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Research Article

Determining Individual Intelligence Types and Cognitive Styles Using AI-Based Automated Text Analysis

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ABSTRACT

Introduction: This study investigates the application of a novel methodology to evaluate the intelligence profiles and cognitive styles of corporate executives using publicly accessible data. Specifically, we conducted an automated text-based psychological assessment leveraging three AI-driven chatbots and a unique linguistic analysis tool. The outputs from these systems were systematically compared across all evaluation metrics and further benchmarked against manual psychological content analyses performed by the research team. This approach aims to validate the consistency and reliability of AI-powered tools in replicating expert human judgment for leadership trait assessment.

Objectives: The main objective of the work is to evaluate individual intelligence types and cognitive styles using AI-based automated text analysis.

Methods: The tools used for automated text evaluation and analysis included AI chatbots (ChatGPT, Gemini, and Gigachat), a specialized program for psychological text analysis (LIWC), and expert content analysis. The estimates obtained using these tools were verified using rank statistics based on the chi-square criterion.

Results: Based on the study's results, we can form a cognitive portrait of a top manager. 1) The level of intelligence, erudition, and analytical thinking was assessed as high. 2) The author has a high emotional and social intelligence; social recognition is essential to him. 3) Predominant type of thinking: verbal-logical and abstract-symbolic. 4) The author has a high cultural level. This is confirmed by the complex structure of speech, rich vocabulary, absence of cognitive distortions, and grammatical and logical errors. 5) Originality of thinking can be considered average or low. Many industrial and professional cliches were found in the speech. However, this is a standard situation when a specialist uses them in a relatively formalized finance and business automation area. 6) The manner of speech can be characterized as direct and open rather than secretive and evasive.

Conclusions: Based on the work results, the authors concluded that the level of intelligence and cognitive styles can be measured using automated text analysis tools. Statistical tests yielded reasonably reliable estimates. The data showed a significant positive correlation between human expert analysis and artificial intelligence. In our opinion, the study confirmed the primary hypothesis that the analysis of texts from open sources allows us to form an idea of the critical cognitive characteristics of a person. We also confirmed the hypothesis that chatbots based on artificial intelligence can be used for the psychological analysis of texts to assess a person's cognitive characteristics.

Keywords: automated text analysis, intelligence, cognitive style, psychometrics, computational psychology, content analysis, psycholinguistics.

INTRODUCTION

Intelligence has long been recognized as a multifaceted cognitive construct, a cornerstone of psychological inquiry. Conventional assessments, rooted in standardized tests, have focused on quantifying logical reasoning, spatial aptitude, and verbal proficiency. While these methods remain foundational for evaluating cognitive capacities, they

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are inherently constrained by their reliance on individual psychometric performance within controlled settings (Sundberg, 1961; Nisbett et al., 2012; Woo, Harms & Kuncel, 2007; Adams & Callahan, 1994; Zeidner & Matthews, 2000; Aiken, 2004; Rust & Golombok, 2014; Eysenck, 2019; Luckin, 2017; Muthukrishnan et al., 2020).

The advent of advanced computational technologies, particularly breakthroughs in machine learning and natural language processing, has revolutionized cognitive research paradigms. Where earlier studies depended on limited participant samples, modern tools now enable the automated extraction and analysis of large-scale datasets from digital platforms like social networks. This shift minimizes human intervention while expanding researchers' capacity to derive insights into cognitive traits such as thinking styles, information processing strategies, and perceptual patterns directly from publicly available textual data (Salah, Al Halbousi & Abdelfattah, 2023; Calvo et al., 2017; Balahur, Hermida & Montoyo, 2012; Kalmykova, Kharchenko & Mysan, 2019, 2021; Nandwani & Verma, 2021; Iliev, Dehghani & Sagi, 2015; Narynov et al., 2021; Uludag, 2024; Wang, 2024; Dave, 2022; Rathje et al., 2024). Such innovations allow for a granular examination of lexical complexity, abstract reasoning, and nuanced cognitive tendencies at scale.

