Borabay Erbay

research assistant of İzmir University of Economics,
Faculty of Arts and Sciences,
Department of Sociology,
İzmir, Turkey;
e-mail: borabay.erbay@ieu.edu.tr

Emin Baki Adaş

PhD, professor of Aydın Adnan Menderes University,
Faculty of Humanities and Social Sciences,
Department of Sociology,
Aydın, Turkey;
e-mail: eadas@gmail.com

Exploring Perceptions of Algorithmic Bias Among Software Engineers: A Case Study of Software Engineers in İzmir, Türkiye

УДК: 004.896(560)
DOI: 10.24412/2079-0910-2024-4-142-162

This study investigates how software engineers perceive artificial intelligence (AI) and algorithmic bias. The study explores whether the human-like characteristics of AI influence their engineering practices, which traditionally hold a dualistic view of technology and society. Based on semi-structured interviews with software engineers in İzmir, Türkiye, the findings reveal both similarities and differences between classical engineering and software engineering. Classical engineering views technology and society as separate entities, while software engineers adopt an ambivalent sociotechnical stance, acknowledging but neglecting their interconnectedness. Software engineers prioritize technical definitions and efficiency in assessing algorithms, often considering social dimensions secondary. However, they view algorithms not just as tools, but as codes shaping everyday life with social and cultural attributes. This departure from conventional understanding highlights the sociotechnical context in which software engineers operate. Moreover, the study shows that software engineers tend to interpret algorithmic bias through a technical lens, overlooking broader social and human contexts. These findings emphasize the urgent need to reassess the relationship between technology and society within the sociology of artificial intelligence, fostering a deeper understanding of sociality in software engineering.

© Эрбей Б., Адаш Э.Б., 2024

Keywords: Software engineering, artificial intelligence, algorithmic bias, technology and society, sociology, science and technology studies.

Introduction

The rapid advancements in digital technologies for the last two decades, particularly in the realm of artificial intelligence (AI) have brought about significant transformations in various domains, ranging from transportation and manufacturing to healthcare and finance. These technological innovations, such as intelligent medical systems, AI-powered financial brokers, several social media platforms etc. have been reshaping the economy, society, culture, and politics. The proliferation of AI based technologies and its ubiquitous presence in contemporary society have prompted a pressing need to comprehend the social and political dimensions associated with the algorithms driving these technologies. AI systems are operated through algorithms that depend on complex statistical modelling and probability to simulate human cognitive abilities through machine learning (ML) and big data [*Verdegem*, 2021, p. 9–10]. This article, through a case of software engineers working in the field of AI technologies in İzmir (Türkiye), examines the perception, interpretation, and experience of AI by software engineers, who play a vital role in the production of these technologies. Specifically, we would like to explore how software engineers interpret and make sense of algorithmic bias — the systematic deviance in the outcomes that algorithms produce — aiming to discern the underlying worldview that shape their understanding of the source of algorithmic biases. Of particular interest here for us is to explore whether the distinctive "human-like" features ('intelligence', 'language ability,' 'decision-making' and communicative interaction abilities) attributed to, and exhibited by AI technologies make any difference on their understanding of interplay between technology and society for software engineers.

Many studies on the history and worldview of engineers and engineering have consistently demonstrated that positivistic rational worldview has been the defining characteristic of the modern engineering habitus [*Ellul*, 1964; *Weber*, 2001; *Hughes*, 1986; *Bucciarrelli*, 1994; *Göle*, 2008; *Newberry*, 2015b]. This worldview operates under the assumption of a technology-society, or science-society dualism, which posits scientific facts and technological artifacts as objective and neutral devoid of any social, political and cultural values and power relations. Within the realm of engineering, efficiency and productivity form the bedrock values that inform the conceptualization of science and technology. This worldview, strongly intertwined with capitalist political and economic interests, we believe, is responsible for "technological fetishism" that has come to dominate modern society and culture. Drawing inspiration from Marx's concept of commodity fetishism, we argue that this perspective, deeply intertwined with capitalist interests and power relations, has given rise to what we refer to as "technological fetishism" —an ideological condition that defines technological products not just as 'collective libidinal objects' for progress and prosperity for entire humanity but also as independent entities detached from the social labor that produces them and separate them from society, politics and culture itself. Technological fetishism risks placing technological phenomena solely in the domain of the technical, which leads to a 'technochauvanistic approach' [*Broussard*, 2018]. As Broussard points out this technochauvanistic tendency among engineers creates a blind faith in technological solutions and overlooks the human experience and ethical considerations. In fact, Broussard's concept of technochauvanism constitutes the essence of what Sadowski aptly called as "Silicon Valley ideology." Sadowski defines this ideology as "a way of thinking, with its set of ideas, beliefs, values, and goals, <...> a contemporary update to an ideology called technocracy" [*Sadowski*, 2020, 66–67]. This ideology creates a condition for misrecognition for technologies such as AI and algorithms as solely technological entities that can be created and maintained with "correct" technical fixes, thus, undermining the social side of these technologies.

Drawing insights from the semi-structured interviews with software engineers we suggest that there is both continuity and emerging divergence between software engineers and classical engineers in terms of their conception of technology. The difference between classical engineering and software engineering regarding the understanding of technology stems from the complexities surrounding the 'human-like' characteristics of AI technologies. While overarching conception of technology-society dualism still powerfully informs software engineers' understanding of technology as solely technical artifacts, as several narratives from our interviews with them reveal this dominant disposition of engineering, the metaphors such as 'intelligence,' 'learning,' 'speaking,' 'decision-making' and so on frequently used by AI communities to describe AI technologies force some software engineers to reckon with symbolic characteristics of algorithms and these technologies as they anthromorphize their relationships with these technological products. For instance, as we will show in the following paragraphes, some software engineers in their narrative posed themselves as 'parents' or 'masters' who trained 'a child' or 'apprentice' during our interviews. This glimpse of departure from the conventional understanding, we believe, reflects the unique context of software engineers, wherein the technical-rational worldview extends beyond the boundaries of their professional domain and permeates into their social perception and practices as the technological products they work on imbued with symbolic cultural qualities. Nonetheless, we observe that the software engineering community in Türkiye tends to perceive algorithmic bias through a predominantly technical lens, largely disregarding its inherent social, political and cultural dimensions. In this regard, the findings of this study parellel with previous research, indicate that engineers often exhibit exceptional proficiency in technical matters but display limited social perceptiveness. Algorithmic bias, commonly regarded as an issue arising from technical deficiencies or inadequacies, is frequently divorced from its broader social and human contexts. Hence, software engineers remain predominantly preoccupied with system efficiency and optimal functionality, while aspects associated with social, political and cultural dimensions of bias are often overlooked.

The essay is structured as follows: After briefly discussing the history and development of AI we provide a literature review that examines the theoretical foundations of both classical engineering and software engineering, highlighting the similarity and contrasting perspectives on the relationship between technology and society. This review establishes the context for understanding the tensions that shape software engineers' understanding of algorithms and AI. Next, we outline the methodology employed in this study, which involved fieldwork conducted with software engineers in the field of AI technologies and applications in İzmir, Türkiye. We describe the data collection process, including interviews and observations, and the analytical framework used to interpret the findings. We then present the empirical findings, which offer insights into software engineers' perceptions and interpretations of algorithms, AI, and algorithmic bias. These findings reveal the distinct dimensions of software engineering and the inherent sociotechnical sociality within the field. The implications of the study's findings are discussed, emphasizing the need to reevaluate the relationship between technology and society within the sociology of AI. We highlight the significance of exploring the technosocial context of software engineers and propose avenues for future research. Finally, we conclude by summarizing the key insights gained from this study and underscoring the importance of further investigation into the complex interplay between software engineering, AI, and society.

