopessimism (3 statements; α = 0,76). The scale consists of 19 items.

The choice of scales was based on research findings confirming a positive relationship between achievement motivation within the context of EVT (Wigfield, Eccles, 2000) and career choice (Eccles, Wigfield, 2002; Lauermann et al., 2017), as well as academic performance (Ivanyushina et al., 2016), which is associated with self-development and career success.

Statistical analysis of the data was performed using the appropriate libraries of the R programming language.

Results

After checking the questionnaires for correct completion and removing records with gaps, the normality of the data distribution was assessed via the values of asymmetry and kurtosis, the modulus of which did not exceed 2.

Factor structure

The questionnaire item correlation matrix was analyzed before conducting exploratory factor analysis to identify pairs with highly significant coefficients (greater than 0,8). As a result, one item from the “Intrinsic Value” subscale was removed.

Exploratory factor analysis (EFA) was performed to test the questionnaire's theoretical structure and item quality using the maximum likelihood method with promax rotation in the psych package of the R programming language. At this stage, items with low factor loadings (below 0,30) and significant cross-loadings were excluded; the theoretical fit of the items to the identified factors was additionally assessed. As a result, the item from the subscale assessing perceived resource expenditure, which showed the highest loading on the expectancy factor, was excluded. The remaining 18 items were distributed between the two factors, with a combined share of explained variance of 56.7%. The correlation structure of the data is characterized by a high proportion of shared variance (Kaiser–Meyer–Olkin test, KMO = 0,95) and a significant Bartlett's test of sphericity (χ^2 = 4218,73; df = 153; p < 0,001).

Confirmatory factor analysis (CFA) was performed using the lavaan package in the R programming language to assess the structure of the questionnaire and the theoretical model (see figure). The second-order factor model based on 18 items demonstrated an acceptable fit to the data (Satorra-Bentler χ^2(128) = 335,08; CFI = 0,95; RMSEA = 0,066 (90% CI from 0,058 to 0,075), SRMR = 0,05). The scale structure and standardized factor loadings are presented in Table 1.

At the end of the analysis, the reliability indices of the subscales were assessed (Table 2). All statements had statistically significant standardized factor loadings of 0,5 or higher (see Table 1), and each latent construct accounted for at least 50% of the variance in the associated indicators, that is, the average variance extracted (AVE) for each subscale was greater than 0,5,

Table 1

Standardised factor loadings of the questionnaire items

Factors	Subscales	Items	Factor loadings
Expectancy		1	0,500
		2	0,798
		3	0,801
		4	0,798

Factors	Subscales	Items	Factor loadings
Value	Attainment	5	0,674
		6	0,816
		7	0,745
		8	0,867
	Utility	9	0,765
		10	0,761
		11	0,736
		12	0,717
	Interest	13	0,676
		14	0,785
		15	0,914
	Costs	16	0,795
		17	0,767
		18	0,809

Note: The item numbers correspond to the content provided in Appendix.

which collectively confirms the convergent validity of the first-order factors (Cheung et al., 2024). The convergent validity of the second-order factor “Value” of the task (activity) was assessed indirectly, through the magnitude and significance of the first-order factor loadings. All standardized loadings were high (λ = 0,865–0,953, p < 0,001), and the confidence intervals did not include zero. In addition, the second-order factor explained a significant proportion of the variance in its subscales (from 75% to 90%), which confirms the convergent validity of the second-order construct.

Based on previous research (Rönkkö, Cho, 2022), the discriminant validity between the first-order latent factor Expectancy and the second-order factor Value was confirmed based on the latent correlation (r = 0,743, p < 0,001) whose confidence interval did not include one [95% CI: 0,676; 0,810].

Validity of the questionnaire

The convergent validity of the questionnaire, along with an examination of its factor structure and AVE scores, was assessed through correlation analysis with theoretically relevant constructs that had previously shown significant relationships with the AI Motivation Scale and the use of digital technologies.

Table 2

Descriptive statistics and reliability indicators of subscales (N = 368)

Subscale	Means	SD	AVE	α	CR
Expectancy	3,20	0,82	0,57	0,81	0,83
Attainment	3,01	1,02	0,61	0,85	0,87
Utility	3,39	1,03	0,56	0,83	0,83
Interest	3,26	1,05	0,65	0,83	0,85
Costs	2,71	1,04	0,63	0,83	0,83

Note: AVE — average variance extracted; α — The Cronbach’s alpha coefficient; CR — construct reliability.

Table 3 presents Spearman correlations. All five dimensions of the AI motivation scale correlate positively with the three components of career engagement, as well as technorationalism and technophilia, with which the relationship is strongest. In most cases, technophobia and technopessimism show no significant correlations with the variables, or their relationships are weakly negative. In this way, only two statistically significant correlations were found: between technopessimism and intrinsic interest in using AI ($r = –0{,}13$, $p < 0{,}05$), and between technophobia and expectancy ($r = –0{,}18$, $p < 0{,}001$). Accordingly, the data from the correlation analysis confirm the convergent validity of the questionnaire.