OBJECTIVES

Contemporary scholarship broadly conceptualizes intelligence as extending beyond the general ability to encompass diverse cognitive styles, including spatial reasoning, creative problem-solving, and dimensions of emotional and social intelligence (Otero, Salgado & Moscoso, 2022; Messick, 2021; Zhang & Sternberg, 2020; Anglim et al., 2022). Building on this framework, our study introduces a multidimensional assessment model to evaluate intellectual abilities and cognitive styles through psychometric analysis of texts such as speeches, interviews, and social media content sourced from open digital repositories.

A distinctive feature of this research lies in its integration of cultural features. While culture is neither an innate cognitive trait nor a direct measure of intelligence, it shapes an individual's volitional capacities, value systems, and professional aspirations. For organizational leaders, cultural orientation traits are integral to effective leadership.

This study's novelty is using AI-driven analytical tools, including specialized linguistic software (LIWC, Crystal, Symanto) and neural network-based chatbots (ChatGPT, Gemini, GigaChat) to conduct psychological text analysis. We aim to (1) validate this integrative methodology for assessing intelligence and cognitive styles and (2) systematically compare AI-generated scores with those derived from traditional expert-led content analysis.

METHODS

Our methodology involved systematically evaluating 65 software platforms with advertised text analysis capabilities alongside 12 prominent neural network-based chatbots. This screening phase aimed to assess their efficacy in detecting psycholinguistic properties, semantic content, and thematic patterns within textual data. Initial candidates were drawn from our prior works detailed in references (27-28). Through rigorous testing, we identified solutions that demonstrated both analytical reliability and functional relevance to cognitive assessment tasks.

Our methodology systematically evaluated 65 software platforms with claimed text analysis capabilities and 12 well-known neural network-based chatbots. This screening phase aimed to assess their performance in detecting psycholinguistic properties, semantic content, and thematic patterns in text data. The programs for validation were taken from our previous work, described in detail in references (Kashkin & Paliy, 2024a, 2024b). Through rigorous testing, we identified solutions that demonstrated both analytical robustness and functional relevance for cognitive assessment tasks.

The LIWC program showed significant results. Its main analytical strength lies in a validated psycholinguistic dictionary that maps lexical patterns to more than 80 psychologically meaningful categories (e.g., emotional tone, cognitive processes, social orientation). Higher word frequency values indicate the category to which these words belong, which correlates with certain personality traits. Rather than simply counting keywords, this methodology follows proven and validated psychometric principles, where stable lexical preferences are the basis for determining psycholinguistic personality traits.

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Table 1. LIWC Expanded Dictionary.

Culture	3.1
politic	0.06
ethnicity	0.06
tech	2.98
Lifestyle	9.09
leisure	0.18
home	0.06
work	7.06
money	3.37
relig	0.09
Physical	0.94
health	0.21
illness	0.09
wellness	0.03
mental	0
substances	0.32
sexual	0
food	0.5
death	0
need	0.71
want	0.03
acquire	0.21
lack	0.18
fulfill	0.27
fatigue	0
reward	0.71

Culture	Culture	car, united states, govern*, phone
Politics	politic	united states, govern*, congress*, senat*
Ethnicity	ethnicity	american, french, chinese, indian
Technology	tech	car, phone, comput*, email*
Lifestyle	lifestyle	work, home, school, working
Leisure	leisure	game*, fun, play, party*
Home	home	home, house, room, bed
Work	work	work, school, working, class
Money	money	business*, pay*, price*, market*
Religion	relig	god, hell, christmas*, church
Physical	physical	medic*, food*, patients, eye*
Health	health	medic*, patients, physician*, health
Illness	illness	hospital*, cancer*, sick, pain
Wellness	wellness	healthy, gym*, supported, diet
Mental health	mental	mental health, depressed, suicid*, trauma*
Substances	substances	beer*, wine, drunk, cigar*
Sexual	sexual	sex, gay, pregnan*, dick
Food	food	food*, drink*, eat, dinner*
Death	death	death*, dead, die, kill
States		
Need	need	have to, need, had to, must
Want	want	want, hope, wanted, wish
Acquire	acquire	get, got, take, getting
Lack	lack	don't have, didn't have, *less, hungry
Fulfilled	fulfill	enough, full, complete, extra
Fatigue	fatigue	tired, bored, don't care, boring
Motives		

reward	0.71
risk	0.21
curiosity	0.74
allure	2.92
Perception	7.53
attention	0.53
motion	1.45
space	5.55
visual	0.41
auditory	0.03
feeling	0.12
time	2.89
focuspast	1.3
focusprese	4.02
focusfutur	1.03
Conversati	0
netspeak	0
assent	0
nonflu	0
filler	0

