



Artificial Intelligence and Social Stratification: Sociological Concepts of Algorithmic Capital, Algorithmic Inequality, and Social Reproduction in India

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Abstract

The rapid expansion of Artificial Intelligence (AI) in Indian society is profoundly influencing not only technological change but also the process of restructuring social and power relations. This paper focuses on the conceptual evolution of 'algorithmic inequality' to understand the interplay between AI and social stratification. The central argument of this paper is that AI is not a socially neutral technology; its development and use are heavily influenced by the social structures, available resources, and prevailing institutional arrangements within which inequalities such as those based on caste, class, gender, region, language, and education etc. persist. On this basis, this paper attempts to develop three interconnected concepts like Algorithmic Capital, Algorithmic Stratification, and Algorithmic Social Reproduction. Algorithmic Capital refers to the capacity derived from access to AI, AI literacy, data resources, social networks, and institutional capabilities that enables specific individuals or groups to leverage AI for their social, educational, and economic benefit. Its unequal distribution can give rise to algorithmic advantage or disadvantage, thereby influencing algorithmic stratification. Consequently, when these advantages or deprivations reinforce existing inequalities by creating enduring disparities in social opportunities and outcomes, the process of algorithmic social reproduction emerges. This paper attempts to extend the concepts of the 'digital divide' to the 'AI divide,' 'capital theory' to 'algorithmic capital,' and 'social stratification' and 'social reproduction' to an algorithmic context. It proposes understanding the relationship between AI and inequality through a sociological co-constructivist perspective rather than through technological determinism.

Keywords: *Artificial Intelligence, Algorithmic Inequality, Algorithmic Capital, Algorithmic Stratification, Social Stratification, Social Reproduction, Digital Divide*

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I. Introduction

Artificial Intelligence (AI) is currently emerging as a significant socio-technical force, one that goes far beyond being merely a subject of technological innovation to reshape various spheres of social life and the social structure itself. In India, the use of AI is steadily increasing across sectors such as education, healthcare, agriculture, finance, public administration, and digital services. Emphasis is also being placed on linking AI with inclusive social development from a policy perspective; NITI Aayog's 'Roadmap on AI for Inclusive Societal Development' (2025) examines the potential of AI and the associated social challenges in this very context. It would be insufficient to view this transformation merely as technological modernization, given that any technology invariably evolves and is deployed within specific social structures, institutional frameworks, and power dynamics. From this perspective, AI is part of the broader process of social transformation in which

information, knowledge, and decision-making processes are increasingly becoming linked to algorithmic systems. From a sociological perspective, social stratification refers to the unequal distribution of resources, opportunities, prestige, and power among individuals or groups in society elements essential for their holistic development. In the context of Indian society, factors such as caste, class, gender, education, occupation, and regional background have long influenced the structure of social opportunities. The expansion of modern digital technology has added a new and significant dimension to this stratification in the form of the 'digital divide.' It is no longer sufficient merely to have access to technology; the ability to use it effectively and the socio-economic benefits derived from it are also being distributed unequally. Research on digital capital demonstrates that economic, social, and cultural capital can be converted into the use of digital resources, and conversely, digital resources can be transformed back into other forms of capital (Calderón Gómez, 2021; Leguina & Downey, 2021). In the context of AI, the question of whether data, AI literacy, algorithmic access, and the like are themselves emerging as new social resources and sources of power becomes increasingly significant. Against the backdrop of the aforementioned facts, the present paper focuses on four interrelated questions. First, how might AI restructure the existing patterns of social stratification in India? Second, can 'algorithmic capital' be conceptualized as a contemporary extension of socio-cultural capital? Third, how do AI-based classification and decision-making processes reproduce or exacerbate social inequalities? And fourth, can algorithmic inequality be understood as a newly emerging dimension of social stratification? Recent discourse in the social sciences, while linking algorithmic decision-making to social inequality, seeks to highlight that inequality can arise not merely from biases inherent in algorithms but from the entire sequence comprising data, institutional contexts, decision-making processes, and their social consequences (Gordon et al., 2022).

