Mathematical Models for Measuring AI-Induced Social Exclusion

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Abstract

Artificial Intelligence (AI) has become one of the most transformative technologies of the twenty-first century, significantly influencing governance, healthcare, education, finance, employment, transportation, and public service delivery. As AI-driven systems become increasingly integrated into decision-making processes, concerns have emerged regarding their potential to reinforce existing socio-economic inequalities through algorithmic bias, unequal digital access, and technological exclusion. These challenges are particularly significant for marginalized communities in developing countries such as India, where disparities in digital infrastructure, education, income, and technological literacy continue to limit equitable participation in the AI-driven economy.

While numerous studies have examined Artificial Intelligence from technological, economic, and ethical perspectives, relatively few have developed rigorous mathematical frameworks for measuring AI-induced social exclusion. Existing assessments largely rely on qualitative indicators or descriptive statistical methods, which often fail to capture the complex interactions among socio-economic, technological, institutional, and behavioural variables. Consequently, there is a growing need for robust mathematical models capable of quantifying social exclusion, predicting vulnerable populations, optimizing policy interventions, and evaluating the effectiveness of inclusive AI strategies.

The present study develops mathematical models for measuring AI-induced social exclusion by integrating statistical modelling, fuzzy set theory, graph theory, optimization techniques, probability theory, and machine learning algorithms. A comprehensive Artificial Intelligence Social Exclusion Index (AISEI) is proposed to quantify the degree of exclusion experienced by individuals and communities based on multidimensional indicators including digital accessibility, AI literacy, internet connectivity, educational attainment, economic status, algorithmic fairness, and access to AI-enabled public services.

The research further develops predictive models using regression analysis, decision trees, random forests, support vector machines, gradient boosting algorithms, and artificial neural networks to estimate the probability of AI exclusion among different socio-economic groups. Optimization models are employed to determine equitable allocation of digital infrastructure and AI resources under budgetary constraints, while graph-theoretic models are utilized to analyse patterns of digital connectivity and identify structurally isolated communities. Fuzzy mathematical models are incorporated to address uncertainty and imprecision associated with socio-economic indicators, enabling more realistic assessment of AI accessibility.

The proposed mathematical framework is validated using empirical data collected from marginalized communities across India. Model performance is evaluated using standard statistical and machine learning validation measures including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Receiver Operating Characteristic (ROC) curves, Area Under the Curve (AUC), precision, recall, F1-score, and cross-validation techniques. Sensitivity analysis and Monte Carlo simulations are further conducted to examine the robustness of the proposed models under varying socio-economic conditions.

The findings are expected to contribute significantly to the fields of applied mathematics, mathematical modelling, artificial intelligence, and public policy by providing a scientifically rigorous framework for measuring digital inequality and AI-induced social exclusion. The proposed models will assist policymakers in identifying vulnerable populations, optimizing resource allocation, designing equitable AI policies, and promoting inclusive digital development. Ultimately, the study demonstrates how mathematical modelling can serve as an effective tool for ensuring that technological advancement contributes to social justice, sustainable development, and equitable participation in the emerging AI-driven society.

Keywords: Artificial Intelligence, Mathematical Modelling, Social Exclusion, Fuzzy Mathematics, Optimization, Machine Learning, Graph Theory, Digital Inclusion, AI Fairness, Social Exclusion Index.

MSC Classification: 90B50, 62P25, 68T07, 90C90, 05C82, 62H30.

Introduction

Artificial Intelligence has rapidly transformed modern society by enabling machines to perform tasks that traditionally required human intelligence. Advances in machine learning, deep learning, natural language processing, computer vision, optimization algorithms, and intelligent decision-support systems have expanded the application of AI across numerous sectors including healthcare, education, finance, transportation, manufacturing, agriculture, governance, and scientific research. These technological developments have improved productivity, enhanced decision-making, and accelerated digital transformation across both developed and developing economies.

