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Artificial Intelligence and Social Change: A Sociological Investigation of Emerging Social Trends

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ABSTRACT:

Artificial intelligence (AI) has evolved from a niche computational discipline to an increasingly ubiquitous social infrastructure that permeates the world of work, communication, knowledge creation and everyday life. The current paper provides a sociological analysis of the social trends that are emerging along with the spread of AI on a global scale and its applicability in the Indian context. The study aims at two aspects: First, it investigates the impact of AI adoption on social structures and trends, and second, it explores the role of AI in both negotiating and perpetuating social inequalities. The research adopts systematic secondary data synthesis design and gathers and analyzes credible data from respected reports from Pew Research Center, World Economic Forum, Stanford HAI, and Telecom Regulatory Authority of India. The documented evidence is appraised in the light of two hypotheses. The findings show that AI is creating some structural shock to the labour market, fueling mixed and age-sensitive public attitudes to AI, and widening the rift between cities and rural areas, and between countries. These trends are placed in a sociotechnical and social-stratification theory context. The paper argues that AI is a catalyst and a reflection of social transformation, and needs a governance approach with a social perspective.

Keywords: *Artificial Intelligence, Social Change, Digital Divide, Sociotechnical Systems, Social Inequality.*

1. INTRODUCTION:

Artificial intelligence is one of the most consequential forces of contemporary social transformation, reorganising the institutions, relationships and everyday practices through which social life is constituted. While the first waves of digitalization changed the velocity and scope of communication, today AI is increasingly influencing hiring, lending, medical care, and information itself, and is thus becoming a part of the social organisation itself. AI is a sociotechnical system and not a neutral device (Joyce & Cruz, 2024) that embeds social values and power dynamics. To understand the trajectory of AI, Davis and Sloane argue that sociological analysis is essential, as it has become a "social

infrastructure" that acts as a mediator between economic structures, politics and interpersonal spheres. It's a massive shift. According to the World Economic Forum (2025), technological advancements, spearheaded by artificial intelligence, are poised to affect the equivalent of 22% of all formal employment by 2030, and Stanford HAI (2025) provides evidence of how quickly AI has become a part of everyday life in a variety of national contexts. These changes are not uniform across the social sectors. The "society of algorithms" is a new society in which the algorithms become the mirrors and reshapers of the existing social hierarchy, prompting questions of who gains and who loses from the automation technology, according to Burrell and Fourcade (2021).

India presents a case in particular that is instructive. The nation is one of the fastest growing markets for AI tools, but also has one of the largest digital divides, with significant rural populations still not online. This juxtaposition is a window into how AI can influence social change in a context where there are already inequalities of caste, class, gender, and region. To grasp these new developments, it is not enough to emphasize celebratory or alarmist stories, but necessary to conduct sociological research based on practical facts. In this paper, we explore how AI adoption is reshaping social norms and how AI diffusion is connected with inequalities that exist in societies, building on credible global and Indian evidence to provide an analysis and policy recommendations for an equitable digital future.

2. Literature Review

The sociological engagement with AI has grown significantly in recent years, bringing together a series of ideas that recognize the algorithmic system as a social object. In an influential call for a sociology of AI with inequalities and structural change as a focus, Joyce et al. (2021) state that the analysis of inequalities and structural change are two of the most important analytical tools for studying automated systems. Zajko (2022) took this one step further, demonstrating that discussions of “algorithmic bias” essentially re-describe longstanding social reproduction processes, and Kasy (2024) critically examined how dominant understandings of “fairness” reflect the interests of decision-makers instead of the interests of disadvantaged groups. In the real world, Vlasceanu and Amodio (2022) showed that the gender disparities found in popular search algorithms amplifies, and becomes even more apparent than, societal disparity, creating a vicious circle between society, AI and users. There is increasing scholarship that situates such dynamics in particular national and relational contexts. Jha (2024) examined algorithmic decision-making in India from a sociological point of view, connecting technical bias with structural injustice, while David et al. (2025) asserted that in India, AI systems have the potential to reinforce caste, religious, and gender-based inequalities due to the limited representation of marginalised communities in data and governance structures. In methodologically, Davidson and Karell (2025) explored the way that generative AI is being used as a research tool, and the way that generative AI is being used to create research tools, indicating a two-fold use of AI as both an object and an instrument of research.

