LUBELSKI ROCZNIK PEDAGOGICZNY
T. XLIV, z. 2 – 2025

DOI: 10.17951/lrp.2025.44.2.59-75

Remigiusz Żulicki
University of Łódź
ORCID – 0000-0003-2624-2422

SKEPTICAL TO AI LIKE A DATA SCIENTIST. RESULTS FROM A POLISH SOCIOLOGICAL STUDY OF THE SO-CALLED ARTIFICIAL INTELLIGENCE DEVELOPERS COMMUNITY AND SUGGESTIONS FOR ACADEMIC TEACHERS*

Introduction: Generative artificial intelligence (AI) systems have sparked another wave of enthusiasm toward AI. This article presents AI from a data science (DS) perspective. DS is involved in developing and implementing AI. In the social sciences, there has been significant interest in AI. However, little is known about DS as a research subject.
Research Aim: The aim of this study is to provide an analysis of the perception and understanding of AI from the perspective of the DS community. Insights can be useful in demystifying AI for non-technical audiences, especially for academic teachers and students.
Research Method: The research adopted a situational analysis approach with multi-site ethnography. In 2016-2019, methods included in-depth interviews (IDIs) with data scientists, participant observation of DS events and workshops, collaborative ethnography, autoethnography, and netnography. In mid-2023, informal interviews and a formal IDI were conducted.
Results: The DS community perceives AI as a non-technical marketing term for various technologies, including machine learning. Business spokespersons use the term "AI" to impress non-technical audiences. Evoking pop-culture images of AI creates an illusion of AI as magical. In contrast, the preparation of a machine learning model is seen in DS as laborious and experimental. Data scientists associate machine learning with Python, a programming language. On the other hand, DS associates AI with PowerPoint slides to illustrate the unrealistic or unclear promises made by spokespersons for commercial purposes.
Conclusion: Data scientists' skeptical approach to AI may help explain AI to non-technical audiences, including students. Practical suggestions for academic teachers are given.

Keywords: artificial intelligence, data science, critical data studies, magic, bricolage

* Suggested citation: Żulicki, R. (2025). Skeptical to AI Like a Data Scientist. Results from a Polish Sociological Study of the So-Called Artificial Intelligence Developers Community and Suggestions for Academic Teachers. *Lubelski Rocznik Pedagogiczny*, *44*(2), 59–75. http://dx.doi.org/10.17951/lrp.2025.44.2.59-75

INTRODUCTION

In recent years, so-called artificial intelligence (AI) systems have gained immense popularity worldwide (Van Noorden & Perkel, 2023). The emergence of generative AI systems, accessible to non-technical users on various devices, including mobile ones, has sparked another wave of enthusiasm (Sætra, 2023). In Poland, AI was chosen as the word of the year 2023 (Kruszyńska, 2024). Apple's new AI system is called Apple Intelligence (Apple, 2024). OpenAI's ChatGPT, one of the most popular generative AI tools, is breaking records in user acquisition speed. This OpenAI service reached 100 million users in just two months, while TikTok took nine months to achieve the same (Hu, 2023). The growing popularity of such services, aimed at a broad audience, has intensified media discussions about the potential benefits and threats associated with AI and the alleged socio-economic revolution that these technologies are supposed to trigger (Coeckelbergh & Gunkel, 2023).

The mainstream media rhetoric on AI oscillates between technological salvation and world annihilation, echoing religious discourses rooted in Western culture (Knapik, 2018). These discussions often occur without understanding the technologies that make up AI systems, relying primarily on pop-cultural images of autonomous machines (Knapik, 2018). Media messages created by representatives of technology companies also amplify these emotional narratives to increase their corporations' profits (Coeckelbergh & Gunkel, 2023).