Engineering AI: A Theoretical Overview

Although the concept of machines is closely intertwined with modernity and advanced technology, the notion of creating a machine capable of independent thinking and action predates the advent of modern technology by a considerable margin. From ancient Greek myths to the Enlightenment era, various historical periods have witnessed the conceptualization of thinking machines endowed with autonomous agency. These "thinking" machines were envisioned as guardians of divine treasures, entrusted with objectively resolving human disputes or even as rivals or companions capable of engaging in games with humans [*Buchanan*, 2005]. Even in these early conceptions, predating the era of significant technological advancements, machines were perceived as entities engaged in human interaction while maintaining mechanical precision, impartiality, and occasionally displaying superhuman qualities. Hence, machines were seen as possessing both technical and societal characteristics. The creation of a machine that can genuinely emulate human thought processes remains an elusive goal, as it appears to be impractical under current circumstances. Nevertheless, AI stands out among the technologies produced by humanity due to its capacity for human-like learning, decision-making, and interaction, which imbues it with a distinctly social character.

As a conceptual framework, the term "AI" first emerged in discussions during the early decades of the 20th century. Over a span of approximately 65 years, it rapidly evolved from theoretical inquiries into its feasibility to the practical implementation of rudimentary decision-making systems, subsequently progressing towards the development of comprehensive AI systems capable of multifaceted interaction with humans. Similar to any technological advancement, the trajectory of AI technology has experienced fluctuations influenced by economic and social conditions. Despite gaining significant attention following its conceptualization in 1956, a prolonged period of stagnation ensued due to the incomplete understanding of the technology and the failure of its outcomes to justify the allocated research budgets [*Haenlein, Kaplan*, 2019]. Starting from the 2000s, and particularly from 2010 onwards, advancements in computer hardware technologies, notably central processing units (CPUs) and graphics processing units (GPUs), coupled with the ubiquitous proliferation of the internet, facilitated an exponential growth in data collection and processing capabilities. These developments propelled AI research into a new phase, enabling scientific and technological advancements in the field to surpass all preceding eras. Consequently, the rapidly expanding AI industry, fueled by economic growth, along with diverse applications spanning numerous domains of societal life, has transcended the confines of the laboratory to become an integral part of the social fabric [*Sheikh et al.*, 2023].

AI, in its broadest sense, can be defined as a system that emulates human cognition and, to some extent, autonomously performs human-like tasks [*Ibid*., p. 16]. This system, or ensemble of systems, operates based on the principle of processing large datasets through algorithms to identify specific patterns within the data and utilize these patterns in decision-making processes, akin to the way humans make decisions. The method employed in obtaining these patterns is referred to as machine learning. Therefore, the fundamental components constituting AI systems are big data, algorithms, and machine learning [*Russell, Norvig*, 2020]. The working mechanism of AI demonstrates its inherently social character among all technologies developed thus far. Simply put, the learning and application processes of AI exhibit a sociocultural character reminiscent of the human mind. Data serves as the foundational knowledge that enables AI to interpret and understand the world in a manner similar to how a human does. The algorithms that instruct how to detect patterns embedded in the data allow AI to acquire predispositions shaped by specific conditions, akin to how a human develops a habitus [*Airoldi*, 2022]. The decision-making and evaluation mechanisms of AI operate based on these predispositions. In other words, data-driven algorithmic learning processes endow AI with a social character.

Although a relatively new technology, the history of AI is shrouded in mystery and myths. As Natale and Ballatore observed, the narrative on AI revolves around a discursive shift and the prediction of future rather than what is happening now; turning shortcomings of present into expectations of future that creates an unrealistically intelligent and independent AI myth, which shrouds the reality on AI [*Natale, Ballatore*, 2020]. This myth of AI finds its foundations in the intertwinement of different spheres, such as the AI science itself and media [*Natale*, 2021]. Moving on with that, the "decision-making" capability of AI is misrecognized. Thus, AI is percieved as possessing an human-like agency capacity. That gives rise to the neglect of the human factor behind it and leads to attributing a "human-like" character to it, ultimately creating a "black box society" that is beyond human perception or, even if perceived, not fully understood, and regulated by algorithms [*Pasquale*, 2015]. In a broader context, perceiving technological advancements and "technological things" as black boxes, positioning technology as a representative of order, impartiality, and efficiency, which are perceived as independent from value judgments and devoid of social and political character, creates an effect that obscures the social character and functions of technology. This has been one of the fundamental issues in the sociology and philosophy of technology even before the advent of AI. The concept of technological neutrality, based on the idea that technological things are independent of value judgments, hold no intrinsic value, and hence are not of social and political nature, forms the foundation of this perception [*Pitt*, 2014, p. 90]. Following the line of thought encapsulated by the central argument and slogan "guns don't kill people, people kill people" [*Ibid.*], technological things are reduced to mere instruments that are entirely shaped by the intentions of their human users, thereby detached from their societal contexts [*Miller*, 2021].

The emerging field of the sociology of AI, built upon a body of work focused on various applications of AI in the social realm and analyzing the consequences of these applications through humanist-oriented studies and discussions on the agency capacity of AI within posthumanist-oriented studies, is relatively new. While humanist-oriented studies operate within the ontological and epistemological assumptions of mainstream sociology, posthumanist-oriented studies emphasize the excluded aspect of "things' agency" neglected by mainstream sociology. The dominant paradigm in AI sociology appears to be the humanist-oriented approach, which examines AI and algorithms in the context of their social impacts and focuses on diverse implementations in social domains [*Adaş, Erbay*, 2022]. The literature stemming from this paradigm consists mainly of studies aiming to reveal the role of algorithms and AI in reproducing and deepening social inequalities and studies aiming to depict its social character [*Broussard et al.*, 2013; *O'Neill*, 2016; *Eubanks*, 2017; *Beer*, 2013, 2017; *Benjamin*, 2019; *Airoldi*, 2022]. The perception of AI and algorithms as a "black box" makes it difficult to define them. Therefore, in order to comprehend the concept of algorithmic bias, which is the focus of this study, it is necessary to provide a definition that relates algorithms to AI. An algorithm can be defined as a component of an AI system that guides the system to follow a specific path to achieve desired patterns and outcomes [*Lupton*, 2015]. In a sociological context, algorithms are described as the regulators and filters of datasets, imbued with specific contexts, enabling AI to "make decisions" based on them [*Beer*, 2013]. In this sense, algorithms are defined as the digital manifestation of human beings [*Lupton*, 2015]. The capacity of algorithms to perform actions and indirectly interact with humans is an indication of their social character [*Beer*, 2017]. Sociological studies embark on the premise of this assumption when analyzing the social impacts of algorithms in various contexts.

