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SHOULD WE BE WARY OF USING ARTIFICIAL INTELLIGENCE-BASED BIG DATA MANAGEMENT IN SOCIAL RESEARCH?

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Abstract. This study examines the future role of artificial intelligence (AI) in transforming research processes within the social sciences, focusing on how AI may redefine researchers' responsibilities and potentially replace human participants in certain types of studies. Employing the Delphi method, the study collects expert opinions to evaluate both facilitating factors and barriers to the integration of AI into scientific research. Key findings indicate that while technological advancements – such as open-access data and the integration of AI with existing research tools – support the growing role of AI, significant challenges remain. These include the difficulty of verifying AI-generated information and concerns regarding authenticity in AI-driven research. Social factors, particularly the risk of excessive reliance on AI leading to diminished originality, emerged as critical barriers. In contrast, economic considerations, such as declining development costs, were viewed as less influential. The study's practical implications include the need for robust ethical guidelines and enhanced AI training for researchers. By offering original insights into the evolving intersection of AI and social science research, this study highlights both the transformative potential of AI and the urgent need for its responsible integration to preserve research integrity and reliability.

Keywords: artificial intelligence, research process, social science, Delphi method, social factors, economic factors.

JEL Classification: B40, B00, M00.

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1. Introduction

Over the past several decades, the social sciences have undergone significant development and transformation, reflecting broader changes in society, technology, and academic paradigms. Initially, these disciplines often focused on understanding social structures, behaviours, and institutions in relatively straightforward terms, often relying on qualitative methods like case studies and interviews. Gradually, the role of social sciences expanded. The digital age has further transformed social sciences. Natural language processing (NLP) techniques are revolutionizing qualitative research by automating the coding and analysis of interview transcripts, which enhances both the efficiency and accuracy of data interpretation (Siderska, 2020). These innovations contribute to greater methodological rigour in social research. They also offer new ways to investigate complex social phenomena with enhanced accuracy and scale.

The integration of machine learning and artificial intelligence presents itself as a potentially transformative development in the field of social sciences. This transformation encompasses two primary dimensions: firstly, the utilization of artificial intelligence as a novel research tool, and secondly, the application of social scientific methodologies to investigate artificial intelligence itself (Xu et al., 2024).

Artificial intelligence (AI) is reshaping scientific workflows by automating multiple stages of the research process. This shift may ultimately marginalise the role of researchers, reducing their active involvement to identifying scientific gaps and selecting research problems, with AI handling the rest of tasks such as literature review, hypothesis generation, data collection, analysis, etc. In this article, the term "marginalisation" is used to describe the decreasing involvement of human researchers in core stages of the research process due to automation. Related terms such as "automation" and "redefinition" refer respectively to the technical and conceptual aspects of this change.

Many research tasks have already been successfully automated to some degree, and this process is significantly accelerated with the rapid development of Large Language Models (LLMs) – advanced AI systems capable of understanding, generate, and manipulate human language with remarkable proficiency. They can perform various natural language tasks, such as text generation, translation, summarization, and question answering (Agüera Y Arcas, 2022). LLMs can further enhance this process by understanding the unique features and limitations of each database, adapting search queries accordingly, and even identifying potential gaps in coverage due to database embargos or indexing issues (Zhao et al., 2023). Furthermore, LLMs are able to automatically generate concise and accurate summaries of scientific articles (Liu et al., 2024; Pu et al., 2023; Tang et al., 2023), enabling researchers to quickly grasp the main points and assess the relevance of each article without having to read entire manuscripts. Other AI, aids in discovering symbolic models that capture nonlinear and dynamic relationships in social science datasets (Balla et al., 2022).

The examples mentioned above of AI applications in the research process are, on the one hand, a source of fascination; on the other hand, they highlight the progressive marginalisation of the researcher's role and raise important concerns about scientific responsibility

The Authors' research aims to address the following questions:

1. To what extent will the role of researchers be reduced or altered due to the integration of AI in scientific research?
2. Can sufficiently advanced AI systems serve as reliable models of social behaviour, potentially replacing human subjects or social groups in scientific studies?
3. What are the key barriers and driving factors that will shape these developments in the use of AI for social science research?

The remainder of the article includes the following elements: Section 2 literature review aimed at developing research hypotheses as well as identifying facilitating factors and barriers that may impact achieving the conditions reflected in the research hypotheses. Section 3 describing the research methodology, particularly the Delphi study. Section 4 presenting the research findings and discussion of the results. The conclusions, along with an indication of the study's limitations and future research directions, constitute the final part of the article.

2. Literature review

The automation of scientific processes has made significant strides in recent years, particularly in the realm of "hard sciences" (Siderska et al., 2023). More recently, DeepMind's AI models, AlphaProof and AlphaGeometry, have shown remarkable capabilities in solving complex problems in algebra, number theory, and geometry. This development marks a significant advancement in AI's ability to perform advanced mathematical reasoning, approaching levels comparable to human expertise (Google DeepMind, 2024). These advancements underscore the growing potential of AI in automating and accelerating scientific discovery across various disciplines.

Thesis 1: The role of social science researchers will evolve significantly with the advent of AI in the research process. The input of human researchers will be marginalized to the stage of identifying research gaps and selecting appropriate research problems. Meanwhile, specialized AI agents will increasingly take over other stages of the research process, including literature reviews, hypothesis generation, data collection, and results analysis. This marginalisation has the potential to dramatically increase the efficiency and scale of social science research. At the same time, it raises important questions about the nature of scientific inquiry and the role of human intuition in the research process.