Similar ambivalence is found in studies of interpersonal life. AI-mediated communication has been shown to have an impact on language and social interactions (Hohenstein et al., 2023), and Babu et al. (2025), from an Indian institutional perspective, theorise about the emergence of "pseudo-intimacy" as

AI's emotional interaction mimics empathy and companionship. These are complemented by the work of Parul et al. (2025) who have described the increasing capabilities of AI to influence social relations in today's digital world, especially for younger, connected populations. Older adults are the most concerned, as are women and less-connected groups, and in general, concern outstrips excitement for AI across 25 nations, according to public attitudes toward AI measured by survey (Pew Research Center 2025b). Together, this literature has marked AI as a social change agent, both as a transformative and a stratifying power. Many of these are, however, still in a conceptual state or are limited to one specific domain. To address this gap, the current paper brings together some of the established indicators from the cross-national literature and the indicators from India to test the impact of AI on social trends and inequality, based on documented evidence.

3. Objectives

1. To examine how AI adoption is reshaping emerging social trends across work, communication, and everyday life in global and Indian contexts.
2. To analyse how AI diffusion mediates and reinforces social inequality, including the digital divide and demographic variation in public attitudes.

4. Hypotheses

H1: AI adoption is associated with significant transformation of social structures and everyday social practices.

H2: AI diffusion reflects and reinforces pre-existing social inequalities in access, attitudes, and opportunity.

5. Methodology

This study uses a secondary Data analysis which is a qualitative-quantitative synthesis design to examine social trends at the macro level which is difficult to be found by one primary survey. The research does not create any new survey data, but rather gathers, triangulates and interprets verified statistics from credible, publicly available sources. The analytical sample includes recent (2021–2025) data and reports from Pew Research Center, the World Economic Forum, the Stanford Institute for Human-Centered AI, the International Monetary Fund, the Telecom Regulatory Authority of India, and Data Reportal, as well as peer-reviewed sociological literature. The sources were chosen for the following reasons methodological openness, institutional credibility, representativeness of the sample and being recent. Documentary analysis and descriptive statistical compilation were used as the principal tools. Indicators were captured in four analytical areas: public attitudes towards AI; labour-market transformation; exposure of workforce to automation; and the digital divide in structured comparison tables for each of these. All indicators were double checked with their source report in order to ensure accuracy and maintain the unit of measurement specified in the report. The interpretive technique included descriptive statistical reading of the tabulated figures and thematic alignment with frameworks of systems and social stratifications that were sociotechnical.

An evidence-synthesis logic was used to appraise hypotheses: hypotheses were tested in the direction and consistency of the documentary evidence collected, and they were given a "supported" or "not supported" verdict based on the convergence across independent documentary evidence, not on newly computed inferential statistics. This way, data integrity is preserved because the creation of primary statistics from published figures of aggregates would be methodologically incorrect. Some of the design's weaknesses are that the sampling decisions of the source organisations are dependent and that the differently framed surveys pose limitations on comparability. To help neutralize these, several independent datasets were correlated for each analytical claim, enhancing the internal validity of the study so that conclusions are based on multiple and convergent evidence.

6. Results

Table 1. Public optimism toward AI ("more beneficial than harmful"), selected countries, 2025

Country	% viewing AI as more beneficial
China	83
Indonesia	80
Thailand	77
Canada	40
United States	39
Netherlands	36

Source: Stanford HAI (2025), based on Ipsos polling.

Table 1 shows a strong divide across countries in terms of AI optimism. While confident that AI is a good thing rather than a bad one, a majority of emerging economies China (83%), Indonesia (80%), Thailand (77%) are far more optimistic than wealthier Western countries like the United States (39%) and the Netherlands (36%). Such a large difference between China (47%) and the Netherlands (5%) shows that national economic and cultural contexts shape the attitudes towards AI and that a sociological approach is warranted when reading the perception of AI.

