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ARTIFICIAL INTELLIGENCE ON THE WAY TO THE SIXTH TECHNOLOGICAL WAVE: CLOSER THAN IT SEEMS

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ABSTRACT

The emergence of a new cognitive scientific culture is a key consequence of the historical transition from the digital logic of the fifth technological paradigm to the cognitive logic of the sixth, where Artificial Intelligence (AI) ceases to be a tool and becomes an element of collaborative intellectual activity. In this historical context, the coherence of cultural (Q1) and educational (Q2) adaptation to AI becomes a fundamental theoretical question. This study proposes a theoretical model, Q1–Q2–B1, in which cultural attitudes toward AI (Q1) and educational acceptance of AI technologies (Q2) are considered two levels of technological adaptation. The coefficient B1 = Q2/Q1 serves as an indicator of the harmonious transition in this model. Based on an international survey of students from 12 university groups (N = 2,693), data were obtained that confirm the theoretical premise that cultural adaptation outpaces educational adaptation. High empirical values were obtained for Q1 (M = 74.55%) and Q2 (M = 67.23%). Moreover, statistical hypothesis testing shows that in most countries B1 < 1, indicating an uneven transition. Only four countries demonstrate a state close to equilibrium (condition B1 = 1) - this can be interpreted as early examples of a stabilizing cognitive scientific culture. Thus, the proposed Q1-Q2-B1 model allows us to conceptualize the transition to the sixth technological paradigm as a multilevel process. In this transition, the cultural adaptation of students (Q1) is primary, and the educational infrastructure (Q2) is catching up. The study makes a theoretical contribution to understanding the mechanisms of coordination of cultural and educational changes in the context of technological transformation: 1) It proposes a new two-level model of adaptation to AI (Q1-Q2), allowing us to consider cultural and educational acceptance not as independent effects, but as interconnected elements of a single cognitive structure; 2) Introduces the B1 coefficient as an indicator of the harmoniousness of the technological transition, which creates the basis for a quantitative analysis of the formation of cognitive scientific culture in different countries; 3) Interprets the gap between Q1 and Q2 as a structural indicator of the transition from the fifth to the sixth technological paradigm, allowing for the linking of individual student

assessments with historical processes of social change.

KEYWORDS: Artificial Intelligence (AI), Scientific Culture, Cultural Level of Adaptation, Educational Level of Adaptation, Cultural Readiness, Sixth Technological Paradigm, Historical Paradigm Shift.

1. INTRODUCTION

The special issue of Scientific Culture, "AI and Society: Navigating the Intersection of Technological Innovation, Ethics, and Global Human Values," draws readers' attention to a key challenge of the contemporary era: the need to understand how Artificial Intelligence (AI) is changing the foundations of human activity, including higher education (Aguado-García et al., 2025; Wolor et al., 2025; AI and Society, 2025; Artyukhov et al., 2024; Jaiswal et al., 2024; Somner, 2023). We find ourselves at a rare moment in history, namely, at the transition between two technological paradigms, the fifth and sixth (Okulich-Kazarin et al., 2025; Grishnova et al., 2021; Neufeld, 2021; Dosi et al., 2016; Knell, 2011; Perez, 2010; Castellacci, 2007; Cimoli et al., 1996; Cimoli et al., 1995; Dosi, 1982). This historical moment lies between the digital age, focused on information processing, and the cognitive age, in which AI becomes a direct participant in intellectual activity. Universities are among the first spaces where this transition is documented, not in theoretical discussions, but in the real-life experiences of people working with AI daily. In the context of the transition, students' attitudes toward AI acquire scientific significance: they reflect not individual preferences, but deep cultural and cognitive processes (Al-Zahrani, 2025; Okulich-Kazarin et al., 2025; Marshik et al., 2024) characteristic of the historical phase of technological paradigm shift.

The history of technological paradigm shifts shows that each significant change, from mechanization to digitalization, has transformed the ways of producing, storing, and transmitting knowledge (Yang et al., 2024; Neufeld, 2021; Perez, 2010; Cimoli et al., 1995). The fifth technological paradigm, based on digitalization and global information infrastructures, has changed access to knowledge (Alekseieva et al., 2021; Lechman et al., 2019; Knell, 2011; Perez, 2010). The sixth paradigm is distinguished by the fact that one of its central elements (AI) addresses the structure of human thought (Neufeld, 2021; Knell, 2020). At the same time, the role of AI is changing: it is moving from the status of a tool to that of a cognitive partner, capable of participating in the interpretation of information, solving problems, and supporting students' intellectual activity (Okulich-Kazarin et al., 2025; Somner, 2023; Grishnova et al., 2021). At this historical moment, a new scientific culture of learning is emerging, in which the human ability to interact with AI becomes not an add-on but a prerequisite for full participation in the academic environment.

The transition between the fifth and sixth technological paradigms is also reflected in the educational sphere, as universities have historically functioned as institutions sensitive to changing ways of working with information. In the digital age of the fifth paradigm, the ability to access, critically evaluate, and apply information in learning activities has become a central skill. At the beginning of the sixth paradigm, this skill set is no longer sufficient. Students need not only mastery of digital tools but also the ability to interact with AI as an element of their own cognitive process (Okulich-Kazarin et al., 2025; Hamzah et al., 2025; Liu et al., 2025; Jaiswal et al., 2024; Marshik et al., 2024).

This transformation is particularly noticeable in everyday educational practices. Students increasingly use AI to search for sources, analyze data, structure information, and prepare educational materials (Aguado-García et al., 2025; Judson, 2025; Okulich-Kazarin et al., 2025; Marshik et al., 2024; Somner, 2023). AI thus becomes part of their intellectual environment, rather than an external technological resource. This shift cannot be understood without a broader historical context: it is precisely during periods of technological transition that we observe the re-creation of familiar activity patterns, including forms of learning and methods of knowledge processing. A historical perspective, coupled with cross-country comparisons, reveals that students' perceptions of AI are not a random or ad hoc phenomenon (Liu et al., 2025; Mjahad et al., 2025; Jaiswal et al., 2024; Okulich-Kazarin et al., 2024b; Benhayoun et al., 2021). They serve as an indicator of more profound changes occurring in the structure of general and educational culture. While the logic of digital literacy dominated the fifth paradigm, at the beginning of the sixth paradigm, the emphasis shifts to cognitive literacy, that is, the ability to work in a distributed human-AI system. This is not simply a technical skill, but a new academic competence, the formation of which can already be observed today (Aguado-García et al., 2025; Judson, 2025; Hamzah et al., 2025; Liu et al., 2025; Somner, 2023). In this context, students' attitudes toward AI acquire the significance of a historical marker. It reveals the speed with which a new cognitive scientific culture is taking root in the academic environment, as well as the degree of coherence in the transition between its two levels of development: cultural (how AI is perceived in general) and educational (how the role of AI is perceived at the university).

This study aims to identify the characteristics of students' perceptions of AI during the transition from the fifth to the sixth technological paradigm and to determine how these characteristics reflect the formation of a new cognitive scientific culture in higher education. Particular attention is paid to two levels of adaptation: cultural (general attitudes toward AI) and educational (attitudes toward its use in the educational process), as well as the degree of alignment between these two levels.

These are the three research questions (RQs) of the study

- RQ1. How do students from different countries perceive AI in general during the transition between the fifth and sixth technological paradigms?
- RQ2. How do students evaluate the use of AI in university education?
- RQ3. What is the relationship between the cultural level of attitudes toward AI (Q1) and the educational level of its adoption (Q2), and what does this balance reveal about the nature of the transition to an academic environment of the sixth technological paradigm?

The scientific novelty of the study lies in its proposal of a theoretically and empirically grounded model for analyzing student perceptions of AI during the historical transition from the fifth to the sixth technological paradigm. Unlike most studies that examine attitudes toward AI as a single, undifferentiated phenomenon, this study divides them into two fundamental levels: cultural (general attitudes toward AI) and educational (attitudes toward the application of AI in the educational process). This conceptual division allows us to capture not only the degree of technology adoption but also the direction of cognitive and institutional changes occurring in the university environment.

A key element of novelty is the introduction of three research questions that cover both the ideological perception of AI (RQ1) and the educational acceptance of AI at universities (RQ2). This foundation forms the third level of analysis (RQ3), which aims to examine the congruence between the two levels of adaptation. To quantify this relationship, the coefficient B1 = Q2 / Q1 is introduced, reflecting the pace and nature of the transition to a new cognitive scientific culture. The value of the B1 coefficient allows us to identify situations of cognitive lead (when educational acceptance of AI develops faster than cultural acceptance) or cognitive retardation (when cultural readiness outpaces institutional integration).