The problem I see is that although AI is mainly based on machine learning (ML), which is a practical application of mathematical statistics and linear algebra methods on large volumes of digital data (see Goodfellow et al., 2016), the technical aspects of this technologies are not explained to non-technical users in an accessible and rational way. Instead, technology company representatives intensify emotions, present AI as a magical solution to crucial problems, and contribute to an enchantment of the world for commercial purposes. A vivid example of such enchanting through references to pop-cultural representations of AI is recent OpenAI's action regarding the voice feature of ChatGPT. The voice named "Sky" was possibly inspired by the film *Her*, an "AI love story" (Elliott, 2019) where Scarlett Johansson portrays a virtual assistant with whom the human protagonist falls in love. OpenAI CEO Sam Altman seemed to affirm these conjectures, referencing *Her* on social media, a film he has previously expressed admiration for. The company removed the "Sky" voice from the chatbot due to controversy over its similarity to Johansson, who had earlier refused to work with OpenAI (Griffin, 2024).

In this article, I propose to examine the so-called AI, both the technologies that create these systems and the term itself, from the perspective of the community that develops and implements these systems. This community is referred to as data science (DS). DS is a field of practice that combines computer science and statistics and is involved in developing and implementing AI from a technical and methodological standpoint (Grommé et al., 2018; Gutierrez, 2014; Lowrie, 2018;

O'Neil & Schutt, 2015). A data scientist, the individual engaged in DS, is not only an informal term for a community member but primarily a job title. Over a decade ago, DS was dubbed the sexiest profession of the 21st century, and subsequently, it was repeatedly recognized as the best job in the USA (Davenport & Patil, 2012; Junco, 2017; Piatetsky, 2018). Based on over three years of research on the Polish DS community, this article argues that the skeptical perspective of data scientists on AI can help demystify these overhyped AI tools for non-technical users, including laypeople, social scientists, academic teachers, and students.

In the social sciences, there has been significant interest in hyped technologies such as AI or, until recently, big data (Elish & Boyd, 2018). The major line of demystifying research in this field is critical data (or algorithm) studies (Crawford, 2021; Dalton et al., 2016; Dijck van, 2014; Iwasiński, 2020; Krzysztofek, 2015; Zuboff, 2019). However, little is known about DS as a main research subject. Few studies have qualitatively investigated the DS community (Grommé et al., 2018; Lowrie, 2016, 2017, 2018; Thomas et al., 2018), and previous research has not sufficiently included their viewpoint on AI. This gap is surprising, given that data scientists have direct agency over the "smart" components of AI systems through data work and machine learning model training. Excluding their perspective in social studies of AI is akin to excluding cooks' viewpoints in social studies of gastronomy.

While the use of generative AI in higher education is widely recognized as presenting both opportunities and challenges (Cotton et al., 2024), although elements of AI demystification are already appearing in teacher manuals on using and teaching generative AI (Łukawski et al., 2023), these works also do not refer to the perspective of data scientists. Thus, by incorporating the skeptical perspective of data scientists, this paper provides a critical framework that can aid educators in demystifying AI and enhancing the understanding of AI among students and teachers.

RESEARCH AIM AND QUESTION

The aim of this research paper is to provide an analysis of the perception and understanding of AI from the perspective of the DS community. This paper explores how the DS community, as the creators and implementers of AI systems, interpret and use the concept of AI, especially in the context of the hype surrounding it. The paper addresses the research gap in social studies of AI by including the viewpoint of data scientists, who have direct agency over the "smart" parts of AI systems – ML models.

The main research questions that guided this paper are:

RQ1: How do data scientists perceive and define AI?

RQ2: In what ways can the perspective of data scientists be utilized to demystify AI for non-technical audiences, particularly academic teachers and students?

This research aims to contribute to the social studies of AI by incorporating the overlooked perspective of the DS community. It seeks to provide a more nuanced understanding of AI, moving beyond the dichotomy of technological salvation and world annihilation towards a more realistic view of AI as understood by its developers and implementers. This research also aims to provide insights that could be useful for laypeople and social scientists, especially in AI education, for academic teachers and students to understand the realities of so-called AI. Some practical suggestions for teachers are presented in the concluding section of the paper.