Recent studies utilizing LLMs like GPT to simulate human behaviour in strategic games such as the Prisoner's Dilemma and Ultimatum Game have shown promising results. These models exhibit human-like behaviours influenced by assigned traits, react to other players' choices, and provide reasoning insights (Aher et al., 2023; Guo, 2023).

However, current AI models are not yet advanced enough to serve as reliable models of social behaviour. Same study done by Park et al. (2023, 2024) testing GPT-3.5 on psychology studies originally conducted with human subjects found that it could only replicate 37.5% of the results, lower than the replication rate achieved by lab-based human subjects.

Similarly, Phelps and Russell (2024) investigated GPT-3.5's capacity to operationalize natural language descriptions of cooperative, competitive, altruistic, and self-interested behaviour in the iterated Prisoner's Dilemma game. While the AI agents could distinguish between cooperative and competitive traits to some extent, they struggled to adapt their strategies appropriately in response to their partners' behaviours.

Despite these current limitations, the rapid development of AI could potentially lead to more reliable models of social behaviour in the future. Such AI-driven simulations could enable researchers to study social phenomena at an unprecedented scale and speed, while also reducing the ethical and logistical challenges associated with human subject research. Nevertheless, careful validation and alignment with human values will be crucial to ensure that these AI models accurately represent the diversity and richness of human social behaviour. These developments lead to the following thesis:

Thesis 2: Properly trained AI models will become sufficiently reliable representations of social behaviours to serve as substitutes for humans or social groups in research studies. This advancement has the potential to revolutionize social science research by enabling large-scale, controlled studies of complex social phenomena. However, it also raises important questions about the validity of AI-generated data and the ethical implications of replacing human participants with artificial agents in social research.

The scale and scope of AI utilization in social sciences research processes will depend on various factors that both limit and encourage the broader application of this technology. Based on the analysis of the literature, eight factors were identified as possible supporting factors (S) for the anticipated use of artificial intelligence in the social sciences:

(S1) *The decreasing cost of creating AI tools*. The field of artificial intelligence (AI) has witnessed a notable trend in recent years: while the aggregate costs associated with training large-scale language models continue to escalate, the efficiency of this process, measured in terms of cost per parameter (defined as the numerical values learned during the training process that determine a model's capacity to interpret input data and generate predictions), has shown significant improvement. An analysis of several prominent models developed between 2019 and 2023 illustrates this trend. The RoBERTa Large model, released in 2019, which achieved benchmark-setting results on numerous canonical comprehension tasks, incurred a training cost of approximately $160,000. This translates to a cost of $47 per 100,000 parameters. In contrast, the GPT-3 model, introduced in 2020, demonstrated a marked reduction in this metric, with a cost of $2.74 per 100,000 parameters. The trend continued with the release of GPT-4 in 2023, which, despite an estimated total training cost of $78 million, achieved a remarkably low cost of $0.08 per 100,000 parameters (Devlin et al., 2019; Li, 2020; Maslej et al., 2024).

(S2) *Rapidly increasing availability of data in open access* (e.g., scientific texts, statistical data, raw research data). Open access to scientific articles and data is supported by the European Union and individual member states. Open access to scientific information in research and innovation refers to 2 main categories: (1) peer-reviewed scientific publications (primarily research articles published in academic journals); (2) scientific research data: data underlying publications and/or other data (such as curated but unpublished datasets or raw data). Most public funding programmes for science include the need to allow open access to research results.

(S3) *Increasing integration of AI solutions with existing research tools* – The increasing synergy between AI technologies and traditional research tools is reshaping research practices across disciplines. This development improves data processing efficiency, enhances analytical depth, and facilitates the automation of routine tasks. As a result, research methodologies are evolving rapidly, unlocking new possibilities for collaboration and innovation (Vishnumolakala et al., 2024).

(S4) *Researchers' openness to using AI in scientific research* – When analysing the number of publications in the SCOPUS database within the field of social sciences that include the term "artificial intelligence" by year, it is worth noting a marked increase starting from 2018 (Figure 1). Over the last ten years, the number of these publications has increased more than 100-fold (2013 – 30 publications, 2023 – 3521). It is clear that more and more researchers are addressing the topic of artificial intelligence and using it in their research. The sharp increase in publications reflects not only a growing academic interest in AI but may also indicate a trend-driven dynamic, where attention to AI is influenced by external technological enthusiasm. This underscores the need for critical reflection to distinguish between enduring methodological shifts and short-term popularity

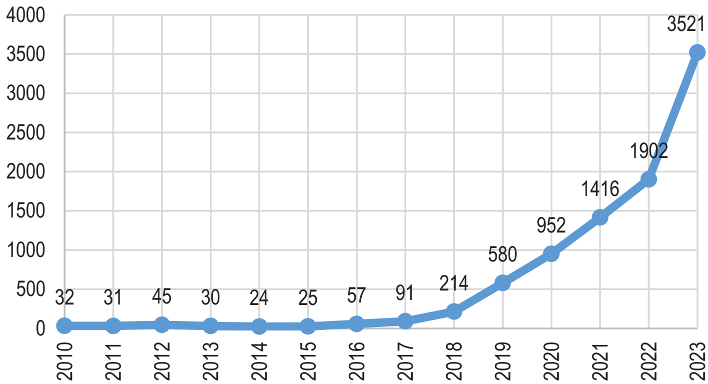

Figure 1. Quantitative analysis of the SCOPUS database from 2010 to 2023 (own elaboration based on SCOPUS)

(S5) *Increasing competition among AI tool developers, forces enhancements to AI reasoning capabilities.* The artificial intelligence (AI) landscape is experiencing rapid growth and intensifying competition, particularly in the development of foundation models. Maslej et al. (2024) report that 149 foundation models were released in 2023, more than doubling the previous year's output. These models, exemplified by GPT-4, Claude 3, and Llama 2, are trained on vast datasets and applicable across numerous domains. To maintain their competitive edge, AI providers continually expand their functionalities. For instance, OpenAI introduced GPT-4o in May 2024, enhancing processing speed and improving capabilities across text, voice, and vision (OpenAI, 2024a). Four months later, they unveiled O1-preview, designed for more comprehensive reasoning in complex tasks, particularly in science, coding, and mathematics (OpenAI, 2024b).