Thus, the scientific novelty of this study lies in the development of a conceptually strengthened and empirically robust a Q1–Q2–B1 theoretical model that demonstrates that students' perception of AI is an indicator of a deeper historical process: the formation of a new cognitive scientific culture emerging at the intersection of two technological eras. This study contributes to the interdisciplinary agenda of the journal Scientific Culture by combining the theory of technological paradigms, the analysis of educational practices, and the cultural and cognitive aspects of adaptation to AI.

The practical significance of this study lies in its results, which enable university leaders to objectively assess their level of readiness for the transition from the educational model of the fifth technological paradigm to the cognitively oriented model of the sixth paradigm. Dividing the perception of AI into a cultural level (Q1) and an educational level (Q2), and introducing the coefficient B1 = Q2 / Q1, creates a tool that can be directly used to analyze the state of university systems and determine the direction of their technological and pedagogical transformation.

The coefficient B1 enables educational institutions to determine whether they are in a situation of cognitive advancement (when students are already actively incorporating AI into the educational process), cognitive inhibition (when students' cultural readiness exceeds institutional integration), or a transitional zone of balance. This approach enables university leaders to make informed decisions based on empirically supported data, rather than relying on intuitive assessments or local observations. **The new results can be used for**

1. Developing strategies for the implementation and regulation of AI in the educational process.
2. Creating programs to improve the digital and cognitive literacy of students and academic teachers.
3. Identifying structural or cultural barriers to the integration of AI.
4. Planning institutional changes aimed at adapting curricula to the conditions of the sixth technological paradigm.
5. Monitoring the dynamics of AI perception in an international comparison, which is especially important for universities striving to maintain a high position in global rankings.

Thus, the practical significance of the study lies in creating a model that enables university leaders to consciously and consistently transition to a new cognitive scientific culture, in which AI becomes a natural element of the academic environment.

2. LITERATURE REVIEW

2.1. The Use of AI In Historical Retrospect

AI can be defined as 'machines, agents, or computer programs that simulate cognitive functions associated with human minds, such as perceiving patterns, abstract reasoning, learning, communicating, and problem-solving' (United States Executive Office of the President, 2016). The emergence of AI can be traced back to the 1950s, with pioneers such as Turing, McCarthy, Newell, and Simon (Caspari-Sadeghi, 2022). Different sources classify the timelines of technology waves differently (Neufeld, 2021; Silva et al., 2016; Perez, 2010). However, their boundaries generally coincide. Our study adopts the technology transition boundaries described by Neufeld (2021).

Scientometric analysis shows the number of documents published for the keyword "Artificial Intelligence" from 1960 to 2024. This analysis includes documents of all types indexed in the Scopus database. Figure 1 displays a total of 649,855 document search results.

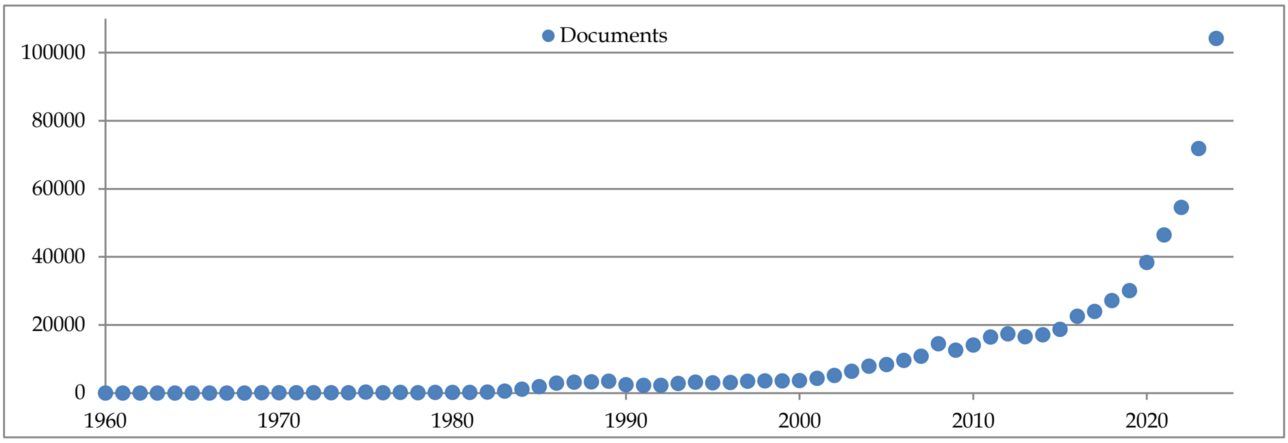

Figure 1: Number of publications on "Artificial Intelligence" in the Scopus database.

Figure 1 shows that, starting in 1961, regular publications using the definition of "Artificial Intelligence" began to appear—at first, their number was less than 10 per year. For example, the paper (Reintjes, 1962) describes electronic computers capable of independently performing selected tasks and even taking over simple decision-making functions. Hunt (1962) combined research in three areas in his book: psychology, logical analysis, and automata theory. In particular, the author mentioned "intelligent automata." In turn, the paper (Samuel, 1962) directly uses the definition of "Artificial Intelligence." In 1964, several specific examples of the functional application of computers for preparing and presenting stimuli, collecting responses, and planning and controlling equipment were described (Rath et al., 1964). The authors indicated that automated systems could perform all of these functions. In 1971, the number of such publications approached one hundred per year—this period corresponds to the widespread adoption of the fourth technological paradigm and the beginning of the fifth (Neufeld, 2021).

The subsequent surge in publication activity occurred between 1984 and 1990. Since the late 1980s, the number of publications on AI has exceeded one thousand per year. This observation roughly marks the beginning of the widespread adoption of fifth paradigm technologies (Neufeld, 2021; Lechman et al., 2019; Perez, 2010). During this period, authors actively published research results on various aspects of AI (Levy et al., 1990; Ishikawa, 1989; McRobbie et al., 1988; Holsapple et al., 1985; Uhr, 1985).

Another surge in publications occurred between 2008 and 2011 – this marked the end of the fourth technological paradigm, the beginning of the free development of the fifth technological paradigm, and the start of the sixth technological paradigm. Here, scientists wrote about increasing the productivity of AI tools, creating intelligent environments for artistic purposes, and the applied use of AI (Alviano, 2011; Fernández et al., 2010; Yakut et al., 2009; Bandini et al., 2008).

The next qualitative leap was noted in 2019. This date marks the convergence of the widespread adoption of the fifth technological paradigm and the emergence of the sixth technological paradigm (Neufeld, 2021; Somner, 2023; Knell, 2020). A particularly rapid increase in the number of publications was noted after 2022. During these years, the number of publications on AI increased by approximately 30,000 per year (Figure 1). This historical period is of interest for a more detailed study. Across contemporary scholarship, AI is increasingly framed as a general-purpose technology that cuts across sectors, reshaping production systems, services and governance. In industrial and infrastructural domains, AI is positioned as a core driver of Industry 4.0 solutions, automating complex processes in municipal waste management and improving risk monitoring on construction sites through image-based analysis (Kajda & Karwot, 2025; Zaryczańska & Karwot, 2025). Strategic investment in ICT and AI is also viewed as essential for telecom operators to adapt to rapidly transforming markets (Sahnouni & Kadri, 2025), while smart-city concepts highlight AI as the backbone of sustainable and resilient urban systems (Kuzior, 2024). In agriculture, the literature links AI with both technological transformation and new risk-management tools, notably cyber-insurance frameworks for digitalized farms (Sitnicki et al., 2024), as well as with broader agendas of women's empowerment and inclusive leadership in rural economies (Moutik, 2025). AI applications extend into innovation management itself, where fuzzy-set approaches are used to assess the commercial potential of new product ideas, signalling a shift towards data-driven decision-making in product development (Sitnicki et al., 2021).

At the level of services, finance and human-centred domains, AI is portrayed as simultaneously enabling personalisation and raising significant ethical, security and regulatory questions. In education and corporate communication, AI-enhanced tools are shown to transform language learning and discourse practices (Pilny & Postrzednik-Lotko, 2025). Meanwhile, in e-banking and e-retail financial services, intelligent systems support seamless customer journeys and influence adoption behavior and satisfaction (Kadri, 2025; Lama et al., 2025). Business studies emphasise AI-driven content analysis for smart customer feedback management (Kildei et al., 2025) and reveal how machine-learning algorithms on social media amplify privacy risks and security concerns, especially for young users exposed to gendered digital harms and ideological manipulation (Wieczorek & Postrzednik-Lotko, 2025; Agyare, 2025). In health-related fields, AI is examined in relation to pharma R&D, post-marketing surveillance and dual-use ethical dilemmas in healthcare and biotechnology (Burrell, 2025; Kritikos et al., 2025; Springs, 2025), as well as in automated traffic enforcement with implications for public health and social justice (Haley, 2025). Parallel work in security and finance indicates that AI both strengthens and undermines integrity systems, being exploited by organised criminals for money laundering while also empowering anti-money laundering and financial monitoring services (Lyeonov et al., 2024, 2025). More broadly, digitalization and AI are viewed as key determinants of cybercrime dynamics, underscoring the need for robust institutional, technological, and ethical safeguards as AI expands into all spheres of socioeconomic life (Yarovenko et al., 2025; Schinello, 2025).