RESEARCH METHOD AND SAMPLE CHARACTERISTICS

This study investigates the DS community in Poland, employing Clarke's (2003, 2015) situational analysis approach. The research main component was initially conducted for my PhD thesis and was the base for the book (Żulicki, 2022). It used heterogeneous data sources inspired by a multi-site ethnography (Clarke et al., 2015; Marcus, 1995) and took place between October 2016 and May 2019. In the qualitative part, methods included in-depth interviews (IDIs) with 26 DS participants, participant observation at 47 different sites (mainly DS events and workshops), and elements of collaborative ethnography, analytic autoethnography, and netnography (Anderson, 2006; Angrosino, 2010; Charmaz, 2006; Kozinets, 2003; Lassiter, 2005). Theoretical sampling was utilized, and the qualitative coding process adhered to grounded theory principles (Charmaz, 2006; Clarke, 2005). The research also incorporated a quantitative analysis of existing data from internal DS surveys and the meetup.com internet platform, which is not presented here due to the aim and scope of this paper. A detailed description of the research between 2016 and 2019 can be found in a dedicated methodological paper (Żulicki, 2024). Moreover, between June and October 2023 I did several informal interviews with data scientists. On the one hand, at the time I was receiving feedback on the newly published book from familiar members of the DS community. (The book, although published to be dated 2022, was available to readers in the spring of 2023.) On the other hand, I took the opportunity to update my insight into the DS community as to the opinions of experienced data scientists about generative AI. One of these collaborations turned into a recorded three-hour formal IDI with a seasoned DS professional who had not been interviewed during 2016–2019.

DATA ANALYSIS PROCEDURE

Situational analysis, a constructivist approach by Clarke, is designed to study social worlds/arenas within the grounded theory framework (Clarke, 2003, 2015). The social world is a social whole characterized by shared commitments to specific activities and a universe of discourse. It is not clearly distinguishable by geographical, membership, or other formal boundaries, with fuzzy and blurry boundaries determined by the interaction and effective communication of the participants (Clarke, 1997; Unruh, 1980). Numerous studies have used that concept to investigate social worlds, including computers (Kling & Gerson, 1978), tattooing and opera (Vail, 1999), and climbing (Kacperczyk, 2016). The defining feature of the social world, according to Strauss (1978), is the existence of one obvious primary activity, which becomes the criterion for distinguishing the social world (Kacperczyk, 2016). I framed the investigation of the Polish DS community as a situational analysis of a social world. I formulated the primary activity in the social world of DS as writing code for data processing, analysis, and modeling (Żulicki, 2022). I considered that limiting DS to an occupation, profession, or job title would close off the possibility of fully capturing this community, including the commercial field and academic, governmental, non-profit, and hobbies. However, I decided to limit it geographically to Poland due to organizational constraints and acculturation advantages.

RESULTS

The results of my research indicate that participants in the social world of DS do not seriously use the concept nor the term "AI" within their group. When they talk about AI among themselves, it is usually a joke or irony. However, the concept of AI is used in DS to communicate with non-technical audiences. Thus, AI functions in DS as a "packaging" (Kacperczyk, 2016, p. 45) for systems based on ML models and even for the activity of the DS world in general.

In commercial DS, the concept of AI is mainly used by business spokespersons of this social world. People in sales and marketing positions who formulate messages directed at clients of DS projects talk about AI. Such spokespersons can also be data scientists as team leaders or owners of small consulting firms: "As a consultant, I easily acquired clients with a piece of paper and a PowerPoint presentation because they did not distinguish AI from BI [business intelligence] and that from a bachelor's degree BS [Bachelor of Science]" (Foreman, 2017, p. 16).