(S6) *Availability of workshops and courses on the use of AI for scientists* (enhancing their skills and competencies in research) – There are a many courses and trainings on how AI tools can be used in scientific work. Importantly, the courses are not only provided by private training companies, which scientists may not trust. Nowadays, many universities are also introducing courses in this area (e.g., Harvard, Boston University, University of Brimingham).

(S7) *Development of AI tools to support adherence to research ethics principles* – With the development of AI tools comes a development towards increasing the ethics of using AI solutions. Wong et al. (2022) in its study provides a critical analysis of 27 AI ethics toolkits, exploring how these tools envision and support the ethical work required in AI development. It identifies gaps in current toolkits, such as a lack of guidance on navigating organizational power dynamics and involving diverse stakeholders in ethical discussions (Wong et al., 2022).

(S8) *Ethical attitudes among scientists* – Scientists, by definition, act in an ethical manner. This translates into public trust in the profession. According to the IPSOS Global Trustworthiness Index 2023 Report, Scientists are the second most trusted profession (IPSOS, 2023, p. 6). It was described as trustworthy by 57% of respondents overall. Every article published in a scientific journal has to pass two reviews, and unethical behaviour carries with it major consequences for scientists. The ethos of science, as described by the high level of ethical behaviour is also influenced by the fact that, since the 1990s, ethics review committees have increasingly been established in the social sciences (Head, 2020, p. 72).

On the other hand, eight barriers (B) to the anticipated use of artificial intelligence in the social sciences were also identified, according to the hypothesis:

(B1) *Difficulties in assessing the credibility and quality of information generated by AI*. The phenomenon known as "AI hallucination" presents a significant obstacle to utilizing Large Language Models (LLMs) as reliable scientific tools. Studies across various domains, including finance Kang and Liu (2023) and scientific document reasoning Munikoti et al. (2023), have demonstrated that these models can generate convincing but factually incorrect or entirely fabricated information.

(B2) *"Political correctness" of AI* (introduction of bias into algorithms resulting from the subjective decisions of individuals preparing the training data). Motoki et al. (2024) found that ChatGPT exhibits significant political bias despite claims of impartiality. Using a novel empirical design, they discovered that the model consistently favours Democrats in the US, Lula in Brazil, and the Labour Party in the UK.

(B3) *Potential misuse of AI tools for manipulating research or creating false theories*. Research conducted by Májovský et al. (2023) demonstrated that an LLM was capable of producing a deceptively authentic-looking scientific article. The generated content closely mimicked genuine academic papers in its use of vocabulary, sentence construction, and overall organization. The AI-crafted piece incorporated typical scientific article components, including an introduction, methodology section, results, discussion, and even a data sheet.

(B4) *The risk of loss of authenticity and originality in scientific work* (caused by excessive reliance on AI-generated content). Language models do not have any knowledge, they aim to capture the probability distribution of words in a language to generate sentences and predict different word sequences (Hadi et al., 2023), however, the content appears to be genuine, and it is difficult to distinguish which is based on authentic data. In addition, artificial intelligence methods often operate in the form of so-called 'black boxes', meaning that users are unable to fully understand how the results were produced, or which inputs were crucial in the process of producing them. Lack of transparency in artificial intelligence models undoubtedly affects the risk of diminishing authenticity scientists applying AI solutions to their work.

In addition to concerns about authenticity, ethical discussions on AI in research increasingly emphasize the importance of transparency, explainability (XAI), and accountability. Recent initiatives suggest embedding ethical reasoning in AI models and enforcing institutional policies to ensure responsible AI design (Ungless et al., 2024; Chang, 2024a). Langer et al. (2021) conducted research on Explainable Artificial Intelligence (XAI), highlighting its potential to make artificial systems more understandable by providing explanatory information to human stakeholders. Their model offers a common ground for researchers across various disciplines engaged in XAI, emphasizing the interdisciplinary potential in both the evaluation and development of explainability approaches.

(B5) *Lack of knowledge about the capabilities and limitations of AI* (among some members of the scientific community) – Mökander and Schroeder (2022) point out in their study that a lack of technical knowledge can lead to "unsubstantiated fears about the social challenges posed by AI" or "unrealistic expectations" regarding its capabilities. In addition, Messeri and Crockett (2024) in their study describe the so-called illusion of objectivity, which is an illusion that accompanies scientists falsely believing that AI tools have no point of view or represent all points of view.

(B6) *Ostracism by the scientific community towards researchers using AI* – In the authors' experience, senior scientists have the greatest prejudice against those using AI tools. Senior academics who are used to more traditional scientific work use artificial intelligence to a lesser extent. Unfamiliarity with AI tools influences less trust in these solutions and, consequently, in the people who use them. The most prominent scientific journals add information about the use of AI in publications to their rules and regulations. For example, the journal Nature (Nature Portfolio, 2024) does not prohibit the use of AI tools, they allow their use if it is included in the Methods section (or other relevant section if no methods exist) of each manuscript. However, they indicate that when reviewing texts, the use of AI tools is not acceptable. While legal issues relating to AI-generated images and videos remain broadly unresolved, Springer Nature journals are unable to permit its use for publication.