Motives		
Reward	reward	opportun*, win, gain*, benefit*
Risk	risk	secur*, protect*, pain, risk*
Curiosity	curiosity	scien*, look* for, research*, wonder
Allure	allure	have, like, out, know
Perception	Perception	in, out, up, there
Attention	attention	look, look* for, watch, check
Motion	motion	go, come, went, came
Space	space	in, out, up, there
Visual	visual	see, look, eye*, saw
Auditory	auditory	sound*, heard, hear, music
Feeling	feeling	feel, hard, cool, felt
Time orientation		
Time	time	when, now, then, day
Past focus	focuspast	was, had, were, been
Present focus	focuspresent	is, are, I'm, can
Future focus	focusfuture	will, going to, have to, may
Conversational	Conversation	yeah, oh, yes, okay
Netspeak	netspeak	:), u, lol, haha*
Assent	assent	yeah, yes, okay, ok
Nonfluencies	nonflu	oh, um, uh, i i
Fillers	filler	rr*, wow, sooo*, youknow

Source: Obtained by the authors from survey data using LIWC

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The LIWC analysis revealed maximum frequencies in three areas (second column of the table): lifestyle/culture, perception/motivation, and technology/financial-time focus.

AI-driven chatbots (ChatGPT, Gemini, GigaChat) significantly outperformed traditional software in semantic interpretation and psychological inference tasks, demonstrating superior contextual awareness and metacognitive analysis capabilities.

The study included groups of tests in the following areas of assessment:

- traditional intelligence tests that focus on assessing analytical and logical abilities;
- tests of cognitive styles and types of thinking and assimilation of information;
- erudition tests based on content analysis;
- emotional and social intelligence tests;
- assessment of common sense and wisdom based on content analysis of the text.

To test the methodology proposed by the authors, a text corpus was collected containing conference materials, interviews, and statements on social networks of a person holding a senior position in a well-known Chinese IT company. Given bilingualism (knowledge of English and Chinese), texts in these languages were selected. There are 12 texts in the corpus. The total number of words by the author was 5787 (91% in Chinese, 9% in English). The results of the programs showed that for a more accurate understanding of the texts, their translation from Chinese into English was required.

RESULTS

Intelligence and logic

Table 2. Intelligence and logic

Assessment parameter/question shorthand	Notes, detail	ChatGPT	Gemini	Giga Chat	LIWC	Expert content analysis
1 General intelligence level	Formulated as a question without reference to a specific test	3	2	X	X	3
2 IQ level	* Bard estimates the IQ of the executive being rated to be “in the range of 120 to 130”	2	2*	X	X	2.5
3 Logic of statements. Presence/absence of logical errors in speech	Formulated as a question without reference to a specific test	2.4	2	2	3	3

Source: developed by the authors

The results of assessing the intelligence and logic of top managers show that they are at a reasonably high level. If we consider IQ (for the authors, it is 120 and above) as the most widely known indicator of intelligence level, then the average IQ of a person is considered to be from 85 to 115. If we consider the average IQ level by country, then Japan is in first place in the world in terms of IQ with an indicator of 106.48 (according to World Population Review research). Most of the research tools used also rated the consistency of the author’s statements as high or above average.

Types of intelligence and thinking

Table 3. Types of intelligence and thinking

Assessment parameter/question shorthand	Notes, detail	ChatGPT	Gemini	Giga Chat	LIWC	Expert content analysis
1. Analyze the author’s speech and	SP (Supplement of	2	1	X	X	2

