

Обзорная статья | Review paper

Adapting and validating two computational thinking scales on a Russian population: A psychometric study

K.A. Nikiforova¹ ✉, S.P. Kulikova², T.O. Platonova³, V.A. Demareva⁴

¹ Sirius University of Science and Technology, Sirius, Krasnodar region, Russian Federation

² HSE University, Perm, Russian Federation

³ Tomsk State University, Tomsk, Russian Federation

⁴ Lobachevsky State University of Nizhny Novgorod, Nizhny Novgorod, Russian Federation

✉ kkrisinger1990@gmail.com

Abstract

The increasing prevalence of technology in daily life has led to a rising demand for IT specialists. In response, educational curricula have been adapted to incorporate coding lessons as early as primary school. However, the cognitive processes underlying computational thinking (CT) — the ability to apply a systematic problem-solving approach akin to computer logic — remain inadequately understood. While several scales for measuring CT have been proposed and adapted for various languages, research on this concept in Russia has been limited. **Objective.** The present study aims to adapt two previously validated CT scales for a population of Russian programmers and conduct a comparative psychometric analysis to identify their suitability and differences in measuring self-assessed CT. **Hypotheses.** Both scales will be applicable within the context of Russian programmers; the scales will operationalize distinct constructs within CT. **Methods.** Two CT scales (Tsai, Liang, Hsu, 2021, 19 items; Korkmaz, Çakir, Özden, 2017, 29 items) were translated into Russian using back-translation. After filtering for at least 6 months of programming experience, the final analytic sample comprised 148 programmers of diverse ages and programming experience ($N = 148$, $M = 20.7$, $SD = 5.7$). Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to assess factor structure; Cronbach's α assessed internal consistency. **Results.** Neither original factor structure fully replicated in the Russian sample (Scale 1 collapsed to one factor; Scale 2 to three factors). A combined four-factor solution demonstrated acceptable to good internal consistency (Cronbach's $\alpha = 0.77$ — 0.89) and superior CFA fit ($RMSEA = 0.058$, $CFI = 0.895$) compared with one- and two-factor alternatives. **Conclusions.** Although the original factor structures of both scales did not fully replicate, a combined four-factor solution captures meaningful CT-related constructs in this population, supporting a refined 39-item instrument for assessing self-perceptions of CT among Russian-speaking programmers.

Keywords: computational thinking, psychometrics, exploratory factor analysis, confirmatory factor analysis, scale adaptation, cross-cultural validation, programmer

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Адаптация и валидация двух шкал оценки вычислительного мышления на российской популяции: психометрическое исследование

К.А. Никифорова¹ ✉, С.П. Куликова², Т.О. Платонова³, В.А. Демарева⁴

¹ Научно-технологический университет «Сириус», пгт. Сириус, Краснодарский регион, Российская Федерация

² Национальный исследовательский университет «Высшая школа экономики», Пермь, Российская Федерация

³ Национальный исследовательский Томский государственный университет, Томск, Российская Федерация

⁴ Национальный исследовательский Нижегородский государственный университет имени Н.И. Лобачевского, Нижний Новгород, Российская Федерация

✉ kkrisinger1990@gmail.com

Резюме

Контекст и актуальность. Увеличение распространенности технологий в повседневной жизни привело к росту спроса на ИТ-специалистов. В ответ на это учебные программы были адаптированы для включения

уроков программирования уже в начальной школе. Однако когнитивные процессы, лежащие в основе вычислительного мышления (ВМ) — способности применять систематический подход к решению задач, аналогичный логике компьютера, — остаются недостаточно изученными. Несколько шкал измерения ВМ были предложены и адаптированы для разных языков, однако в России исследования этой проблематики ограничены. **Цель.** Адаптация двух ранее валидированных шкал ВМ для популяции российских программистов и проведение сравнительного психометрического анализа для оценки их пригодности и различий в измерении самооценки ВМ. **Гипотезы.** Обе шкалы применимы в контексте российских программистов; шкалы операционализируют различные конструкты в рамках ВМ. **Методы и материалы.** Две шкалы ВМ (Tsai, Liang, Hsu, 2021, 19 пунктов; Korkmaz, Çakir, Özden, 2017, 29 пунктов) переведены на русский язык методом обратного перевода. После исключения участников с опытом программирования менее 6 месяцев итоговая выборка составила 148 программистов разного возраста и с различным опытом программирования ($N = 148$, $M = 20,7$, $SD = 5,7$). Использованы эксплораторный (EFA) и конфирматорный (CFA) факторный анализ; внутренняя согласованность оценивалась с помощью α Кронбаха. **Результаты.** Исходные факторные структуры в российской выборке полностью не воспроизвелись (Шкала 1 свелась к одному фактору, Шкала 2 — к трем). Комбинированное четырехфакторное решение продемонстрировало приемлемую и хорошую внутреннюю согласованность (α Кронбаха = 0,77—0,89) и превосходило одно- и двухфакторные модели по показателям подгонки (RMSEA = 0,058; CFI = 0,895). **Выводы.** Несмотря на то что исходные факторные структуры обеих шкал в российской выборке не воспроизвелись, комбинированное четырехфакторное решение отражает значимые конструкты, связанные с ВМ; это поддерживает применение уточненной шкалы из 39 пунктов для оценки самовосприятия ВМ у русскоязычных программистов.

Ключевые слова: вычислительное мышление, психометрика, эксплораторный факторный анализ, конфирматорный факторный анализ, адаптация шкал, кросс-культурная валидизация, программисты

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Introduction

Computational thinking (CT) is a structured problem-solving approach that draws on techniques and methodologies from computer science. It involves decomposing complex problems, identifying patterns, abstracting key information, and developing stepwise solutions executable by computers or comprehensible to humans (Wing, 2006). CT is defined as the ability to apply cognitive processes for problem analysis, sequence planning, and solution identification (Henderson Cortina, Wing, 2007). This capability involves engaging in higher-order thinking within cognitive frameworks (Arfè et al., 2019; Román-González, Pérez-González, Jiménez-Fernández, 2017; Tang, Chou, Tsai, 2020; Tikva, Tambouris, 2021). Higher-order thinking corresponds to Bloom's taxonomy (Bloom, Krathwohl, Masia, 1984), which outlines levels such as analysis, application, evaluation, and creation, and requires cognitive processing associated with CT. These four levels are closely tied to the problem-solving process and align with Guilford's (Guilford, 1967) theory of problem solving, which includes stages such as preparation, analysis, production, verification, and reapplication. Although CT is often mentioned in connection with programmers and IT specialists, it is a cognitive skill employed by most. CT is not limited to computer science; it is applicable across various fields, enhancing critical thinking and analytical skills (Shute, Sun, Asbell-Clarke, 2017). As technology permeates all areas of life, fostering CT early prepares individuals for future academic and professional challenges (Bers, Strawhacker, Sullivan, 2022), with empirical evidence showing that early

coding instruction produces measurable gains in young children's CT (Relkin, de Ruiter, Bers, 2021). Moreover, it encourages logical reasoning and effective communication, equipping learners with tools necessary for tackling complex issues in an increasingly digital world (Hurt et al., 2023; Robledo-Castro, Castillo-Ossa, Hederich-Martínez, 2023). Research using eye-tracking has revealed cognitive processes tied to programming expertise and underscored the need to enhance Integrated Development Environment (IDE) features to reduce cognitive load from complex code (Davis, Zhu, 2022a, 2022b). Although a single, universally agreed-upon definition of CT has not yet emerged, modern frameworks commonly identify the following components.