(B7) *Increasing economic value of data on social behaviour, limiting the potential for AI development* – In the coming years, the economic value of data is poised for a significant surge, despite the ever-increasing volume of generated and collected information across both scientific and private domains (Taylor, 2025). This increase can be attributed to two primary trends: escalating demand for data and increasing data access restrictions. There is a rapidly growing need for data training of AI models. Concerns are already arising about potential data scarcity for training next-generation LLMs (Maslej et al., 2024). Beyond AI training, data is increasingly valuable for various business and research applications, including targeted marketing strategies and user experience enhancement (Napoli, 2023).

(B8) *Reluctance by institutions funding science to support social research using AI tools* – Institutional reluctance to fund social research that leverages AI tools reflects a complex set of concerns, from budgetary constraints to ethical considerations and perceived risks.

3. Research methodology

To addressing the research questions posed, the Delphi method was employed. The Delphi method is a structured communication technique originally developed as a systematic, interactive forecasting method that relies on a panel of experts. It is widely used in various fields, particularly in situations where precise data may not be available or where subjective judgments are crucial. The Delphi method is particularly valued for its ability to harness expert opinion systematically and to build consensus in areas where empirical data might be lacking or difficult to obtain (Szpilko, 2014; Ejdys et al., 2023). Currently, many researchers are using Delphi studies in the context of future applications of AI in various areas, such as achieving sustainable development goals (Ametepey et al., 2024), healthcare (Gupta & Srivastava, 2024), civil engineering (Hu et al., 2024), ethical challenges (Rokhshad et al., 2024). The choice of the Delphi method for this study, instead of other qualitative and quantitative approaches, was driven by its ability to systematically integrate expert opinions (through participation in two research rounds) in a novel research area concerning AI, where empirical data remains limited and difficult to obtain. Thus, a research process consisting of five stages was developed (Figure 2).

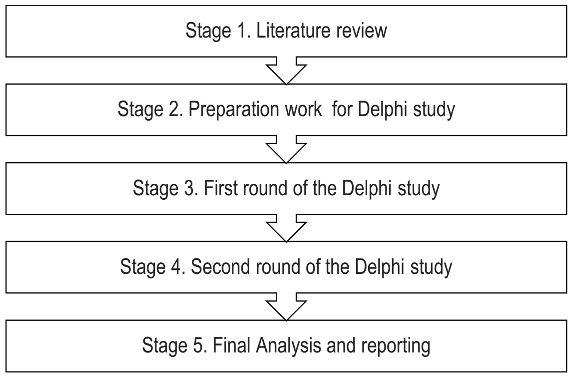

Figure 2. Research process

The literature review (stage 1) aimed to develop Delphi theses and identify factors that support and hinder their implementation. Two research theses have been formulated, along with 16 factors that could have a significant impact on them (8 supporting factors and 8 barriers).

The preparation phase of the research (stage 2) included the selection of experts and the development of the questionnaire for the Delphi study. The experts were identified based on keywords relating to the topic of the research in the Web of Science database. Thus, the first-round Delphi questionnaire was sent to a total of 465 Polish researchers in the social sciences. A group of experts with relevant knowledge and experience was selected to participate in the process. The selection of experts was purposeful. It included representatives from various disciplines within the social sciences, in particular sociology, economics and management sciences. This diversity was intended to provide a multi-faceted perspective on the issue under analysis. The selection criteria for experts included a minimum of five years of academic experience, having publications in the field of social sciences, and a Hirsch index of at least 3 in the WoS database. The structure of respondents was diverse in terms of gender, age, and academic qualifications. The use of an expert panel composed exclusively of Polish researchers entails certain limitations regarding the generalisability of the findings. Cultural, institutional and systemic differences in other countries may influence how AI-based solutions are perceived and implemented. Therefore, caution is advised when applying the conclusions beyond the national context. At the same time, the adopted research methodology can be successfully replicated in other countries. This allows for the verification of results and the comparison of perspectives in an international context. The second stage also included the development of a preliminary version of the Delphi research questionnaire.

In round 1 of the Delphi survey (stage 3), experts were given a questionnaire to collect their opinions, predictions or answers to the research questions. These initial responses were collected independently and anonymously. Each expert received an invitation that included a brief overview of the research and its primary goals, detailed instructions for completing the survey, a link to access the survey, and a unique token. For this phase of the study, 115 completed questionnaires were obtained.

To conduct the second round of Delphi thesis evaluation (stage 4), experts were provided with detailed results from the first round of the survey. Both the first and second rounds of the Delphi survey were administered using the CAWI (Computer Assisted Web Interviewing) method. The second-round questionnaires were sent to the same group of experts who participated in the first round. Similar to the first round, the invitation for the second round included: a thank you for participating in the initial round, a brief overview of the research and its main objectives, instructions for completing the survey, a link to the survey, and a unique token. Additionally, certificates of appreciation were sent to all participating experts. A total of 86 responses were received in the final round.

After the second round, the results were analysed and summarized (stage 5). The final report includes the consensus, range of opinions, and any insights derived from the process.