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identify his intelligence according to each parameter of the Amthauer test IST (Amthauer et al., 2000)	Proposals)					
	WE (Word Exclusion)	3	1	X	X	3
	An (Analogy)	2	2	X	X	3
	Gn (Generalization)	3	2	2	X	3
	AT (Arithmetic Tasks)	1	1	X	X	X
	NS (Number Series)	2	1	X	X	X
	SI (Spatial Imagination)	0	1	X	X	X
	SG (Spatial Generalization)	0	1	X	X	X
	MA (Memory, Mnemonic Abilities)	2	2	X	X	2
2. Is it possible to determine the traits of intelligence expressed in this text following the **Amthauer intelligence test (Yasiukova adaptation)**? (Yasiukova, 2009)	General Awareness	2	2	2	X	2.5
	Intuitive Conceptual Thinking	2	1	2	X	2
	Conceptual, logical thinking	2	2	2	3	3
	Conceptual categorization	2	1	2	X	3
	*Mathematical intuition:	1	1	X	X	1
	Abstract thinking:	2	2	2	X	2.5
	Figurative synthesis	1	1	X	X	3
	Spatial thinking:	0	1	X	X	X
	*Logical RAM	2	2	X	X	2
3. Evaluate the analytical thinking of the text writer		2	2	2	3	3
4. The predominant type of thinking according to Bruner's method classification (Bruner, 1986)	Subject-effective	X	1	2	X	X
	Abstract-symbolic	2	3	2	X	2
	Verbal-logical	3	2	X	X	3
	Visual-figurative	X	2	X	X	X
	Creativity	1	2	2	X	2
5. Evaluate the author's intelligence using **Gardner's criteria for multiple intelligences** (Gardner, 1983)	Language Intelligence	3	3	X	X	3
	Logical-mathematical intelligence	2	3	1	X	2
	*Spatial-visual intelligence	0	1	X	X	X
	*Musical intelligence	0	0	X	X	X
	*Body-kinetic intelligence	0	0	X	X	X
	Interpersonal intelligence	2	1	0.5	X	1.5
	Intrapersonal intelligence	3	2	X	X	2
	*Naturalistic intelligence	0	0	X	X	X
	Existential Intelligence	2	1	X	X	X

Source: developed by the authors

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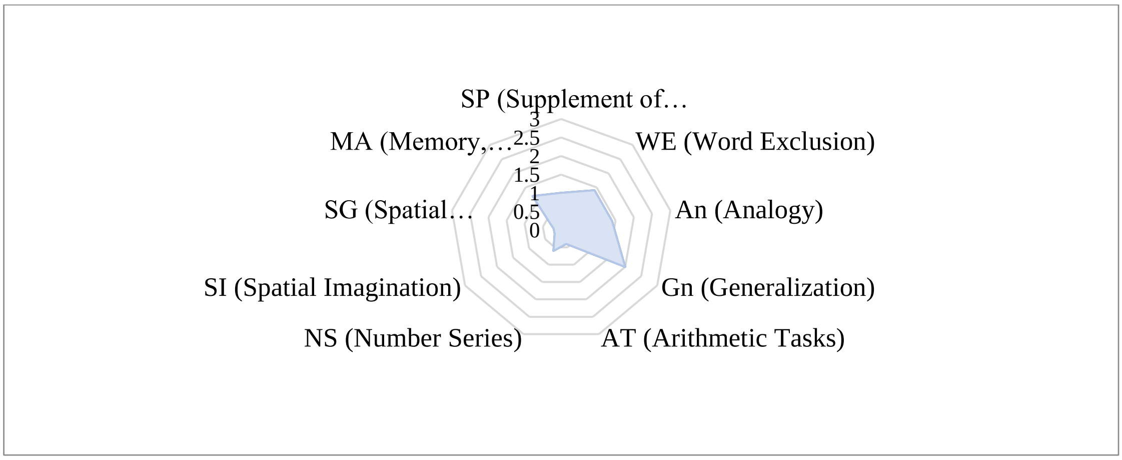

Figure 1. Psycholinguistic assessment of the Amthauer test parameters

Source: developed by the authors

The author has a dominant verbal-logical type of thinking, which the use of concepts and logical constructions can characterize. The abstract-symbolic kind of thinking is also quite evident. The highest scores in linguistic and verbal intelligence also confirm this. The ability to generalize at a high level is expressed, according to the Amthauer test.

Conceptual-logical thinking and abstract thinking are expressed (Figure 2, Amthauer test, adaptation by Yasyukova). Analytical thinking is expressed.