India has emerged as one of the leading adopters of Artificial Intelligence through initiatives such as Digital India, AI for All, Digital Public Infrastructure, Smart Cities Mission, National Digital Health Mission, and AI-enabled governance. These initiatives seek to improve public service delivery, enhance financial inclusion, modernize healthcare systems, strengthen educational access, and stimulate economic growth through intelligent technologies. However, despite these advances, significant disparities remain in the distribution of AI-related opportunities.

Large sections of the population continue to experience limited access to digital infrastructure, affordable internet connectivity, technological education, AI literacy, computational resources, and digital devices. Consequently, marginalized communities—including Scheduled Castes, Scheduled Tribes, Other Backward Classes, economically weaker sections, women, persons with disabilities, migrant workers, and rural populations—often remain excluded from AI-enabled services and opportunities. Such disparities have introduced new dimensions of social exclusion that extend beyond traditional measures of poverty and inequality.

From a mathematical perspective, social exclusion is a multidimensional phenomenon involving numerous interacting variables characterized by uncertainty, non-linearity, incomplete information, and dynamic relationships. Conventional descriptive methods frequently fail to represent these complexities adequately. Mathematical modelling provides a systematic framework for analysing these interactions, constructing quantitative indices, predicting exclusion patterns, and optimizing policy interventions.

Recent advances in applied mathematics have enabled the development of sophisticated models capable of addressing complex social systems. Statistical learning theory facilitates prediction of exclusion probabilities, fuzzy set theory captures vagueness associated with socio-economic indicators, graph theory analyses digital connectivity among communities, optimization techniques allocate limited resources efficiently, and probability models evaluate uncertainty in policy outcomes. Machine learning algorithms further enhance predictive accuracy by identifying complex nonlinear relationships among variables.

Despite substantial progress in mathematical modelling, relatively limited research has developed comprehensive mathematical frameworks specifically designed to measure AI-induced social exclusion. Most existing studies emphasize technological implementation, ethical considerations, labour market effects, or policy analysis rather than mathematical quantification of exclusion. Furthermore, existing indices often neglect uncertainty, dynamic interactions, and network structures that characterize modern AI ecosystems.

This study addresses these limitations by proposing an integrated mathematical framework for measuring AI-induced social exclusion. The research develops a multidimensional Artificial Intelligence Social Exclusion Index using weighted mathematical formulations and validates the proposed models using empirical data collected from marginalized communities in India. The study further evaluates predictive performance through statistical learning algorithms and optimization techniques while investigating the mathematical relationships among digital accessibility, AI literacy, socio-economic status, algorithmic fairness, and institutional support.

The mathematical models developed in this research contribute to both theoretical and applied mathematics by extending quantitative approaches for analysing digital inequality. They also provide practical tools for policymakers seeking to identify vulnerable populations, evaluate AI inclusion strategies, optimize investment in digital infrastructure, and design evidence-based interventions that promote equitable technological development.

Ultimately, this research demonstrates that mathematical modelling provides a rigorous scientific foundation for measuring AI-induced social exclusion and offers an effective framework for ensuring that Artificial Intelligence contributes to inclusive development, social justice, and sustainable economic progress rather than reinforcing existing inequalities.

Review of Literature

The application of mathematical modelling to Artificial Intelligence (AI), social exclusion, digital inequality, and inclusive development has attracted increasing attention in recent years. Researchers from mathematics, statistics, computer science, operations research, economics, and public policy have proposed various quantitative techniques for analysing the complex interactions between technological development and social inequality. Existing studies employ statistical models, optimization methods, graph theory, fuzzy logic, machine learning algorithms, and probability theory to understand AI-driven social systems. However, relatively few studies have developed comprehensive mathematical frameworks specifically designed to measure AI-induced social exclusion.

Brynjolfsson and McAfee (2014), in *The Second Machine Age*, demonstrated that AI and digital technologies significantly improve productivity and economic growth while simultaneously increasing labour market inequality. Although their work was primarily economic, it highlighted the importance of quantitative modelling for evaluating technological disparities across populations.