4. Research results

4.1. Significance of the theses

The significance indicators for two theses concerning the future role of AI in social science research were calculated. Thesis 2 received a higher significance rating from respondents (62.21). This thesis assumes that well-trained AI models will become sufficiently reliable to represent social behaviours and act as substitutes for human individuals or groups in research studies. In contrast, Thesis 1 received a slightly lower rating (56.69). It suggests that social science researchers will primarily focus on identifying research gaps and selecting relevant problems, while AI will carry out the remaining stages of the research process. The results indicate that experts currently consider the potential of AI to replace human research subjects as more significant than its role in supporting researchers throughout the process (Figure 3). This may reflect growing interest in the cognitive modelling capabilities of AI. Experts increasingly recognise its potential to simulate elements of human behaviour. This opens theoretical discussions about the boundary between simulated and real social actors.

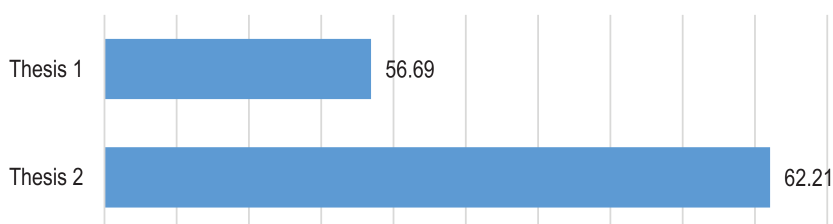

Figure 3. Values of significance indicators for the theses (own study)

Experts were asked to indicate when each of the two theses might be realised. In the case of Thesis 1, 52.33% of respondents indicated the period 2026–2030. This thesis assumes that researchers will primarily identify research gaps, while AI will handle the remaining stages of the process. Another 30.23% pointed to the period 2031–2040. Only 2.33% believed it would happen before 2025. At the same time, 12.79% stated that such a scenario would never be realised (Figure 4).

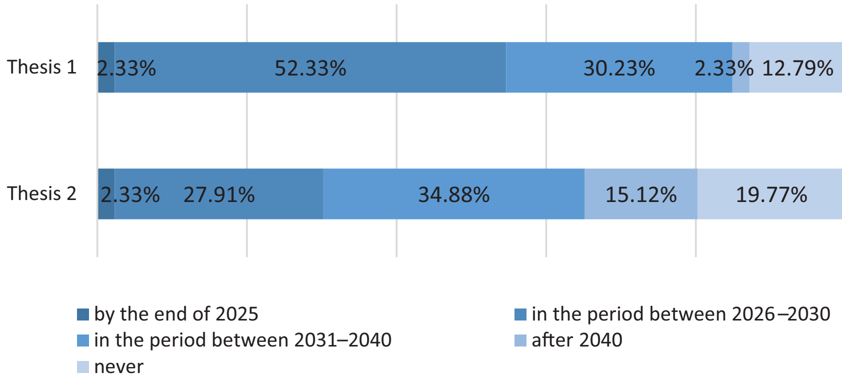

Figure 4. Timescale for implementation of the theses (own study)

The estimates for Thesis 2 were more cautious. This thesis assumes that AI will become a sufficient substitute for human or group subjects in research. Only 27.91% of experts saw it as likely between 2026 and 2030, while 34.88% pointed to the period 2031–2040. For 15.12%, the scenario might occur only after 2040. A further 19.77% believed it would never happen. These results suggest that the supporting role of AI in research is seen as more realistic in the near future than its ability to replace human participants entirely. These findings suggest a cautious practical stance among experts. They acknowledge technical progress in AI but question its readiness to replicate complex human behaviours. The perceived time frame reflects both optimism and restraint.

4.2. Supporting factors

Among the seven factors analysed, respondents rated "Growing integration of AI solutions with existing research tools" (82.97 for Thesis 1; 75.54 for Thesis 2) and "Rapidly increasing availability of data in open access" (81.04 and 76.65) as the most important (Figure 5). There are particularly relevant to Thesis 1, which assumes that researchers will focus on formulating problems, while AI will support subsequent stages. Access to data and well-integrated tools are seen as essential for such a model to work (Figure 5). This supports the idea that the adoption of AI depends on the broader research infrastructure. Well-integrated tools and accessible data are seen as basic enablers. They form the foundation for AI-supported research workflows.

Relatively high scores were also given to researchers' openness to using AI and the availability of training and workshops. These factors suggest that building competencies and positive attitudes among scientists are important in both theses.

The factor that received the lowest significance rating was "Ethical attitudes among scientists" (66.57 for Thesis 1; 61.80 for Thesis 2) which can be interpreted as suggesting that the ethical attitudes of scientists (concerning high levels of ethics) due to researchers' concerns may not support the realization of hypotheses generally reflecting the replacement of elements of the research process by AI. Without a doubt, the issue of scientists' ethical attitudes, as a factor either supporting or limiting the broader use of AI in scientific research, should be the subject of further and more in-depth studies.

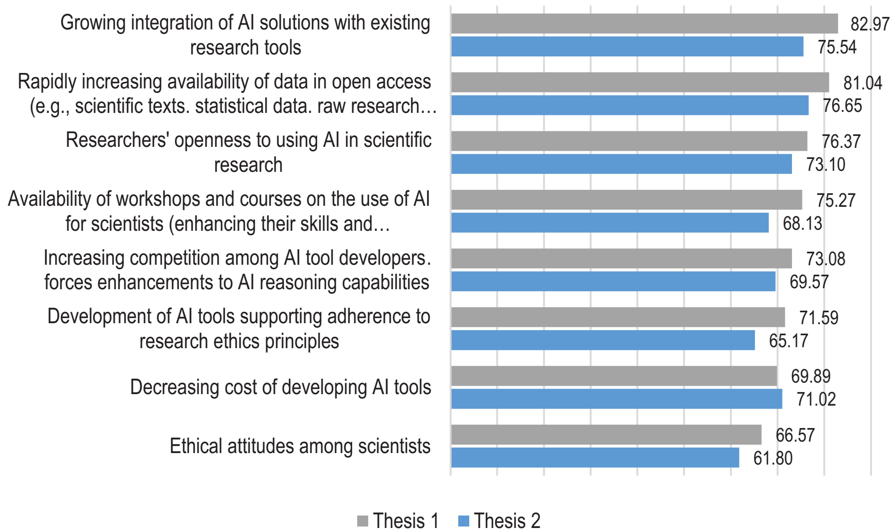

Figure 5. Values of indicators relating to factors supporting the implementation of the theses (own study)