The social character and effects of algorithms are addressed within sociological studies in two fundamental contexts. The first context involves the influence of the algorithm's creators, namely humans, and their social/cultural characteristics on algorithms. The second context examines the impact of the cultural/social characteristics of the fundamental source of algorithms, namely data, on the social character of algorithms. In line with the idea of technological neutrality, which asserts that technology itself and technological tools cannot possess a social or political character and that all sociopolitical aspects are determined by the intentions of the human [*Pitt*, 2014], algorithms are positioned against human vulnerabilities such as arbitrariness, error-proneness, and intentionality. They are presented as carriers of stability, order, and impartiality reminiscent of a machine system, detached from human influence [*Airoldi*, 2022, p. 37]. This perception, combined with the notion that technology itself and technological tools cannot carry inherent value [*Pitt*, 2014], creates a myth of AI and algorithms as entities capable of fulfilling human tasks completely independently, thereby obscuring their social dimensions and presenting them as metaphysical entities beyond humans and all things human [*Hoffman et al.*, 2022]. However, sociology, which aims to bring the hidden into visibility, takes a contrary position to this idea by asserting that technology itself is a social and political phenomenon, and therefore, technological tools also possess social and political character. For example, designing underpasses in a certain area of a city at a height that prevents public transportation vehicles from passing while not impeding access for private vehicle owners can clandestinely perpetuate class or ethnic distinctions [*Winner*, 1980]. A speed bump on the road can enforce compliance with state-imposed speed limits without requiring direct supervision by any human authority [*Latour*, 1994]. A microscope can enhance human perception by making organisms visible that cannot be seen with the naked eye [*Latour*, 2000]. In other words, technological tools and technology itself shape human perception through their filters, presenting not reality itself, but a framed version of reality [*Heidegger*, 1977]. In this context, technological tools are not disconnected from the social and political context; on the contrary, they possess social and political character. Furthermore, when considering the social and political character of technology, it is essential to take into account the predispositions and inclinations engineers acquire throughout their professional education. Engineering is built upon a sociotechnical fabric grounded in a social/technical dichotomy, thus the analysis of their political worldview is as important as the analysis of their sociotechnical engagement [*Ellul*, 1964; *Hughes*, 1986].

Behind the myth of AI as an entity independent from humans, as mentioned above, lies the influence of humans as inherently biased beings in social and cultural contexts. Algorithms and AI carry traces of the social world, just like the individuals who write, code, and create them. Therefore, algorithms cannot be value-neutral and unbiased; on the contrary, they necessarily carry values and biases [*Joyce et al.*, 2021]. Moreover, the datasets that form the fundamental source of algorithms, determining what and how they "learn," are created by humans, making neutrality impossible [*Panch et al.*, 2019]. While these characteristic features give algorithms a social character, they also pose a risk of deepening and reproducing existing inequalities in the social sphere [*Broussard*, 2018]. The social effects generated by algorithms, which cannot be conceived independently from humans, have been extensively examined in various domains, considering both design and operational contexts. For example, Eubanks' study [*Eubanks*, 2017] demonstrates how algorithms forming facial recognition systems deepen ethnic and class discrimination by bringing it into the digital realm within the context of security applications. Furthermore, an investigation into the general relationship between big data and algorithms highlights the perpetuation of racism through these technologies in the digital world, strengthening existing social inequalities [*Benjamin*, 2019]. Analyzing the use of algorithms in the workplace, another study reveals that employees are forced to conform to mechanistic conditions dictated by algorithms, leading to dehumanization and the imposition of algorithmic precision in labor processes [*Crawford*, 2021]. All these examples underscore the significant impact of algorithmic bias in the social sphere.

The rich vein of sociological studies on technology in general, AI in particular reveal how technologies are embedded in cultural, political and economic power relations. Burrell and Fourcade shows how the world of coding and algorithms acquire their social character as they are intrinsically embedded in cultural, political and economic powers [*Burrell, Fourcade,* 2021]. Following this argumentation, in our perspective, it is mandatory to understand how software engineers, as the main creators of algorithms and AI conceptualize the notion of bias since it is the "human" factor, the individuals who write, code, and create algorithms and AI systems, that embodies the social character of these technologies [*Joyce et al.*, 2021]. Studies conducted on classical engineering demonstrate that engineering has its own sociotechnical character [*Ellul*, 1964; *Hughes*, 1986; *Bucciarrelli*, 1994; *Newberry*, 2015b]. This sociotechnical character encompasses the tension between the rational-technical engineering perception, which embraces order and efficiency as its core value, and the chaotic nature of the social world [*Bucciarelli*, 1994; *Faulkner*, 2015; *Newberry*, 2015a]. In other words, engineering imposes a techincal-rational worldview, which propels engineers to solve problems in the most analytical manner possible while disregarding the complexity of the social realm [*Bucciarelli*, 1994], presenting it as a path to achieve the highest degree of efficiency, which is the fundamental value of engineering [*Newberry*, 2015a]. This model presents technical excellence as the key to efficiency, starting from the design and production processes of a product, and erects a wall between the engineer and the social dimensions of their creation. Behind this wall, the engineer becomes distant from contemplating the social dimensions of their creation [*Winner*, 1986], assuming an attitude of social indifference commensurate with their extensive knowledge of how technological tools are created and function [*Devon*, 2004].

Studies describing the sociality of engineering are predominantly built on classical engineering [*Bucciarelli*, 1994; *Hughes*, 1986; *Newberry*, 2015a; 2015b]. However, software engineering, which is the form of engineering that writes and codes algorithms, creates AI, appears to differentiate itself in technical and social contexts in some aspects compared to classical engineering. This differentiation can be considered from two dimensions. Firstly, unlike classical engineering disciplines such as machinery, construction, and industrial engineering, software engineering is not obligatorily based on formal engineering education. Therefore, it is debatable to what extent self-taught software engineers without formal education are involved in the aforementioned technical-rational engineering perception. Secondly, software engineering differentiates itself in the context of the products produced compared to classical engineering. For instance, a mechanical engineer has no human-like interactions with the engine they produce, and a civil engineer has no human-like interaction with the building they construct. However, a software engineer can interact with the algorithms and AI systems they create in a human-like, anthropomorphic manner. Although the interactive capacity of AI suggests that software engineering may have a different dimension within the sociotechnical character than classical engineering, software engineering is perceived similarly to classical engineering, where the technical dimension is highly dominant, and the social dimension is equally recessive [*Robinson*, 1990].

The two main forms of differentiation mentioned above, especially the capacity of AI to interact with software engineers in a human-like manner, suggest that software engineering may have similarities as well as differences compared to classical engineering. Therefore, sociology needs to analyze the social interactions of AI in the production field and decipher the sociotechnical character of software engineers who produce it, thus emphasizing the importance of focusing on the production field of AI as much as its social effects. As mentioned earlier, studies and theoretical approaches in the literature prioritize the analysis of the social effects of AI in the sociological approach. However, this situation carries the risk of concealing the specific sociality of software engineering and not fully understanding the social character of AI. While the question of how AI has social effects constitutes the central area of discussion, the question of why the technology has the capacity to create these effects is often overshadowed, and its social character is accepted as an inherent truth. In this context, the analysis of the worldview of software engineers who produce AI, their interactions with the “thing” they create, the exploration of their sociality, and the understanding of the background of the social effects created by AI and algorithms are crucial aspects that sociology should address.