The central argument of this paper is that AI is not a socially neutral technology; it is shaped by the social structures, resources, forms of capital and power relations within which it is created and deployed. Therefore, rather than viewing AI solely through the lens of efficiency or innovation, it is essential to examine its social and distributional consequences. Recent sociological literature also emphasizes the need to link the study of AI with questions of social inequality and structural change (Joyce et al., 2021). This subject is particularly significant in the Indian context, as NITI Aayog has highlighted the need for high quality and representative datasets to ensure AI systems are inclusive and non-discriminatory, as well as the challenges associated with the existing digital divide in India. Therefore, understanding algorithmic inequality is essentially an attempt to comprehend how traditional social inequalities can assume new algorithmic forms in the digital age.

From Social Stratification to Algorithmic Inequality: Theoretical and Conceptual Foundations

The concept of social stratification helps us understand the unequal distribution of resources, opportunities, prestige, and power among individuals and groups in society. Karl Marx primarily viewed and interpreted stratification in terms of control over the means of production and class relations, positing that the unequal relationship regarding resources and power between the capitalist and working classes gives rise to social inequality (Marx & Engels, 1970). Expanding upon this analysis, Max Weber identified status and power alongside class as independent dimensions of social stratification (Weber, 1978). Subsequently, Pierre Bourdieu developed the concepts of social capital and cultural capital alongside economic capital, explaining how these diverse forms of resources are convertible into one another within social life, thereby influencing the social standing of individuals and groups in various ways (Bourdieu, 1986). This theoretical tradition fosters the understanding that inequality is not merely the result of the unequal distribution of material wealth; unequal access to knowledge, relationships, cultural competencies, and power also perpetuates stratification. In the context of the rise of AI, a crucial question arises: are data, computational resources, and AI literacy becoming new resources for securing social advantages?

The unprecedented spread of digital technology in the current era has made the 'digital divide' a significant dimension in the discourse on social stratification. While early discussions on the digital divide primarily focused on unequal access to the internet and digital devices, recent studies indicate that mere technical access does not guarantee digital equality. According to Helsper (2021), digital inequality cannot be understood in isolation from social inequalities, as people's social circumstances influence their digital engagement as well as the outcomes derived from it. On this basis, the digital divide can be understood in terms of three interconnected levels: access, ability, and outcomes. The 'Access' level encompasses the availability of the internet, devices, and connectivity; 'Ability' includes digital literacy, skills, and the capacity for effective usage; and 'Outcomes' comprise the educational, economic, political, and social benefits derived from digital resources. This divide becomes even more complex in the context of AI, as an individual might have internet access yet lack the necessary knowledge, adequate language proficiency, computational resources, or institutional support required to effectively utilize AI tools. At this juncture, it becomes essential to establish the conceptual distinction between algorithmic bias and algorithmic inequality. Algorithmic bias generally refers to a situation where the design, training data, or decision-making process of an algorithmic system yields results that are systematically biased against a particular social group (Mehrabi et al., 2021); however, the presence of bias does not, in itself, elucidate broader social inequality.

‘Algorithmic inequality’ is a broader sociological concept that relates not only to the outcomes of algorithms but also to the social conditions under which they are developed and deployed. To understand the social impacts of algorithmic decision-making, Gerdon et al. (2022) emphasize the need to look beyond the algorithm itself and consider its broader social context and the decision-making process. Therefore, in this paper, ‘algorithmic inequality’ refers to the systemic inequalities that differentially affect the opportunities, resources, visibility, and outcomes of various social groups through AI and algorithmic systems. On this basis, the present study proposes ‘Algorithmic Inequality’ as a distinct sociological concept which can be defined as: “Algorithmic Inequality is the social process wherein AI and algorithm-based systems generate, perpetuate, or reproduce inequalities in the distribution of opportunities and social outcomes mediated by factors such as unequal access, resources, data representation, and digital capabilities among social groups.” In this definition, inequality is not viewed merely as the result of technical errors or bias; rather, it is seen as a process rooted in social structures. For instance, a group possessing high AI literacy, superior digital infrastructure, quality data, and institutional networks can derive relatively greater benefits from AI-driven opportunities. On the other hand, groups that are underrepresented in data or possess limited digital capabilities may lag behind in accessing the opportunities generated by algorithmic systems. Thus, algorithmic capacity itself can emerge as a form of social resource.