A historical analysis of publication activity reveals that the development of AI follows a logic of technological waves, characterized by a shift in paradigms from the mid-20th century to the present day. The first studies in the 1960s reflected the development of fundamental AI ideas and coincided with the onset of widespread adoption of fourth-paradigm technologies. The transition to the fifth technological paradigm was accompanied by a significant increase in applied research and a sharp rise in publications in the 1980s and 1990s, as AI began to be applied in expert systems, automation, and data analysis.

An analysis of Scopus data (Figure 1), including 649,855 documents from 1960 to 2024, confirms the structural relationship between technological paradigms and the dynamics of scientific attention. The surges in publication activity in the 1970s, late 1980s, and 2008–2011 are associated with these waves. The data from 2023 to 2024, and especially from 2019 onward, correspond to key phases of the fifth and early sixth technological paradigms, characterized by the transition from digital solutions to cognitive systems. The acceleration of publication growth in 2022–2024 (≈30,000 new documents annually) reflects the unprecedented expansion of AI applications—from industry and urban infrastructure to finance, healthcare, education, and social policy.

At the same time, the data confirm the well-known cyclical nature of AI development: periods of intense growth were followed by "AI winters" associated with disappointment, insufficient technological development, and reduced funding. These declines were not definitive, but rather phases of regrouping, followed by new technological and theoretical advances.

Thus, the dynamics of scientific publications demonstrate that AI development is not a linear but a wave-like process, closely linked to the historical shift in technological paradigms. The current stage—the phase of transition to the sixth paradigm—is characterized by a sharp expansion of the fields of AI application and the formation of a new cognitive scientific culture, making the current historical moment key for further research.

2.2. Theoretical Framework

Many researchers consider the modern development of AI as an element of the transition to the sixth technological paradigm, in which cognitive, digital, and bioinformatics technologies are becoming key (Somner, 2023; Grishnova et al., 2021; Neufeld, 2021; Knell, 2020; Perez, 2010). AI ceases to be a tool and becomes a cognitive partner (Judson, 2025; Okulich-Kazarin et al., 2025; Marshik et al., 2024), capable of participating in data interpretation, problem-solving, and supporting human thought. This change affects the fundamental nature of university education, where the traditional model of knowledge transfer is gradually giving way to a model of joint human-algorithm thinking (Al-Zahrani, 2025; Jaiswal et al., 2024; Benhayoun et al., 2021). The pedagogical process is becoming not only digital but also cognitively distributed, and the didactic skills that students foster begin to include the ability to effectively interact with AI as an element of the academic environment (Al-Zahrani, 2025; Liu et al., 2025; Mjahad et al., 2025; Okulich-Kazarin et al., 2025; Somner, 2023).

The emergence of a new form of scientific culture accompanies the transition to the sixth paradigm. It is based on the recognition of AI not as an external resource, but as an internal element of the educational structure (Aguado-García et al., 2025; Judson, 2025; Liu et al., 2025; Okulich-Kazarin et al., 2025; Jaiswal et al., 2024). Several features characterize this cognitive scientific culture:

- Human-AI interaction becomes the norm of academic activity;
- Technology is perceived not as an auxiliary component, but as integrated into thinking;
- The ability to work with AI becomes a key component of educational and professional literacy.

In such a culture, the boundaries between human and machine thinking become increasingly blurred. Students begin to perceive AI as part of their learning experience, rather than as an external service. A new model of academic subjectivity emerges: people remain the authors of their decisions, but interact with the cognitive infrastructure, as AI enhances their ability to analyze, interpret, and create.

Students' attitudes toward AI become a key indicator of how deeply and sustainably the new cognitive scientific culture has taken root in the academic environment. Two levels of perception are critical here:

- Q1 – cultural (students' attitudes toward AI as a technological phenomenon);
- Q2 – educational (students' attitudes toward the use of AI directly in the learning process). The distinction between the cultural level of attitude toward AI (Q1) and the educational level of its adoption (Q2) allows us to consider students' perception of technology as a multidimensional process, reflecting the nature of the transition from the digital paradigm of the fifth paradigm to the cognitive logic of the sixth paradigm. Comparing the values of Q1 and Q2 creates an analytical framework within which four typological zones can be identified, each describing a different trajectory of adaptation to AI (Figure 2).

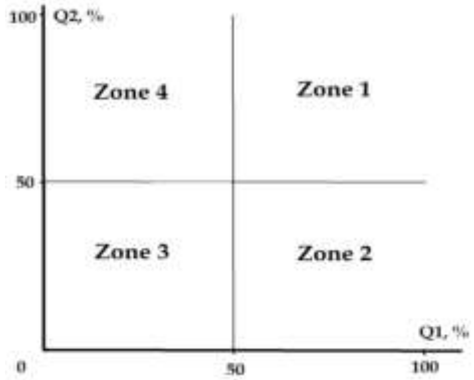

Figure 2: Correlation between the educational level of acceptance of AI (Q2) and the cultural level of attitude towards AI (Q1).

Figure 2 illustrates the analytical logic of the Q1–Q2 model, which identifies four typical zones of adaptation to AI in the context of the transition from the fifth to the sixth technological paradigm. The position in each zone reflects the nature of the consistency or gap between the cultural perception of AI and its educational integration.

The first zone in Figure 2 (Zone 1) represents a state where both students' cultural attitudes toward AI (Q1) and their level of educational acceptance (Q2) are high. This configuration indicates an environment in which the transition to the sixth technological paradigm is already underway. Students perceive AI as a highly valuable technology and are already actively using it in their learning activities. A new cognitive scientific culture is emerging here, in which interaction with AI is perceived as natural and integrated into the educational process.

The second zone (Zone 2) is characterized by a high cultural attitude toward AI but a low level of its practical use in the educational process. This zone indicates that students perceive AI positively as a technological phenomenon. However, the university environment is still in the early stages of integrating AI tools into educational practices. This misalignment may be typical for systems that still retain elements of the fifth technological paradigm, where digital infrastructure is present but has not been transformed into cognitively oriented educational models.

The third zone (Zone 3) denotes a simultaneous low cultural attitude toward AI and a low level of its practical use in the educational process. This zone reflects a conservative adaptation model characteristic of systems that still primarily operate within the logic of the late digital (fifth) paradigm and show no signs of an active transition to the cognitive model of the sixth paradigm. Students show little interest in AI. Universities, in turn, are failing to integrate AI into the educational process, indicating structural or cultural limitations.

The fourth zone (Zone 4) corresponds to a situation in which the educational use of AI (Q2) is relatively high, despite a moderately low cultural attitude toward the technology (Q1). This configuration can arise under conditions of administrative or institutional pressure, when AI is introduced "from above" faster than positive cultural perceptions can develop among students. In the context of the transition to the sixth technological paradigm, this zone represents the early phase of forming a new cognitive scientific culture, where practices are adopted more rapidly than the scientific culture of academic teachers and students can adapt.

The selected indicators: Q1 (general attitude toward AI) and Q2 (attitude toward the use of AI in higher education) allow us to capture the transition between two cognitive levels: from the ideological to the practical. This transition is the central characteristic of the formation of a new cognitive scientific culture at universities. Therefore, the authors introduce the new coefficient, $B1 = Q2 / Q1$, into scientific circulation. The coefficient B1 allows us to quantitatively capture the relationship between the educational and cultural levels of adaptation to AI. It reflects the degree of alignment between the general ideological attitude toward AI and its adoption in university teaching practices. In other words, the B1 is an indicator of the "speed" of the formation of a new cognitive scientific culture:

- If $B1 > 1$, then university practice is ahead of cultural acceptance (the formation of a new culture is proceeding rapidly).
- If $B1 < 1$, then cultural acceptance is ahead of practice (the university is "slowing down" the integration of AI).
- If $B1 \approx 1$, then a harmonious transition between the two levels of adaptation is underway.

Thus, the B1 value above one indicates a situation in which educational acceptance of AI is ahead of cultural readiness, indicating the rapid formation of a new cognitive scientific culture. A value below one means that cultural acceptance is developing faster than institutional integration, which may indicate structural or pedagogical barriers. Here, the B1 coefficient serves as an indicator of the pace and nature of the transition to an academic environment of the sixth technological paradigm. Zone 1 and Zone 3 allow both harmonic ($B1 = 1$) and asynchronous configuration ($B1 \neq 1$).