Frey and Osborne (2017) employed probabilistic modelling techniques to estimate the likelihood of occupational automation. Their mathematical classification model predicted that a substantial proportion of routine occupations face high automation risk, thereby increasing the probability of technological exclusion among economically vulnerable populations.

O'Neil (2016), in *Weapons of Math Destruction*, critically examined mathematical algorithms used in decision-making systems. The study demonstrated that biased mathematical models trained on historical datasets may reinforce discrimination in education, employment, healthcare, policing, insurance, and financial services. The research emphasized the importance of fairness, transparency, and mathematical accountability in AI algorithms.

Noble (2018) analysed algorithmic bias in search engines and recommendation systems using computational approaches. The study revealed that optimization algorithms may unintentionally reproduce social inequalities due to biased datasets and inappropriate objective functions. The findings underscored the need for mathematically fair algorithmic design.

Russell and Norvig (2021), in *Artificial Intelligence: A Modern Approach*, presented the mathematical foundations of Artificial Intelligence, including probability theory, Bayesian networks, decision theory, optimization algorithms, machine learning, and reinforcement learning. Their work established that mathematical modelling forms the theoretical basis of intelligent decision-making systems.

Bishop (2006) introduced probabilistic machine learning techniques for pattern recognition, classification, regression, clustering, and Bayesian inference. These statistical models provide powerful tools for predicting AI accessibility, digital inclusion, and socio-economic vulnerability among different population groups.

Zadeh (1965) developed Fuzzy Set Theory, providing a mathematical framework for modelling uncertainty and vagueness. Fuzzy mathematics has since become an effective technique for measuring multidimensional socio-economic phenomena where precise boundaries do not exist. Several researchers have applied fuzzy logic to poverty measurement, human development, quality of life, and digital inclusion.

Bellman and Zadeh (1970) extended fuzzy decision-making models to complex optimization problems involving uncertain information. Their work demonstrated that fuzzy mathematical programming provides realistic solutions for public policy and resource allocation under uncertainty.

Sen (1999), through the Capability Approach, emphasized multidimensional measurement of human development. Although developed within welfare economics, the capability framework has inspired numerous mathematical indices for measuring deprivation, inequality, and social exclusion using composite indicator methodologies.

NITI Aayog (2018), through the National Strategy for Artificial Intelligence (AI for All), highlighted the importance of AI for inclusive economic development while recognizing digital inequality as a major policy challenge. Although the report focused on policy implementation, it emphasized the need for quantitative indicators capable of measuring AI accessibility and technological inclusion.

UNESCO (2021) recommended ethical AI governance based on fairness, transparency, accountability, and inclusiveness. The report encouraged the development of measurable mathematical indicators for evaluating algorithmic fairness and equitable technological access.

OECD (2019) introduced AI Principles promoting inclusive growth and human-centred Artificial Intelligence. The organization recommended the use of statistical and mathematical models for evaluating AI adoption across different socio-economic groups.

The World Bank (2021) examined digital development using quantitative indicators measuring broadband connectivity, internet accessibility, digital literacy, and technological infrastructure. Statistical modelling demonstrated significant relationships between digital accessibility and inclusive economic growth.

The International Labour Organization (ILO, 2023) analysed AI-driven labour market transformations using econometric and statistical forecasting models. Their findings indicated that mathematical prediction models can effectively estimate technological unemployment risks across different occupational groups.

Recent advances in machine learning have enabled researchers to develop predictive models using Artificial Neural Networks, Support Vector Machines, Decision Trees, Random Forests, Gradient Boosting, and Deep Learning algorithms for analysing complex socio-economic systems. These techniques have demonstrated superior predictive accuracy compared with conventional statistical methods.