This concept can be understood through a broad conceptual chain as Social Structure leads to Unequal Resources which leads to Unequal Data & Digital Capacity which make base for Algorithmic Processing that leads towards Unequal Opportunities/Outcomes which makes Social Reproduction. This illustrates how pre-existing social structures such as caste, class, gender, region, language, and education influence the unequal distribution of resources and digital capabilities; these inequalities permeate data and algorithmic systems and can ultimately lead to disparities in opportunities and social outcomes. If such outcomes reinforce the social standing of the same groups, a process of ‘algorithmic social reproduction’ emerges. Thus, algorithmic inequality can be viewed here not merely as a technical extension of the digital divide, but as a sociological concept that helps understand the interconnections between social stratification, capital, technology, and social reproduction.

Algorithmic Capital: From Social Capital to Algorithmic Capital

Pierre Bourdieu’s theory of capital provides a crucial framework for understanding social inequality by demonstrating that power in society is not determined solely by economic wealth. Bourdieu (1986) conceptualized economic, social, and cultural capital as resources that influence an individual’s social standing and the opportunities available to them, noting that these forms of capital can also be converted into one another. Economic capital encompasses wealth and material assets; social capital comprises resources derived from social relationships and networks; while cultural capital includes knowledge, skills, language, and cultural tastes. The significance of these forms of capital has further increased in the digital society, as access to digital resources and their effective utilization have begun to profoundly influence an individual’s education, employment, access to information, and social participation. In this context, viewing digital technology merely as a medium of communication is insufficient; it has now become a domain for the creation and transformation of social capital itself. Against this theoretical backdrop, the concept of a new form of capital - Algorithmic Capital-can be developed for the age of AI. The concept of digital capital helps in understanding this transition. Digital capital refers to digital resources, technical competencies, devices, connectivity, information, networks, and the like, which an individual can transform into beneficial outcomes in their social life. Viewing digital capital as an extension of Bourdieu’s concept of capital, Ragnedda (2018) links it to the resources and benefits derived from the effective use of digital technologies. Similarly, Calderón Gómez (2021) explains digital capital as a process interconnected with economic, social, and cultural capital. With the development of AI, this concept of digital capital has reached a new level; mere access to the internet or digital devices is no longer sufficient. It has become crucial to understand AI tools, provide them with appropriate prompts, properly evaluate the information they generate, recognize the limitations of algorithmic systems, and effectively utilize AI in education, employment, and other professional activities. Therefore, in this paper, Algorithmic Capital is proposed as an emerging, distinctive digital-social resource. In this paper, ‘Algorithmic Capital’ refers to the knowledge, skills, resources, data-richness and institutional capacity that enable an individual or a social group to leverage AI and algorithmic systems for social, educational, economic, or professional gain. This concept is not limited merely to an individual’s proficiency in using AI; it also encompasses their social standing and the broader resources available to them. This can be understood in terms of five interconnected components. First, AI Access Capital, which encompasses access to AI tools, computing infrastructure, reliable connectivity, and the like. Second, AI Literacy Capital that is, the ability to understand and use AI, and to critically evaluate its outputs within their proper context. Third, Data Capital, referring to access to high-quality, useful data and the capacity to transform that data into socio-economic benefits. Fourth, Network Capital that is, professional and social networks linked to the AI ecosystem. Fifth, Institutional Capital that is, connections with educational, business, or administrative institutions that provide the resources and opportunities necessary for the use of AI. To understand Algorithmic Capital in the context of social stratification, its relationship with other forms of capital is crucial. For instance, Economic Capital leads to Better Technology Access which makes Algorithmic Access possible; economically advantaged

groups can secure relatively greater access to expensive devices, high-speed connectivity, and advanced AI services.