4.3. Barriers limiting the realization of research hypotheses

Next, the barriers limiting the realization of research hypotheses were assessed. The most significant barrier for both Thesis 1 and Thesis 2 was "Difficulties in assessing the credibility and quality of information generated by AI", rated at 87.50 for Thesis 1 and 86.54 for Thesis 2. This result indicates widespread concerns about the reliability of AI-generated content in scientific contexts (Figure 6). This points to a fundamental problem of trust in AI-based knowledge. Researchers are wary of delegating control over the validation of scientific findings. This reflects deeper concerns about responsibility and credibility in AI-supported research.

For Thesis 1, the second most important barrier was "The risk of loss of authenticity and originality in scientific work (caused by excessive reliance on AI-generated content)", which received a high rating of 84.89. This highlights concerns that increased involvement of AI may reduce the unique contribution of researchers. It could also undermine their intellectual independence and weaken the creative dimension of scientific inquiry.

In the case of Thesis 2, the next highest barrier was "Potential misuse of AI tools for manipulating research or creating false theories", rated at 83.79. Since this thesis assumes that AI could substitute human participants, experts express particular concern about ethical risks. They also point to the potential for misuse or fabrication when AI takes on a central role in the research process.

Other barriers included the lack of knowledge about AI among researchers (72.01 for Thesis 1; 68.48 for Thesis 2) and "Political correctness" of AI, referring to algorithmic bias introduced through subjective training decisions, rated at 79.49 for Thesis 2. These findings suggest that beyond technical limitations, social and ethical issues remain major obstacles to the full implementation of AI in the research process. These barriers show that technical readiness is not the only challenge. Social acceptance and ethical preparedness are equally important. Researchers may resist AI integration if they lack trust in its transparency and fairness. Addressing these concerns requires both institutional frameworks and long-term educational efforts.

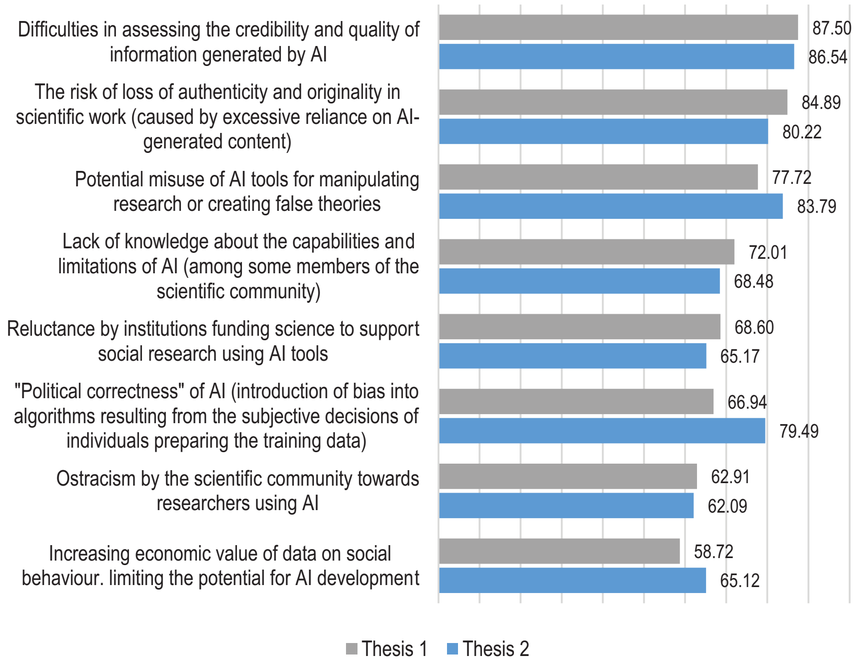

Figure 6. Values of indicators of barriers to the implementation of the theses (own study)

5. Discussions

The findings of this study suggest that the broad application of AI tools, which marginalise the researcher's role by reducing it to identifying knowledge gaps and selecting research problems, could significantly impact the shape of social sciences (Thesis 1). The significance index for this thesis was 62.21, with 51% of experts indicating very high or high significance (scores 1 and 2 on a 5-point Likert scale), while 22% indicated very low or low significance. At the same time, only 14% of respondents believed that the prediction in Thesis 1 would never materialize. The estimated timeframe for the realization of this thesis is relatively short, with 75% indicating that it will occur between 2026 and 2040.

The study also explored a more radical proposition in Thesis 2, suggesting that appropriately trained AI models could potentially serve as reliable substitutes for human subjects or social groups in studies. Regarding this scenario, experts demonstrated greater scepticism. The significance index for this thesis was noticeably lower, at 56.69. Only 40% of experts indicated very high or high significance, while the indications of very low or low significance were similar to those in Thesis 1 (20%). Additionally, a higher number of experts (compared to Thesis 1) believe that the prediction in Thesis 2 will never materialize (almost 20%), and if it does occur, it is expected to be farther in the future. Some experts highlight scepticism about AI's ability to understand and modelling human behaviour and emotions.

