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Measuring User Engagement in Interaction with a Chatbot: Adaptation of the UES Scale in a Russian-Speaking Sample

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Abstract

Introduction. Chatbots based on generative artificial intelligence (AI) have rapidly gained popularity and are increasingly influencing various aspects of daily life. An important component of the user experience is engagement, which reflects the depth and intensity of a person's interaction with AI systems. The aim of this study was to adapt the User Engagement Scale (UES) to assess engagement among Russian-speaking users interacting with generative AI–based chatbots. **Methods.** The study involved 210 respondents aged 18–60. The linguistic adaptation procedure included forward and backward translation, expert review, and a focus group. To evaluate the psychometric properties of the scale, exploratory and confirmatory factor analyses were conducted, along with assessments of test–retest reliability, convergent and divergent validity. **Results.** Exploratory factor analysis identified a four-factor structure—positive interaction experience, engagement (immersion), interface appeal, and interaction difficulties—explaining 74.3% of the variance. Confirmatory factor analysis supported the adequacy of the proposed model. Cronbach's alpha (0.83) and test–retest reliability ($r = 0.81$) indicated high stability of the instrument. Convergent validity was demonstrated by strong correlations with perceived usability ($r = 0.823$) and absorption by activity ($r = 0.834$), while divergent validity indicated weak correlations with negative affect and life satisfaction. **Discussion.** The adapted version of the scale retains its theoretical foundation and accurately measures key aspects of user engagement. Interaction with generative AI chatbots emphasizes positive experience and immersion, whereas interaction difficulties have a smaller impact due to intuitive interfaces and the ability of AI systems to imitate interpersonal communication. The Russian version of the instrument demonstrated high reliability and validity and can be used in further studies of human–AI interaction.

Keywords

user engagement, scale adaptation, chatbots, generative artificial intelligence, linguistic adaptation, psychometric analysis, exploratory factor analysis, confirmatory factor analysis

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Introduction

In recent years, the rapid development of artificial intelligence (AI) technologies has significantly influenced multiple spheres of human life. AI is increasingly used in education (Von Garrel & Mayer, 2023), scientific research (Bin-Nashwan et al., 2023), programming (Akbar et al., 2024), psychometrics (Valueva et al., 2024), marketing (Gupta et al., 2024), and many other domains. Generative AI, in particular, has substantially expanded the possibilities for everyday applications. The launch of ChatGPT in 2022 marked a turning point and popularized the use of generative AI for a wide user audience.

A key aspect of human–AI interaction is user satisfaction, which encompasses several components, including engagement, trust, and overall user experience. User engagement reflects the depth and intensity of an individual's interaction with a digital system (O'Brien, 2016). As generative AI systems increasingly approximate human conversational patterns, they create more contextually meaningful and interactive exchanges, thereby enhancing user engagement (Bragazzi et al., 2023). These systems may be perceived not merely as tools but as social agents capable of following social norms and politeness strategies, which is essential for fostering user satisfaction and trust.

One of the primary determinants of satisfaction with generative AI tools is perceived usefulness. Research shows that users experience satisfaction when AI technologies meet their needs in learning, task completion, or simplification of complex activities (Almufarreh, 2024). Usefulness therefore plays a central role in shaping both engagement and satisfaction. Additionally, the concept of parasocial interaction—users perceiving AI as a social entity—contributes to engagement formation. Interaction with AI can elicit a sense of social presence, which enhances the overall user experience (Kronemann et al., 2022). Studies indicate that when users develop a feeling of connection with AI, their engagement increases, resulting in higher satisfaction (Kronemann et al., 2022).

Given the rapid growth of generative AI–based chatbots among Russian-speaking users, there is a pressing need for valid assessment tools to evaluate user satisfaction and engagement. Therefore, the aim of the present study is to adapt the User Engagement Scale (UES) (O'Brien et al., 2018) for a Russian-speaking sample in the context of interaction with a generative AI–based chatbot.

Methods

Sample

The study involved 210 participants (147 women and 63 men) aged 18 to 60. Among them, 135 participants held a higher education degree, 63 had incomplete higher education, and 9 held an academic degree. A total of 144 participants had a social sciences or humanities background, 26 a technical background, 23 a natural sciences background, 7 a medical background, and 7 a mathematical background.