Method and Data

This study is a descriptive research conducted with the aim of exploring how software engineers understand and define algorithmic bias and how this conception affects the reproduction of bias in AI. We aim to shed light not only to identify the factors that contribute to the emergence of algorithmic bias but also to answer the question of why algorithms contain bias. For this purpose, both the worldviews of the individuals who write, code, and deploy algorithms, namely software engineers and their connection to the social world needs to be examined. In this context, the qualitative method, which is used to describe and explain a social phenomenon as well as its underlying causes and subjective perceptions of social actors, namely software engineers, forms the methodological basis of this study [*Konecki*, 2017, p. 34]. The adoption of the qualitative method in the study is deemed suitable because it allows for the analysis of the subjective perceptions of engineers and their engineering practices.

The study is based on a purposive sampling of software engineers who reside and work in Izmir, Türkiye. İzmir is the third largest metropolitan city of Türkiye housing eight public and private universities and four technoparks/techno-centers affliated with these universities that aim to promote colloboration between science and technology. In addition to the private companies operating in these technoparks, there are several independent software development companies in İzmir, which develop AI technologies in health, defense, smart manufacturing sytems, education, and transportation [*T.C. Cumhurbaşkanlığı Bilim*..., 2021]. While the majority of AI-related companies are located in Istanbul and Ankara, the research is conducted in İzmir solely out of convenience as both of the authors reside in Izmir area. Since the aim of the study is to understand how question of algorithmic bias is perceived by the software engineers, a purposive sampling strategy, which is expected to obtain the most comprehensive data related to the research problem, has been adopted as the main sampling technique. In the selection of the sample, in order to understand the influence of engineering education on the perception of algorithmic bias, it was aimed that all participants have received formal engineering education, with a minimum requirement of a bachelor's degree, have graduated from software or computer engineering departments of universities, and actively work in the field of AI. Residing in Izmir was considered as a prerequisite during the sampling process to increase the accessibility to the participants. No sectoral boundaries or gender quotas were set in order to ensure the generalizability of the obtained data to all sectors and genders, and in this context, achieving maximum diversity was targeted.

Semi-structured interviews were used as the primary data collection tool, which was expected to be suitable for the aforementioned descriptive and exploratory purposes of the qualitative method. In line with the study's objective, a interview guide consisting of questions under four main topics was designated: the nature of engineering education, conceptualization of AI and algorithms, the connection between AI and ethics, and algorithmic bias. During the interviews conducted with all participants, this interview guide was followed, and additional questions were asked when necessary within the topics to understand the participants' perceptions and the influence of their worldviews on these perceptions. The interviews lasted between 60—75 minutes and were conducted face-to-face. All participants were provided with information about the research in advance, and an informed consent form was delivered and signed before the interviews. Audio recordings were made during the interviews, and the recordings were transcribed using the transcription method and presented in textual form. Extensive notes were taken during interviews with participants who did not give consent for audio recording.

The sample of the study consists of 21 software engineers, 17 of them identify as men and 4 identify as women. This distribution indicates that the field of software and computer engineering is structured as a male-dominated field, consistent with studies indicating gender inequality in this field [*Chang*, 2019; *Campero*, 2021]. When examining the professional distribution of the participants, it is observed that 4 of them hold academic positions in software engineering departments at universities, 2 work as analysis engineers in research centers, and 15 are employed as software engineers in various fields such as design and control in the private sector. As mentioned above, as a result of the purposive sampling strategy chosen as the sampling method, all participants have at least a bachelor's degree in computer or software engineering. This suggests that the value of efficiency, which is a fundamental value of engineering [*Newberry*, 2015a], will be highly significant and dominant over other values. It is known that particularly in the private sector, efficiency is closely related to the fundamental motto of capitalism, which is profit maximization.

The findings of the study were obtained through content analysis of the 21 semi-structured interviews after being transcribed into text format. Three main themes were derived from the conversion of codes obtained from the analysis of the texts into themes. Among these themes, efficiency stands out and appears as an overarching theme that influences all other themes. The participants' discourse in the interviews indicates that efficiency shapes their definitions of algorithms and AI as algorithmic realities, as well as their perspectives on algorithmic bias and AI ethics. The prominence of efficiency as a powerful theme that influences all other themes can be associated with engineering education and the sociotechnical sociality learned during this educational process. The findings of the study will be discussed around these three themes.

The Roots of Efficiency Fetishism in Engineering

Engineering is a highly technical-rational domain that exists in a sociotechnical world where society and technology are intertwined [*Hughes*, 1986]. In this context, it is structured by teaching its members the idea that problems can be solved using the tools of mathematics and analytical methods, thereby juxtaposing the disorderly, arbitrary, and chaotic nature of society with the orderly and efficient character of technology [*Faulkner*, 2015; *Newberry*, 2015a]. Naturally, no one is born an engineer, and the "learning" of this social character of engineering is necessary. This learning process, which starts the quest for efficiency and is characterized by the dominant techical aspects is closely linked to education [*Noble*, 1977], just like any other learning process. In this regard, the technical and analytical, rational character of formal engineering education plays a crucial role in acquiring this social character. The points emphasized by the participants when discussing their educational experiences highlight the highly technical-rational worldview instilled by engineering education. All participants responded with "mathematics" when asked about the fundamental science underlying software/computer engineering education. This becomes evident when participants are asked to describe their educational backgrounds:

> *The foundation of engineering education lies in advanced mathematics. We took advanced mathematics courses in the first two semesters, followed by courses that encompassed the technical applications of software in the curriculum. These applications are based on mathematical models, so having knowledge advanced mathematics is a prerequisite above all* (P12, 32, Academician[1]).

The format of education is built upon mathematics and structured in a highly technical manner. Within this technical and rational education, an engineer also learns that efficiency is the most important value. All tasks must be carried out efficiently and delivered on time. The efficient use of time appears to be the initial step toward efficiency becoming a fundamental value.

> *The technical intensity was extremely high, of course. Applied courses were demanding at a certain point, I remember. You were expected to complete an assignment in these courses, and you had a limited time to meet the deadline. We often stayed up all night because it took a long time, and it had to be completed before the deadline* (P12, 32, Academician).

Engineers who learn efficiency as a value undergo an education that focuses on maximizing this value. In engineering education, where technical applications and mathematical precision prevail, the social and ethical dimensions of the issue are — at least in the categorization of social scientists — excluded from formal education. When asked if they have tak-

[1] The participant list is applied at the very end of the paper.

en a course on AI ethics, the response received was that there is no such course in the curriculum that would encompass the entire sample. This situation, similar to classical engineering, limits software engineers' development of a limited perception of the social dimension [*Joyce et al.*, 2021, p. 5], confining the engineer to being the individual who technologically implements the requirements of a (specific) task [*Goldberg*, 2006]. The technical-rational worldview that constitutes the social character of engineering is acquired through education and, after education, transitions into professional life in a similar manner, transforming the software engineer into a master of efficiency. From a sociological perspective, the more significant aspect of this process is that the efficiency-based technical-rational worldview takes shape and structures the engineer's perception of everyday life and social concepts.