Categorizing the supporting factors and barriers into three groups enable gaining clearer insights into their relative impacts on the implementation of each thesis (Table 1).

Table 1. Categorisation of supporting factors and barriers

Group	Supporting factors	Barriers
Techno-logical	■ Growing integration of AI solutions with existing research tools ■ Rapidly increasing availability of data in open access ■ Development of AI tools supporting adherence to research ethics principles	■ Difficulties in assessing the credibility and quality of information generated by A ■ "Political correctness" of AI (introduction of bias into algorithms resulting from the subjective decisions of individuals preparing the training data)
Human/ Social	■ Researchers' openness to using AI in scientific research ■ Availability of workshops and courses on the use of AI for scientists ■ Ethical attitudes among scientists	■ Potential misuse of AI tools for manipulating research or creating false theories ■ Lack of knowledge about the capabilities and limitations of AI (among some members of the scientific community) ■ The risk of loss of authenticity and originality in scientific work (caused by excessive reliance on AI-generated content) ■ Ostracism by the scientific community towards researchers using AI
Economic	■ Decreasing cost of developing AI tools ■ Increasing competition among AI tool developers, forces enhancements to AI reasoning capabilities	■ Increasing economic value of data on social behaviour, limiting the potential for AI development ■ Reluctance by institutions funding science to support social research using AI tools

Technological aspects are perceived as the most important in relation to both theses, with these barriers being more significant for the more radical Thesis 2. Slightly less important is the group of supporting factors and human/social barriers (Figure 7).

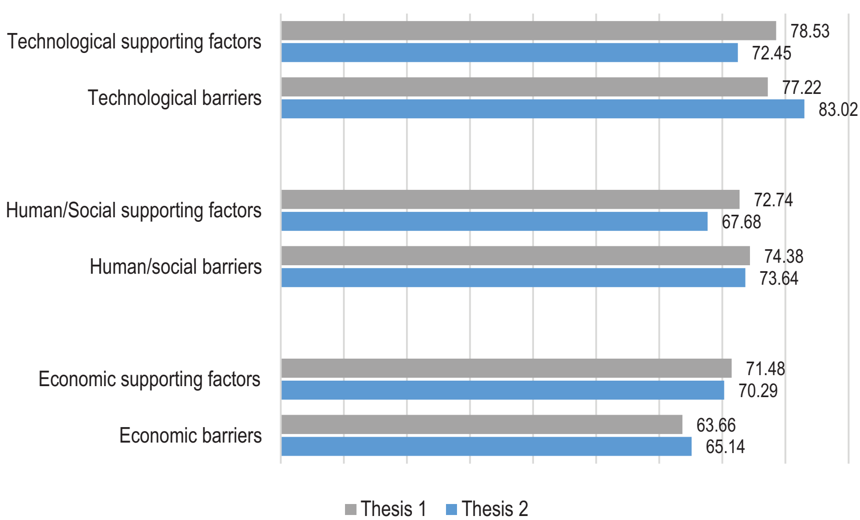

Figure 7. Values of groups of indicators (own study)

The results of the Spearman's rho test confirmed a statistically significant correlation between the expert evaluation levels of individual supporting factors and barriers with respect to both theses (Table 2). This suggests that experts perceived their significance in a similar way for both theses.

Table 2. Results of Spearman's rho test

Group of factors	rho-Spearman correlation (thesis 1 – thesis 2)
Technological supporting factors	0.491**
Human/social supporting factors	0.618**
Economic supporting factors	0.559**
Technological barriers	0.467**
Human/social barriers	0.608**
Economic barriers	0.681**

Note: ** the adopted level of statistical significance was 0.01.

5.1. Technological factors

Experts identified two key areas: (1) expanding the functionality of research tools through their integration with AI technologies and (2) increasing the amount of digital data available in open access.

Regarding the first issue, there is indeed an accelerating trend in integration. Example is the Web of Science Research Assistant, provided by Clarivate Analytics, which supports researchers in searching and analysing scientific literature (Buckland, 2023). On the other hand, a barrier in this area may be the current direction of AI technology development. Experts are particularly concerned about issues related to the reliability of AI-generated information, associated with language model hallucinations and political correctness bias. This issue poses a significant obstacle to using AI as a credible model of social behaviour, serving as a substitute for individuals or social groups in scientific research. The situation is worsened by the fact that currently available LLMs lack mechanisms for verifying generated content, which severely complicates researchers' ability to assess the credibility and quality of AI-generated information.

In terms of open access data availability, there has been an increase in the number of scientific publications available in this format. According to Scopus data, the annual growth rate of such publications averaged 18 percentage points from 2013 to 2024. In 2024, the ratio of scientific materials published in open access to those available by subscription was 1:1.5 in favour of the latter, whereas ten years prior, it was only 1:6.7. However, challenges remain, such as the slow growth in the availability of raw data for analysis. For example, only a few scientific journals require researchers to provide raw research data along with their publications.

A slightly less significant (though still important) factor was related to technological support for the ethical oversight of researchers using AI tools. Experts indicated that this issue should rely more heavily on legal and institutional solutions than on technological ones.

5.2. Human/social factors

Factors from this group are more often perceived by experts as barriers rather than as supportive elements for the realization of both theses.