Similarly, the progression from Cultural Capital to better AI literacy and effective algorithmic use suggests that high levels of educational and linguistic proficiency can facilitate the understanding and utilization of complex AI systems. Meanwhile, through the pathway of Social Capital leading to better information and networks, and ultimately to algorithmic opportunities social connections can provide access to AI-related information, training, and employment prospects. Thus, rather than viewing 'Algorithmic Capital' as a resource entirely unrelated to Bourdieu's concept of capital, it is more useful to understand it as a digital-algorithmic transformation of economic, social, and cultural capital. This very process explains why the benefits of AI are not automatically distributed equally across society.

In the Indian context, the distribution of 'algorithmic capital' is likely to be influenced by existing inequalities within the social structure. Factors such as caste, class, gender, education, income, language, and rural-urban location can differentially impact an individual's access to digital resources and AI capabilities. For instance, families with high income and educational capital can develop the capacity to make more effective use of AI-enabled educational and professional applications whereas limitations regarding connectivity, infrastructure, and digital literacy in rural areas may restrict the benefits of AI. The availability and utility of AI in Indian languages will also play a crucial role in the creation of algorithmic capital. It is important to clarify here that the unequal distribution of algorithmic capital does not inevitably lead to permanent inequality; AI can also mitigate certain social barriers by providing access to knowledge and expertise at a low cost. Therefore, its sociological significance lies in the question of who has access to AI, who can effectively understand and utilize it, who possesses the relevant data and networks and who has the institutional capacity to translate these resources into social benefits. On this basis, 'Algorithmic Capital' can be developed as a useful sociological concept for understanding the emerging algorithmic stratification in India.

Algorithmic Stratification: The Restructuring of Social Stratification by AI

In this paper, algorithmic stratification is conceptualized as an emerging process of social stratification. It refers to the process wherein AI and algorithmic systems link individuals and social groups to distinct opportunities and social outcomes based on their data status, digital capabilities, behavioral patterns and institutional access. In traditional Indian society, factors such as an individual's caste, class, education level, occupation, and social standing have influenced the distribution of social opportunities; in the digital society, data and algorithmic processing are also becoming intertwined with these structures. However, algorithms do not themselves constitute an independent cause of social stratification; rather, they can reorganize pre-existing social relations and resource inequalities through a new medium. Discussing algorithmic opacity, Burrell (2016) demonstrated that the functioning and outcomes of algorithmic systems are often difficult to comprehend. For this reason, it is useful to view AI-mediated classification not merely as a technical process, but as a process of social classification and resource distribution.

To understand the distinction between traditional and algorithmic stratification, it is essential to recognize that social status can now be influenced not only by overt social categories but also by digital data and algorithmic evaluation. While caste has historically shaped an individual's social status and opportunities within traditional stratification, algorithmic systems now enable the classification of individuals based on their digital identities and potential behaviors through data categorization. Digital and AI capabilities may become significant alongside class; AI literacy may become linked to education; algorithmic visibility could emerge as a factor alongside social prestige; access to data and technology may become associated with economic resources; and influence over algorithmic decision making systems could represent a new dimension of institutional power. This does not imply the disappearance of traditional caste or class structures; rather, the argument is that traditional stratification and algorithmic processes interact to shape social opportunities. Thus, it is more appropriate to view algorithmic stratification as a potential digital reconfiguration of existing stratification, rather than a replacement for it. The core process of algorithmic stratification can be understood as Data - Classification - Prediction - Decision. AI systems process vast amounts of data to identify patterns and, based on these, can generate recommendations, predictions, and decisions. In the realm of employment, algorithmic systems can potentially be used to match candidates with jobs; similarly, in the financial sector for risk assessment or credit-related evaluations; in education for personalized learning and recommendations; in digital advertising to segment users into various categories; and in public services for processes such as welfare targeting. The crucial point here is that these applications should not, in themselves, be considered evidence of inequality. From a sociological perspective, the crucial questions concern the type of data used, the groups represented within it, the social characteristics prioritized by the classification, and how the algorithmic output translates into institutional decisions. If the data reflects pre-existing social inequalities, the algorithm is likely to reproduce those patterns (O'Neil, 2016; Barocas & Selbst, 2016). In this context, 'algorithmic visibility' emerges as a useful new sociological concept. In a digital society, alongside the actual presence of an individual or an object, the degree of visibility accorded to them by an algorithm is also significant. The visibility of a vacancy or candidate in job recommendation systems, the reach