Efficiency and the Conceptualization of Algorithms and AI

Another finding of the study is that engineers relate the meanings attributed to engineering concepts to everyday life, evaluating both the concepts of engineering and everyday life through the lens of efficiency. This reflects the distinct sociotechnical sociality of the engineering world [*Hughes*, 1986] in a clear manner. This finding is evidenced by the definitions of the concepts of algorithm and AI provided by the participants. When defining AI and algorithms, software engineers draw attention to the algorithmic reality of everyday life before delving into their technical definitions:

> *We can think of it as a typical day we live. Everything we do after waking up is algorithmic. You wash your face, drink water, have breakfast, go to work; everything we do throughout the day is algorithmic, from getting out of bed in the morning until getting back into bed at night* (P2, 33, Academician).

Even when transitioning to the technical definition of algorithms, the connection to everyday life is maintained, and metaphors from everyday life are used. This seemingly simple situation reveals how engineers perceive the world in the tension between the technical and social dimensions and how this tension creates an intertwined sociotechnical reality:

> *An algorithm can be defined as a series of steps that need to be followed for solving a problem. It is not limited to being associated with computers only. Cooking is also an algorithm; a product is produced by following specific steps. Of course, we do this using programming languages in our profession. It is possible to write an algorithm in multiple languages and then ensure that the computer follows it. One of the essential things about algorithms is that we do not want them to carry any indecisiveness so that the computer can define and follow them* (P3, 27, Private Sector).

The requirement for algorithms to be free from indecisiveness clearly indicates an emphasis on efficiency in the technical-rational world of engineering. An algorithm should function as efficiently as possible so that it can perform the task it was designed for accurately and precisely. Here, efficiency, highlighted as one of the foundational elements of engineering identity by Newberry [*Newberry*, 2015a], appears to have assumed the status of a fundamental value. The concept indicates a technical precision devoid of indecisiveness, where the emphasis lies on working not just the fastest or the most comprehensive but rather the most efficient way. Similarly, the definitions of AI provided by the participants resemble the definitions of algorithms, encompassing a highly technical precision, efficient functioning, and decision-making guided by this efficiency and technical precision. All participants comprising the sample emphasized the aspect of "decision-making" when discussing AI. This ability to make decisions, again, is described as a series of technical steps that operate efficiently and encompass the necessary decisions in light of this efficiency and technical precision:

> *AI can be defined as a system or set of systems capable of making decisions, perhaps without human intervention. However, this decision-making process takes place with a predetermined decision path and decision trees, unlike humans. People often confuse AI with the 'if' command, but they are not the same. For example, if the doorbell rings three times, notify that the homeowner is not home; this is not AI, it is an 'if' command. For us to talk about AI, the system needs to make decisions within a context* (P5, 37, Private Sector).

The definition of AI as a system capable of making decisions within a context evokes a technological conception of AI that Airoldi [*Airoldi*, 2022] referred to as AI habitus, which acknowledges the undeniable social character of AI in relation to humans, or Jaton's [*Jaton*, 2020] notion of algorithms that act in conjunction with humans, benefiting from and providing benefits to human agency. However, with a further explanation of the context, it becomes clear that the mentioned context refers to correct modeling and appropriate techniques, embodying an analytical and rational engineering concept:

> *After the data collection and processing process, you need to choose a model that suits your problem. There are previously tested mathematical models that can be used to solve your problem. Of course, this is a somewhat experimental field. A model that yields correct results in one case may not yield the same accuracy in another case, or by modifying certain aspects of the model, you can achieve much better results* (P1, 35, Private Sector).

The context is seen to be constituted by the mathematical models and the technical "truths and falsehoods" taught to AI. These truths and falsehoods must be organized through calculable and accurate technical interventions to form an efficient whole. Even in describing the unsupervised learning method, which seems to be the form of machine learning furthest from human influence, the "motivations" of AI during the learning process are attributed to mathematical precision and the most efficient form of learning:

> *We have software in our hands, and first, we need to see what this software can do in the (digital) environment. We can achieve this through supervised or unsupervised learning, and we need to decide on that. If we choose supervised learning, we will have to sit down and teach, saying this is that, that is this. If we are going to use unsupervised learning, we say, 'Here is the environment, and here you go, explore'. The software is left in an environment and learns by itself. Some actions are predetermined and coded, and if it performs the correct actions, its score increases. It decreases the score with incorrect actions. You say to AI, 'Our goal is to increase the score'. As it performs the actions that increase the score, it becomes inclined to perform those actions on its own* (P2, 33, Academician).

Once again, the perception of engineers is shaped by the technical precision and mathematical certainty that efficiency provides as a fundamental construct. The "correct" actions that AI must perform to increase its score actually refer to the most accurate mathematical models, accurately written code, and efficient methods. The technical-rational worldview of engineering is the primary structuring force in defining concepts and processes. However, the findings on algorithms and the production of AI indicate that engineers interpret these concepts in a highly “human” context within this technical-rational perception. This demonstrates that AI occupies a different position from the traditional productions of engineering and is directly attributed a quasi-social character by software engineers. In a sense, AI becomes a social actor that is nurtured and developed by its creator through data. So much so that one of the participants, who developed a chess application for his masters thesis, stopped playing chess after being unable to defeat the AI they created:

> *It made me feel very weird. First, chess died for me. Then I realized that, when you make the right move, you end up with a draw. All moves can be planned in advance. If you have a powerful supercomputer, you can think of all the moves you can make and make a move against it, and your best outcome is to end up with a draw* (P2, 33, Academician).

The story of an engineer who cannot defeat their own creation in a game they love resembles Frankenstein’s monster. There is a creation that is superior, faster, smarter, and stronger than its creator. However, this story does not end tragically. The engineer and the AI, unlike Dr. Frankenstein and his monster, coexist without the urge to conquer each other. The feeling of pride, akin to a father’s pride in their child’s success, represents the most human aspect of the interaction between the engineer and AI:

> *You create, you try, you try again, and you can’t win, you know how it’s done. You know the algorithm, you know how it’s written. But you can’t win, I went crazy. Since that day, I’ve played chess maybe once or twice. <...> This doctoral work is like that too; it became like my child. It hasn’t yielded very accurate results yet, but ultimately, there is only one of it in the world, and it’s mine. It has a special place for me* (P2, 33, Academician).

When software engineers think about algorithms and AI conceptually, the technical-rational worldview instilled in them by engineering leads them to perceive these technological tools as highly technical matters. The essence of an algorithm and AI application is efficiency, determining the meanings attributed to these concepts based on the fundamental values of efficiency [*Newberry*, 2015a] and technical excellence [*Buccianeri*, 1994], which are essential elements of the engineering identity. Interestingly, engineers express their definitions of these concepts within the context of everyday life before delving into their technical definitions, describing everyday life as an algorithmic process. This suggests that the sociotechnical sociality of engineering, contrary to many studies in the literature where the social dimension is almost entirely marginalized, actually encompasses the social context but interprets it in a technical context. This observation, along with the frequent use of the “child” metaphor when discussing algorithms and AI, indicates that the dichotomy of the engineering identity, which is considered to be the fundamental tension between the technical and the social [*Newberry*, 2015b], necessitates a reconsideration of the intertwined and inseparable nature of the technical and the social as a whole [*Latour*, 1993; 1994; *Ihde*, 1979; *Verbeek*, 2005]. In other words, STS literature should be introduced into the sociology of AI and algorithms more.