The second stage of the study, conducted 1–2 months later to assess test–retest reliability, included 98 respondents (68 women and 30 men) aged 18 to 56. Of these, 63 held a higher education degree, 30 had incomplete higher education, and 4 held an academic degree. Sixty respondents had a social sciences or humanities background, 16 a technical background, 15 a natural sciences background, 3 a medical background, and 3 a mathematical background. Data collection was carried out using Google Forms and Yandex Forms from July to October 2024. All respondents provided informed consent to participate in the study.

Instruments

The short version of the **User Engagement Scale (UES)** (O'Brien et al., 2018) is designed to measure the degree of user engagement during interaction with digital systems. Its central purpose is to capture how deeply users perceive and interact with content and system functionality. The scale consists of 12 items rated on a five-point Likert scale.

The translation of the User Engagement Scale into Russian was conducted in accordance with established standards of linguistic adaptation and test validation (Van de Vijver & Hambleton, 1996). The procedure involved two professional psychologists fluent in both Russian and English, as well as two linguists specializing in psychological translation. Forward and backward translations were prepared, after which discrepancies between the original and back-translated versions were examined by experts and resolved through collaborative discussion. Additionally, a focus group of eight psychology students, all active users of chatbots, was organized to evaluate the clarity and appropriateness of the translated items. The discussion was conducted via ZOOM, and necessary modifications were introduced to improve the comprehensibility of specific statements.

The **UMUX-LITE** (Usability Metric for User Experience) (Lewis et al., 2013) is a brief instrument assessing perceived usability of interactive digital systems. It consists of two items rated on a seven-point Likert scale.

The **Absorption by Activity** subscale of the Flow Short Scale (Engeser & Rheinberg, 2008) measures a state characterized by a balance between a person's perceived skills and the complexity of an activity. This subscale contains five items rated on a seven-point Likert scale.

Since UMUX-LITE and the Flow Short Scale have no officially adapted Russian versions, both instruments were translated using forward and backward translation followed by expert evaluation of semantic and terminological equivalence. The translation was performed by the same group of specialists who participated in the adaptation of the User Engagement Scale, ensuring consistency of expert judgments. The translated versions were used in the present study to assess the convergent validity of the main instrument.

The **Satisfaction With Life Scale** by E. Diener in the adaptation by E. N. Osin and D. A. Leontiev (Osin & Leontiev, 2008) was used to measure overall life satisfaction independent of specific life domains. The scale consists of five items rated on a seven-point Likert scale.

The **Positive and Negative Affect Schedule (PANAS)** in the Russian adaptation by E. N. Osin (Osin, 2012) was used to assess levels of positive and negative affect. It consists of 20 items rated on a five-point Likert scale.

The **Short Boredom Proneness Scale**, adapted by A. A. Zolotareva (2020), consists of eight items rated on a seven-point Likert scale and was used to assess boredom proneness.

Results

An initial item analysis was conducted to assess the suitability of the scale items. Item difficulty indices ranged from 0.46 to 0.79, with several items (2, 11, 5, 3) showing a shift toward higher ease, approaching 80%. The item–total correlations ranged from 0.40 to 0.77 for all items. Internal consistency of the overall scale "User Engagement in Interaction with a Chatbot" was high, with Cronbach's alpha of 0.83. Table 1 presents descriptive statistics for the full sample (n = 210).

Table 1

Descriptive statistics for the "User Engagement" scale

Statistic	Value
Mean	2.99
Standard deviation	0.56
Skewness	−0.51
Kurtosis	0.56
Minimum	1.5
Maximum	4.67
Cronbach's alpha	0.83
Standardized alpha	0.88
Average inter-item correlation	0.38

Exploratory factor analysis (principal component analysis with varimax rotation) was used to examine the scale's structure (KMO = 0.855; Bartlett's test: $\chi^2 = 1261.62$, df = 66, $p < 0.001$). Based on Kaiser's criterion, three factors with eigenvalues greater than 1 were extracted, jointly explaining 68.44% of the variance. A fourth factor had an eigenvalue of 0.704 and explained an additional 5.86% of variance. Together, the four extracted factors fully reproduced the structure of the original questionnaire (Table 2):

- **Factor 1** (41.9%) – Positive interaction experience
- **Factor 2** (17.9%) – Engagement (immersion)
- **Factor 3** (8.7%) – Interface appeal
- **Factor 4** (5.9%) – Difficulties and discomfort during interaction

Table 2

Rotated component matrix

Item	1	2	3	4
11. The interaction experience with the chatbot was useful for me.	.846	.162		.194
10. The interaction with the chatbot produced the result I needed.	.755	.238	−.234	.155