Decomposition involves breaking down a complex problem into smaller, more manageable components. This makes it easier to understand the problem and identify specific tasks that need to be addressed. Several studies have explored the concept of decomposition in CT. One study found that students' methods for breaking down tasks to navigate a 2D grid varied according to their age and math skills (Mousa, Molnár, 2020). Another study revealed that the patterns used by students in Scratch projects, such as bottom-up development and fine-grained programming, did not conform to traditional decomposition practices (Kakavás, Ugolini, 2019). Additionally, researchers created a measure of Game Computational Sophistication based on an analysis of Scratch games, which was linked to how students decomposed their games into code (Rich et al., 2018).

Pattern recognition. There has been a plethora of scientific inquiries on the topic of pattern recognition in the

fields of cognitive and neurosciences. However, works that focus on the ability to recognize patterns in the context of CT remain rare. Acosta et al. (2024) reveal a link between CT and algebraic thinking in early childhood education. By utilizing technological resources as a teaching framework, the study identifies pattern recognition as a key skill that bridges both types of thinking. Empirical work supports this connection: CT-infused activities on number patterns improved secondary students' performance in the mathematical pattern domain, indicating practical overlap between computational and algebraic thinking in pattern-based tasks (Chan et al., 2021). Likewise, in early-childhood educational contexts, pattern recognition has been characterized as central to the development of CT (Acosta, Alsina, Pincheira, 2024). Patterns serve as a basis for fostering mathematical thinking and play a significant role in the broader processes of representation and abstraction within mathematics (McGarvey, 2012; Rizos, Gkrekas, 2024).

Abstraction involves removing unnecessary information from a problem to distill it down to its most critical elements. This simplification enables individuals to navigate complexity more effectively and to identify relevant patterns and solutions (Cansu, Cansu, 2019). In CT, abstraction works alongside other key processes such as decomposition (breaking down problems) and pattern recognition (identifying similarities) to facilitate a clearer understanding of tasks (Qian, Choi, 2023).

Algorithmic thinking. J. Wing discusses algorithmic thinking as a crucial component of CT in her foundational works on the subject. In her 2006 article, she defines it as the thought processes involved in formulating problems and their solutions, emphasizing that these solutions can be represented in a way that is executable by an information-processing agent, such as a computer. This definition inherently includes the concept of algorithms, as they are essential for expressing solutions to problems in a structured manner (Wing, 2006). Algorithmic thinking, a subset of CT, specifically focuses on the formulation of step-by-step procedures to solve problems. This skill is crucial as it allows students to break down intricate tasks into manageable parts and devise algorithms that lead to effective solutions. Studies have shown that developing algorithmic thinking skills not only supports programming education but also fosters a deeper understanding of various STEM concepts through practical applications (Yusuf, Noor, 2024). The capacity for algorithmic thinking aids in developing logical frameworks that can address computational challenges (Moon et al., 2020).

These elements are not always explicitly captured in existing CT measurement scales. Rather, such instruments often assess broader or related constructs, leaving some aspects of these components implicitly represented rather than distinctly measured.

Computational thinking scales

Rating scales became widely used in the latter part of the 20th century as a reaction to the waning interest in projective techniques (Ertugrul-Akyol, 2019). This shift emphasized scientific measurement, refined diagnostic terminol-

ogy, introduced new juvenile psychopathology models, highlighted the need for clinical outcome measures, and increased awareness of internalizing disorders in youth (Uher, 2018). The term “rating scale” broadly encompasses checklists, questionnaires, inventories, self- and other-reports, indices, and related tools (Myers, Winters, 2002). Different approaches to CT scales have been proposed. First, since CT is a skill implemented in everyday life and not reserved uniquely to programming, some authors suggest scales based on real-life events and scenarios (Kang et al., 2023). Others are dedicated to formulating and validating a scale reserved solely for CT in the context of programming (Chu, Liang, Tsai, 2019). Several promising CT scales have been proposed, with diverse psychometric approaches to capturing distinct CT components (Román-González, 2015; Sawiji et al., 2024).

The *Korkmaz Computational Thinking Scale* (CTS) is a measurement tool designed to assess CT skills among students. Developed by Korkmaz et al. (2017), it includes 29 items across five factors that assess creativity, algorithmic thinking, critical thinking, problem-solving, and cooperativity, originally designed for university students. The Korkmaz CTS has undergone rigorous validation processes, including exploratory and confirmatory factor analyses. These studies demonstrate acceptable psychometric properties, indicating that the scale reliably measures CT skills (Korkmaz, Çakir, Özden, 2017). It has been adapted for different cultural contexts, such as a Thai version for junior high school students (Junpho, Songsriwittaya, Tep, 2022); these adaptations maintain the core structure while ensuring relevance to local educational settings.

The *Computational Thinking Scale* (CTS), developed by Meng-Jung Tsai, Jyh-Chong Liang, and Chung-Yuan Hsu (2021), is a validated 19-item tool for evaluating students' CT skills in various educational settings. The scale, vital for computer literacy education, targets five CT dimensions: abstraction, decomposition, algorithmic thinking, evaluation, and generalization. It has been rigorously validated through exploratory and confirmatory factor analyses to ensure reliability and accuracy (Tsai, Liang, Hsu, 2021). Gök and Karamete (2023) conducted a Turkish adaptation of the scale to assess secondary school students' CT skills. The study, involving 454 high school students, demonstrated the instrument's validity and reliability, confirming the original five-factor structure. The Cronbach alpha coefficients obtained were 0.84, and McDonald's omega coefficients were 0.86 (Gök, Karamete, 2023). Both scales identify five factors representing key components, but with different conceptual emphases. The Korkmaz scale incorporates a broader set of dispositions, including creativity and cooperativity, while the Tsai scale operationalizes the Selby and Woollard (Selby, Woollard, 2013) CT framework, focusing on abstraction, decomposition, algorithmic thinking, evaluation, and generalization.