Algorithmic Bias as a Technical Issue

The technical definition of algorithmic bias is formulated as a systematic deviation in the outputs of an algorithm that is designed to achieve the desired outcome in the most efficient way possible [*Danks, London*, 2017; *Fazelpour, Danks*, 2021]. It is believed to originate from normative issues such as the data on which the algorithm is based, the mathematical model, and the learning method [*Fazelpour, Danks*, 2021]. In other words, algorithmic bias can arise if the data processed by an algorithm contains bias, if the model is incorrectly chosen, or if the correct learning method is not employed. In the sociology literature, there are many studies on algorithmic bias and its societal consequences, which reveal how algorithmic bias reinforces various forms of social inequality in different contexts [*Barocas, Selbst*, 2016; *Benjamin*, 2019; *Katz*, 2020; *Crawford*, 2021]. However, while these studies focus on the consequences of algorithmic bias, they do not pay the same attention to its causes and tend to implicitly assume the influence of software engineers and the technical-rational worldview of engineering, which are the key actors in the production processes of algorithms. Understanding how algorithmic bias is perceived and categorized by software engineers is important for shedding light on its root causes.

In this context, participants were asked about their understanding of algorithmic bias in order to learn how they perceive this issue. The results indicate that the technical-rational worldview of engineering emphasizes a technical approach and highlights the difference between efficiency and inefficiency when categorizing algorithmic bias. Before considering its societal and ethical dimensions, algorithmic bias is perceived as a technical problem that causes the algorithm to operate in an "inefficient" manner. The participants' statements collectively show that they prioritize the technical aspects of algorithmic bias and overlook the social and ethical dimensions of the issue. Additionally, the emphasis on the antagonistic relationship between efficiency and inefficiency provides insights into the lack of proper technical interventions and technical implementation:

> *You develop an algorithm and say that under certain conditions, you will do this. The algorithm continues to do it under those conditions, but not in the way you intended, rather in a different way. Maybe you still achieve the desired outcome, but you don't achieve it in the right way. The process becomes inefficient; for example, it takes longer to reach the results. This situation creates a bias when the algorithm deviates from the decisions you want* (P6, 25, Private Sector).

The definition of algorithmic bias solely in a technical context, independent of its societal character and consequences, is believed to be associated with the technical-rational worldview of engineering, which defines concepts in an analytical, rational, and mathematically precise manner [*Bucciarelli*, 1994]. The findings of this study demonstrate that the engineering identity, shaped by the technical-rational worldview, which places a fundamental value on efficiency [*Ellul*, 1964; *Winner*, 1986; *Faulkner*, 2015; *Newberry*, 2015a], evaluates itself primarily based on efficiency. Thus, while software engineering, with its organizational model and the technological tools it produces such as AI and algorithms, exhibits a clear societal character, it appears to maintain the technical-rational worldview of traditional engineering and develops a limited perception of the social dimension [*Joyce et al.*, 2021].

When participants were asked to provide information about the causes of algorithmic bias and potential solutions, they predominantly focused on the mismatch between the used data sets and the model or possible issues with the mathematical foundations of the model. This finding once again demonstrates the strong influence of the technical-rational worldview of engineering in interpreting these processes. If algorithmic bias leads to problematic or harmful outcomes, it is perceived as a technical problem that results from technical errors:

> *Algorithmic bias essentially occurs when the algorithm takes shortcuts and thus decreases its efficiency. We can say that bias occurs when the algorithm leans more towards one side than the other when making decisions* (P8, 41, Private Sector).

This emphasis indicates that engineers are aware of the human influence in algorithmic bias. However, despite acknowledging that the technology, created by engineers, is a cultural being and a societal entity, their description of human influence remains within a technical and rational context. The human factor is interpreted as a "technical inadequacy" and is expressed in technical terms. In the participants' discourse, the human factor is not considered in its social or cultural context but as technical process:

> *In my opinion, bias comes from the person who writes and codes the algorithm. Because algorithms need to undergo extensive testing before being used. There are many processes involved in algorithm design, such as modeling, writing, testing, and retesting. Sometimes we see that some of these processes are skipped. If something goes wrong, it means these steps were not properly applied* (P9, 26, Private Sector).

Out of the 21 participants, only one participant suggested that algorithmic bias stems from the fact that a technological tool, created by humans, cannot be neutral. While this proportion is extremely low, even this participant ultimately completes the social process by referring back to technical considerations and claiming that attempting to encode cultural and societal causes into algorithms and AI is either impossible or would "disrupt the system" and deviate it from its intended purpose. In a way, the social aspects are sacrificed in favor of the technical aspects, as society is considered chaotic and inefficient, while efficiency is prioritized:

> *There are things in the data that are not visible, and the algorithm will not consider that something is wrong in this case. Let's think about it: we live by the seaside and teach a child about birds. If the child only sees seagulls, they will think that a bird is equivalent to a seagull. They may say it's not a bird when they see a pigeon. Because based on the data they have, a bird equals to a seagull. So, there is a problem with the learning process here. In theory, it is possible to correct the data, but in reality, since humans generate the data, there will always be a problem related to bias. We can say, let's change this weight, let's focus on this side. But in that case, the performance will decrease significantly. Maybe we will correct the gender bias, but it is highly likely that we will disrupt something else* (P12, 32, Academic).

In cases where data leads to algorithmic bias, it is important to consider that the data may not be wrong but can be seen as correct. If AI produces biased results against a specific social group, the idea that this "bias" can actually be "unbiased" and reflect reality, alongside the technical-mathematical perfectionism of the technical-rational worldview, may open the door to a more radical technocratic perception where society is completely excluded:

> *If I'm not mistaken, this situation exists in law; algorithms were more likely to find Black people guilty. Behind this could be the fact that the data supports this situation. In other words, unfortunately, there is a reality of poverty and being pushed into crime in Black communities. If we try to correct this, this technology will become useless for us* (P12, 32, Academic).

Ultimately, the findings indicate that engineers perceive algorithmic bias not as a concept with societal dimensions and consequences but as a collection of technical deficiencies and inadequacies. It is conceptualized in a technical-rational manner. In other words, engineers approach algorithmic bias in a significantly different way than social scientists who perceive and problematize it. This suggests that the sociotechnical character of engineering, which is based on education and a technical-rational foundation [*Hughes*, 1986], leads engineers to prioritize the technical aspects, overlook the social dimension, and conceive technical efficiency as a fundamental value and practice.

Conclusion

This study aimed to examine how software engineering conceptualizes algorithms and AI and how software engineers, as the creators of these technologies, particularly in relation to the concept of algorithmic bias. The findings of the study indicate that the technical-rational worldview of engineering and its fundamental value of efficiency have a significant influence on the conceptualization of algorithms, AI, and the interpretation of algorithmic bias. Software engineers evaluate algorithms and AI based on their technical definitions and how efficiently they work. It is expected that a technical professional group would make such a characterization. In this regard, two points draw attention in the sociological context. The first is that engineers conceptualize algorithms not only as technological tools or products but also as a behavioral code or a set of behaviors that enable the most efficient way of living everyday life. This suggests that the technical-rational worldview imposed by engineering has a strong impact not only on professional concepts and career but also on everyday life, thereby shaping the social perception of engineers.