Table 2. Concern versus excitement about AI, 2025

Sentiment	United States (%)	25-country median (%)
More concerned than excited	50	34
Equally concerned and excited	38	42
More excited than concerned	10	16

Source: Pew Research Center (2025a, 2025b).

As seen in table 2, ambivalence is the dominant sentiment in the public, rather than enthusiasm. 50% are more concerned than excited up from 37% in 2021 in the United States, and 10% are predominantly excited. The 25-country median is less negative (34% concerned, 42% equally balanced), but in none of the countries surveyed does excitement lead. This entanglement among populations suggests that there's a broad, structured kind of anxiety about change created by AI, along with the adoption of it.

Table 3. Projected global labour-market transformation by 2030

Indicator	Value
New jobs created	170 million
Jobs displaced	92 million
Net employment change	+78 million
Structural labour-market churn	22%
Core skills disrupted (2025–2030)	39%
Employers expecting AI transformation	86%

Source: World Economic Forum (2025).

Structural impact of AI on work is quantified in table 3. That's a positive net gain of 78 million jobs, but the high churn rate (22%) and skills disruption (39%) show that there is a great deal of dislocations hidden beneath that surface. The data point to a direction of reorganisation of the workforce rather than growth or decline, with 86% of employers saying they expected AI-driven transformation. From a sociological perspective, the churn has an uneven distribution of risk among workers, with reskilling becoming a new axis of advantage, as the transition figures in the Table 3 suggest.

Table 4. Estimated workforce exposure to AI, by economy type

Economy type	% of jobs exposed to AI
Advanced economies	~60
Emerging-market economies	~40
Low-income economies	~26
Global average	~40

Source: Cazzaniga et al. (2024), International Monetary Fund.

Table 4 shows that the level of AI exposure is also segmented by development level. The highest exposure is in advanced economies (~60%) because they are most likely to have cognitive and clerical occupations, whereas the lowest exposure is in low-income economies (~26%) because of the labour structure. This difference is caused by the fact that the global average is ~40% with an apparent large variation. Importantly, exposure involves augmentation and displacement, which means that the impact of automation on society will be unevenly spread along the economic hierarchy, a key issue in stratification analysis, and this is reflected in Table 4.

Table 5. India digital-divide indicators, 2024–2025

Indicator	Value
Internet subscribers per 100 (overall)	68.86
Urban subscribers per 100	111.64
Rural subscribers per 100	44.99
Internet users (penetration)	806 million (55.3%)
Social-media user identities	491 million (33.7%)
Population offline	44.7%

Source: Telecom Regulatory Authority of India (2025); Kemp (2025).

Table 5 reveals hidden inequality in India in access to AI. In early 2025, there were nearly two-and-a-half times more people online in urban areas (111.64 per 100) than in rural areas (44.99 per 100), and 44.7% of the population was offline. The connectivity that is essential to access AI tools is unevenly distributed, with just 33.7% using social media. This means that the use of AI is likely to disproportionately benefit those who are already successful and increase rather than resolve social inequality, as suggested by Table 5.

Table 6. US public assessment of AI's societal impact, 2025

Indicator	Value (%)
Have heard of AI	95
Rate societal risks as high	57
Rate societal benefits as high	25
Say AI worsens creative thinking	~50
Say AI worsens meaningful relationships	~50

Source: Pew Research Center (2025a).

Table 6 further clarifies the attitudinal picture: awareness is virtually universal (95%) and perceived risk (57%) is more than double that of perceived benefit (25%). About half think AI will reduce creativity and meaningful relationships, indicating that they are worried not only about the economic impact but also about the social and cognitive effects of AI. Table 6, read along with Table 2, shows that public concern is focused in the same interpersonal areas that are the building blocks of social cohesion and identity in the sociological literature.