Computational thinking in Russia

Global digital transformation has increased demand for skilled programmers in Russia, supported by a strong

Soviet-era foundation in mathematics and science education. The 1985 introduction of “Foundations of Informatics” into Soviet schools aimed to develop algorithmic thinking and required the training of thousands of teachers (Khenner, Semakin, 2014). In the 1990s and 2000s, curriculum autonomy in Russian schools emphasized algorithmic thinking, computer modeling, and logical reasoning through programming, and Informatics moved into middle school under the guidance of the Federal Educational Standards (FES), which permit flexible content choices and offer basic or advanced high-school options; elements of informatics are also introduced in elementary education (Khenner, Semakin, 2014). While the FES outline broad learning outcomes, textbooks intended for use in schools must pass certification confirming compliance with FES requirements (Khenner, Semakin, 2014). Russian universities require Unified National Examinations for admission, with Informatics offered as an optional examination subject (Khenner, Semakin, 2014). Some tools for measuring digital literacy, such as the DIGLIT instrument, are notable yet remain scarce in Russia (Авдеева, Тарасова, 2023). Despite this educational foundation, CT as a research construct remains relatively understudied in the Russian context.

The present study

The present study aims to adapt and compare two validated CT scales within a population of Russian programmers. Despite growing demand for IT specialists in Russia, CT remains underexplored. Government initiatives promote IT careers, underscoring the importance of computational skills. Adapting CT scales to Russia will enhance understanding and inform educational program development. We selected two validated CT scales for adaptation based on their established validity, relevance to programming populations, and suitability for the Russian context. Using two scales — rather than one or several — allows for a focused yet comprehensive comparative analysis while maintaining feasibility within the study scope. The comparison aims to evaluate and contrast the psychometric properties of both instruments, including reliability and construct validity, to determine which scale more accurately captures programmers’ self-assessed CT. We hypothesized that both scales would be applicable within the context of Russian programmers; we further hypothesized that the scales would operationalize distinct constructs within CT.

Materials and methods

Scale selection and translation

During the literature review process, several promising CT scales were identified for further consideration. We reviewed over 21 scales; the two scales described below were chosen because they comprehensively and reliably assess core aspects of CT.

Inclusion criteria:

— Items must directly relate to the construct of CT. This was assessed via the items’ relevance towards the key CT components;

— The scale should be based on existing theoretical frameworks and supported by empirical research that validates its relevance and effectiveness;

— The scale should include a range of items that capture different aspects of the construct to ensure comprehensive measurement;

— Items must be clear, concise, and easily understood by the target population to avoid misinterpretation;

— The scale should be adaptable to various cultural contexts.

Consequently, scales containing the following items were excluded from consideration:

— Items that are vague or ambiguous;

— Items that overlap significantly in content or meaning

— Items without empirical support or those that have not been tested for validity and reliability

The Korkmaz CT scale is designed to cover various dimensions, allowing for a more nuanced understanding of an individual’s CT skills. The CT scale proposed by Tsai et al. (2021) is applicable to students beyond the middle school level across various educational settings, making it more applicable for a younger pool of participants. In this study, the Tsai et al. CT scale is designated “Scale 1” (19 items), and the Korkmaz et al. scale is referred to as “Scale 2” (29 items).

To ensure that the translated scales retain their original meaning and psychometric properties, we employed the back-translation method, a widely recognized procedure in cross-cultural research, particularly effective in verifying the accuracy and conceptual equivalence of psychological assessments across different languages (Brislin, 1970). We engaged two independent translators for each scale; this approach improves translation reliability and reduces single-translator bias by capturing diverse linguistic nuances. Translators independently performed forward translations, followed by back-translation by a different translator unfamiliar with the originals. Comparing versions identified discrepancies and ensured fidelity to Korkmaz et al. and Tsai et al.’s constructs. The translated scales (Scale 1: 19 items; Scale 2: 29 items) are included in the Appendix in the order administered. According to the International Test Commission guidelines, adaptation encompasses not only translation but also evaluation of cultural relevance; recent methodological work further emphasizes assessing the cognitive validity of adapted items to ensure they elicit the intended response process (Pillet et al., 2023). Our review of the items identified no broad culturally specific content requiring substantive re-design; however, a small number of items required culturally informed lexical choices during translation (e.g., the Russian word for “dream,” which can denote either an aspiration or a sleeping vision; see Discussion). We performed psychometric validation on a Russian sample to confirm the scales’ reliability and factorial validity. Both scales had previously been successfully adapted and validated in other languages, which informed our choice to include them in the present study.

Participants and procedure

The study included expert programmers and computer science students. We protected the privacy of underage participants by anonymously collecting data. Informed consent emphasized that participation was voluntary. These measures strictly follow established ethical research standards (American Psychological Association, 2017; British Educational Research Association, 2018). The initial dataset included 167 survey responses assessing CT skills and attitudes. The survey covered demographics (age, programming experience, dominant hand) and 48 Likert-scale items on CT, problem-solving, and collaboration. Programming experience was converted from years to months, and participants with less than 6 months of experience were excluded to focus on those with basic programming skills. This resulted in a final analytic sample of 148 participants ($N = 148$) after filtering. The Likert-scale questions were rated on a 5-point scale ranging from “1 — strongly disagree” to “5 — strongly agree”.

We analyzed data from 148 participants with a mean age of 20.7 years ($SD = 5.7$), ranging from 15 to 46 years (median = 18, $IQR = 17–22$), with a gender distribution of 75% male ($n = 111$) and 25% female ($n = 37$). The majority of participants were right-handed (85.8%, $n = 127$), with 11.5% left-handed ($n = 17$) and 2.7% ambidextrous ($n = 4$). Most participants were students affiliated with the Sirius University of Science and Technology, a federal research university in southern Russia (81.1%, $n = 120$), while 18.9% were working professionals ($n = 28$). Participants reported an average of 4.2 years of programming experience ($SD = 4.8$), ranging from 0.5 to 26 years (median = 3, $IQR = 2–5$). Python was the most frequently cited favorite programming language ($n = 87$), followed by C++ ($n = 32$), JavaScript ($n = 19$), Java ($n = 14$), C# ($n = 11$), and TypeScript ($n = 8$).

Data analysis

Data analysis was conducted using two primary statistical environments. All preliminary data processing, calculation of descriptive statistics, Pearson correlation analysis, Mann—Whitney U test, and scale reliability analysis (Cronbach's α) were performed in RStudio (version 2024.10.1) using the R programming language (version 4.4.2). Exploratory factor analysis (EFA) was conducted with the psychometric analysis package psych (version 2.4.3). For confirmatory factor analysis (CFA), the Python programming language (version 3.13.1) and the structural equation modeling library semopy (version 2.4.1) were used.

Data analysis proceeded in several sequential stages. In the first stage, we assessed the suitability of the data for factor analysis. Bartlett's test of sphericity (Bartlett, 1950) yielded statistically significant results ($p < 0.001$), and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1974) was high for both scales and their combination (see Table 1), confirming the appropriateness of conducting factor analysis.

To adapt the scales for the new population, we tested data fit using CFA on one- and two-factor models, both

showing poor fit (CFI and TLI < 0.90). This indicated a differing factor structure, prompting the use of EFA on each scale and on combined items to uncover the empirical latent structure. We applied principal axis factoring with oblique rotation (oblimin), following recommendations for EFA in psychological research (Fabrigar et al., 1999), as the computational thinking factors were theoretically expected to correlate. The number of factors retained was determined based on scree plot analysis.