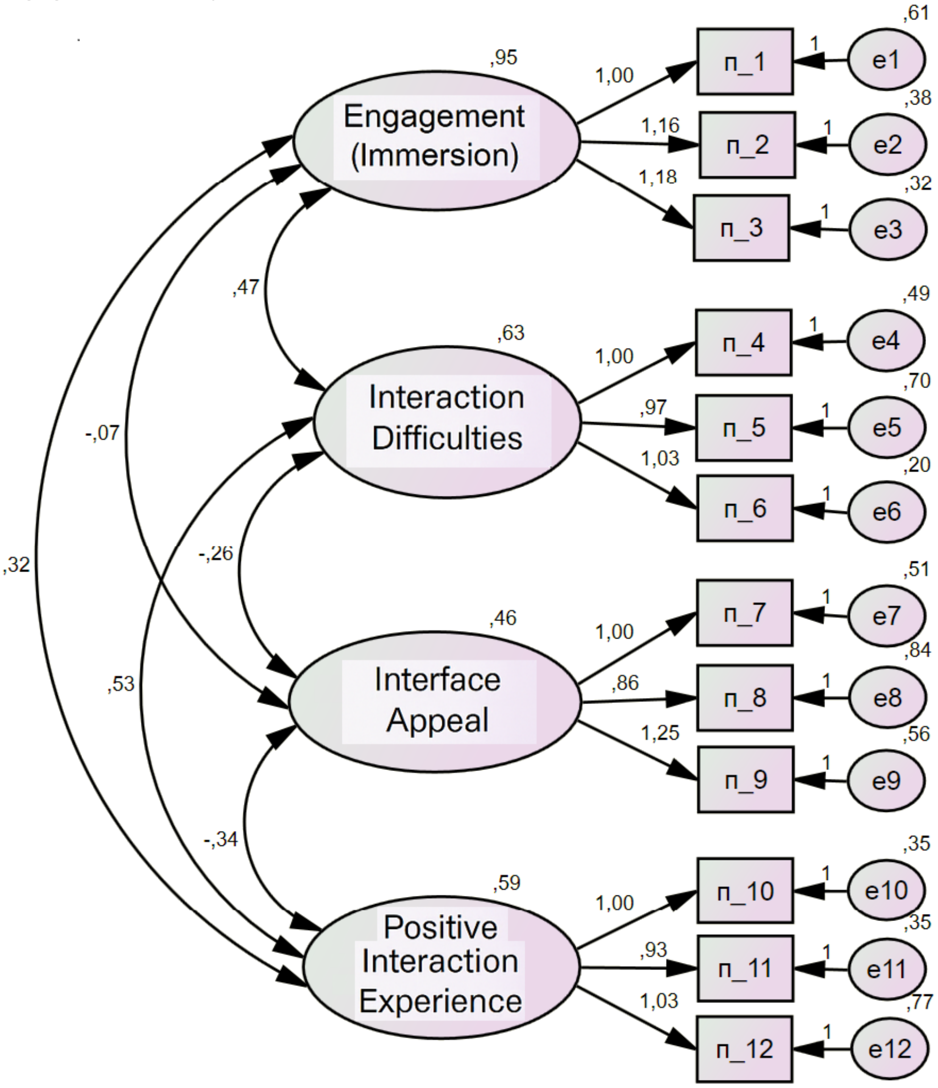
Item	1	2	3	4
12. I found it interesting to interact with the chatbot.	.674		−.425	
3. I was completely absorbed in interacting with the chatbot.		.902		.186
2. While interacting with the chatbot, I did not notice how time passed.	.124	.888		.187
1. I became deeply immersed in the interaction with the chatbot.	.246	.813		.180
8. The chatbot looked aesthetically pleasing.			.799	−.160
7. The chatbot's interface was appealing.	−.284		.761	
9. The interaction with the chatbot was pleasant.	−.332		.710	−.136
5. The chatbot seemed confusing to use.	.138	.300	−.135	.850
6. Interacting with the chatbot was tiring.	.578	.241	−.225	.596
4. I was disappointed with my interaction with the chatbot.	.521	.325		.573

Extraction method: Principal Component Analysis; Rotation method: Varimax with Kaiser normalization; rotation converged in 6 iterations.