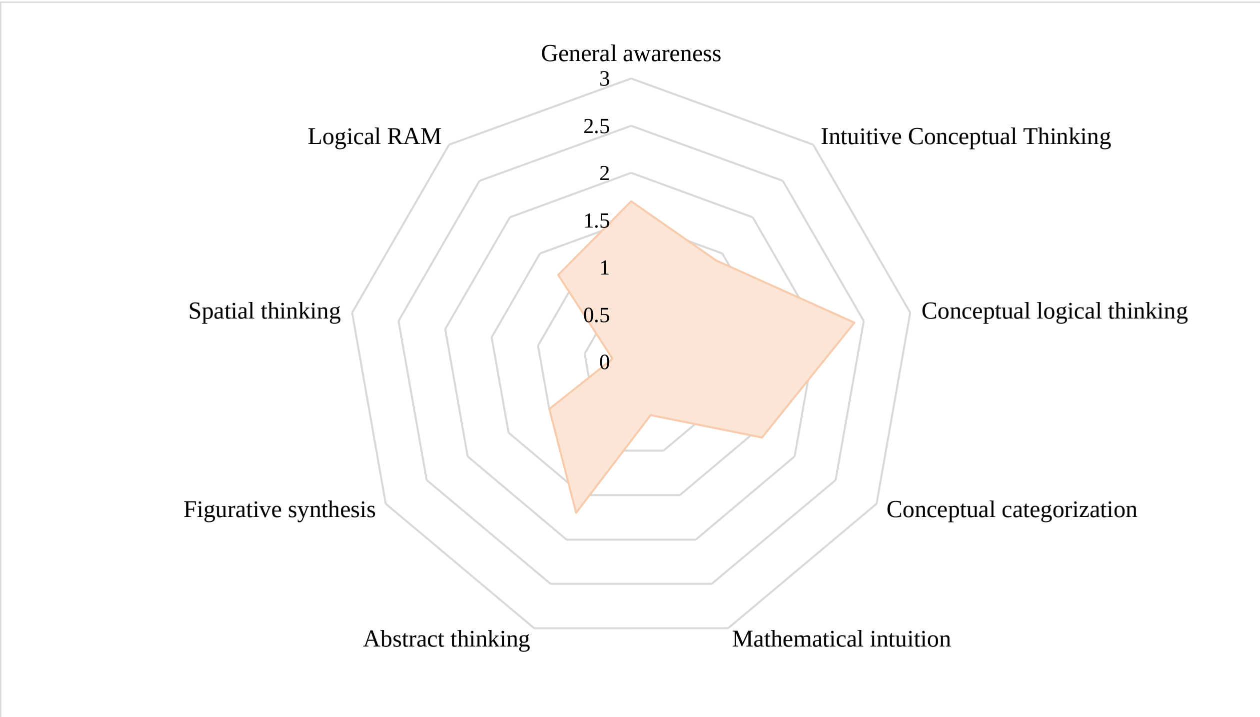

Figure 2. Psycholinguistic assessment of the Amthauer test parameters (Yasukova adaptation)