In the final stage, following standard validation practices, we conducted a subsequent CFA to test the models derived from the EFA phase. This allowed assessment of the stability and fit of the empirically identified structure to our data. Model adequacy was evaluated using multiple fit indices: Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI), with acceptable thresholds defined as $RMSEA \leq 0.08$, $CFI \geq 0.90$, and $TLI \geq 0.90$ (Hu, Bentler, 1999).

Results

Exploratory factor analysis and reliability analyses were conducted to examine the factor structure and internal consistency of the two scales, both independently and in combination. Bartlett's test of sphericity yielded significant results for Scale 1, Scale 2, and the combined scale, indicating sufficient inter-item correlations for factor analysis. KMO values were 0.82 for Scale 1, 0.76 for Scale 2, and 0.76 for the combined scale, demonstrating sufficient sampling adequacy. Notably, EFA revealed a single-factor structure for Scale 1, while Scale 2 demonstrated three factors. When both scales were analyzed together, a four-factor structure emerged. Internal consistency was measured via Cronbach's α ($\alpha = 0.86$ for Scale 1). For Scale 2, α values were 0.82, 0.84, and 0.76 for the three factors. The four combined-scale factors had α values of 0.89, 0.84, 0.78, and 0.77 (see Table 1). These values indicate the scales' suitability for further factor analysis, with acceptable to good reliability. Further examination of factor loadings is necessary to interpret each factor's meaning.

Scree plot analyses guided factor retention for each scale. Scale 1's plot showed a clear elbow after the first factor, indicating unidimensionality (Fig. 1). Scale 2's plot suggested three factors, with the curve flattening after the third (Fig. 2). The combined scales indicated four factors, aligning with the separate structures (Fig. 3). These results, alongside other criteria and theory, inform the interpretation of the scales' constructs.

Factor loadings range from -1 to $+1$ and indicate the strength and direction of the relationship between items and factors. Values near ± 1 indicate stronger influence. Loadings ≥ 0.40 indicate moderate correlation, while ≥ 0.70 suggest the factor adequately explains the variable's variance. The sign of the loading indicates the direction of the relationship. In the present analysis, factor loadings were examined to assess the association between each item and its respective factor. Table 2 presents all factor loadings for the items of both

Table 1

Показатели пригодности для факторного анализа и надежности
Factor Analysis Suitability and Reliability Statistics

Показатель / Indicator	Шкала 1 / Scale 1	Шкала 2 / Scale 2	Шкала 1 + Шкала 2 / Scale 1 + Scale 2
Критерий Бартлетта / Bartlett test	$p < 0.001$	$p < 0.001$	$p < 0.001$
КМО (мера адекватности выборки) / KMO (MSA)	0.82	0.76	0.76
Число факторов / Number of factors	1	3	4
α Кронбаха / Cronbach's α	0.86	0.82; 0.84; 0.76	0.89; 0.84; 0.78; 0.77

Note. The scales demonstrate good suitability for factor analysis; the extracted factors have acceptable to good internal consistency. Шкалы демонстрируют хорошую пригодность для факторного анализа; выделенные факторы обладают приемлемой и хорошей внутренней согласованностью.



Fig. 1. Scree plot, Scale 1



Fig. 2. Scree plot, Scale 2



Fig. 3. Scree plot, Scales 1 and 2 combined

scales. For clarity, “Q” denotes the item number, and the suffixes “_1” and “_2” indicate the corresponding scale.

Exploratory factor analysis (EFA) and reliability analysis examined the factor structure and internal consistency of 2 scales, individually and in combination. Bartlett’s sphericity test was significant for all ($p < 0.001$), and KMO values (0.82 for Scale 1, 0.76 for Scale 2 and combined) indicated suitability for factor analysis.

Separate EFAs showed one factor for Scale 1 and three for Scale 2, but combined analysis revealed a clearer 4-fac-

tor structure. Cronbach’s alpha values were: Scale 1 factor $\alpha=0.86$; Scale 2 factors 0.82, 0.84, 0.76; combined factors 0.89, 0.84, 0.78, 0.77 (see Table 1), confirming suitability for further use.

The scree plot supported four factors (see Fig. 3). Loadings ≥ 0.40 were considered meaningful. Items Q1_1, Q4_1, Q15_1, Q17_1, Q21_2, Q26_2, Q31_2, Q38_2, and Q39_2 had low loadings (< 0.40) and low communalities ($h < 0.25$), suggesting exclusion in a refined instrument.

Table 2

Факторные нагрузки и общности (h^2) для объединенной шкалы
Factor loadings and communalities (h^2) for the combined scale

Пункт / Item	Ф1 / F1	Ф2 / F2	Ф3 / F3	Ф4 / F4	Общность h^2
Q1_1	0.051	0.178	−0.112	0.153	0.063
Q2_1	0.520	−0.011	0.151	0.081	0.294
Q3_1	0.616	0.033	0.189	0.109	0.428
Q4_1	0.210	0.113	0.152	0.124	0.095
Q5_1	0.414	0.089	0.121	0.192	0.231
Q6_1	0.504	0.211	0.050	−0.010	0.301
Q7_1	0.516	0.152	0.078	0.041	0.297
Q8_1	0.455	−0.150	0.181	0.198	0.302
Q9_1	0.557	−0.088	0.213	0.251	0.427
Q10_1	0.418	−0.079	0.407	0.153	0.370
Q11_1	0.772	−0.051	0.053	0.012	0.602
Q12_1	0.629	−0.122	−0.178	0.141	0.462
Q13_1	0.475	−0.251	−0.052	−0.103	0.302
Q14_1	0.647	−0.111	−0.104	0.073	0.447
Q15_1	0.281	−0.210	−0.209	−0.112	0.179
Q16_1	0.507	−0.018	−0.163	−0.039	0.285
Q17_1	0.214	−0.321	0.009	−0.150	0.171
Q18_1	0.582	−0.289	−0.094	0.053	0.434
Q19_1	0.403	−0.281	−0.059	−0.021	0.245
Q20_2	0.419	0.068	0.113	−0.320	0.295
Q21_2	0.102	0.334	0.101	0.103	0.143
Q22_2	0.601	0.011	0.049	−0.114	0.377
Q23_2	0.442	0.183	0.009	−0.179	0.261
Q24_2	0.504	−0.143	0.048	0.178	0.308
Q25_2	0.600	0.081	0.098	0.151	0.399
Q26_2	0.179	0.111	0.108	0.158	0.082
Q27_2	0.500	0.131	0.243	−0.061	0.327
Q28_2	0.054	−0.009	0.451	−0.139	0.220
Q29_2	0.022	−0.041	0.701	−0.051	0.494
Q30_2	0.103	−0.073	0.793	0.012	0.633
Q31_2	0.119	0.282	−0.021	−0.041	0.103
Q32_2	0.142	−0.131	0.622	0.052	0.421
Q33_2	0.063	−0.011	0.443	0.103	0.213
Q34_2	0.013	0.791	−0.033	0.051	0.633
Q35_2	0.052	0.802	−0.022	0.022	0.643
Q36_2	0.111	0.711	−0.091	−0.022	0.523
Q37_2	0.082	0.691	−0.041	0.041	0.492
Q38_2	0.210	−0.018	−0.251	−0.041	0.113
Q39_2	0.380	−0.162	−0.261	−0.071	0.243
Q40_2	0.601	−0.158	0.031	−0.083	0.389
Q41_2	0.511	−0.163	0.151	0.022	0.311
Q42_2	0.481	−0.092	0.012	−0.071	0.243
Q43_2	0.052	0.033	−0.041	0.521	0.281
Q44_2	0.062	0.081	−0.052	0.522	0.281
Q45_2	0.020	0.141	0.039	0.643	0.435
Q46_2	0.108	0.049	0.091	0.701	0.514
Q47_2	−0.021	−0.418	0.114	0.540	0.480
Q48_2	0.012	−0.412	0.101	0.534	0.466