of content in recommendation engines, the discoverability of a seller or product in digital marketplaces, and the visibility of a profile on professional networking platforms can all influence an individual's social opportunities. From this perspective, algorithmic visibility can be understood as a new digital medium for symbolic recognition and opportunity allocation. Individuals, institutions or content presented more prominently by algorithmic systems may gain greater access to interactions, information, or opportunities. Conversely, despite a social presence, low visibility can lead to a state of algorithmic invisibility. Therefore, by linking Bourdieu's concept of symbolic capital with algorithmic visibility, one can study how recognition and visibility in the digital sphere translate into social benefits. Another significant aspect of algorithmic stratification manifests as algorithmic exclusion. Simply put, this can be understood as: Low Digital Capacity added with Poor Data Representation and Limited AI Literacy leads to Potential Algorithmic Exclusion. Individuals or groups with limited access to AI tools, those whose language or social experiences are not adequately represented in training data, or those with limited capacity to understand algorithmic systems may find it difficult to leverage AI-mediated opportunities.

Selbst et al. (2019) have emphasized the need to understand the socio-institutional context of algorithmic fairness, rather than limiting it to the question of computational accuracy. In the Indian context, this issue becomes even more complex because caste, class, gender, region, language, and digital capability are interconnected social conditions. Therefore, it would be insufficient to limit the concept of algorithmic stratification merely to the relationship between class and technology. It is more appropriate to understand this as the intersection of caste, class, gender, region, language, and digital capacity. From this intersectional perspective, algorithmic stratification can be understood not as a process that eliminates older forms of social stratification, but rather as an algorithmic restructuring of social opportunities and inequalities that interacts with those existing forms.

Algorithmic Social Reproduction: The Process of Reproducing Inequality

The sociological concept of social reproduction helps us understand that social inequalities do not originate at a single point in time or within a single institution; rather, they are continuously reproduced through the family, education, the economy, culture, and institutional systems. Pierre Bourdieu, in particular, elucidated that various forms of capital such as economic, social, and cultural afford individuals differing life chances, and that families and educational institutions play a crucial role in the transmission of these resources (Bourdieu, 1986). Through their studies, Bourdieu and Passeron (1977) demonstrated that the education system does not eliminate social inequalities; rather, in many instances, it contributes to the reproduction of the social structure by legitimizing existing cultural capital. From this perspective, social reproduction can be understood not merely as the transfer of resources from one generation to the next, but as a process of the institutional reconstruction of opportunities, capabilities, prestige, and social status. With the rise of AI, the question arises as to whether this same process of social reproduction can now also operate in a new digital form through data and algorithmic systems.

On this basis, the present paper proposes 'Algorithmic Social Reproduction' as a novel sociological concept. It refers to the process wherein pre-existing inequalities within the social structure are translated into social outcomes through data, algorithms, and AI-mediated institutions. This does not imply that algorithms themselves generate social inequality; rather, it means that algorithmic systems operate using socially constructed data and institutional practices. If a social group is underrepresented in the data, if a group has limited access to AI tools and digital skills, or if an algorithmic system relies on variables linked to pre-existing social disparities, then existing inequalities can be reproduced through new technological mediums. In this context, Barocas and Selbst (2016) demonstrated that data-driven decision systems can reflect socially unequal patterns in their decisions. Thus, the central question of 'Algorithmic Social Reproduction' is: how does social inequality enter an algorithmic system and find its way back into society through algorithmic outcomes? This process can be understood as a gradual sequence in which existing social inequalities shape the way different groups are represented in data. These unequal patterns of data representation can then influence algorithmic processing and classification, which may result in differential access to opportunities. Over time, unequal opportunities can produce unequal outcomes, ultimately reinforcing the social inequalities that existed in the first place. For instance, if the distribution of education, income, and digital resources within a society is unequal, the digital footprints and data profiles of various social groups will also differ. AI systems can process these data patterns to generate distinct predictions or recommendations, which, in turn, can influence institutional decisions. Thus, initial social inequality can be transformed into new social outcomes through an algorithmic intermediary. Crucially, this process is neither inevitable nor mechanical; algorithmic design, institutional safeguards, data quality, and human oversight can alter the outcomes. For this reason, Selbst et al. (2019) emphasize the need to understand algorithmic fairness within its broader sociotechnical context, rather than viewing it merely as a matter of computational accuracy. Algorithmic social reproduction can be understood through theoretical examples drawn from various social spheres in Indian society. For instance, in the realm of education, relatively more educated families are better positioned to access AI-enabled learning resources and develop the capacity to use them effectively, thereby securing additional educational advantages for their children. Similarly, in the realm of employment, AI literacy, digital skills, and an understanding of algorithmic platforms can influence job-search