Moreover, DS spokespersons can also work in human resources, formulating messages to people interested in a DS job. Therefore, AI as a packaging for the activity of the DS world is a packaging prepared for clients and future data scientists. A striking example of the fact that participants in the DS world perceive AI as a non-technical packaging for their technical activity, which consists primarily of writing code for processing, analyzing, and modeling digital data, is a humorous sentence that gained community popularity at the beginning of 2019: "The difference between ML and AI: If it is written in Python, it's probably ML. If it is written in PowerPoint, it's probably AI" (Alekseichenko, 2019). This "sentence" was uttered by Curt Simon Harlinghausen, who is not a participant in the DS world but an entrepreneur in the internet industry, during a speech at a non-technical conference. It was probably supposed to be a message to educate potential clients ordering services based on ML models. However, the "sentence" was adopted in DS. In 2019, it was repeated many times in IDIs:

> Researcher (Res.): So, I heard this joke that if it's machine learning, it's probably written in Python.
> Interviewee (Int.): [laughs]
> Res.: You know what I'm talking about?
> Int.: Yeah, and AI is in PowerPoint [laughs]
> Res.: Exactly. Could you explain this joke?
> Int.: Well, in my opinion, it's because people in marketing like to use the term AI because it sounds exotic. People have these images of artificial intelligence created by movies and media, so that's why PowerPoint is associated with a dynamic manager trying to sell you something, and machine learning sounds a bit more boring, and that's exactly the people who sit and code in Python (interview 20)

> Res.: Well, do you find the joke funny – artificial intelligence is written in PowerPoint, and ML in Python?
> Int.: No, because I do artificial intelligence in PowerPoint myself. C'mon, I'm joking [smiling]. Whenever I make slide decks, I say well, now I deal with AI [smiling]. It's a bit like that because we like to exaggerate (interview 22)

However, technically, using the term "AI" is not incorrect. ML is recognized as a sub-discipline of AI (Goodfellow et al., 2016; Raschka, 2018; Russel & Norvig, 2009). The term "AI" was not invented by contemporary marketers but almost seven decades ago by academic computer scientists (McCarthy et al., 1955) who wanted to give an umbrella term for their field. However, from the perspective of participants in the DS world, the term "AI" is so ambiguous and emotionally biased that its technical use cannot be accepted. From the perspective of DS, what is non-technically called AI does not exist.

Preliminarily, in the DS community, the approach to AI has not changed with the popularization of generative AI systems. In the IDI from 2023, the interlocutor presented a position consistent with the findings from the earlier part of the research:

> Int.: Corporate departments often compete doing the same things, so the concept of artificial intelligence is used to shine among other departments and organizations,

> which are not entirely able to identify that this concept is a little too general. (...) In my opinion, the statement that artificial intelligence is a PowerPoint slide or what metaphorically means such a marketing move is unfortunately still justified. (...) You can see a completely different language or such conceptual ranges used by, let's assume, managerial decision-makers, sellers, and domain specialists. We [data scientists] usually say: machine learning, this and that algorithm. On the other hand, the other side commonly uses the term artificial intelligence. And very often, we supplement someone's statement, which starts with the words: "We will make your artificial intelligence, which does something," and the specialist adds, "Yes, it will be a machine learning system working in this and that way."(...) I also laugh at this term [AI], and for me, if someone starts a conversation and uses the term artificial intelligence, it is most likely a person who does not know the subject or is trying to sell me something. This is a red flag for me right away. (interview 27)

That is why I call the data scientists' approach to AI skeptical – because they doubt the widely accepted term "AI" as too general, empty, and aimed at enchanting non-technical audiences. Participants in the DS world rather negatively assess the use of the term "AI" by their spokespersons to people interested in working in DS. Data scientists do not want people attracted to work by promises of AI in their teams. There is a belief in DS that it is better to avoid companies recruiting under the slogan "AI" with a small number of technical details in job offers. However, the term "AI" is used in the names of meetup groups dealing with DS, and attracting people interested in working in DS to meetings is one of the goals of companies supporting meetup organizations. AI is just colorful packaging for various systems that may or may not operate based on trained ML models. Among 2,800 European start-ups claiming to deal with AI, 40% seem to have nothing in common with even loosely defined AI systems. The term "AI" was used to increase the attractiveness of these start-ups in investors' eyes (Schulze, 2019). However, I have come across the opinion that without AI as packaging for DS, it would be impossible to operate on the market. According to one of the interviewees (interview 25), people dealing with DS must declare that they deal with AI; the "DS" term does not arouse clients' interest.