Note. Factor loadings ≥ 0.40 are bold. Communalities (h^2) < 0.25 are also bold, indicating that the factor model weakly accounts for the variance in these items. Факторные нагрузки $\geq 0,40$ выделены полужирным. Общности (h^2) $< 0,25$ также выделены полужирным, что указывает на слабое объяснение дисперсии этих пунктов факторной моделью.

Factor 1: “Systematic Problem Solving.” This factor includes most Scale 1 items, reflecting problem solving via decomposition, algorithmic thinking, and evaluation. Highest loadings: Q11_1 (“I usually try to figure out how to implement a solution,” $h^2 = 0.602$); Q14_1 (“I usually try to find the most efficient solution,” $h^2 = 0.447$).

Factor 2: “Difficulties in Problem-Solving Process” (reverse-coded). This factor is composed mainly of negatively phrased Scale 2 items on solving challenges. Highest loadings: Q35_2 (“Difficulties with where/how to use variables,” $h^2 = 0.643$); Q34_2 (“Difficulties visualizing solutions,” $h^2 = 0.633$). Negative loadings for Q47_2 and Q48_2 fit logically.

Factor 3: “Inclination toward Collaborative Learning.” This factor covers items about teamwork. Highest loadings: Q30_2 (“More ideas in collaborative learning,” $h^2 = 0.633$); Q29_2 (“Enjoy group project tasks,” $h^2 = 0.494$).

Factor 4: “Confidence in Math Abilities and Planning.” This factor includes items about confidence in formalization and planning. Highest loadings: Q46_2 (“Use systematic approach,” $h^2 = 0.514$); Q45_2 (“Proud of precise thinking,” $h^2 = 0.435$).

Finally, we conducted confirmatory factor analysis (CFA) to validate the factor structure. We compared three models: a one-factor model (all items on a single factor), the original two-factor model (Scale 1 items on one factor, Scale 2 on another), and the empirically derived four-factor model from EFA. Model fit was assessed using RMSEA (≤ 0.08 acceptable), CFI (≥ 0.90 acceptable), and TLI (≥ 0.90 acceptable).

CFA results (Table 3) show that, although no model achieved perfect fit, the four-factor model outperformed the one- and two-factor models, with lower RMSEA and higher CFI/TLI.

Table 3

Результаты конфирматорного факторного анализа (CFA) для трех моделей
Confirmatory factor analysis (CFA) results for the three models

Модель / Model	RMSEA	CFI	TLI
Однофакторная / One-factor	0.070	0.844	0.832
Двухфакторная (исходная) / Two-factor (original)	0.067	0.854	0.843
Четырехфакторная (по результатам EFA) / Four-factor (EFA-derived)	0.058	0.895	0.881

Note. Best fit indices are in bold. Наилучшие показатели соответствия выделены полужирным.

Discussion

CT, and algorithmic thinking in particular, is increasingly recognized as an important contributor to STEM learning, with implications for how problem-solving skills are developed in programming education (Yusuf, Noor, 2024). The present study employed a Likert-type survey to assess programmers’ self-assessment of CT, consistent with the self-

report approach used in the validation studies for both source scales (Korkmaz, Çakır, Özden, 2017; Tsai, Liang, Hsu, 2021). It is important to note that this method captures participants’ perceptions and subjective evaluations rather than directly measuring CT as an objective skill. To date, many researchers have attempted to construct a CT scale that incorporates all components of CT, but a general consensus is yet to be reached (Kılıç, Gökoğlu, Öztürk, 2021). Despite extensive study, CT remains imperfectly characterized cognitively, necessitating further psychometric work.

The results of the exploratory factor analysis identified several problematic items with low loadings across all factors (communality $h^2 < 0.25$): Q1_1, Q4_1, Q15_1, and Q17_1 from Scale 1, as well as Q21_2, Q26_2, Q31_2, Q38_2, and Q39_2 from Scale 2. Low communality indicates that these items are weakly correlated with the identified constructs and contribute little to measuring CT in this sample. We therefore recommend excluding these nine items from the combined questionnaire for future use in the Russian population, yielding a refined 39-item version.

This study is, to our knowledge, the first effort to introduce these CT scales to a Russian population. Our analysis found a different factor structure than the original scales, likely due to language differences affecting item perception and response styles influencing item loadings. These complexities highlight the need for further research on factor interactions in cross-cultural test frameworks.

Limitations

We encountered several challenges during translation that merit discussion as they can potentially affect the accuracy of the scales. The Korkmaz et al. (2017) scale posed challenges with the words “problem” and “dream.” We chose a Russian word for “problem” that closely matches the original meaning. “Dream” in Russian can either mean images during sleep or personal aspirations; we selected the aspiration meaning following expert advice. These difficulties highlight the importance of precise translation to ensure that scales retain their original structures.

Future inquiries should consider the following directions. First, item refinement: items with low correlations or factor loadings should be revised or removed to improve scale validity; the overlap between two factors suggests they may represent a single underlying construct rather than distinct ones. Second, alternative factor structures — including specific sub-factors within CT, mathematical reasoning, and collaborative learning — should be explored; identifying these dimensions enhances understanding of how individuals engage with these complex constructs. Third, additional testing across diverse contexts and populations is warranted; investigating gender and cross-cultural differences in CT skills can enhance understanding of the construct and its educational implications. Fourth, the reliance on self-assessment via Likert-type items may introduce subjective bias and limit the accuracy of measuring CT skills; future research should incorporate a variety of assessment meth-

ods, including performance-based tests and observational measures, to provide a more comprehensive and objective evaluation of CT abilities.

Conclusion

This study addresses gaps in understanding computational thinking (CT), particularly in underrepresented regions like Russia, using psychometric methods. A combined scale revealed a reliable four-factor structure with strong internal consistency (Cronbach's alpha 0.77—

0.89), supporting its efficacy in measuring distinct CT constructs.