Based on this model, the study's logic is grounded in the hypothesis that the formation of a new cognitive scientific culture is a multilevel process. In this process, cultural adaptation outpaces educational adaptation. Their combination could lead to the sustainable consolidation of the logic of the sixth technological paradigm in higher education.

2.3. Bibliometric Analysis

The pairing of scientific culture and artificial intelligence is increasingly emerging as a conceptual bridge across the history and philosophy of science, scientometrics, technology studies, and education. Contemporary work on AI in organisational management and culture shows that intelligent systems are not merely tools but active factors in reshaping norms of decision-making, innovation and leadership, thus reconfiguring what is understood as "good" scientific and managerial practice in knowledge-intensive organisations (Bilan et al., 2022; Kuzior et al., 2023; Temerbulatova et al., 2025). System-level analyses of the "economy–education–digitalisation–national security" chain further position AI as a structural driver of convergence between scientific knowledge production, policy priorities, and security logics, reinforcing the idea that scientific culture is now co-constructed with digital and algorithmic infrastructures (Samusevych et al., 2021). Debates on the future of AI, oscillating between fear, hope and indifference, reveal how social imaginaries of science and technology feed back into research agendas, regulatory expectations and public trust, making scientific culture itself an object of contestation in the age of AI (Yarovenko et al., 2024; Haley & Burrell, 2025).

Within education and academic practice, the scientific culture–AI nexus is evident in the redefinition of learning, integrity, and professional socialization. Studies of AI in education and language learning describe how intelligent technologies transform curricula, literacy, and discourse, while also demanding new forms of critical and ethical competence among students and educators (Zimosz & Ober, 2025; Pilny & Postrzednik-Lotko, 2025). At the same time, work on academic integrity and AI literacy highlights that governance quality, institutional culture and explicit ethical guidance shape whether AI tools are integrated as extensions of rigorous scientific practice or as shortcuts that erode trust in scholarly work (Borissov & Liuta, 2025; Mujtaba, 2024). These developments echo parallel discussions in applied fields, such as law enforcement, where the integration of AI foregrounds questions of socioeconomic inequality, legitimacy, and value conflicts, again placing scientific norms and ethical standards at the centre of technological design and deployment (Haley & Burrell, 2025). This literature suggests that "scientific culture + artificial intelligence" functions not only as a thematic pair but also as an integrative framework for analyzing how different disciplines negotiate the meanings, boundaries, and responsibilities of science in an AI-mediated world.

Query:

TITLE-ABS-KEY ("artificial intelligence" AND "science" AND "culture") AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2023) OR LIMIT-TO (PUBYEAR, 2024) OR LIMIT-TO (PUBYEAR, 2025) OR LIMIT-TO (PUBYEAR, 2026)) AND (LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "SOCI")).

Total number of articles in Scopus database: 1174.

Period of analysis: 2022–ongoing (November 24, 2025).

Areas: social sciences; decision sciences.

Number of articles after limitation: 230.

Dataset for analysis: 230 from 230.

Total number of keywords in VOSviewer: 1510.

Keywords for analysis: first 1000 keywords.

The visualization in Figure 3 presents a complex, multi-cluster bibliometric landscape centered on the concept of AI, surrounded by a variety of cultural, ethical, educational, technological, and socioeconomic research directions. While AI appears as the dominant node, the map includes numerous smaller but meaningful keywords that reflect diverse conceptual trajectories. Among these are academic integrity, industrial revolutions, and paradigm shifts, which—although present on the map—are positioned at its periphery. Their marginal placement suggests that these themes are acknowledged in scholarly discourse but remain only loosely integrated into mainstream AI research.

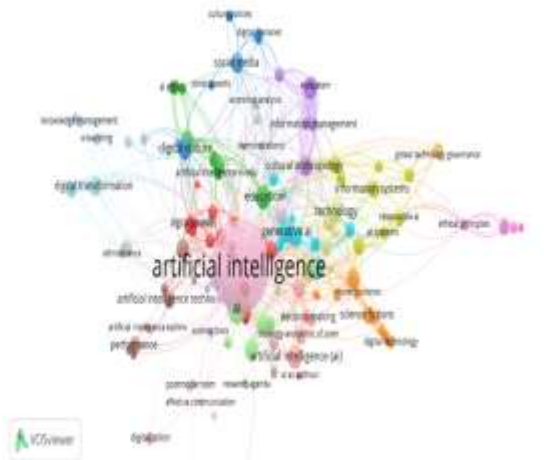

Figure 3: Query "artificial intelligence" AND "science" AND "culture": keyword map (https://www.scopus.com, accessed on November 24, 2025; analysis tool—VOSviewer).

A prominent feature of the map (Figure 3) is a well-developed cluster associated with ethics and responsible AI. Terms such as AI ethics, ethical principles, and responsible AI are highly interconnected, indicating that ethical considerations form a substantial and coherent research domain. Academic integrity, by contrast, appears as an isolated node, implying that integrity-related discussions arise primarily in connection with concerns about AI-generated content, authorship, and educational misuse but do not yet form a robust research stream. This distinction underscores that ethics in AI governance is significantly more developed than inquiries into how AI influences the norms and values of scientific work.

Another densely connected thematic zone includes digital culture, digital literacies, cultural anthropology, and social media. These terms reveal that cultural research in this dataset is strongly oriented toward digital society and digital behaviour rather than traditional cultural studies or scientific culture. The absence of nodes referring to cultural heritage preservation or scientific culture confirms that current investigations focus on socio-digital interactions rather than broader cultural transformations associated with AI. The education-related nodes (education, AI in education, and digital literacies) form a smaller cluster, indicating that educational adaptation to AI remains less developed than cultural adaptation.

Figure 3 also displays several peripheral nodes—industrial revolutions, paradigm shifts, academic integrity, postmodernism, and modern science—

whose limited connectivity signals the early phase of cognitive transformation within the research community. These terms represent recognition of historical and epistemic shifts. Still, they are not yet integrated into a unified theoretical framework that explains AI as a driver of large-scale societal change. Their distance from the central AI cluster suggests a conceptual gap between empirical studies of AI applications and theoretical reflection on technological paradigms and cognitive transitions.

Equally important are the conceptual absences. Nodes related to scientific culture, cognitive culture, cognitive paradigm, technological paradigms, knowledge transformation, student adaptation, and cognitive readiness do not appear on the map. Their absence highlights the need for theoretical and empirical frameworks to understand AI not only as a technological tool but also as an actor in shaping a new form of cognitive scientific culture. This omission, combined with the peripheral placement of industrial revolutions and paradigm shifts, indicates that the theoretical dimension of the transition to the sixth technological paradigm remains insufficiently explored.

Taken together, these structural features of the keyword landscape underscore the relevance of the Q1–Q2–B1 model proposed in the study. By differentiating cultural adaptation (Q1) from educational adaptation (Q2) and introducing the B1 coefficient as an indicator of harmonicity, the model provides a conceptual bridge between fragmented empirical observations and the broader historical logic of technological transformation. The dominance of cultural keywords such as digital culture, social media, and AI ethics, and the relatively weak development of educational keywords, mirrors the empirical pattern in which Q1 exceeds Q2 across most countries. This imbalance supports the interpretation that cultural adaptation to AI is progressing more rapidly than the adaptation of educational systems.

In this way, the map not only visualizes the fragmentation and thematic asymmetry of contemporary AI research but also strengthens the argument that a coherent cognitive-cultural paradigm has yet to be formed. The Q1–Q2–B1 model offers a theoretical and methodological foundation for conceptualizing and measuring this emerging paradigm, capturing the multilevel dynamics of cultural and educational adaptation in the transition to the sixth technological paradigm.

2.4. Summary

Taken together, the presented historical analysis and the dynamics of publication activity create the conceptual backdrop necessary for interpreting the results of the empirical study. Shifting technological paradigms, the undulating development of AI, and the acceleration of scientific publications in recent years indicate a shift from digital solutions to cognitive systems. This shift is changing not only the technological landscape but also the structure of expectations, norms, and practices in higher education. It is within this logic that the Q1–Q2–B1 model acquires analytical depth: cultural attitudes toward AI (Q1) and educational acceptance of its use (Q2) reflect the complex adaptation of the university environment to a new cognitive reality. The B1 coefficient allows us to quantitatively assess how coherently these two levels respond to this historical shift. Thus, the empirical part of the study is not a separate element, but a direct continuation of the historical-paradigmatic analysis, which allows us to assess how the global transformation of AI manifests itself in student perceptions and the emergence of a new cognitive scientific culture.