Source: developed by the authors

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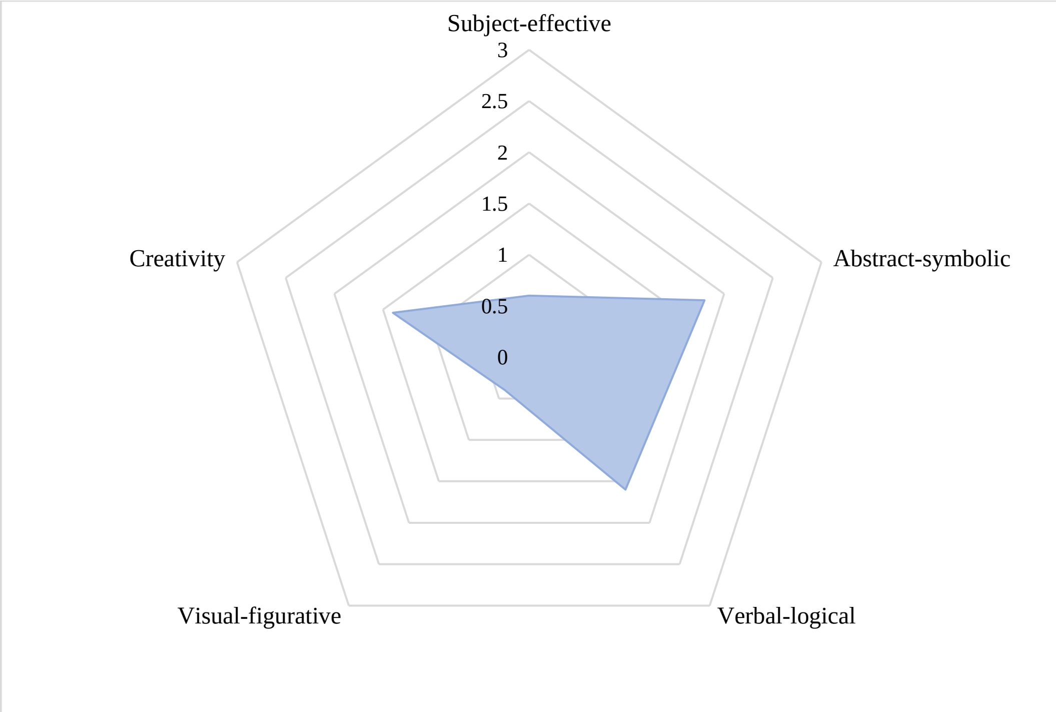

Figure 3. Psycholinguistic assessment of the Bruners method parameters

Source: developed by the authors

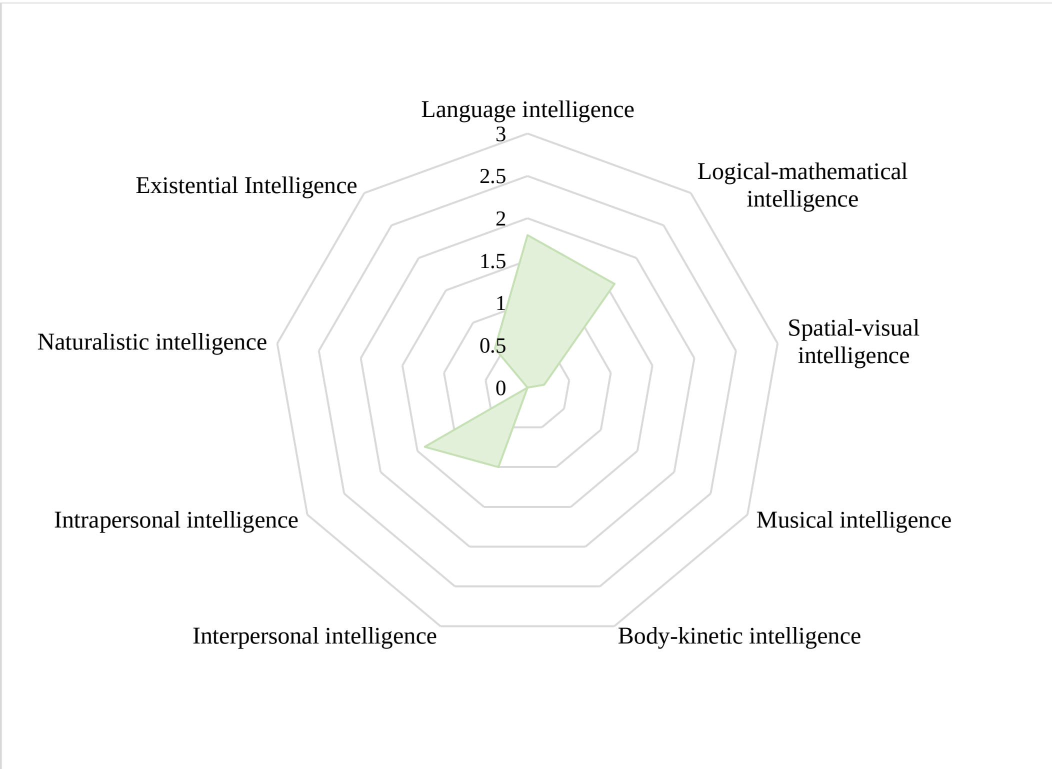

Figure 4. Psycholinguistic assessment of the Gardners multiple intelligence test parameters

Source: developed by the authors

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Chatbots noted insufficient data in the text for some parameters (marked *) of intelligence and thinking tests, especially for mathematical parameters and computing abilities. Thus, the low score here does not reflect the expression of the parameter in the text and not the lack of mathematical abilities of the authors.