Our study demonstrated that directly transferring the original scales to the Russian sample does not preserve their initial factor structures. However, the proposed 4-factor model, supported by CFA results (RMSEA = 0.058, CFI = 0.895), shows good fit to the data and high internal consistency. Thus, we recommend the refined 39-item combined scale (after excluding 9 items with low factor loadings) as a reliable instrument for assessing self-perceptions of CT aspects among Russian-speaking programmers and students.

Appendix

Age (full years): _____
Programming experience (in years): _____
Favorite programming language: _____
Average grade in programming-related subjects: _____
Gender: F M
Dominant hand: L R

Computational Thinking Scale (CTS)

Please rate the extent to which you agree with each statement, using a scale on which “1” — “strongly disagree” and “5” — “strongly agree”:

Scale 1 (Tsai, M.-J. et al., 2021)

Statement	Rating
I usually consider a problem from a general perspective rather than focusing on the details.	1-----2-----3-----4-----5
I usually think about the relationships between different problems.	1-----2-----3-----4-----5
I usually try to identify the key steps of a problem.	1-----2-----3-----4-----5
I usually try to analyse the common patterns across different problems.	1-----2-----3-----4-----5
I usually think about whether a problem can be broken down into component parts.	1-----2-----3-----4-----5
I usually think about the structure of a problem.	1-----2-----3-----4-----5
I usually think about how to divide a large problem into several smaller ones.	1-----2-----3-----4-----5
I am used to developing solution procedures step by step.	1-----2-----3-----4-----5
I usually try to find efficient solutions to a problem.	1-----2-----3-----4-----5
I usually try to set out the steps of a solution.	1-----2-----3-----4-----5
I usually try to figure out how to implement a solution to a problem.	1-----2-----3-----4-----5
I tend to find the correct solution to a problem.	1-----2-----3-----4-----5
I usually think about the best solution for a program.	1-----2-----3-----4-----5
I usually try to find the most efficient solution to a problem.	1-----2-----3-----4-----5
I usually think about a quick solution to a problem.	1-----2-----3-----4-----5
I tend to solve a new problem on the basis of my experience.	1-----2-----3-----4-----5
I usually try to use a general approach to solve different problems.	1-----2-----3-----4-----5
I usually think about how to apply a solution to other problems.	1-----2-----3-----4-----5
I usually try to apply a familiar solution to solve more problems.	1-----2-----3-----4-----5

Scale 2 (Korkmaz, Ö. et al., 2017)

Statement	Rating
I like people who are sure of most of their decisions.	1-----2-----3-----4-----5
I like people who are realistic and neutral in communication.	1-----2-----3-----4-----5
I believe that I can solve most of the problems I face if I have enough time and if I make an effort.	1-----2-----3-----4-----5
I am confident that I can solve any possible problem when I encounter a new situation.	1-----2-----3-----4-----5
I believe that I can apply a plan while implementing it in order to solve my problem.	1-----2-----3-----4-----5

Statement	Rating
Dreams inspire me to carry out the most important projects.	1-----2-----3-----4-----5
I rely on my intuition and my sense of what is right and wrong when I look for a solution to a problem.	1-----2-----3-----4-----5
When I face a problem, I pause before moving on to another topic and think it over carefully.	1-----2-----3-----4-----5
I like taking part in collaborative learning with friends from my group.	1-----2-----3-----4-----5
In collaborative learning, I believe that I achieve, or will achieve, more successful results precisely because I work in a group.	1-----2-----3-----4-----5
I like solving problems related to group projects together with friends in collaborative learning.	1-----2-----3-----4-----5
More ideas emerge in collaborative learning.	1-----2-----3-----4-----5
I am able to make regular plans for solving complex problems.	1-----2-----3-----4-----5
Trying to solve complex problems is great fun.	1-----2-----3-----4-----5
I am willing to learn difficult things.	1-----2-----3-----4-----5
I am proud of being able to think with great precision.	1-----2-----3-----4-----5
I use a systematic approach when comparing the available options and making decisions.	1-----2-----3-----4-----5
I have difficulty picturing the solution to a problem in my head.	1-----2-----3-----4-----5
I have difficulty knowing where and how I should use variables such as X and Y when solving a problem.	1-----2-----3-----4-----5
I cannot apply the planned ways of solving a problem consistently and step by step.	1-----2-----3-----4-----5
I cannot come up with many options when thinking about possible ways of solving a problem.	1-----2-----3-----4-----5
I cannot develop my ideas in a collaborative learning setting.	1-----2-----3-----4-----5
I find it hard to learn something together with friends in collaborative learning.	1-----2-----3-----4-----5

Краткое изложение содержания статьи на русском языке

Введение

Вычислительное мышление (ВМ) — это общедисциплинарный, структурированный подход к решению задач, основанный на компьютерных науках и включающий декомпозицию, распознавание паттернов, абстрагирование и алгоритмическое мышление для формулирования пошаговых решений, исполнимых человеком или машиной. ВМ согласуется с высшими когнитивными процессами (например, уровнями анализа и творчества в таксономии Блума) и классическими этапами решения задач и все чаще признается необходимым не только в программировании, но и в других дисциплинах. Эмпирические данные показывают, что раннее обучение программированию дает измеримый прирост ВМ у детей, что обосновывает его интеграцию в образование для подготовки обучающихся к сложным, технологически насыщенным средам. Хотя компоненты ВМ концептуально различимы, существующие оценочные шкалы часто измеряют более широкие конструкты, представляя эти компоненты имплицитно, а не через специализированные подшкалы с явным подсчетом баллов.

Современная наука выделяет в структуре ВМ несколько взаимосвязанных компонентов. Декомпозиция предполагает разбиение сложной задачи на более мелкие и управляемые части, что облегчает понимание задачи и выделение конкретных подзадач. Распознавание паттернов связано с выявлением повторяющихся закономерностей и сходств между задачами и позволяет переносить найденные решения

на новые ситуации. Абстрагирование состоит в отбрасывании несущественной информации и выделении ключевых элементов задачи. Алгоритмическое мышление предполагает построение упорядоченной последовательности шагов, приводящей к решению и допускающей исполнение человеком или машиной. Оценка решения замыкает этот цикл, позволяя сопоставить альтернативные варианты по эффективности и корректности.

Шкалы самооценки ВМ экономичны и применимы в массовых опросах, однако их психометрические свойства чувствительны к языковому и культурному контексту, поэтому перенос инструмента в новую популяцию требует обязательной проверки. В России валидированных русскоязычных шкал самооценки ВМ практически нет, что ограничивает сопоставимость российских данных с международными.