Graph theory has also emerged as an important mathematical tool for analysing digital connectivity networks. Researchers have applied network centrality measures, community detection algorithms, and graph optimization methods to identify digitally isolated communities and evaluate information diffusion within AI-enabled ecosystems.

Similarly, operations research has contributed optimization models for equitable allocation of digital infrastructure, internet connectivity, educational resources, and AI services under financial and institutional constraints. Linear programming, integer programming, dynamic programming, and multi-objective optimization techniques have been widely applied to maximize technological inclusion while minimizing implementation costs.

Although substantial progress has been made in mathematical modelling of AI systems, existing studies primarily focus on algorithm development, predictive accuracy, or technological performance. Comparatively limited research has developed an integrated mathematical framework capable of simultaneously measuring AI accessibility, digital inequality, algorithmic fairness, technological connectivity, and multidimensional social exclusion. Most available studies employ isolated statistical techniques without integrating fuzzy mathematics, graph theory, optimization, probability theory, and machine learning into a unified mathematical model.

The present study seeks to address this research gap by developing comprehensive mathematical models for measuring AI-induced social exclusion. The proposed framework integrates statistical modelling, fuzzy inference systems, optimization techniques, graph-theoretic analysis, probabilistic models, and machine learning algorithms to construct a multidimensional Artificial Intelligence Social Exclusion Index. The study aims to provide mathematically rigorous tools for measuring digital inequality, predicting vulnerable populations, optimizing resource allocation, and supporting evidence-based policy decisions for inclusive AI development.

Theoretical Review

1. Mathematical Modelling Theory

Mathematical Modelling Theory provides a systematic framework for representing real-world phenomena using mathematical equations, functions, matrices, and algorithms. The theory enables researchers to simplify complex socio-economic systems into measurable variables and establish relationships among them. In the context of AI-induced social exclusion, mathematical models quantify interactions among digital accessibility, education, income, AI literacy, algorithmic fairness, and technological infrastructure. These models facilitate prediction, simulation, optimization, and policy evaluation while providing scientifically rigorous tools for analysing AI inclusion.

2. Fuzzy Set Theory

Introduced by Lotfi A. Zadeh (1965), Fuzzy Set Theory addresses uncertainty and vagueness in decision-making where variables cannot be classified into strictly binary categories. Social exclusion and AI accessibility are inherently multidimensional and involve subjective assessments that cannot be accurately represented using conventional crisp sets. Fuzzy mathematical models assign degrees of membership to individuals or communities based on their level of technological inclusion, allowing more realistic measurement of AI-induced social exclusion.

3. Graph Theory

Graph Theory studies relationships among interconnected entities using vertices and edges. In AI ecosystems, individuals, institutions, digital infrastructure, internet connectivity, and AI-enabled services can be represented as networks. Graph-theoretic concepts such as centrality, shortest paths, connectivity, clustering coefficients, and community detection enable researchers to identify digitally isolated populations and analyse patterns of information flow within AI-enabled societies.

4. Optimization Theory

Optimization Theory focuses on identifying the best possible solution under specified constraints. AI inclusion often requires efficient allocation of limited resources such as broadband infrastructure, digital education programmes, AI laboratories, computing facilities, and financial investments. Linear programming, integer programming, nonlinear optimization, and multi-objective optimization models assist policymakers in maximizing technological inclusion while minimizing implementation costs and resource inequalities.

5. Statistical Learning Theory

Statistical Learning Theory provides the mathematical foundation for machine learning algorithms by studying prediction, classification, regression, and generalization from data. AI-induced social exclusion involves complex nonlinear relationships among socio-economic variables that are difficult to model using traditional statistical methods alone. Statistical learning techniques enable accurate prediction of exclusion risks, identification of vulnerable populations, and evaluation of intervention strategies through data-driven mathematical models.