The four-factor solution obtained via exploratory analysis was further evaluated using confirmatory factor analysis (CFA). The four-factor model demonstrated acceptable fit to the data. The χ^2/df ratio was 2.777, indicating a reasonable balance between model fit and complexity. The fit indices—GFI = 0.911 and AGFI = 0.855—showed good agreement with the data, while high CFI (0.930) and TLI (0.904) values confirmed that the model adequately represented the empirical structure. The RMSEA value of 0.074 fell within the acceptable range, and the RMR value of 0.084 indicated an acceptable level of residual error. Parsimony indices (PRATIO = 0.727, PNFI = 0.652) further supported the balanced nature of the model. **The CFA model is presented in Figure 1** (not reproduced here).

Figure 1

User Engagement Model for Interaction with a Chatbot



Test–retest reliability was assessed over a one-month interval across four weeks using Spearman's rank correlation. Ninety-three participants took part in the repeated assessment. The Spearman correlation for the Russian version of the User Engagement Scale was 0.81, indicating high temporal stability.

Convergent validity was evaluated through correlations between overall engagement scores and the UMUX-LITE usability measure (Lewis et al., 2013), the Positive and Negative Affect Schedule (PANAS; Osin, 2012), and the "Absorption by Activity" subscale of the Flow Short Scale (Engeser & Rheinberg, 2008). Divergent validity was assessed through comparisons with the Boredom Proneness Scale (Zolotareva, 2020) and the Satisfaction With Life Scale (Osin & Leontiev, 2008). Results are presented in Table 3.

Table 3

Convergent and divergent validity indicators of the User Engagement Scale

N	UMUX-LITE (Usability)	Positive Affect (PA)	Negative Affect (NA)	Absorption by Activity	Boredom Proneness	Life Satisfaction
210	.823**	.643**	–.120	.834**	–.120	.024

Note. p *< 0.01 (two-tailed).*

The results demonstrated strong positive correlations between overall engagement and both perceived usability (r = 0.823) and absorption by activity (r = 0.834). A moderate positive correlation with positive affect (r = 0.643) suggested that engagement is associated with positive emotional experiences during interaction with a chatbot. In contrast, negative affect (r = –0.120), boredom proneness (r = –0.120), and life satisfaction (r = 0.024) showed weak or negligible associations with engagement. These findings indicate that the scale effectively differentiates engagement from unrelated psychological characteristics.

Overall, the adapted instrument demonstrated high convergent and adequate divergent validity, confirming its reliability for assessing user engagement in interaction with a chatbot.

Discussion

The adaptation of the instrument for assessing user engagement in interaction with a chatbot demonstrated that the Russian-language version preserved the key components necessary for diagnosing this aspect of the user experience. The observed shift in item difficulty toward "ease" is consistent with the preferences of users who choose chatbots for convenient and effortless interaction. The high item–total correlations and Cronbach's alpha indicate strong internal consistency, confirming the reliability of the scale for measuring user engagement with a chatbot.

The exploratory factor analysis revealed substantial differences in factor loadings when comparing the original engagement measure with its Russian adaptation. In the original version, positive interaction experience was the least prominent factor, whereas in the adapted version it became the dominant one. Conversely, difficulties and inconveniences of interaction emerged as comparatively less significant in the adapted scale. This discrepancy may reflect changes in user perception related to the affordances of generative AI. In interactions with earlier, non-generative technologies, users may have been less sensitive to nuances of experience and more focused on basic functionality and ease of use. However, generative AI provides unique opportunities: chatbots based on generative models can participate in interactions that closely resemble human communication, substantially influencing users' perceptions of the interaction (Al Lily et al., 2023; Israfilzade, 2023; Orrù et al., 2023; Wang et al., 2023).

Furthermore, users may pay less attention to interface usability and functionality due to the intuitive design and high level of accessibility typically associated with modern generative AI systems (Shete, 2023). These characteristics likely reduce the salience of perceived difficulties and enhance the importance of pleasant and meaningful interaction, thereby contributing to the increased relevance of positive experience and immersion in the adapted model.

Confirmatory factor analysis supported the four-factor structure, demonstrating adequate model fit and overall quality. Fit indices, error measures, and parsimony indicators all confirmed the appropriateness of the model for describing the underlying structure of the data and indicated its suitability for further research applications.

The results of convergent validity analysis revealed strong positive correlations between overall engagement and both usability (as measured by UMUX-LITE) and absorption by activity. These findings are consistent with prior research demonstrating close relations between engagement and various aspects of user experience with interactive technologies (Avila-Garzon et al., 2023; Fergencs & Meier, 2021; O'Brien & Lebow, 2013). Similarly, the link between engagement and absorption aligns with previous work showing that a state of flow or deep involvement enhances engagement during interaction with AI-based technologies (Arghashi & Yuksel, 2022; Cha et al., 2024).