3. METHODS

3.1. General Design

Overall, the study spans a 65-year historical period, from 1960 to 2024. However, we focused on the years of the most intense discussion of AI in scientific circles (2022-2025). The study utilized both qualitative and quantitative methods:

- scientometric analysis using the keywords "artificial Intelligence" from 1960 to 2024,
- bibliometric analysis using the keywords "artificial intelligence," "science," and "culture" for the period 2022–ongoing,
- theoretical and conceptual modeling,
- a survey of students from nine countries in Central and Eastern Europe, Central Asia, and Central Africa and preliminary statistical analysis of the results (Kingston University, 2010; Okulich-Kazarin, 2024a),
- graphical interpretation of the empirical results,
- verification of statistical hypotheses (Kingston University, 2010).

The theoretical part of the study employed theoretical and conceptual modeling to develop a new analytical framework for describing the transition from the digital logic of the fifth technological paradigm to the cognitive logic of the sixth. Within this method, a multilevel model was developed. The model Q1–Q2–B1, allowing us to conceptualize the cultural (Q1) and educational (Q2) acceptance of AI as two interrelated levels of technological adaptation.

The coefficient B1 = Q2/Q1 was theoretically interpreted as an indicator of the harmonious transition, which allowed us to represent the process of forming a new cognitive scientific culture as a structural alignment of cultural and institutional-educational changes. This theoretical and conceptual modeling provides the basis for transforming the theoretical model into measurable indicators, forming a bridge between the history of technological paradigms and the contemporary empirical characteristics of AI perception in the university environment.

The empirical part of the study is based on an international survey of students from 12 university groups (N = 2,693), conducted between 2023 and 2025. Two key indicators were used for the quantitative analysis: cultural attitudes toward AI (Q1) and educational acceptance of its use in the educational process (Q2). Both indicators were ordinal Likert scales with five response categories, which allowed us to obtain comparable data with a high degree of sensitivity to differences in AI perceptions were collected.

In the first stage, frequency distributions, the proportions of positive and negative responses, as well as means and standard deviations for each indicator, were calculated. We now have a basic description of the structural characteristics of the sample, enabling us to identify general patterns of AI perception within the international context.

In the second stage, a two-dimensional analysis was applied, including mapping university groups in a coordinate system (Q1, Q2). This positioning allowed us to visually and quantitatively assess the consistency of cultural and educational levels of adaptation, as well as attribute differences to the four analytical zones of the model. In addition, the coefficient B1 = Q2/Q1 was calculated, serving as an integral indicator of the harmonious transition.

In the third stage, statistical hypotheses were verified regarding the absence of differences between Q1 and Q2 (B1 = 1) in each country and in the overall sample. For this, methods for testing means and standard deviations were used. This stage enabled the determination of whether the difference between adaptation levels was statistically significant. This approach ensured a rigorous empirical assessment of the theoretical model, allowing us to interpret the results in the context of the transition from the fifth to the sixth technological paradigm.

3.2. Organization of Data Collection

Empirical data collection was conducted between 2023 and 2025 using a standardized questionnaire developed for a comparative study of perceptions of AI among student groups from different countries (Okulich-Kazarin et al., 2025). The questionnaire was translated into the working languages of the participating countries and maintained a consistent format, ensuring comparability of results across national contexts. Data was collected via an online survey (the questionnaire was hosted in the cloud of the Higher School of Business, Poland). Student participation was voluntary and anonymous, which reduced the likelihood of socially desirable responses and increased the reliability of the assessments.

Twelve university groups from different countries participated in the survey, resulting in a total sample size of N = 2,693 respondents, which demonstrated high statistical reliability. The list of countries and their proportions in the total sample are presented in Table 1, which reflects the geographic, cultural, and gender diversity of the student population.

Table 1: General Characteristics of the Respondents.

№	Country, Group	Degree of study	Number of Respondents			
			Male	Female	Other	Total
1	Bulgaria	Bachelor	30	61	2	93
2	Cameroon	Bachelor	29	114	0	143
3	Czech	Bachelor	37	57	0	94
4	Kazakhstan	Bachelor	151	231	2	384
5	Latvia	Bachelor	26	113	2	141
6	Poland	Bachelor	81	283	0	364
7	Slovakia	Bachelor	33	28	0	61
8	Ukraine-1	Bachelor	145	134	5	284
9	Ukraine-2	Bachelor	48	289	2	339
10	Ukraine-3	Bachelor	397	169	4	570
11	Ukraine-4	Bachelor (Kyiv)	54	88	3	145
12	Uzbekistan	Bachelor	36	38	1	75
13	Sum	-	1067	1605	21	2693

Table 1 presents 2,693 respondents from 9 countries in Africa, Asia, and Europe. A preliminary analysis of the data in Table 1 reveals a balanced sample distribution, with respondent group sizes ranging from 61 (Slovakia) to 570 (Ukraine-3). Large, medium, and small samples add value to the obtained results, as they demonstrate cognitive and educational patterns in structurally important contexts for analysis. Female respondents accounted for 59.6%, while male respondents accounted for 39.6%. So, the gender composition of respondents does not exhibit a gender anomaly.

Thus, the data collection approach allowed us to obtain a broad international sample, reproducing important cultural, institutional, and technological differences between universities. This sample provides a sufficient basis for subsequent analysis of the mechanisms by which the student environment adapts to AI in cultural and educational contexts, as well as for verifying the Q1-Q2-B1 theoretical model in various settings.

To ensure methodological rigor, the empirical data were tested for reliability and validity in accordance with generally accepted standards for quantitative research. The reliability of the measurement instruments was assessed through the internal consistency of responses to two key indicators: cultural attitudes toward AI (Q1) and educational acceptance of AI (Q2). Both measures are based on five-point Likert scales (Likert, 1932), ensuring the robustness and replicability of the results in large sample settings. A distributional consistency check revealed the absence of atypical responses, confirming the instrument's stability across diverse national contexts.

Construct validity is ensured by relying on the Q1–Q2–B1 theoretical model, which describes two levels of technological adaptation: cultural and educational, within the logic of the historical transition to the sixth technological paradigm. The Q1 and Q2 values demonstrated the expected structural properties: close mean values within groups, stable ranks between countries, and a predictable pattern of correlations. This pattern confirms that the indicators accurately reflect the conceptual levels embedded in the study's theoretical framework.

Criterion validity was further tested by verifying the hypotheses regarding the equality of adaptation levels (B1 = 1). The statistical results obtained, namely, the significant advantage of cultural assessments over educational ones, are consistent with the theoretical assumption of an uneven transition, thereby confirming the consistency of the empirical indicators with the theoretical framework. The use of a large and internationally diverse sample enhances external validity, enabling the interpretation of the results in a comparative and cross-cultural context.

Taken together, the conducted tests confirm that the measurement instruments used have sufficient reliability and validity for analyzing the mechanisms underlying the alignment of cultural and educational levels of adaptation to AI during the historical period of technological transitions.

3.3. Statistics

To verify the statistical hypotheses about the equality of adaptation levels (B1 = 1), comparisons of means and standard deviations were used (Kingston University, 2010). These procedures enabled the establishment of whether the difference between Q1 and Q2 was statistically significant, both at the level of individual countries and in the overall sample. This approach ensured the quantitative rigor of interpreting the Q1–Q2–B1 theoretical model, making it possible to conclude the nature of the transition to a new cognitive scientific culture.

Two standard statistical hypotheses were formulated for all respondent groups and the overall sample:

H_0 (null hypothesis): M(Q1) – M(Q2) = 0.

The null hypothesis states that the cultural and educational levels of adaptation are in a state of equilibrium, the transition is harmonious, and B1 = 1.

H_1 (alternative hypothesis): M(Q1) – M(Q2) ≠ 0.

The alternative hypothesis states that there is a statistically significant difference between the two adaptation levels; the transition is not yet harmonious; B1 ≠ 1.

To verify the hypotheses, the Z-statistic was used at a significance level of $\alpha = 0.05$ and a sampling error of 0.02 (Okulich-Kazarin, 2024a). This choice is due to the large sample size (N = 2693), which allows us to rely on the asymptotic properties of the distribution of means and correctly apply parametric comparison methods (Kingston University, 2010).

The Z-test is a standard tool for assessing the statistical significance of differences between means in large samples and is used to test the hypothesis B1 = 1 within the proposed model. Its application follows a research logic aimed at identifying the structural gap or coherence between the cultural (Q1) and educational (Q2) levels of adaptation to AI.

The use of alternative procedures (eg, nonparametric analogues) would not change the interpretation of the results obtained. The use of the Z-test in this case ensures methodological rigor, comparability and transparency of statistical inference in the context of international and large-scale empirical analysis.

4. RESULTS

4.1. Respondents' answers to the 1st and 2nd Research Questions

Respondents' responses to RQ1 are summarized in Table 2 and Figure 4. Table 2 presents responses for each respondent group and for the total sample. Figure 4 presents the results of processing the respondents' responses for the overall sample (Okulich-Kazarin, 2024a).

Table 2: Structure of responses to RQ1.