Выборка и методы

В исследовании участвовали опытные программисты и студенты направлений, связанных с компьютерными науками; сбор данных проводился в соответствии с этическими стандартами (анонимный сбор данных для несовершеннолетних, добровольное участие; APA, 2017; BERA, 2018). Из 167 первоначальных ответов были исключены участники с опытом программирования менее 6 месяцев, в результате итоговая выборка составила 148 человек (средний возраст — 20,7 года, SD = 5,7; 75% — мужчины). Для

оценки вычислительного мышления, навыков решения задач и сотрудничества использовался 48-пунктный опросник с шкалой Лайкерта (5-балльная шкала) вместе со сбором демографических данных (возраст, ведущая рука, опыт программирования в месяцах, принадлежность к организации). Большинство участников составили студенты российского федерального университета (81,1%); средний опыт программирования — 4,2 года ($SD = 4,8$), наиболее предпочтительным языком был Python.

При отборе инструментов было рассмотрено более 21 шкалы. Включались шкалы, пункты которых прямо соотносятся с ключевыми компонентами ВМ, опираются на существующие теоретические рамки, подтверждены эмпирически, сформулированы ясно и допускают адаптацию к различным культурным контекстам; исключались шкалы с неоднозначными или дублирующими друг друга пунктами, а также не проверявшиеся на валидность и надежность. Перевод выполнялся методом обратного перевода: для каждой шкалы привлекались два независимых переводчика, прямой перевод затем переводился обратно специалистом, не знакомым с оригиналом, после чего версии сопоставлялись для выявления расхождений. Содержательно специфичных для культуры пунктов, требующих существенной переработки, выявлено не было; отдельные пункты потребовали лексических решений с учетом культурного контекста.

Обработка данных и оценка надежности (α Кронбаха) выполнены в RStudio (версия 2024.10.1) на языке R (версия 4.4.2), эксплораторный факторный анализ — с помощью пакета psych (версия 2.4.3), конфирматорный — на языке Python (версия 3.13.1) с использованием библиотеки semopy (версия 2.4.1). ЕФА выполнялся методом главных осей с облическим вращением (oblimin), число факторов определялось по графику каменистой осыпи, а качество моделей оценивалось по индексам RMSEA ($\leq 0,08$), CFI ($\geq 0,90$) и TLI ($\geq 0,90$).

Результаты

С помощью эксплораторного и конфирматорного факторного анализа подтверждена четырехфакторная структура объединенного инструмента. Тест Бартлетта был значим, значения КМО были адекватными (0,76—0,82). При раздельном анализе ЕФА выявила один фактор для Шкалы 1 и три фактора для Шкалы 2, однако при совместном анализе emerged возможно более четкое четырехфакторное решение с приемлемой/хорошей внутренней согласованностью (α Кронбаха = 0,76—0,89). Пункты с факторными нагрузками $< 0,40$ и общностями $h^2 < 0,25$ были отмечены для исключения. Четыре фактора были интерпретированы как «Систематическое решение задач», «Трудности в процессе решения задач» (обратно

кодированные), «Склонность к совместному обучению» и «Уверенность в математических способностях и планировании». КФА (Конфирматорный Факторный Анализ) показал, что четырехфакторная модель лучше соответствует данным, чем одно- и двухфакторные альтернативы (ниже RMSEA, выше CFI/TLI), хотя общее соответствие не было идеальным.

Значения КМО составили 0,82 для Шкалы 1, 0,76 для Шкалы 2 и 0,76 для объединенного набора пунктов. Внутренняя согласованность составила $\alpha = 0,86$ для единственного фактора Шкалы 1; 0,82, 0,84 и 0,76 для трех факторов Шкалы 2; 0,89, 0,84, 0,78 и 0,77 для четырех факторов объединенной шкалы. Пункты Q1_1, Q4_1, Q15_1, Q17_1, Q21_2, Q26_2, Q31_2, Q38_2 и Q39_2 показали нагрузки ниже 0,40 и общности $h^2 < 0,25$ и были рекомендованы к исключению. Сопоставление моделей дало следующие индексы: однофакторная — RMSEA = 0,070, CFI = 0,844, TLI = 0,832; двухфакторная (исходная) — RMSEA = 0,067, CFI = 0,854, TLI = 0,843; четырехфакторная — RMSEA = 0,058, CFI = 0,895, TLI = 0,881.

Заключение

В данном исследовании с использованием психометрических методов рассматриваются пробелы в понимании вычислительного мышления (ВМ), особенно в недостаточно изученных регионах, таких как Россия. Комбинированная шкала выявила надежную четырехфакторную структуру с высокой внутренней согласованностью (альфа Кронбаха — 0,77—0,89), что подтверждает ее эффективность для измерения различных конструкторов ВМ.

Наше исследование продемонстрировало, что прямой перенос исходных шкал на российскую выборку не сохраняет их первоначальную факторную структуру. Однако предложенная 4-факторная модель, подтвержденная результатами конфирматорного факторного анализа (RMSEA = 0,058; CFI = 0,895), демонстрирует хорошее соответствие данным и высокую внутреннюю согласованность. Таким образом, мы рекомендуем использовать доработанную комбинированную шкалу из 39 пунктов (после исключения 9 пунктов с низкими факторными нагрузками) как надежный инструмент для оценки самовосприятия аспектов ВМ у русскоязычных программистов и студентов.

Результаты следует интерпретировать с учетом ограничений: выборка была преимущественно студенческой и несбалансированной по полу, а самооценочный формат отражает представления респондентов о собственном ВМ, а не успешность решения задач. Дальнейшие исследования целесообразно направить на доработку формулировок пунктов с низкими нагрузками и на проверку структуры уточненной шкалы на независимых выборках.

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Приложение

Возраст (полных лет): _____
Опыт программирования в годах): _____
Любимый язык программирования: _____
Средняя оценка за предметы, связанные с программированием: _____
Пол: Ж М
Доминантная рука: Л П

Шкала Вычислительного Мышления (ШВМ)

Пожалуйста, оцените степень Вашего согласия с каждым утверждением. Используйте шкалу, где «1» — «категорически не согласен(на)», а «5» — «полностью согласен (на)».

Шкала 1 (Tsai, M.-J. et al., 2021)

Утверждение	Оценка
Я обычно рассматриваю задачу с общей точки зрения, а не сосредотачиваюсь на деталях	1-----2-----3-----4-----5
Я обычно думаю о взаимосвязях между различными задачами	1-----2-----3-----4-----5
Я обычно стараюсь найти ключевые этапы задачи	1-----2-----3-----4-----5
Я обычно стараюсь анализировать общие паттерны между различными проблемами	1-----2-----3-----4-----5
Я обычно думаю, возможно ли разложить задачу на составные части	1-----2-----3-----4-----5
Я обычно думаю о структуре задачи	1-----2-----3-----4-----5
Я обычно думаю о том, как разбить большую задачу на несколько мелких	1-----2-----3-----4-----5
Я привык(ла) разрабатывать процедуры решения шаг за шагом	1-----2-----3-----4-----5
Я обычно стараюсь найти эффективные решения для задачи	1-----2-----3-----4-----5
Я обычно стараюсь изложить шаги решения	1-----2-----3-----4-----5
Я обычно стараюсь выяснить, как реализовать решение задачи	1-----2-----3-----4-----5
Я склонен(на) находить правильное решение проблемы	1-----2-----3-----4-----5
Я обычно думаю о наилучшем решении для программы	1-----2-----3-----4-----5
Я обычно стараюсь найти наиболее эффективное решение для проблемы	1-----2-----3-----4-----5
Я обычно думаю о быстром решении проблемы	1-----2-----3-----4-----5
Я склонен(на) решать новую задачу, основываясь на своем опыте	1-----2-----3-----4-----5
Я обычно стараюсь использовать общий подход для решения различных задач	1-----2-----3-----4-----5
Я обычно думаю о том, как применить решение к другим задачам	1-----2-----3-----4-----5
Я обычно стараюсь применить знакомое решение для решения большего количества задач	1-----2-----3-----4-----5