It's important to note that motivation for AI use is determined more by positive factors (technophilia, techno-rationalism, and the three dimensions of career engagement) than by negative attitudes (technopessimism and technophobia). Accordingly, strategies for stimulating AI use should focus less on overcoming fears and more on fostering interest, confidence, and the meaningful use of AI in professional and career settings.

Discussion

Factor structure

As a result of the EFA and CFA, two factors were identified in accordance with the theory of J. Eccles and A. Wigfield (2000): expectancy and subjective value of the task (activity), the latter of which consists of four motivational components. The results obtained are generally consistent with the questionnaire proposed by Yurt and Kasarci (2024). However, as a result of the analysis, two statements were excluded, meaning our final version consisted of 18 items. Thus, our validated ques-

Table 3

Results of correlation analysis

Motives of AI use / Career engagement and attitudes toward technologies	Expectancy	Attainment	Utilities	Interest	Costs
Career engagement					
Career planning	0,35***	0,31***	0,29***	0,31***	0,29***
Career networking	0,30***	0,27***	0,23***	0,22***	0,24***
Career self-development	0,32***	0,31***	0,29***	0,25***	0,25***
Attitudes towards Technology					
Technophilia	0,60***	0,64***	0,63***	0,65***	0,61***
Technopessimism	–0,08	–0,08	–0,06	–0,13*	–0,09
Technophobia	–0,18***	0,04	–0,03	–0,06	0,04
Technorationalism	0,36***	0,35***	0,38***	0,42***	0,34***

Note: «*» — correlation is significant at the 0,05 level; «**» — correlation is significant at the 0,01 level; «***» — correlation is significant at the 0,001 level.

tionnaire contains 18 statements, distributed among five subscales for assessing motivation for using AI (see Appendix).

Validity

A literature review revealed a positive relationship between expectancy and subjective task (activity) values within the EVT framework (Wigfield, Eccles, 2000) and career choice (Eccles, Wigfield, 2002; Lauermann et al., 2017), as well as academic performance (Ivanyushina et al., 2016), which is related to self-development and career. Accordingly, a theoretical hypothesis was put forward about the relationship between the scale proposed by Yurt and Kasarci (2024) based on this theory and career engagement as a form of proactive career behavior (Hirschi et al., 2014), which is expressed through career planning, career self-development and the establishment of professional connections, which together influence a person's professional development (Volkova et al., 2026). Furthermore, the use of AI applications is closely linked to attitudes toward technology (Soldatova et al., 2021). Correlation coefficients showed significant positive correlations with positive variables (technophilia, technorationalism, and three dimensions of career engagement), and weak or no correlations with technopessimism and technophobia, confirming the questionnaire's validity. Thus, it can be concluded that the questionnaire is a valid and reliable instrument for use with a Russian-speaking sample, both in terms of its formal psychometric properties and in terms of its psychological focus and substantive content.

Practical implications

It is important to note that all five dimensions of motivation for AI use demonstrated moderately high positive correlations ($r \approx 0{,}54–0{,}75$). Accordingly, an increase in one motivational component (e.g., practical utility or interest) is highly likely accompanied by an increase in others, and motivation for AI use can be viewed as a complex system. In this context, interventions aimed at increasing it, for example, through training programs, should be designed with the simultaneous enhancement of all five motivational components within the context of the EVT.

On the other hand, the use of AI is perceived not as an isolated technological practice, but as a career development tool, since all motivational indicators are moderately and significantly correlated with career planning, career networking, and career self-development ($r \approx 0{,}22–0{,}35$). Accordingly, the promotion of AI applications will be more effective if they are positioned as a means of enhancing career prospects or as a resource for professional growth and expanding professional networks.

A positive emotional-value attitude toward technology significantly enhances motivation to use AI applications, which can be facilitated by developing a positive technological experience. Skeptical or anxious expectations about technology, expressed through technopessimism, generally do not play a decisive role in shaping motivation to use AI. However, technophobia, which is significantly and moderately negatively related to expectancy, reduces motivation by undermining confidence in one's ability to successfully use AI. Accordingly, training and support measures should be aimed at increasing self-efficacy, especially for individuals with high levels of anxiety.

Technorationalism is moderately correlated with all motivational variables ($r \approx 0{,}34–0{,}42$) and is also strongly related to technophilia and negatively related to technophobia. Accordingly, a rational, balanced attitude toward technology through an awareness of its capabilities and limitations will support motivation to use AI without excessive optimism or fear.