DISCUSSION

This study systematically assessed the reliability of the ratings given by the AI-based tools (Gemini, ChatGPT, GigaChat), the LIWC, and human experts (expContAn variable). First, we conducted paired comparisons of all chatbot ratings, with each chatbot treated as a separate variable in the analysis. Measurements were taken on a scale from 0 to 3 (0 = no feature; 3 = strong feature).

Unrated responses marked with an “X” were retained for dataset integrity. Often, the AI provided a decimal score, which was also retained.

We analyzed the consistency of estimates using contingency tables, Cramer’s V coefficients and Kendall’s Tau coefficients. These statistics are based on the chi-square test. The calculations showed similar results, so the authors adopted the more compact results of the Kendall rank statistics calculations.

Rank correlation allows us to determine the direction of the relationship between features that were assessed using point estimates. In this case, we counted pairs of objects with mutually increasing, mutually decreasing, and equal values of variables.

Kendall’s Tau varies from -1 to +1 and is calculated as the difference between matching and discordant pairs divided by the sum of the two values. A matching pair is defined as one in which the second value is strictly greater than the first; otherwise, it is discordant.

Tau is calculated using the following formula (Newson, 2002).

$$\tau_b = \frac{Con - Div}{Con + Div} \tag{1}$$

where Con are consistent convergent pairs, Div are inconsistent divergent pairs.

To determine the strength of the relationship by the correlation coefficient, we will use the scale the Ray-Parker scale, where (the upper limit of the range is not included) 0,00-0,10 – negligible, 0,10-0,20 – weak, 0,20-0,40 – moderate, 0,40-0,60 – relatively strong, 0,60-0,80 – strong, 0,80-1,00 – very strong.

Kendall correlation coefficients were calculated for all pairs of variables, with a significance level of $p > 0.05$ (Table 4).

So, the way it was received seven statistically significant coefficient correlations:

1 ChatGPT and GeminiBard – 0.5280 – relatively strong correlation;

2 ChatGPT and GigaChat – 0.3889 – average correlation;

3 ChatGPT and ExpContAn – 0.5221 – relatively strong correlation;

4 GeminiBard and GigaChat – 0.3551 – average correlation;

5 GeminiBard and LIWC – -0.8367 – very strong (negative);

6 GeminiBard and ExpContAn – 0.2673 – average correlation;

7 GigaChat and ExpContAn – 0.5136 – relatively strong correlation.

Table 4. Kendall correlation coefficients

Parameter1	Parameter2	tau	CI_low	CI_high	z	p	n_Obs
ChatGPT	GeminiBard	0.5280	0.4118	0.6273	0.6273	3.6060E-08	79
ChatGPT	GigaChat	0.3889	0.2052	0.5461	0.5461	3.0158E-03	45
ChatGPT	LIWC	-0.2673	-0.6928	0.2964	0.2964	4.2034E-01	9
ChatGPT	ExpContAn	0.5221	0.3935	0.6306	0.6306	1.0225E-06	67
GeminiBard	GigaChat	0.3551	0.1697	0.5163	0.5163	6.0439E-03	46
GeminiBard	LIWC	-0.8367	-0.9457	-0.5584	-0.5584	1.4306E-02	9
GeminiBard	ExpContAn	0.2673	0.1103	0.4113	0.4113	1.2278E-02	67
GigaChat	LIWC	0.1637	-0.3921	0.6319	0.6319	6.3047E-01	9
GigaChat	ExpContAn	0.5136	0.3476	0.6483	0.6483	8.9851E-05	44
LIWC	ExpContAn	0.4458	-0.0996	0.7852	0.7852	1.9043E-01	9

Source: calculated by the authors

Note that the LIWC calculations were performed on small samples. As a result, the correlation estimates have a wide confidence interval that includes the zero value, which requires additional data.

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