This technical-rational worldview gives rise to what can be called as "technological fetishism" which detaches technological products from social contexts such as culture, politics and labor that produces them. Thus, AI and algorithms seem to be trapped in the domain of technical by the people who create them. Adopting this ideological position, software engineers tend to understand algorithms and AI as technological objects that can be created and maintained solely by "right" technical fixes. The concept of algorithmic bias is also conceptualized by engineers as a technical matter, with the social dimensions being ignored. In this regard, it is similar to previous studies that indicate how the technical and analytical worldview of engineers creates a sociality with highly competent technical but limited social perceptions. For engineers, the main focus is on efficiency and the optimal functioning of systems. Anything that is social and cultural is positioned against this efficiency and considered as "inefficient." In summary, the general findings of the study can be summarized as follows: The technical-rational worldview on which engineering is built positions the social dimension against efficiency and dictates to engineers that algorithms and AI should be seen as tools that can work most efficiently with the right technical interventions.

Regarding algorithmic bias, the findings of this study indicate how the way software engineers conteptualize algorithmic bias has not only technical but also social outcomes. Conceptualizing algorithmic bias from a technical-rational point of view which has a foundational value in efficiency risks ignoring the social character and outcomes of it as well. Understood mainly through a technical point, algorithmic bias stands as a technical issue which can be corrected by right technical engineering fixes. This approach might have not only a continuing but a deepening effect on the social inequalities that algorithmic bias has been built on since the creators of algorithms are culturally biased human beings and the data algorithms train on is obtained from the same human beings with cultural, political and economic ties to the social world. In order to understand and deal with the algorithmic bias and the inequalities it maintains and amplifies as mentioned above, the long standing duality between social sciences and engineering must be exceeded as this study can be taken as a point of departure for both sociologists and engineers to come together around AI and algorithms in order to understand and deal with inequalities both in the actual and the digital world.

One final comment is worth noting here. While acknowledging the influence of classical engineering on the social perception of software engineering, study also highlights the emergence of a new orientation unique to the field. Notably, software engineers, propelled by their rationalized worldview, conceive of everyday life and social interactions through an algorithmic lens. This algorithmic perception of reality, in unison with the arising, unique symbolic form of interaction — dealing with a "learning" technology on a daily basis in particular — between the engineer and AI seem to lead engineers to perceive AI and algorithms as technological entities with somewhat social capabilities. Although not the main point of the study, this transition in the technical dimension of classical engineering holds substantial significance within the context of AI and software engineering. For further studies, it is worth investigating this unique feature of AI engineering through a sociotechnical approach as Science and Technology Studies (STS) school proposes. Such an inclusive approach has the potential to yield considerable contributions to the extant sociological literature. This study, as an exploratory endeavor into the technosocial context of software engineers, lays the groundwork for future research endeavors that delve deeper into this phenomenon, employing a sociological lens to elucidate its intricacies.

References

Adaş, E., Erbay, B. (2022). Yapay zekâ sosyolojisi üzerine bir değerlendirme [An evaluation on the sociology of artificial intelligence], *Gaziantep University Journal of Social Sciences*, *21* (1), 326–337 (in Turkish). DOI: 10.21547/jss.991383.

Airoldi, M. (2022). *Machine Habitus: Toward a Sociology of Algorithms*, Cambridge: Polity Press.

Barocas, S., Selbst, A.D. (2016). Big Data's Disparate Impact, *California Law Review*, *104* (3), 671–732. Available at: http://www.jstor.org/stable/24758720 (date accessed: 09.22.2024).

Beer, D. (2013). *Popular Culture and New Media: The Politics of Circulation*, London: Palgrave Macmillan.

Beer, D. (2017). The Social Power of Algorithms, *Information, Communication & Society, 20* (1), 1–13. DOI: 10.1080/1369118X.2016.1216147.

Benjamin, R. (2019). *Race after Technology: Abolitionist Tools for the New Jim Code*, Cambridge: Polity Press.

Broussard, M. (2018). *Artificial Unintelligence: How Computers Misunderstand the World*, Cambridge: MIT Press.

Bucciarelli, L.L. (1994). *Designing Engineers*, Cambridge: MIT Press.

Buchanan, B.G. (2005). A (Very) Brief History of Artificial Intelligence, *AI Magazine, 26* (4), 53–60. DOI: 10.1609/aimag.v26i4.1848.

Burrell, J., Fourcade, M. (2021). The Society of Algorithms, *Annual Review of Sociology*, no. 47, 213–217. DOI: 10.1146/annurev-soc-090820-020800.

Campero, S. (2021). Hiring and Intra-Occupational Gender Segregation in Software Engineering, *American Sociological Review*, *86* (1), 60–92. DOI: 10.1177/0003122420971805.

Chang, E. (2019). *Brotopia: Breaking up the Boys' Club of Silicon Valley*, New York: Portfolio/Penguin.

Crawford, K. (2021). *Atlas of AI: Power, Politics and the Planetary Costs of Artificial Intelligence*, Yale University Press: New Haven.

Danks, D., London, A.J. (2017). Algorithmic Bias in Autonomous Systems, in C. Sierra (Ed.), *Proceedings of the 26th International Joint Conference on Artificial Intelligence* (pp. 4691–4697), Melbourne: AAAI Press.

Devon, R. (2004). Towards a Social Ethics of Technology: A Research Prospect, *Techné*, *8* (1), 99–115.

Ellul, J. (1964). *The Technological Society*, New York: Vintage Books.

Eubanks, V. (2017). *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*, New York: Saint Martin's Press.

Faulkner, W. (2015). 'Nuts and Bolts and People': Gender Troubled Engineering Identities, in S. Christensen, C. Didier, A. Jamison, M. Meganck, C. Mitcham, B. Newberry (Eds.), *Engineering Identities, Epistemologies and Values: Engineering Education and Practice in Context,* Vol. 2 (pp. 23–40), Cham: Springer Press.

Fazelpour, S., Danks, D. (2021). Algorithmic Bias: Senses, Sources, Solutions, *Philosophy Compass*, *16* (8), 1–16. DOI: 10.1111/phc3.12760.

Goldberg, D.E. (2006). *The Entrepreneurial Engineer*, Hoboken: Wiley.

Haenlein, M., Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence, *California Management Review, 61* (4), 5–14. DOI: 10.1177/0008125619864925.

Heidegger, M. (1977). *The Question Concerning Technology and Other Essays*, New York: Garland Publishing.

Hoffman, S.G., Joyce, K., Alegria, S., Bell, S.E., Cruz, T.M., Noble, S.U., Shestakofsky, B., Smith-Doerr, L. (2022). Five Big Ideas about AI, *Contexts*, *21* (3), 8–15. DOI: 10.1177/15365042221114975.

Hughes, T. (1986). The Seamless Web: Technology, Science, Etcetera, Etcetera, *Social Studies of Science*, *16* (2), 281–292.

Ihde, D. (1979). *Techincs and Praxis*, Boston: D. Reidel Publishing.

Jaton, F. (2020). *The Constitution of Algorithms: Ground-Truthing, Programming, Formulating*, Cambridge: MIT Press.