Responses	Gr-1	Gr-2	Gr-3	Gr-4	Gr-5	Gr-6	Gr-7	Gr-8	Gr-9	Gr-10	Gr-11	Gr-12	Total
Definitely	38	53	19	15	16	60	26	10	73	18	38	25	788

positively				3				4		3			
Rather positively	27	55	41	185	70	164	30	136	162	283	71	38	1262
Hard to say	23	30	24	36	44	100	4	32	78	68	24	10	473
Rather negatively	2	1	9	6	10	32	1	10	15	27	8	2	123
Definitely negatively	2	4	1	4	1	6	0	2	9	7	3	0	39
Sum	92	143	94	384	141	362	61	284	337	568	144	75	2685

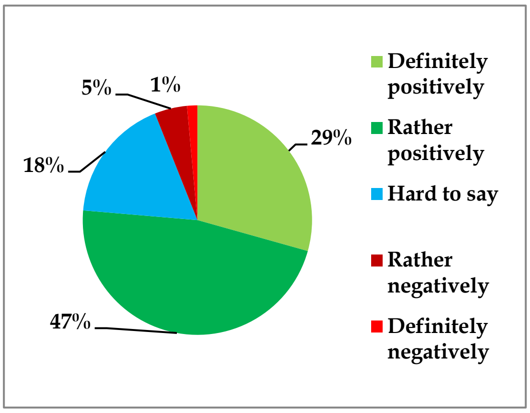

Figure 4: Structure of respondents' answers to RQ1, %.

Table 2 and Figure 4 present a structured distribution of responses across categories, ranging from "Definitely positively" to "Definitely negatively." Data analysis reveals a clear predominance of positive responses. Their sum is 788 "Definitely positively" and 1,262 "Rather positively" responses, or 2,050 positive responses and approximately 76.3% of all responses. Positive perceptions predominate in all 12 groups. Therefore, students' cultural attitudes toward AI have already formed and are clearly positive, which aligns well with the theoretical framework for transitioning to the sixth paradigm.

The number of doubters (473 responses with "Hard to say") ranges from 6% to 32% across groups. Statistically, this is a significant finding: doubtful students constitute a distinct cultural community, characteristic of the transition phases between technological paradigms. The number of negative responses is small: "Rather negatively" and "Definitely negatively" = 162 responses, or approximately 6%. In two of the twelve groups, the proportion of the "Definitely negatively" response is zero.

Table 2 and Figure 4 clearly confirm that RQ1 has a definite positive answer. Students generally perceive AI positively. They view AI technologies as a vital and valuable component of the modern technological landscape. This cultural acceptance forms the foundation for the transition to a cognitive model of interaction within the sixth technological paradigm.

Respondents' responses to RQ2 are summarized in Table 3 and Figure 5. Table 3 presents the responses for each respondent group and for the overall sample. Figure 5 presents the results of processing the respondents' responses for the overall sample.

Table 3: Structure of responses to RQ2.

Responses	**Gr-1**	**Gr-2**	**Gr-3**	**Gr-4**	**Gr-5**	**Gr-6**	**Gr-7**	**Gr-8**	**Gr-9**	**Gr-10**	**Gr-11**	**Gr-12**	**Total**
Definitely positively	35	41	18	136	10	71	27	92	53	157	30	29	664
Rather positively	31	49	41	168	65	156	24	126	164	222	55	28	1098
Hard to say	17	31	21	48	37	82	7	47	85	120	25	14	517
Rather negatively	6	20	11	23	26	43	3	14	25	57	26	2	250
Definitely negatively	4	2	3	9	3	12	0	5	12	12	8	2	68
Sum	93	143	94	384	141	364	61	284	339	568	144	75	2690

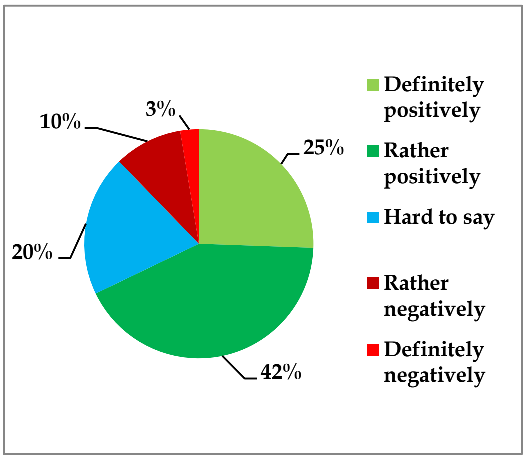

Figure 5: Structure of respondents' answers to RQ2, %.

Table 3 and Figure 5 present a structured distribution of responses across categories, ranging from "Definitely positively" to "Definitely negatively." Data analysis reveals several key trends that characterize student attitudes toward the use of AI in higher education—and thus reflect the degree of readiness of university systems to transition from the digital logic of the fifth technological paradigm to the cognitive model of the sixth paradigm.

The total number of positive responses is 664 "Definitely positively" and 1,098 "Rather positively," totaling 1,762 positive ratings, which is approximately 65.5% of all responses. The proportion of positive ratings remains high across all twelve respondent groups. Thus, the majority of students not only have a positive attitude toward AI as a technological phenomenon (Q1) but also support its use in education (Q2). Thus, the academic environment is demonstrating a significant level of adaptation to AI technologies. Compared to the same category in RQ1 (Table 2), the proportion of uncertain responses ("Hard to say") for RQ2 increased. The value varied between 5% and 26% across groups, but totaled 517 responses, or approximately 20%. Therefore, students have a more uncertain attitude toward the practical application of AI in education.

The total proportion of negative responses was 250 "Rather negatively" and 68 "Definitely negatively," totaling 318, or approximately 13%. These responses are significantly higher than for RQ1, where negative responses were approximately 6%. The proportion of the "Definitely negatively" response was zero in only one group. Consequently, students are more critical of the use of AI in the educational process than of AI as a technological phenomenon.

Thus, Table 3 and Figure 5 demonstrate that the perception of AI use in educational practice is consistently positive, but is characterized by a higher level of critical assessments than cultural attitudes toward AI. Positive responses predominate in all groups. The proportion of negative assessments increases significantly. The proportion of uncertain responses increases slightly. Therefore, students perceive the use of AI in the educational process as a valuable tool. At the same time, they identify risks, limitations, and institutional barriers (Erul et al., 2025; Ruano-Borbalan, 2025; Marshik et al., 2024; Okulich-Kazarin et al., 2024b; Okulich-Kazarin et al., 2024c). These results confirm that educational acceptance of AI develops within the transition from the fifth to the sixth technological paradigm and reflects the formation of a new cognitive scientific culture.

4.2. How do the cultural level of attitude towards AI (Q1) and the educational level of its acceptance (Q2) relate to RQ3

The logic of the distinction that is clearly presented in Figure 2 allows us to consider cultural and educational adaptation to AI as an interconnected, but not always synchronous process. To obtain a quantitative answer to the research questions, we need the values of the main statistical indicators. These indicators are summarized in Table 4. Table 4 contains the values of M(x) (mean values on the perception scale), δx (standard deviations), and the number of respondents N for all groups and the overall sample for two indicators:

- Q1 - cultural level of attitude toward AI,
- Q2 - educational level of AI acceptance.

These data allow us to move from a qualitative analysis of distributions (Tables 2 and 3) to a quantitative interpretation of the relationships between the two levels of student adaptation to AI.

Table 4: Statistics for RQ1 and RQ2 responses.

Responses	**Gr-1**	**Gr-2**	**Gr-3**	**Gr-4**	**Gr-5**	**Gr-6**	**Gr-7**	**Gr-8**	**Gr-9**	**Gr-10**	**Gr-11**	**Gr-12**	**Total**
	The main statistical indicators for RQ1												
N	92	143	94	384	141	362	61	284	337	568	144	75	2685
M(x), %	76.36	76.57	68.09	81.05	65.96	66.57	83.20	79.05	70.40	76.76	73.09	78.67	74.55
δ_x, %	24.27	23.13	23.18	19.20	20.04	22.79	16.77	20.26	22.81	21.48	22.84	18.57	22.17
-	The main statistical indicators for RQ2												
N	93	143	94	384	141	364	61	284	339	568	144	75	2690
M(x), %	73.39	68.71	65.96	75.98	59.40	65.87	80.74	75.18	66.30	70.03	62.67	76.67	67.23
δ_x, %	27.39	26.52	25.49	24.09	23.36	25.69	20.94	22.98	23.71	25.49	29.17	23.92	25.04

Table 4 demonstrates high values for Q1 and Q2 (M(x)). The average values for all groups are within the following ranges:

- for Q1, in the range of 66%–83%,
- for Q2, in the range of 59%–81%.

The overall average level is M(Q1_total) = 74.55%, and M(Q2_total) = 67.23%. These values confirm that students generally have a consistently positive cultural attitude toward AI (Q1). They also significantly support the use of AI in the educational process (Q2).