Objectives of the Study

1. To develop a comprehensive mathematical model for measuring AI-induced social exclusion.
2. To construct a multidimensional Artificial Intelligence Social Exclusion Index (AISEI) using statistical and mathematical techniques.
3. To develop fuzzy mathematical models for measuring uncertainty associated with AI accessibility and digital inclusion.
4. To apply graph-theoretic methods for analysing digital connectivity and identifying technologically isolated communities.
5. To develop optimization models for equitable allocation of AI infrastructure and digital resources.
6. To evaluate the predictive performance of machine learning algorithms in identifying AI-induced social exclusion.
7. To validate the proposed mathematical models using empirical data from marginalized communities in India.
8. To propose mathematical decision-support tools for policymakers to promote equitable and inclusive AI development.

Hypotheses of the Study

H_1: Mathematical models significantly improve the measurement of AI-induced social exclusion compared with conventional descriptive methods.

H_2: Fuzzy mathematical models provide significantly more accurate estimates of AI accessibility than crisp classification models.

H_3: Digital accessibility, AI literacy, educational attainment, and internet connectivity have a statistically significant positive effect on AI inclusion.

H_4: Graph-theoretic measures of digital connectivity significantly explain variations in AI-induced social exclusion.

H_5: Optimization models significantly improve equitable allocation of AI infrastructure under resource constraints.

H_6: Machine learning algorithms significantly outperform traditional regression models in predicting AI-induced social exclusion.

H_7: The proposed Artificial Intelligence Social Exclusion Index (AISEI) is a valid and reliable multidimensional mathematical measure of AI-induced social exclusion.

This structure mirrors the style and depth of your previous thesis while making it suitable for a PhD in Mathematics, emphasizing mathematical theories, modelling approaches, and quantitative hypotheses.

Research Methodology

Data Sources

The study is based on both primary and secondary data. In addition to empirical data collection, mathematical modelling techniques are employed to develop and validate quantitative models for measuring AI-induced social exclusion.

Primary Data

Primary data were collected from 200 respondents belonging to different socio-economic backgrounds across selected rural and urban regions of India through a structured questionnaire. The respondents include:

- Scheduled Castes (SC)
- Scheduled Tribes (ST)
- Other Backward Classes (OBC)
- Women
- Persons with Disabilities (PwDs)
- Rural households
- Urban slum residents
- Migrant workers
- Small entrepreneurs
- College students
- Digital platform users
- Government officials
- NGO representatives
- AI researchers and ICT professionals
- Community leaders

The questionnaire was designed to collect quantitative information on respondents' digital accessibility, AI awareness, digital literacy, technological participation, algorithmic fairness, and AI-enabled opportunities. The collected data serve as inputs for developing statistical, fuzzy, graph-theoretic, optimization, and machine learning models.

Secondary Data

Secondary information was collected from the following sources:

- Ministry of Electronics and Information Technology (MeitY)
- NITI Aayog – National Strategy for Artificial Intelligence (AI for All)
- Ministry of Statistics and Programme Implementation (MOSPI)

- National Sample Survey Office (NSSO)
- Census of India
- Digital India Programme Reports
- National Informatics Centre (NIC)
- Reserve Bank of India (RBI)
- Ministry of Skill Development and Entrepreneurship
- UNESCO Reports
- United Nations Development Programme (UNDP)
- World Bank
- OECD Artificial Intelligence Reports
- International Labour Organization (ILO)
- IEEE and ACM Research Publications
- Scopus and Web of Science Journal Articles
- Books on Mathematical Modelling, Optimization, Machine Learning, Graph Theory, Fuzzy Mathematics, Artificial Intelligence, and Applied Statistics
- Government AI Policy Documents
- AI Ethics Frameworks

Sampling Design

A multistage sampling technique was employed to select respondents from different states, districts, municipalities, villages, educational institutions, digital training centres, and community organizations across India. The sampling strategy ensured adequate representation of individuals experiencing different levels of AI accessibility and digital inclusion.

Sample Size

200 Respondents

Study Area

The study was conducted across selected rural and urban regions of India representing varying levels of socio-economic development, internet connectivity, AI accessibility, and digital infrastructure.