Conclusions

1. We see potential for further development of this research in the adaptation of existing international methodological tools, as well as in the development of new, domestic ones, allowing us to address the psychological phenomena caused by the emergence and development of AI. Our study demonstrated that AI capabilities expand and deepen the individual's motivational sphere, can be used to develop self-efficacy, and enhance the value of activity, which is a crucial resource for students and education in general.

2. Psychometric adaptation. An adapted version of the “Artificial Intelligence Use Motives” scale for a Russian-speaking sample confirmed its reliability and validity. In accordance with the EV theory of J. Eccles and A. Wigfield (Wigfield, Eccles, 2000), the scale includes two factors: “expectancy” and “value” of the task (activity). The “Value” factor consists of four motivational components: 1) attainment value, 2) utility value, 3) interest value, and 4) expected resource expenditure or cost value.

3. The results confirm the applicability of Eccles and Wigfield's (2002) theory, based on the expectancy of success and subjective values of activity, to the analysis of motivation for using AI in the Russian language.

4. The scale allows for a differentiated assessment of motivational components, which may be useful for educators and career counselors. For example, low scores on the “Expected Resource Expenditure (costs)” subscale may indicate a lack of understanding of scenarios where AI skills may be useful and, therefore, require specific training.

5. The adapted questionnaire can serve as a basis for developing motivation programs for students and employees of organizations aimed at enhancing the use of AI technologies. Accordingly, the methodological arsenal of practicing psychologists has been supplemented with another reliable and valid psychodiagnostic tool.

6. Technorationalism is viewed as a protective factor, expressed in a rational, balanced attitude toward technology, as well as an awareness of its advantages and limitations, and acts as a stable factor in supporting motivation for the use of AI.

Limitations. The study is limited to a sample of students from major Russian cities. In the future, it is advisable to test the scale on other samples, including less populated locations and respondents of different ages. In addition, it is promising to further study the influence of a wider range of socio-demographic factors on the motivation for using neural networks.

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Appendix

A Questionnaire of Artificial Intelligence Use Motives

Dear participant!

Please rate your agreement with the following statements: 1 = completely disagree, 2 = disagree, 3 = don't know, 4 = agree, 5 = completely agree.

Items

1. I can learn the skills that enable effective use of artificial intelligence applications.
2. My general knowledge about artificial intelligence is more than sufficient compared to many people.
3. I am better than most of my peers in effectively using artificial intelligence applications.
4. My potential to effectively use artificial intelligence applications surpasses many people in my surroundings.
5. The ability to effectively use AI is important to me.
6. Learning and implementing innovations in artificial intelligence applications are a priority for me.
7. It is important for me to stay updated on developments related to artificial intelligence.
8. I attach great importance to strengthening my skills in using artificial intelligence applications.
9. Artificial intelligence applications will assist me in becoming a proficient professional.
10. Artificial intelligence enhances my overall efficiency, making my life more effective.
11. In daily life, artificial intelligence helps me streamline my tasks.
12. Artificial intelligence helps me study various subjects and courses.
13. I enjoy experiences related to artificial intelligence.
14. Following the development of artificial intelligence is an interesting activity for me.
15. Developing my skills in using artificial intelligence is a delightful learning process for me.
16. Investing time and effort to learn artificial intelligence applications is worthwhile for me.
17. I am inclined to sacrifice time from other activities to learn artificial intelligence applications.
18. I am not hesitant to invest a considerable amount of time and effort to enhance my skills related to artificial intelligence.

Processing and interpreting the results

The questionnaire consists of five dimensions, for each of which the mean values must be calculated.

Dimensions	Number of Items	Intervals of mean values		
		Below average	**Average**	**Above average**
Expectancy	1–4	1–2,3	2,4–3,6	3,7 and greater
Values				
Attainment	5–8			
Utility	9–12			
Intrinsic/interest value	13–15			
Costs	16–18			

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Nikita V. Kochetkov — annotation, literature review; visualization of research results.

Vera A. Chiker — ideas; planning of the research; control over the research.

All authors participated in the discussion of the results and approved the final text of the manuscript.

Вклад авторов

Волкова Н.В. — сбор и анализ данных; применение статистических и математических методов для анализа данных; написание и оформление рукописи.

Кочетков Н.В. — аннотирование, обзор литературы; визуализация результатов исследования.

Чикер В.А. — идеи исследования; планирование исследования; контроль за проведением исследования.

Все авторы приняли участие в обсуждении результатов и согласовали окончательный текст рукописи.

Conflict of interest
The authors declare no conflict of interest.

Конфликт интересов
Авторы заявляют об отсутствии конфликта интересов.

Ethics statement
Informed consent was obtained from all study participants.

Декларация об этике
От всех участников исследования получено согласие о его прохождении.

Поступила в редакцию 07.02.2026 Received 2026.02.07
Поступила после рецензирования 02.04.2026 Revised 2026.04.02
Принята к публикации 15.06.2026 Accepted 2026.06.15
Опубликована 30.06.2026 Published 2026.06.30