Regarding communication with clients, the term "AI" is assessed ambivalently in the DS world. Exaggerated expectations based on unclear visions and technical ignorance may attract them to start cooperating with companies offering services related to ML. However, many projects end already at the early stages, and clients may be disappointed with the lack of a solution to their business problem. Clients often have difficulty accepting the experimental nature of DS projects and the fact that even the most refined systems based on ML do not have 100% effectiveness. One of the interviewees (interview 22) believes that clients are becoming more and more educated. They start to perceive DS less and less as magic and more and more as tinkering.

In the work of data scientists, the execution of an ML model, which helps to solve a real problem and is suitable for implementation in business, requires a lot of tinkering. This work can be tedious and tiring, sometimes requires creativity and an unconventional approach, always involves a bit of experimenting, and its results are uncertain. However, data scientists indicate that clients and novice participants in the DS world perceive ML models as magically solving problems. Magical means not rationally explainable, miraculously working, on principle – take a problem, add ML, and problem solved. Magic means an alternative system of cause-and-effect sequences in which an impressive effect is achieved mysteriously; it is unknown how. This is a fetishization of ML models and, among clients, even a fetishization of their packaging, i.e. AI.

A fetish is a material object imbued with capabilities that are not inherently properties or functions of the object itself (Thomas et al., 2018). These surplus capabilities are generated at the intersection between individuals of different positions, expanding the scope of their social, cultural, and economic outcomes. This social, cultural, and economic contribution is mistakenly recognized as the promise of the fetishized object or replaced by this object. This replacement or misrecognition is effective in itself: the fetishized object enables something that would not have happened without it (Thomas et al., 2018).

Declaring that technology works magically is intended to evoke an association of impressive and trouble-free functionality. The end result of such technology is astonishing, and how the effect was achieved are irrelevant, even inscrutable. In the early 1970s, writer Arthur C. Clarke claimed that any sufficiently advanced technology is indistinguishable from magic (Elish & Boyd, 2018). Therefore, the magical operation has a positive connotation. It means that the technology is advanced and convenient, allowing its users not to worry about technical details but only to enjoy the effects of its use. A defining feature of magical technologies is also costlessness. The operation of magic is diminished by adverse elements, such as struggle and effort. Thus, the appeal to magic involves providing an alternative system of cause-and-effect relationships and diverting attention from the methods and resources technically necessary to achieve a certain effect (Elish & Boyd, 2018).

During the fieldwork, I was told that knowing about the fetishization of magical, advanced technologies on the client's side, data scientists may deliberately use more complicated tools or methods than the project requires. There is also a practice of packaging relatively simple solutions in declared "advancement," also in the communication of the DS team with the internal client:

> Int.: Our employer and budget provider is [company name]. From them, we get problems we must solve using tools, preferably more advanced ones. It is more advanced because then, of course, it looks nice on presentations [laughter], but generally, indeed, we use such machine learning things to solve it and then also to sell it nicely. (interview 18)

Tinkering is an analytical category modeled on the classic concept of bricolage and bricoleur by Claude Lévi-Strauss. In sociology, the categories of bricolage/bricoleur have been applied in information technologies, modern science, and engineering. Also, in DS, there is a bricolage activity consisting of using ready-made materials and adapting them to their needs, also contrary to the original purpose (Szpunar, 2012), and pragmatic manipulation of tools and apparatus in order to obtain working and reproducible systems, taking the form of testing various configurations of materials and techniques, which does not have to be accompanied by theoretical reflection (Afeltowicz & Pietrowicz, 2008). Like Zaród (2018), I confirm, based on DS, theses of Coleman and Söderberg that the creation and modification of tools are necessary for becoming a participant and participating in some social worlds. This phenomenon has been observed in diverse professional collectives such as engineers, hackers, researchers, and loggers (Zaród, 2018). However, tinkering in DS is not mythical, as opposed to science and engineering, as Lévi-Strauss wanted. This specific quality distinguishes DS from academic computational science and software engineering/development. In contemporary approaches, the category of tinkering refers to science and engineering (Afeltowicz & Pietrowicz, 2008). However, data scientists distinguish their social world from these fields also by referring to DS as a "more tinkering" community.