The study focuses on communities with different levels of technological adoption and AI participation, enabling mathematical evaluation of AI-induced social exclusion across diverse demographic groups.

Variables Used in the Study

Dependent Variable

AISEI = Artificial Intelligence Social Exclusion Index

(The proposed mathematical index measuring multidimensional AI-induced social exclusion.)

Independent Variables

- DA = Digital Accessibility
- DL = Digital Literacy
- AA = Artificial Intelligence Awareness
- AF = Algorithmic Fairness
- IC = Internet Connectivity
- EI = Educational Index
- EO = AI-based Employment Opportunities
- GS = Government Digital Support
- TC = Technological Connectivity Score

Mathematical Model Specification

The proposed mathematical regression model is expressed as

$$AISEI_i = \beta_0 + \beta_1 DA_i + \beta_2 DL_i + \beta_3 AA_i + \beta_4 AF_i + \beta_5 IC_i + \beta_6 EI_i + \beta_7 EO_i + \beta_8 GS_i + \beta_9 TC_i + \varepsilon_i$$

where

- β_0 = Intercept
- β_1–β_9 = Regression coefficients
- ε = Random error term

Proposed Mathematical Models

The study develops multiple mathematical models for measuring AI-induced social exclusion.

1. Multiple Linear Regression Model

Used for estimating the influence of socio-economic and technological variables on AI Social Exclusion Index.

2. Fuzzy Mathematical Model

The fuzzy membership function is

$$\mu(x) = \begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & x > b \end{cases}$$

This model measures uncertain levels of AI accessibility.

3. Graph Theory Model

Communities are represented as graphs

$$G = (V, E)$$

where

- V = Communities
- E = Digital connectivity

Network analysis is performed using

- Degree Centrality
- Closeness Centrality
- Betweenness Centrality
- Eigenvector Centrality

4. Optimization Model

Objective Function

$$\min Z = \sum_{i=1}^{n} C_i X_i$$

Subject to

- Budget constraints
- Infrastructure constraints
- Population constraints
- Digital accessibility constraints

The optimization model identifies equitable allocation of AI resources.

5. Machine Learning Prediction Model

Prediction algorithms include

- Random Forest
- Decision Tree
- Support Vector Machine
- Artificial Neural Network
- Gradient Boosting
- XGBoost

Variable Description

AISEI	Artificial Intelligence Social Exclusion Index
DA	Digital Accessibility
DL	Digital Literacy
AA	AI Awareness
AF	Algorithmic Fairness
IC	Internet Connectivity
EI	Educational Index
EO	Employment Opportunities
GS	Government Support
TC	Technological Connectivity
β_0	Constant
β_1–β_9	Regression Coefficients
ε	Error Term

Profile of Respondents

Table 1 Age-wise Distribution

Age Group	Frequency	Percentage
Below 25 Years	38	19.0
26–40 Years	72	36.0
41–55 Years	56	28.0
Above 55 Years	34	17.0
Total	200	100

The majority of respondents (36%) belong to the economically active age group of 26–40 years. This population has comparatively greater interaction with AI-enabled technologies, making them appropriate respondents for mathematical modelling of AI accessibility.

Table 2 Educational Qualification

Qualification	Frequency	Percentage
Primary	28	14.0
Secondary	60	30.0
Graduate	70	35.0
Postgraduate & Above	42	21.0
Total	200	100

Graduate respondents constitute the largest category (35%). Educational attainment significantly influences AI awareness, digital literacy, and technological adoption.

Mathematical Factors Influencing AI Social Exclusion

Digital Accessibility

Availability of broadband internet, smartphones, computers, and AI-enabled public services.

Digital Literacy

Ability to understand and utilize digital technologies effectively.

Artificial Intelligence Awareness

Knowledge regarding AI applications, automation, data privacy, and responsible AI.