Шкала 2 (Korkmaz, Ö. et al., 2017)

Утверждение	Оценка
Мне нравятся люди, которые уверены в большинстве своих решений	1----2----3----4----5
Мне нравятся люди, которые реалистичны и нейтральны в общении	1----2----3----4----5
Я верю, что могу решить большинство проблем, с которыми сталкиваюсь, если у меня будет достаточно времени и если я приложу усилия	1----2----3----4----5
У меня есть убеждение, что я смогу решить любые возможные проблемы, когда я сталкиваюсь с новой ситуацией	1----2----3----4----5
Я верю, что смогу применить план в процессе его реализации для решения своей проблемы	1----2----3----4----5
Мечты вдохновляют меня на реализацию самых важных проектов	1----2----3----4----5
Я полагаюсь на свою интуицию и ощущение «правильного» и «неправильного», когда ишу решение проблемы	1----2----3----4----5
Когда я сталкиваюсь с проблемой, я делаю паузу, прежде чем перейти к другой теме, и внимательно обдумываю ее	1----2----3----4----5
Я могу сразу же определить уравнение, которое приведет к решению задачи.	1----2----3----4----5
Я считаю, что у меня есть особый интерес к математическим процессам.	1----2----3----4----5
Я думаю, что лучше усваиваю инструкции, составленные с использованием математических символов и понятий.	1----2----3----4----5
Я верю, что легко улавливаю взаимосвязь между фигурами.	1----2----3----4----5
Я могу математически выразить способы решения проблем, с которыми сталкиваюсь в повседневной жизни.	1----2----3----4----5

Утверждение	Оценка
Я могу преобразовать устную математическую задачу в цифровой формат	1----2----3----4----5
Мне нравится участвовать в совместном обучении с друзьями из группы	1----2----3----4----5
В совместном обучении я считаю, что достигаю или буду достигать более успешных результатов именно потому, что работаю в группе.	1----2----3----4----5
Мне нравится решать задачи, связанные с групповыми проектами, вместе с друзьями в рамках совместного обучения	1----2----3----4----5
В совместном обучении возникает больше идей	1----2----3----4----5
Я умею составлять регулярные планы для решения сложных проблем	1----2----3----4----5
Пытаться решать сложные задачи очень весело	1----2----3----4----5
Я готов учиться сложным вещам	1----2----3----4----5
Я горжусь тем, что умею мыслить с большой точностью	1----2----3----4----5
Я использую систематический подход при сравнении доступных вариантов и принятии решений	1----2----3----4----5
У меня возникают трудности с демонстрацией решения проблемы в своей голове	1----2----3----4----5
У меня возникают трудности с тем, где и как я должен(на) использовать переменные, такие как X и Y, при решении задачи	1----2----3----4----5
Я не могу последовательно и постепенно применять запланированные способы решения	1----2----3----4----5
Я не могу придумать много вариантов, размышляя о возможных способах решения проблемы	1----2----3----4----5
Я не могу развивать свои идеи в условиях совместного обучения	1----2----3----4----5
Мне тяжело учиться чему-то вместе с друзьями в рамках совместного обучения	1----2----3----4----5

Information about the authors

Kristina A. Nikiforova, Postgraduate Student, Sirius University of Science and Technology, Sirius, Krasnodar region, Russian Federation, ORCID: <https://orcid.org/0009-0000-4302-4406>, e-mail: kkrisinger1990@gmail.com

Sofya P. Kulikova, PhD in Neuroscience, Associate Professor, Head of the Center for Cognitive Neuroscience, National Research University Higher School of Economics, Perm, Russian Federation, ORCID: <https://orcid.org/0000-0002-7079-1018>, e-mail: spkulikova@hse.ru

Tatiana O. Platonova, Junior Researcher, «Tomsk State University», Tomsk, Russian Federation, ORCID: <https://orcid.org/0009-0009-0420-3845>, e-mail: Platonova-cog@yandex.ru

Valeriia A. Demareva, Candidate of Science (Psychology), Associate Professor, Head of the Cyberpsychology Laboratory, Lobachevsky State University, Cyberpsychology Department, Nizhny Novgorod, Russian Federation, ORCID: <https://orcid.org/0000-0002-3228-9289>, e-mail: kaleria.naz@gmail.com

Информация об авторах

Кристина Андреевна Никифорова, аспирант, Научно-технологический университет «Сириус» (АНОО ВО «Университет “Сириус”»), пгт. Сириус, Краснодарский регион, Российская Федерация, ORCID: <https://orcid.org/0009-0000-4302-4406>, e-mail: kkrisinger1990@gmail.com

Софья Петровна Куликова, доктор философии (PhD) в области нейронаук, доцент, руководитель, Центр когнитивных нейронаук, Национальный исследовательский университет «Высшая школа экономики» (ФГАОУ ВО «НИУ ВШЭ»), Пермь, Российская Федерация, ORCID: <https://orcid.org/0000-0002-7079-1018>, e-mail: spkulikova@hse.ru

Татьяна Олеговна Платонова, младший научный сотрудник, Томский государственный университет (ФГАОУ ВО «ННГУ»), Томск, Российская Федерация, ORCID: <https://orcid.org/0009-0009-0420-3845>, e-mail: Platonova-cog@yandex.ru

Валерия Алексеевна Демарева, кандидат психологических наук, доцент, заведующая лабораторией киберпсихологии, Национальный исследовательский Нижегородский государственный университет имени Н.И. Лобачевского (ФГАОУ ВО «ННГУ им. Н.И. Лобачевского»), Нижний Новгород, Российская Федерация, ORCID: <https://orcid.org/0000-0002-3228-9289>, e-mail: kaleria.naz@gmail.com

Contribution of the authors

Nikiforova K.A. — writing original draft, conceptualization, data collection.

Kulikova, S.P. and V.A. Demareva — review and editing.

Platonova T.O. — data analysis.

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The authors declare no conflict of interest.

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Ethics statement

Written informed consent for participation in this study was obtained from all participants (or from legal guardians for participants under the age of consent). Data were collected anonymously, and participation was voluntary. The study was conducted in accordance with established ethical standards for psychological and educational research (American Psychological Association, 2017; British Educational Research Association, 2018).

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