DISCUSSION

Presented results are partly in line with those obtained by some critical data scholars in social sciences (Crawford, 2021), philosophy (Hicks et al., 2024) as well as in computer science (Bender et al., 2021). However, these publications are not based on empirical studies of the DS community. Apart from academic texts, there are similar examples of AI skepticism arising from journalism authored by people representing technical communities close to DS (Kozyrkov, 2018; Lanier, 2023). Moreover, there are hints of such skepticism in non-technical AI education textbooks (Łukawski et al., 2023). Crawford (2021) argues that AI is neither artificial nor intelligent. Instead, it is embodied and material, constructed from natural resources and human labor. AI systems are not fully autonomous, rational, or capable of recognizing anything without extensive computational power for training on large data sets or without predefined rules and rewards. Contemporary AI is dependent on political and social structures. Due to the capital required to build large-scale AI and the recognition of scaling as a method of optimization of such systems, AI systems are designed to serve existing dominant interests simply because such dominant organizations have the capital for computing power and hiring data scientists. In this sense, AI is a record of power. Crawford's perspective challenges conventional views of AI as an independent and intelligent entity, highlighting its dependence on broader societal structures and power dynamics (Crawford, 2021). Thus, the practice of using AI as a marketing term that I have described in this paper may be interpreted as a practice of perpetuating the power of Big Tech companies such as IBM, Meta/Facebook, Alphabet/Google, Microsoft/OpenAI, Amazon or Tencent (see Luchs et al., 2023) and regarding fewer know organizations, a practice of fighting for power.

Last year's emergence of generative AI systems accessible to non-technical users does not change the presented arguments. A language model as a type of ML application used in services such as ChatGPT is just a statistical mechanism that links sequences of linguistic forms present in its training data. This is based on the probabilistic associations of these forms (Bender et al., 2021). This linking process does not take into account the meaning of linguistic forms. A language model is a "stochastic parrot" (Bender et al., 2021) – it reproduces language sequences based on their likelihood rather than a comprehension of their significance. This probabilistic way in which chatbots based on language models operate causes a problem called "hallucinations", "confabulations", and even "bullshit" production (Hicks et al., 2024). Leaving aside considerations about the most appropriate term to name this problem, these chatbots are not capable of being concerned with truth. They are engineered to generate fluent text that appears to be truth-apt but without regard for its veracity (Hicks et al., 2024). Although the authors do not criticize the concept of AI itself, I consider the two cited articles skeptical in the sense presented in this paper. Both rip off the colorful packaging of AI and reveal the technical limitations of the ML solutions used.

Cassie Kozyrkov (2018), a former Decision Scientist at Google, argued that AI has never been a strictly defined technical concept and functions as an umbrella term for ML, for deep learning – a subset of ML utilizing neural networks algorithms, and for reinforcement learning – approach for training models without data but predefined rewards. The author cites a sentence well-known in DS: "if it is written in PowerPoint, it is probably AI", however, she does not explicitly call AI a marketing term. She expresses acceptance of its loose usage in a non-technical discourse. Besides, she reminds readers that there was an "AI winter" period when the mainstream interest in those technologies and the term was reduced, while the opposite trend is currently occurring (Kozyrkov, 2018). Jaron Lanier (2023), a Microsoft researcher and essayist, entitled the cited work *There Is No A.I.* He names the term "AI" misleading and calls for its demystifying. Lanier highlights the saturation of pop culture visions of AI in data scientists and argues that mythologizing or demonizing the technology leads to irrational decisions, even in tech communities. Highlighting the probabilistic methods and the vast amounts of data that the so-called AI is based on, the author also calls for weakening the power of Big Tech by compensating people who are, in any sense, sources of ML training data (Lanier, 2023).