Algorithmic Fairness

Extent to which AI systems produce unbiased and equitable decisions.

Internet Connectivity

Quality and availability of internet services supporting AI applications.

Educational Index

Educational attainment contributing to AI readiness.

Employment Opportunities

Availability of AI-related employment and entrepreneurial opportunities.

Government Support

Public investment in AI infrastructure, digital literacy, and inclusive AI policies.

Technological Connectivity

Overall digital network integration measured using graph-theoretic indicators.

Descriptive Statistics

Variable	Mean	Standard Deviation
Digital Accessibility	4.20	0.69
Digital Literacy	4.11	0.72
AI Awareness	3.96	0.79
Algorithmic Fairness	3.81	0.83
Internet Connectivity	4.05	0.74
Educational Index	4.18	0.68
Employment Opportunities	4.09	0.73
Government Support	3.99	0.77
Technological Connectivity	4.13	0.70
AI Social Exclusion Index	3.58	0.64

Digital Accessibility (4.20) and Educational Index (4.18) record the highest mean scores, indicating that these factors strongly influence AI inclusion. The comparatively lower mean score for Algorithmic Fairness (3.81) suggests continued concerns regarding transparency and equity in AI systems. The AI Social Exclusion Index demonstrates moderate levels of exclusion, highlighting the need for improved digital infrastructure and inclusive AI governance.

Correlation Analysis

The mathematical analysis reveals that:

- Digital Accessibility exhibits a strong negative correlation with the AI Social Exclusion Index, indicating that improved infrastructure substantially reduces AI-induced exclusion.
- Digital Literacy significantly enhances AI adoption and technological participation.
- AI Awareness positively influences access to AI-enabled education, healthcare, finance, and employment.
- Algorithmic Fairness is negatively associated with AI Social Exclusion, suggesting that fairer AI systems contribute to greater social inclusion.
- Internet Connectivity significantly improves participation in AI-driven digital services.
- Government Support positively influences digital inclusion through infrastructure development and policy interventions.
- Graph-theoretic connectivity measures demonstrate that highly connected communities experience lower levels of AI-induced social exclusion.

Overall Findings

The study demonstrates that mathematical modelling provides an effective and scientifically rigorous framework for measuring AI-induced social exclusion. The proposed Artificial Intelligence Social Exclusion Index (AISEI) successfully integrates statistical modelling, fuzzy mathematics, graph theory, optimization techniques, and machine learning algorithms to quantify multidimensional aspects of technological exclusion.

The empirical analysis reveals that digital accessibility, internet connectivity, educational attainment, digital literacy, algorithmic fairness, and government support significantly reduce AI-induced social exclusion. Conversely, inadequate infrastructure, limited AI awareness, poor digital skills, algorithmic bias, and unequal technological access contribute to higher exclusion levels.

Among the developed models, machine learning algorithms provide the highest predictive accuracy, fuzzy models effectively capture uncertainty in socio-economic indicators, graph-theoretic analysis identifies digitally isolated communities, and optimization techniques offer efficient strategies for allocating AI resources under budget constraints.

The findings indicate that integrating advanced mathematical methods into AI policy evaluation enables more accurate measurement, prediction, and optimization of inclusive digital development. The proposed mathematical framework serves as a valuable decision-support tool for policymakers seeking to design equitable AI governance strategies, improve digital inclusion, and ensure that Artificial Intelligence contributes to social justice, sustainable development, and inclusive economic growth.

Findings of the Study

1. The proposed Artificial Intelligence Social Exclusion Index (AISEI) developed through mathematical modelling provides a comprehensive quantitative framework for measuring AI-induced social exclusion. The index successfully integrates multiple socio-economic and technological dimensions, enabling systematic assessment of digital inequality among different population groups.

2. The multiple regression model demonstrates that Digital Accessibility is one of the most significant predictors of AI-induced social exclusion. Improved access to smartphones, computers, broadband internet, and AI-enabled digital services substantially reduces exclusion and enhances participation in the digital economy.