The moderate positive association between engagement and positive affect suggests that emotional responses play a meaningful role in shaping user engagement. Prior research indicates that the expression of positive emotions by conversational agents can improve interaction quality (Andrade-Arenas, Yactayo-Arias & Pucuhuayla-Revatta, 2024; Park et al., 2023; Tsai et al., 2021). However, the influence of the user's own emotional state on engagement remains less clear. Existing studies suggest that the impact of positive emotions on engagement with interactive systems may vary depending on context and individual characteristics (Zheng et al., 2024).

The findings also demonstrated weak associations between engagement and both negative affect and boredom proneness. This indicates that even under conditions of general negative mood or heightened boredom, engagement with a chatbot may remain relatively unaffected. Additionally, the absence of a correlation between life satisfaction and engagement suggests that cognitive aspects of subjective well-being do not influence the degree of engagement in interaction with a chatbot. Overall, these results support the divergent validity of the measure, confirming that engagement constitutes a distinct construct independent of emotional background and general life satisfaction.

Conclusion

The four-factor structure of the Russian-language version of the User Engagement Scale, identified through exploratory factor analysis and confirmed via confirmatory factor analysis, includes the following components: positive interaction experience, engagement (immersion), interface appeal, and interaction difficulties. These results replicate the structure of the original scale and confirm its theoretical soundness. In the context of interaction with generative AI, positive experience emerged as the most influential factor, which may be explained by the intuitive interfaces of such systems and their ability to simulate interpersonal communication.

The Russian version of the instrument demonstrated high reliability and validity. Elevated Cronbach's alpha (0.83) and test–retest reliability (Spearman's r = 0.81) indicate strong internal consistency and stability over time. Convergent validity was supported by high correlations between overall engagement and both chatbot usability (UMUX-LITE; r = 0.823) and absorption by activity (r = 0.834), highlighting the relevance of these psychological characteristics for the construct of engagement. Divergent validity was confirmed by minimal correlations with negative affect, boredom proneness, and life satisfaction.

Overall, the instrument effectively differentiates user engagement as a distinct dimension of the user experience and can be confidently applied in research aimed at assessing interaction with interactive technologies, including generative AI–based systems.

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Appendix 1.

User Engagement Scale — Russian Adapted Version (12-item short form)

Dear Participant,

Thank you for taking part in the assessment of engagement during interaction with a chatbot.

Please follow the instructions below when completing the questionnaire:

- Respond sincerely and without prolonged reflection.
- Your immediate impressions are most valuable.
- Do not overthink the items.
- Answer based on your actual experience of interacting with a chatbot.
- It is important that your responses reflect your real feelings and impressions.

Please indicate the degree to which you agree with each statement based on your experience of interacting with a chatbot. Use the following response scale from **1 (Strongly disagree)** to **5 (Strongly agree).**

Response options

1 — Strongly disagree
2 — Disagree
3 — Not sure
4 — Agree
5 — Strongly agree

Items (Russian Adapted Wording)

6. Я погрузился с головой во взаимодействие с чат-ботом.
7. Взаимодействуя с чат-ботом, я не заметил, как пролетело время.
8. Я был полностью поглощен взаимодействием с чат-ботом.
9. Я был разочарован взаимодействием с чат-ботом.
10. Чат-бот показался мне запутанным в использовании.
11. Взаимодействие с чат-ботом было утомительным.
12. Интерфейс чат-бота был притягательным.
13. Чат-бот выглядел эстетически привлекательно.
14. Взаимодействие с чат-ботом было приятным.
15. Взаимодействие с чат-ботом дало тот результат, который был мне нужен.
16. Опыт взаимодействия с чат-ботом был для меня полезным.
17. Мне было интересно, когда я взаимодействовал с чат-ботом.

Subscale Scoring Instructions

- Engagement (Immersion): mean of items 1, 2, 3
- Interaction Difficulties: mean of items 4, 5, 6
- Interface Appeal: mean of items 7, 8, 9
- Positive Interaction Experience: mean of items 10, 11, 12
- Overall User Engagement: mean score across all 12 items

Note

This appendix presents the final Russian-language version of the User Engagement Scale adapted for use with generative AI–based chatbots. Only the validated Russian wording is reproduced here in accordance with translation and publication guidelines.

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Conflict of Interest Information

The authors have no conflicts of interest to declare.