Elements of the discussed skepticism towards AI, on the example of chatbots, are also in the textbook addressed by the hitherto Ministry of Education and Science in Poland to teachers (Łukawski et al., 2023). Before the instructional chapters on prompting language models the authors explain that while those models can generate text and answer questions, they do not understand it like humans do. Models see text as patterns, not meaningful information. Despite seeming conscious, they are not. Models learn and adapt in a machine way, but they do not remember conversations. Their short-term memory is simulated by the web application used to interact with them, which summarizes and sends the entire conversation to the model for each query (Łukawski et al., 2023).

CONCLUSION

The research indicates that data scientists perceive and define AI primarily as a non-technical marketing term rather than a precise technical concept. Within the data science (DS) community, AI is often used humorously or ironically and is seen as a "packaging" for systems based on machine learning (ML) models. Data scientists view AI as a term employed by business spokespersons to impress non-technical audiences, while they prefer more specific terminology like ML when discussing their technical work. This skepticism towards the term AI stems from its ambiguous and emotionally charged nature, which contrasts with their work's precise and laborious nature in developing ML models. Additionally, data scientists highlight that executing an ML model involves significant tinkering, creativity, and experimentation, which is often misunderstood by clients and novices who perceive ML models as magical solutions to problems. These findings answer RQ1: How do data scientists perceive and define artificial intelligence?

Moreover, I would like the conclusion of this article to provide some suggestions for academic teachers, as in the work cited above (Łukawski et al., 2023). The suggestions are based on my research results and the critical literature presented in this paper. Regarding the teaching approach, I base it on two of Petty's (2013) principles of intelligible explanation: inferring from the concrete and relying on students' existing knowledge. The suggestions are aimed at demystifying explanation of AI to non-technical students, mainly in the field of social sciences, and may be used before or during the first practical instructions of prompting chatbots, generating images, or any other user-level tasks with so-called AI systems:

- the term "AI" is a non-technical umbrella term for various methods of computer task automation, and it has a marketing character; thus, it is aimed at persuasion, not only at information (explanation at the level of doctoral school of social sciences);

- so-called AI systems often operate thanks to statistical models that estimate a probable outcome, just like a weather forecast or a linear regression model; they can be wrong (for second-degree or uniform master's studies);
- like a washing machine is an automatic laundry device, ChatGPT and its friends is an automatic chatting and writing device; remember that a chatbot is a chatting robot, a conversational machine that works thanks to statistics and data (first-degree bachelor's studies, suitable for the freshman year before statistics or quantitative research methods courses).

I would also like to share three suggestions to consider regarding the general approach for teaching AI to non-technical students at any level of higher education:

1. Avoid emotionally charged language, do not uncritically present the discourse between AI salvation and annihilation, and do not instill fear of being left behind while the world moves forward.

2. Avoid anthropomorphizing AI systems; say "it generated…" instead of "he/she generated…"; do not say that the systems think, know, or want anything.

3. After an introductory, demystifying explanation of what AI is, try to avoid the term "AI" in favor of the names of specific systems, services, or technologies; as an umbrella term, consider the possible use of "so-called AI", which indicates skepticism about the unreflective use of the term in the mainstream sense.

The above suggestions can foster the learning process insofar as, in my opinion, they are geared towards a rational approach to AI. This rational approach is not fostered by either technophobia or technophilia, as was indicated long before the current AI boom (Szpunar, 2006). Provided suggestions answer the RQ2: In what ways can the perspective of data scientists be utilized to demystify AI for non-technical audiences, particularly academic teachers and students?