The standard deviations δx indicate the stability of student assessments. The range of δx by group:

- for Q1: 16.77% - 24.27%,
- for Q2: 20.94% - 29.17%.

These standard deviations indicate that the spread for Q2 is higher than the spread for Q1. Therefore, students give more ambivalent assessments of the use of AI in the educational process than of their perception of AI as a technology.

A consistent trend is observed across all groups: the average value for cultural attitude (Q1) exceeds the average value for educational acceptance (Q2). The decrease from Q1 to Q2 ranges from 2% to 11% depending on the group. This is a key quantitative result: students perceive AI as a phenomenon more positively than its specific application in the educational process. This gap can be explained by the specifics of the transition from the digital logic of the fifth paradigm (AI is part of the infrastructure) to the cognitive logic of the sixth (AI is part of thinking and pedagogy). This gap is reflected in the coefficient B1 = Q2 / Q1, which is less than one in almost all groups. Therefore, the formation of a new cognitive scientific culture is already underway, although it is not yet complete. Both indicators are significantly above the neutral zone of 50%, confirming the pattern of high adoption rates characteristic of Zone 1 (Figures 2). A generalized representation of the relationship between Q1 and Q2 indicators for all countries is shown in Figure 6, where each point reflects the position of the corresponding university group in the Q1–Q2 model. Figure 6 demonstrates the pattern of student perceptions of AI during the historical transition from the fifth to the sixth technological paradigm (European countries are indicated by triangles. Circles indicate countries in Africa and Asia).

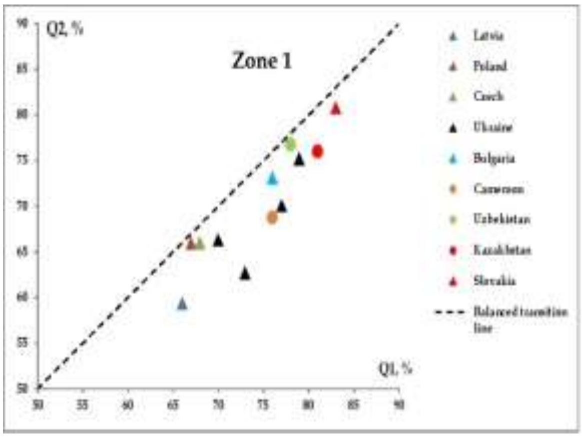

Figure 6: Model of student perception of AI at the time of the historical transition from the fifth to the sixth technological paradigm.

The position of countries in coordinates Q1–Q2 (Figure 6) reflects the level of cultural and educational adaptation to AI. All groups are located in the zone of high values of both indicators, while the shift of points below the line Q2 = Q1 indicates the rapid development of cultural acceptance of AI compared to its educational integration. So, all 12 respondent groups demonstrate high values for both cultural and educational acceptance of AI. We have strong empirical support for the transition to the sixth technological paradigm, obtained in quantitative form. The fact that no group fell into zones 2, 3, or 4 indicates the absence of systemic resistance or cultural barriers in the academic environment. Figure 6 also demonstrates the synchronicity of AI acceptance across different countries and cultural contexts. The position of the dots in Figure 6 shows that all respondent groups lie below the Y = X line. This fact corresponds to the quantitative result: Q2 < Q1. This result indicates that cultural attitudes toward AI are more developed than its actual use in the educational process.

Although coefficient B1 is not calculated, the shape of the dot cloud in Figure 6 clearly shows that Q2 is lower than Q1 in all cases. Only a few groups approach equilibrium, B1 ≈ 1. This situation is typical for Poland, the Czech Republic, Uzbekistan, and Slovakia. Thus, Figure 6 visually confirms the quantitative conclusion that B1 < 1 in all groups. However, the four aforementioned respondent groups suggest that in some countries, B1 = 1, ignoring random variations. It means that some countries may reach the "Balanced Transition Line" and experience a harmonious transition between the two levels of adaptation.

In summary, Table 4 and Figure 6 demonstrate a high degree of consistency between cultural attitudes toward AI (Q1) and educational acceptance of AI (Q2) across all respondent groups. The mean values of both indicators exceed 50%, so all points in the two-dimensional model fall in zone 1 (Figures 2 and 6). Therefore, students perceive AI as an essential part of the educational process. At the same time, the gap between Q1 and Q2 (Q2 < Q1 in all groups) reflects the characteristic phase of the transition to the sixth technological paradigm. Cultural acceptance of technology is developing somewhat faster than the integration of AI into the educational process. Thus, the model of an emerging cognitive scientific culture receives both visual and quantitative confirmation.

4.3. Testing statistical hypotheses for B1 = 1 and interpretation of the results

The statistical hypothesis test aimed to establish whether there is an empirical basis for asserting that certain countries exhibit a harmonious transition between the cultural level of attitudes toward AI (Q1) and the educational level of its adoption (Q2). This state corresponds to a coefficient value of the B1 = Q2 / Q1 = 1, i.e., a situation where the two levels of adaptation are equal in magnitude. From the perspective of the theoretical framework of the study and RQ3, this represents a state in which the emergence of a new cognitive scientific culture occurs without a gap between cultural and educational levels.

The interpretation of the test indicates that in the countries mentioned above (Poland, the Czech Republic, Uzbekistan, and Slovakia), the Z-statistic does not exceed the critical value of 1.96. Therefore, the null hypothesis is accepted: no statistically significant differences were detected between the mean values of Q1 and Q2.

This interpretation means that the countries are extremely close to the state of B1 = 1, i.e., demonstrating a balanced transition between the two levels of adaptation. From the perspective of the sixth technological paradigm, this configuration means that the technological implementation of AI in education does not encounter significant barriers or resistance. This configuration can be interpreted as the earliest phase of stabilization of a new cognitive scientific culture. Historically, these countries form a "line of equilibrium transition." They are the first examples of a cognitive balance between the perception of AI and its use in the educational process.

For the remaining groups of reviewers, |zstat| significantly exceeds the critical value. So, the null hypothesis is rejected and the alternative hypothesis is accepted. There is a significant gap between Q1 and Q2, with Q1 > Q2.

Students in these groups demonstrate the most pronounced gap between the cultural and educational levels of AI acceptance (B1 < 1). This outcome suggests a rapid cultural acceptance of AI as a technological solution, but a delay in educational adaptation to AI. In fact, Bulgaria, Cameroon, Kazakhstan, Latvia, and Ukraine are at a threshold stage of transition, where cultural acceptance of AI has already entered the sixth paradigm. Still, educational institutions remain partially within the fifth paradigm. This is a classic example of cognitive misalignment occurring in the context of accelerated historical processes.

For the overall sample, $|z_{stat}| = 133.644$, which is many times higher than the threshold of 1.96. This fact means that the null hypothesis is clearly rejected, and the alternative hypothesis is accepted. In other words, a harmonious transition has not yet been achieved in the international sample. This is not a weakness of the system. It is a natural structural effect of the historical transition between two technological paradigms.

Overall, the results of statistical hypothesis testing demonstrate significant differences between countries in the degree of alignment between cultural attitudes toward AI (Q1) and the educational level of its acceptance (Q2). For Poland, the Czech Republic, Uzbekistan, and Slovakia, the null hypothesis is accepted, indicating a state close to a harmonious transition (condition B1 = 1). In these countries, cultural and educational adaptation levels are developing synchronously, indicating the formation of a stable cognitive scientific culture.

For Bulgaria, Cameroon, Kazakhstan, Latvia, and Ukraine, the null hypothesis is rejected, indicating a statistically significant gap between Q1 and Q2 (condition B1 < 1). Despite high levels of cultural acceptance of AI, educational practices are adapting more slowly, a characteristic of the historical phase of transitioning from the digital logic of the fifth paradigm to the cognitive reasoning of the sixth. For the overall sample, the null hypothesis is also rejected. This observation confirms that a harmonious transition has not yet been achieved at the international level. The formation of a new cognitive scientific culture is in an active phase but is not yet complete.

Thus, the results of the statistical testing reasonably confirm the central conclusion of RQ3: the transition to the academic environment of the sixth technological paradigm is occurring, but unevenly, with a pronounced advancement of the cultural level of adaptation relative to the educational one.

5. DISCUSSION

5.1. Interpretation of RQ1: Cultural acceptance of AI as an indicator of a historical shift

The results for RQ1 demonstrate a consistently positive cultural attitude toward AI among students (Q1 is close to 75%). The dominance of the categories "definitely positive" and "rather positive" across all twelve groups indicates that AI has already become institutionalized in students' worldviews. The low proportion of negative assessments and the relatively high proportion of uncertain responses ("hard to say") indicate that cultural acceptance of AI is in its final stages.