capacity and the opportunities available. Regarding language, English proficiency can provide relatively broad access to certain AI resources and digital information, whereas groups with limited linguistic resources may face distinct types of barriers. Similarly, the unequal distribution of infrastructure, connectivity, and digital skills across the rural-urban divide can influence the utilization of AI-enabled opportunities. These examples should be viewed as potential sociological mechanisms rather than empirical findings. Their significance lies in demonstrating how inequality in 'Algorithmic Capital' can translate into 'Algorithmic Advantage' or 'Disadvantage'.

However, it would be inappropriate to view algorithmic social reproduction solely as a negative process. While AI can exacerbate or reproduce existing inequalities in certain circumstances, the same technology can also provide marginalized groups with new access to knowledge, education, employment, and public services. Therefore, the central argument of this article is not that 'AI creates inequality,' but rather that the social consequences of AI depend on its technological design as well as on social structures, the distribution of resources, and institutional arrangements. On this basis, the proposed theoretical relationship suggests that higher levels of algorithmic capital can provide individuals and groups with greater algorithmic advantages while limited algorithmic capital may create corresponding disadvantages. When these advantages and disadvantages gradually translate into stable differences in access to resources, opportunities, and social positions, they may contribute to processes of social reproduction and, eventually, to broader patterns of stratification. Thus, the concept of 'Algorithmic Social Reproduction', extending Bourdieu's framework of social reproduction to an AI and data-driven society seeks to explain how existing social inequalities shape interactions with algorithms and how algorithmic systems, in turn, may reproduce and reshape social structures in the digital age.

II. Conclusion

The central conclusion of this paper is that viewing artificial intelligence in India merely as a tool for technological innovation or enhancing efficiency is insufficient to grasp its broader social implications. AI is expanding within a society where the distribution of resources, opportunities, and digital capabilities is traditionally unequal based on caste, class, gender, region, language, education, and income. In this context, the paper proposes three interconnected concepts: Algorithmic Capital, Algorithmic Stratification, and Algorithmic Social Reproduction. Algorithmic Capital represents an individual's or group's access to AI, AI literacy, data resources, networks, and institutional capabilities; its unequal distribution can give rise to Algorithmic Advantage or Disadvantage which subsequently shapes Algorithmic Stratification. The process of 'Algorithmic Social Reproduction' emerges when these algorithmic advantages or disadvantages generate relatively enduring outcomes in areas such as education, employment, information, finance or social opportunities, thereby reinforcing existing social inequalities. Thus, the proposed model explains how existing social structures shape access to digital resources which in turn influences the development of algorithmic capital through AI access, literacy, data, and social networks. Differences in algorithmic capital can create varying levels of advantage or disadvantage contributing to the emergence of algorithmic stratification and unequal access to social opportunities and outcomes. Over time, these unequal patterns may become embedded in social structures through a process of algorithmic social reproduction. Theoretically, this model highlights four important shifts: first, from the digital divide to the AI divide; second, within Bourdieu's theory of capital, from cultural and digital capital to algorithmic capital; third, from traditional social stratification to algorithmic stratification; and fourth, from social reproduction to algorithmic social reproduction. However, AI does not inherently generate inequality; the same technology can also create new opportunities for marginalized groups. Therefore, its social impact depends not only on technological design but also on social structure, resource distribution, and institutional arrangements.

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