The strongest barrier for Thesis 1 (84.89) is the risk of loss of authenticity and originality in scientific work (caused by excessive reliance on AI-generated content). This concern is supported by scientific literature and relates to the broader issue of researcher marginalisation in the context of automated knowledge production. Grimaldi and Ehrler (2023, p. 879) in their study indicate that one of the main risks associated with AI is the potential homogenization of writing style. AI, relying on vast data sets, tends to generate content that may blend into a uniform style, leading to a loss of individual characteristics and diversity in authors' writing. This could result in scientific papers losing the unique character expressed by researchers, especially in areas where qualities such as intuition or creativity are essential (e.g., conclusions, proposals for further research, etc.). Without systematic solutions to address this issue, researchers may hesitate to use AI in the ways suggested in Theses 1 and 2. This could also increase ostracism by the scientific community towards researchers using AI, which experts also identified as significant, though it has the least impact compared to other analysed barriers.

For Thesis 2, the most serious barrier is the potential misuse of AI tools for manipulating research or creating false theories (83.79). Even at the current stage of AI development, LLMs can generate texts that closely resemble scientific studies (Májovský et al., 2023). The ability to easily produce such texts increases the likelihood of unethical behaviour, not only from researchers but also from fraudsters and those spreading misinformation. In response to this problem, researchers are looking for practical solutions, both technical and institutional. The former include: embedding into LLMs ethical reasoning or ethical guardrails and model audits (Chang, 2024b; Pantha et al., 2024). The second group includes such solutions as: development of ethical frameworks and guidelines (Ungless et al., 2024), transparency and disclosure policies (Hartka, 2024).

The most important social supporting factors that could partially mitigate these barriers are researchers' openness to using AI in scientific research and the availability of workshops and courses on the use of AI for scientists. Given that texts on artificial intelligence in social sciences have been growing exponentially since 2017 (Figure 1), and an increasing number of well-known universities are offering courses and workshops on the use of AI in social sciences, this may lead to overcoming social barriers and realizing the proposed theses. It is also worth noting that researchers recognize a strong need for training on the use of AI tools in scientific work.

5.3. Economic factors

Economic factors are the least significant conditions for implementing both theses. Market competition, which drives continuous improvement in AI models' inferencing capabilities, is a more important supporting factor for the realization of Thesis 1. Conversely, the decreasing cost of developing such models is more significant for Thesis 2. However, in both cases, the differences are minor. Greater differences were observed regarding the barrier associated with the rising market value of data needed to train AI models. Experts view this phenomenon as a more significant barrier to creating reliable substitutes for individuals or social groups in research. This reflects a higher level of scepticism among experts regarding the feasibility of this scenario.

6. Conclusions

The research specifically focused on determining the role that artificial intelligence will play in the future in the context of selected processes for conducting scientific research in the social sciences. The findings highlight that, technological factors play a crucial role in supporting AI's application in research, which is related to growing integration of AI solutions with existing research tools and rapidly increasing availability of data in open access. Among the technological factors, barriers such as difficulties in assessing the credibility and quality of information generated by AI remain significant.

Social/human factors were more often perceived by experts as barriers rather than as facilitators for the application of AI in research. The strongest barrier is the risk of loss of authenticity and originality in scientific work (caused by excessive reliance on AI-generated content) and potential misuse of AI tools for manipulating research or creating false theories. Lack of knowledge about the capabilities and limitations of AI (among some members of the scientific community) remains also important.

The third group of factors – economic factors – plays not so much important role in the future applications of AI in scientific research. Factors such as: Decreasing cost of developing AI tools and increasing competition among AI tool developers were rated the lowest by experts in the category of factors facilitating ongoing changes.

Despite these insights, the study faces limitations. First, the sample of expert opinions may not fully capture the diverse perspectives across all scientific disciplines. The geographical homogeneity of the Delphi panel, which consisted exclusively of Polish researchers, is also an important limitation of this study. This introduces a potential sampling bias and limits the generalizability of the findings to broader international research communities. Second, the analysis is based on current AI capabilities and trends, which are evolving rapidly, non-linear and inherently unpredictable. Accordingly, the implications we have outlined should be treated as conditional on the ability of the research community to navigate these harsh conditions. Additionally, the reliance on self-reported expert opinions introduces the possibility of bias, as views may vary with personal or institutional experiences with AI.

The findings indicate a need for more precise training on the use of AI in social science research. This training should include how to assess the quality of AI-generated content, understand ethical risks, and use basic AI tools. It should be adjusted to different levels of experience and included both in university education and professional courses. Universities and research institutes should take the lead in these efforts. They should be supported by national research agencies and scientific associations. These institutions can offer practical guidance, promote ethical standards, and help manage risks related to the misuse of AI.

In this context, it is worth referring to existing ethical and regulatory frameworks. Examples include the UNESCO Recommendation on the Ethics of Artificial Intelligence and the OECD Principles on AI. These documents emphasise the need for mechanisms that ensure transparency and oversight. They also call for clear accountability in decisions supported by AI systems. Institutional safeguards, such as research ethics committees, can play an important role in reviewing and supporting projects involving AI. Including such tools in research practice may help to reduce the risk of unethical or unreliable use of the technology.

Future research should focus on addressing these limitations by broadening the scope of expert samples to include a more diverse range of scientific fields and geographical regions. Longitudinal studies could also provide insights into how these perceptions evolve alongside AI advancements. Further investigation is needed to explore how ethical guidelines, legal frameworks, and technological solutions can enhance the reliability of AI-generated content, which is essential for its broader acceptance in social science research. Expanding access to AI training and examining how social factors influence the adoption and ethical use of AI in research can also deepen our understanding of its long-term impact.

Furthermore, future studies should explore transnational comparative research to account for cross-cultural and institutional differences in AI adoption. Experimental research designs could also be employed to empirically assess the effectiveness and limitations of AI systems as behavioural substitutes for human participants in social science studies.

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