Table 7. Hypothesis-testing summary

Hypothesis	Evidence base	Direction of evidence	Decision
H1: AI transforms social structures and practices	Tables 3, 4, 6	Strong, convergent	Supported
H2: AI reinforces pre-existing inequalities	Tables 1, 2, 5	Strong, convergent	Supported

Source: Authors' synthesis of Tables 1–6.

The summary of evidence appraisal can be seen in Table 7. Convergent labour-market and attitudinal data (Tables 3, 4, 6) showing measurable structural and relational transformation support H1. Stratified optimism (Table 1), demographically patterned worry (Table 2) & India's stark urban–rural digital divide (Table 5) support H2. Table 7 shows strong, triangulated confirmation that AI functions simultaneously as both a driver of social inequality and an amplifier of it, because both hypotheses receive converging support from multiple independent sources.

7. Discussion

Cumulatively, this implies that AI is revolutionizing emergent social trends while replicating long-stranding systems of privilege directly speaking to both research objectives. With regard to the first goal, both the labour-market data (reported in Table 3) and our exposure estimates (shown in Table 4) confirm

that AI is producing large-scale structural churn rather than simple job losses or new net-creations. An estimated churn rate of 22% with almost 39% of core skills disrupted means the experience of work is being rapidly reconfigured, equality and risk are moving across the workforce. It corroborates our H1 in agreeing with the World Economic Forum (2025) description of AI as the biggest change to work since the industrial revolution. From a sociological perspective, this churn does not just shift workers about between jobs, it reconstructs occupational identities and meanings of work much like Burrell and Fourcade (2021) describe how algorithms reshape social organisation. Attitudinal evidence (Tables 2 and 6) indicates that such a transformation is met with pervasive ambivalence. That about half of Americans believe AI will undermine both creative thinking and relationships that matter, fits in with the fact the interpersonal sphere appears to elicit anxiety; this coincides with Hohenstein et al. Work and (at your social relationships, as Babu et al. 's (2025) concept of pseudo-intimacy. These fears should not be dismissed as a simple case of irrational technophobia, but rather understood sociologically as an important reaction to the perception that human connection and thus social cohesion (Parul et al., 2025) is under threat.

The other is about inequality, where the evidence is just as clear. Aligning with H2, Tables 1 and 5 reveal a cross-national optimism gap around AI, while Table 5 shows the connectivity divide in India that accompanies AI's diffusion. With 111.64 per100 urban penetration versus 44.99 rural, and 44.7% of the population offline (Kemp,2025; TRAI,2025). AI's productivity gains will tend to be invested moredeeply in already-advantaged pockets. This is reminiscent of the structural-reproduction processes described by Joyce et al. (2021), and the country-specific risks of caste, gender, and religious bias detailed by Jha (2024) and David et al. (2025). The non-homogeneous exposure by economy type (Table 4) provides further evidence that the costs and benefits of automation will be spread across a global development spectrum. Significantly, bias is not an incidental feature but a systemic one: Vlasceanu & Amodio 2022; Kasy 2024 illustrate that algorithmic outputs can embody and propagate social inequalities, and Joyce & Cruz 2024; Davis & Sloane 2025 assert that to address this issue requires conceptualizing AI as a socio-technical system situated in power dynamics. The incorporation of AI within research itself (Davidson & Karell, 2023) suggests that sociology needs not only to critically engage with but also formulate methodology about AI. In summary, the discussion shows that fair outcomes are less conditioned by the technology but rather by regulatory and social frameworks affecting its implementation.

8. Conclusion

This case study shows that, in fact, AI is both a cause and consequence of social change. The collated evidence shows that AI is having profound structural effects on work, communication, and everyday life while strengthening existing inequalities of geography, demography and socioeconomic position. Converging, validated data supported both hypotheses. Here, for India and the Global South more broadly, the test is not so much adoption, which is already rapid as it is achieving inclusion to prevent AI from exacerbating existing social divides through connectivity, digital literacy and representative

datasets. An approach informed by sociology paying attention to power, structure, and experience is a necessary way to steer AI into social outcomes that are just rather than one sided. Future research should seek to supplement the macro-level trends mapped here with micro, longitudinal and regionally located fieldwork

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