STUDY LIMITATIONS

The main limitation of this paper is the preliminary nature of the research, conducted during a new wave of increased enthusiasm for AI, particularly its generative variety. Another limitation is that I am not a trained educator or a scholar in higher education didactics. The suggestions presented here are soft suggestions from a sociologist who takes responsibility for the presented results of DS community research but makes suggestions to academic teachers only as one of them for further discussion and research.

Future research could quantitatively assess differences between AI education strategies in higher education. Considering the skeptical AI strategies proposed for teachers in this article as a starting point, it would be worthwhile to investigate the differential educational effects of conducting courses using various approaches. I would distinguish three approaches: skeptical, techno-enthusiastic/technophilic (emphasizing AI as salvation), and technophobic (AI as annihilation and fear of being left behind). Assuming a measurable educational outcome effect in the course, and with control of other variables such as the course's content, length, and participants' characteristics, that kind of study would allow answering the question of whether the advantages of a skeptical approach hypothesized here are confirmed empirically.

Moreover, social research is still needed in emerging professional communities working with AI systems, such as prompt engineers, but also in unexposed and underpaid ones, such as "click workers" labeling data. To my knowledge, there is also a lack of research presenting the perspective of those communities I call DS or AI spokespersons – CEOs, marketers, salespeople, and HR professionals. Insights from each of these groups could further demystify AI and further disenchant the world in the Weberian sense (Weber, 1989).

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SCEPTYCZNY WOBEC AI JAK *DATA SCIENTIST*. WYNIKI BADAŃ SOCJOLOGICZNYCH POLSKIEGO ŚRODOWISKA PROGRAMUJĄCYCH TAK ZWANĄ SZTUCZNĄ INTELIGENCJĘ I SUGESTIE DLA NAUCZYCIELI AKADEMICKICH

Wprowadzenie: Generatywna sztuczna inteligencja (AI) wywołała kolejną falę entuzjazmu wobec AI. Artykuł prezentuje AI z perspektywy *data science* (DS). DS zajmuje się programowaniem i implementacją AI. W naukach społecznych istnieje znaczne zainteresowanie AI, niemniej rzadko traktowano DS jako podmiot badań.
Cel badań: Celem pracy jest analiza odbioru i rozumienia AI z perspektywy społeczności DS. Wyniki mogą być przydatne w demistyfikacji AI wobec odbiorców nietechnicznych, zwłaszcza dla nauczycieli akademickich i studentów.
Metoda badań: W badaniu zastosowano analizę sytuacyjną wraz z etnografią wielostanowiskową. W latach 2016–2019 zastosowano metody wywiadu pogłębionego (IDI) ze specjalistami *data scientist*, obserwację uczestniczącą wydarzeń i warsztatów DS, etnografię opartą na współpracy, autoetnografię i netnografię. W połowie 2023 roku przeprowadzono nieformalne wywiady i formalne IDI.
Wyniki: Społeczność DS postrzega AI jako nietechniczny termin marketingowy stosowany dla różnych technologii, w tym uczenia maszynowego. Rzecznicy biznesowi używają terminu „AI", aby wywrzeć wrażenie na nietechnicznej publiczności. Przywoływanie popkulturowych obrazów AI tworzy iluzję sztucznej inteligencji jako magicznej. W przeciwieństwie do tego przygotowanie modelu uczenia maszynowego jest widziane w DS jako pracochłonne i eksperymentalne. Specjaliści *data scientist* kojarzą uczenie maszynowe z Pythonem, językiem programowania, AI zaś ze slajdami PowerPoint, które ilustrują nierealistyczne lub niejasne obietnice składane przez rzeczników w komercyjnych celach.
Wnioski: Sceptyczne podejście DS do AI może być pomocne w wyjaśnianiu AI odbiorcom nietechnicznym, w tym studentom. Podano praktyczne sugestie dla nauczycieli akademickich.

Słowa kluczowe: sztuczna inteligencja, *data science*, krytyczne studia nad danymi, magia, majsterkowanie