Joyce, K., Smith-Doerr, L., Alegria, S., Bell, S., Cruz, T., Hoffman, S.G., Noble, S.U., Shestakofsky, B. (2021). Toward a Sociology of Artificial Intelligence: A Call for Research on Inequalities and Structural Change, *Socius*, no. 7, 1–11. DOI: 10.1177/23780231219995.

Katz, Y. *Artificial Whiteness*, New York: Columbia University Press.

Konecki, K.T. (2017). *The Meaning of Contemplation for Social Qualitative Research*, New York: Routledge.

Latour, B. (1993). *We Have Never Been Modern,* Cambridge: Harvard University Press.

Latour, B. (1994). On Technical Mediation: Philosopy, Sociology, Genealogy, *Common Knowledge, 3* (2), 29–64.

Latour, B. (2000). *Pandora's Hope: Essays on the Reality of Science Studies*, Cambridge: Harvard University Press.

Lupton, D. (2015). *Digital Sociology*, New York: Routledge Press.

Marvasti, A.B. (2003). *Qualitative Research in Sociology*, Thousand Oaks: SAGE.

Miller, B. (2021). Is Technology Vallue-Neutral?, *Science, Technology, & Human Values, 46* (1), 53–80. DOI: 10.1177/0162243919900965.

Natale, S. (2021). *Deceitful Media: Artificial Intelligence and the Life after the Turing Test*, NY: Oxford University Press.

Natale, S., Ballatore, A. (2020). Imagining the Thinking Machine: Technological Myths and the Rise of Artificial Intelligence, *Convergence*, *26* (1), 3–18. DOI: 10.1177/1354856517715164.

Newberry, B. (2015a). Efficiency Animals: Efficiency as an Engineering Value, in S. Christensen, C. Didier, A. Jamison, M. Meganck, C. Mitcham, B. Newberry (Eds.), *Engineering Identities, Epistemologies and Values: Engineering Education and Practice in Context,* Vol. 2 (pp. 199–215), Cham: Springer Press.

Newberry, B. (2015b). The Dialectics of Engineering, in S. Christensen, C. Didier, A. Jamison, M. Meganck, C. Mitcham, B. Newberry (Eds.), *Engineering Identities, Epistemologies and Values: Engineering Education and Practice in Context,* Vol. 2 (pp. 9–22), Cham: Springer Press.

Noble, D.F. (1977). *America by Design: Science, Technology and the Rise of Corporate Capitalism*, New York: Alfred A. Knopf Publishing.

Panch, T., Mattie, H., Atun, R. (2019). Artificial Intelligence and Algorithmic Bias: Implications for Health Systems, *Journal of Global Health*, *9* (2), 1–5. DOI: 10.7189/jogh.09.020318.

Pasquale, F. (2015). *The Black Box Society: The Secret Algorithms That Control Money and Information*, Cambridge: Harvard University Press.

Pitt, J.C. (2014). “Guns Don't Kill, People Kill”: Values in and/or Technologies, in P. Kroes, P.-P. Verbeek (Eds.), *The Moral Status of Technical Artefacts* (pp. 89–101), Cham: Springer Press.

Robinson, H. (1990). Towards a Sociology of Human-Computer Interaction: A Software Engineer's Perspective, in P. Luff, N. Gilbert, D. Frohlich (Eds.), *Computers and Conversation* (pp. 39–49), Cambridge: Academic Press.

Russell, S., Norvig, P. (2020). *Artificial Intelligence: A Modern Approach*, Hoboken: Pearson Press.

Sadowski, J. (2020). *Too Smart: How Digital Capitalism Is Extracting Data, Controlling Our Lives, and Taking over the World*, Cambridge: MIT Press.

Sheikh, H., Prins, C., Schrijvers, E. (2023). *Mission AI: The New System Technology*, Cham: Springer Press.

T.C. Cumhurbaşkanlığı Bilim, Teknoloji ve Yenilik Politikaları Kurulu (CBPYTK) (2021). [Presidency of Türkiye Science, Technology and Innovation Policies Board], *Yapay zekâ teknoloji yol haritası* [AI technology roadmap]. Available at: https://tubitak.gov.tr/sites/default/files/18842/btypk_yapay_zeka_tyh_sonuc_raporu.pdf (date accessed: 09.11.2024) (in Turkish).

Verbeek, P. (2005). *What Things Do: Philosophical Reflections on Technology, Agency and Design*, Pennsylvania: Pennsylvania University Press.

Verdegem, P. (2021). Introduction: Why We Need Critical Perspectives on AI, in P. Verdegem (Ed.), *AI for Everyone?* (pp. 1–18), London: University of Westminster Press.

Winner, L. (1980). Do Artifacts Have Politics?, *Daedalus*, *109 (1)*, 121–136. Available at: http://www.jstor.org/stable/20024652 (date accessed: 09.11.2024).

Winner, L. (1986). *The Whale and the Reactor*, Chicago: Chicago University Press.

Изучая предвзятость алгоритмов искусственного интеллекта: Case Study инженеров-программистов в г. Измир (Турция)

Б. Эрбей

Измирский университет экономики,
Измир, Турция;
e-mail: borabay.erbay@ieu.edu.tr

Э.Б. Адаш

Айдынский университет имени Аднана Мендереса,
Айдын, Турция;
e-mail: borabay.erbay@ieu.edu.tr

В исследовании изучается, как инженеры-программисты понимают искусственный интеллект (ИИ) и алгоритмическую предвзятость. Исследование выявляет, влияют ли человекоподобные характеристики ИИ на их инженерные практики, которые традиционно имеют в виду дуалистический взгляд на технологии и общество. Основанные на полуструктурированных интервью с инженерами-программистами в г. Измир (Турция), результаты исследования показывают сходства и различия между классической инженерией и программной инженерией. Классическая инженерия предпочитает технические определения и эффективность в оценке алгоритмов, часто при этом рассматривая социальное измерение как вторичное. Отход от традиционного понимания показывает социотехнический контекст, в котором работают инженеры-программисты. Более того, исследование показывает, что инженеры-программисты склонны интерпретировать алгоритмический предрассудок с технической точки зрения, не обращая внимание на более широкий социальный и культурный контексты. Результаты исследования подчеркивают острую необходимость провести переоценку отношений между технологией и обществом в рамках социологии искусственного интеллекта, поддерживая более глубокое понимание социальности среди инженеров-программистов.

Ключевые слова: инженеры-программисты, искусственный интеллект, алгоритмическая предвзятость, технология и общество, социология, исследования науки и техники.

Participant list

CODE	OCCUPATION	GENDER	AGE
P1	Academic	Male	32
P2	Academic	Male	33
P3	Private Sector	Male	27
P4	Private Sector	Male	29
P5	Private Sector	Male	37
P6	Private Sector	Female	25
P7	Academic	Female	32
P8	Private Sector	Male	41
P9	Private Sector	Female	26
P10	Analysis Engineer (Research Center)	Male	31
P11	Analysis Engineer (Research Center)	Male	36
P12	Academic	Male	32
P13	Private Sector	Male	24
P14	Private Sector	Male	25
P15	Private Sector	Male	28
P16	Private Sector	Male	35
P17	Private Sector	Male	32
P18	Private Sector	Male	29
P19	Private Sector	Female	33
P20	Private Sector	Male	25
P21	Private Sector	Male	31