Within the theoretical framework of the transition from the fifth technological paradigm (digital) to the sixth (cognitive), these results can be interpreted as confirmation that cultural adaptation to AI is developing more rapidly than institutional and pedagogical adaptation. In this study, cultural acceptance of AI serves as an early but stable sign of the formation of a new cognitive scientific culture, in which human interaction with AI is becoming a familiar norm.

5.2. Interpretation of RQ2: Educational Acceptance of AI as a Dimension of Institutional Readiness

Results for RQ2 indicate that educational acceptance of AI is also high, with the overall share of positive Q2 ratings exceeding 65%. However, unlike cultural perceptions, students exhibit a more critical attitude toward the inclusion of AI in educational processes. This fact is reflected in a higher proportion of negative responses (≈12%) and higher standard deviation values, indicating heterogeneity in perceptions and possibly the presence of specific pedagogical and organizational barriers.

This difference between the cultural and educational dimensions can be interpreted as a manifestation of the structural inertia of universities that still operate within the logic of the fifth paradigm. This manifestation refers to the perception of AI technologies as auxiliary tools rather than cognitive partners. The observed heterogeneity indicates that the processes of implementing AI in educational practice have not yet fully adapted to the requirements of the sixth paradigm. However, the high level of educational acceptance (Q2 > 50% in all countries) demonstrates students' fundamental readiness to transition to the demands of the sixth paradigm.

5.3. Interpretation of RQ3: The relationship between Q1 and Q2 as evidence of a cognitive emerging scientific culture

RQ3 examines the relationship between two levels of adaptation: cultural (Q1) and educational (Q2). A comprehensive analysis of mean values, visualization (Figure 6), and statistical verification of the hypotheses yield a clear conclusion: in the overall sample, Q1 > Q2, meaning that cultural acceptance of AI is developing faster than its integration into education. The coefficient B1 = Q2/Q1 is significantly lower than one for most countries. Testing the hypothesis B1 = 1 revealed that, in Poland, the Czech Republic, Uzbekistan, and Slovakia, the two levels of adaptation do not differ statistically significantly.

This result has important theoretical implications. The gap between Q1 and Q2 suggests that the educational systems of most countries remain in a state of institutional-cognitive mismatch, a phenomenon historically characteristic of phases of technological transition. The transition to the sixth paradigm necessitates a restructuring of pedagogical practices, methodological principles, and organizational structures, as cultural understandings of technology undergo rapid transformation. This transformation is occurring through the internet, academic and popular culture, as well as students' personal experiences with AI.

The fact that all points in Figure 6 are located in the high Q1-Q2 zone confirms that the transition to the cognitive model has yielded positive results. However, differences between countries in the Q2/Q1 ratio indicate that this transition is uneven. Some countries (Poland, the Czech Republic, Uzbekistan, and Slovakia) are showing signs of a nearly harmonious transition. Their university practices are catching up with the cultural acceptance of AI. In other countries (Bulgaria, Cameroon, Kazakhstan, Latvia, and Ukraine), education systems are lagging, reflecting institutional limitations, staff unpreparedness, regulatory gaps, or the lack of a comprehensive infrastructure. Thus, the results of RQ3 confirm the research hypothesis.

6. CONCLUSION

The study results showed that students' attitudes toward AI are characterized by a consistently positive attitude both at the cultural level (Q1) and at the level of its use in the educational process (Q2). Analysis of distributions, mean values, and positioning zones in the two-dimensional Q1–Q2 model confirms that all respondent groups are in the high adaptability zone. This model indicates the beginning of a transition to the cognitive logic of the sixth technological paradigm.

The results of statistical hypothesis testing indicate that cultural adaptation to AI is developing faster than educational adaptation (B1 < 1 in most groups). Poland, the Czech Republic, Uzbekistan, and Slovakia demonstrate a state close to an equilibrium transition, where cultural and educational levels of adaptation are almost identical. Other groups exhibit a discrepancy, reflecting differences in the rate of transformation of the cultural and academic environments. The combined responses to RQ1–RQ3 confirm that the formation of a new cognitive scientific culture has already begun, albeit unevenly.

6.1. Theoretical Implications

The study confirms that the transition to the sixth technological paradigm is a multilevel process in which cultural and educational adaptation develop at different rates. The presented Q1-Q2 model and coefficient B1 facilitate the analysis and understanding of the mechanism for the formation of a new cognitive scientific culture. These tools can be used to develop a theory of technological paradigms applicable to higher education.

6.2. Methodological Implications

Using the B1 coefficient as an indicator of the consistency of two levels of adaptation demonstrates high sensitivity and analytical precision. The two-dimensional representation of university groups along the Q1 and Q2 axes creates a new tool for comparative research. This tool can be applied in transnational and inter-university comparative analyses of cultural and educational levels of AI adoption.

6.3. Practical Implications

For universities, the transition to the logic of the sixth technological paradigm requires simultaneous work in two areas:

- strengthening the cultural acceptance of AI through digital literacy,
- accelerating the institutional integration of AI into the educational process, for both academic teachers and students.

The study's results show that, at a cultural level, students are already ready for a more systematic use of AI in the educational process. This result opens opportunities for developing new pedagogical practices, adapting educational programs, and creating infrastructure that supports AI-oriented learning processes.

6.4. Multilevel Recommendations

At the education policy level, the following are recommended:

1. Create a regulatory environment that encourages the responsible implementation of AI in education.
2. Consider international differences in B1 levels when creating global educational programs and initiatives.
3. Support universities in developing their own cognitive-oriented strategies.

At the university level, the following are recommended:

1. Improve the qualifications of academic teachers, reducing the gap between AI capabilities and their actual use.
2. Develop a unified AI integration strategy that integrates cultural, pedagogical, and technological aspects.
3. Create conditions for the development of a cognitive-oriented academic environment where AI is not a passive tool, but an active partner.
4. Actively integrate AI into the educational process at levels that meet student expectations and the requirements of the sixth technological paradigm.

At the research level, the following are recommended:

1. Analyze the impact of AI on students' cognitive performance over time.
2. Study the institutional factors influencing the gap between cultural and educational acceptance of AI.
3. Use the Q1-Q2-B1 theoretical model for more in-depth cross-cultural research.

At the level of academic teachers, it is recommended to:

1. Consider the gap between Q1 and Q2 in educational decisions.

Since the cultural acceptance of AI outpaces the educational acceptance, academic teachers should create conditions that enable students to translate their cultural acceptance of AI into real-world learning practices. This fact means designing learning tasks that incorporate AI, teaching students to evaluate the quality of their data, and developing students' skills in problem setting, argument validation, interpreting results, and critical analysis of digital solutions.

2. Support the development of a new cognitive scientific culture.

The academic teacher is a central figure in transforming the academic environment and culture. It is their pedagogical decisions that determine how students will perceive AI. Is it a threat or a component of a new pedagogical technology? The academic teacher sets the norms for human-AI collaboration. It also fosters an ethic of interaction and develops students' ability to think in partnership with AI technologies.

3. Develop their own digital and cognitive competence.

The transition to the sixth technological paradigm necessitates continuous professional growth, encompassing the mastery of new AI models, assessment methods, and skills in analyzing large datasets, as well as an understanding of the limitations of AI technologies. All of this is part of the new academic competence.

6.5. Limitations and Directions for Future Research

Despite the large scale and multicultural nature of the study, it has several limitations that should be considered:

- The sample is limited to students from nine countries, preventing the results from being generalizable to the entire global student population.
- The use of self-report scales may increase subjectivity; the large sample size mitigates this effect.
- Differences in national education systems, cultural norms, and digital infrastructure were not taken into account and may influence Q1 and Q2 scores.
- AI technology is a dynamic phenomenon. The study results reflect the state of affairs from 2023 to 2025 and may change as AI technologies continue to develop.

The presented limitations do not reduce the explanatory value of the results obtained, but outline directions for further empirical validation of the proposed Q1–Q2–B1 model.

First, expanding the geography of the study and including universities from other regions will allow us to test the stability of the identified relationship between cultural (Q1) and educational (Q2) levels of adaptation to AI in various institutional and sociocultural contexts.

Secondly, a promising direction is longitudinal analysis, which allows us to trace the dynamics of indicators Q1, Q2 and coefficient B1 over time. This approach will make it possible to empirically record how a new cognitive scientific culture is formed and stabilized as the transition to the sixth technological paradigm deepens.

Third, future research could focus on expanding the sample to include other academic groups (master's students, graduate students, university teachers), as well as taking into account institutional factors that influence the gap or consistency between cultural and educational levels of AI adoption.

Thus, the identified limitations should be considered not as weaknesses of the study, but as the basis for the consistent development and refinement of the Q1–Q2–B1 model within the framework of interdisciplinary studies of scientific culture in the context of AI-mediated transformation of education.

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