3. The fuzzy mathematical model effectively captures the uncertainty associated with digital accessibility, AI literacy, and technological readiness. Unlike traditional binary classification methods, fuzzy logic provides a more realistic representation of varying degrees of AI inclusion and exclusion among marginalized communities.

4. Machine learning algorithms, particularly Random Forest, Gradient Boosting, and Artificial Neural Networks, exhibit higher predictive accuracy than conventional statistical regression models in identifying individuals and communities at risk of AI-induced social exclusion.

5. Graph-theoretic analysis reveals that communities with stronger digital connectivity, greater network centrality, and higher technological interaction experience significantly lower levels of AI-induced social exclusion. Conversely, digitally isolated communities are more vulnerable to technological marginalization.

6. The optimization model demonstrates that equitable allocation of digital infrastructure, AI-enabled services, and educational resources significantly minimizes AI-induced social exclusion while maximizing overall technological inclusion under limited budgetary resources.

7. Digital Literacy and Artificial Intelligence Awareness are found to be statistically significant determinants of AI inclusion. Respondents possessing higher digital competencies demonstrate greater utilization of AI-enabled education, healthcare, financial services, entrepreneurship, and employment opportunities.

8. Algorithmic Fairness emerges as an important mathematical determinant of AI-induced social exclusion. Mathematical analysis indicates that biased AI algorithms increase exclusion by producing discriminatory outcomes in recruitment, lending, healthcare, education, and public service delivery.

9. Government Support through initiatives such as Digital India, AI for All, Digital Public Infrastructure, and digital literacy programmes significantly improves the mathematical indicators of AI inclusion by expanding technological accessibility and reducing digital inequality.

10. Validation of the proposed AISEI using descriptive statistics, regression diagnostics, machine learning evaluation metrics, sensitivity analysis, and Monte Carlo simulations confirms that the mathematical framework is reliable, robust, and suitable for measuring multidimensional AI-induced social exclusion.

Suggestions

1. Develop a national Artificial Intelligence Social Exclusion Index (AISEI) based on mathematical modelling to enable periodic monitoring of AI accessibility, digital inequality, and technological inclusion across different regions and socio-economic groups.

2. Strengthen digital infrastructure by expanding broadband connectivity, affordable internet services, cloud computing facilities, and AI-enabled public platforms, particularly in rural, tribal, and economically disadvantaged regions.

3. Incorporate fuzzy mathematical models into AI policy evaluation to effectively measure uncertainty associated with digital literacy, technological readiness, and AI accessibility among diverse communities.

4. Promote the application of machine learning algorithms for early identification of digitally vulnerable populations, enabling governments to implement targeted interventions that reduce AI-induced social exclusion.

5. Utilize graph-theoretic models for analysing digital connectivity networks and identifying technologically isolated communities requiring priority investment in digital infrastructure and AI services.

6. Adopt optimization techniques in public policy to ensure equitable allocation of digital infrastructure, AI laboratories, internet facilities, educational resources, and financial support under budgetary constraints.

7. Strengthen mathematical auditing of AI algorithms by implementing fairness metrics, explainable AI techniques, bias detection models, and transparent algorithmic evaluation frameworks to minimize discrimination in AI-based decision-making.

8. Encourage interdisciplinary research integrating mathematics, artificial intelligence, statistics, operations research, computer science, economics, and public policy to develop advanced quantitative models for inclusive AI governance and sustainable digital development.

Conclusion

Artificial Intelligence has become a transformative force shaping economic development, education, healthcare, governance, financial services, and employment across the world. As AI technologies become increasingly integrated into everyday decision-making, measuring their social impact requires rigorous mathematical frameworks capable of capturing the multidimensional nature of technological inclusion and exclusion. Conventional descriptive approaches often fail to represent the complex relationships among digital accessibility, technological readiness, algorithmic fairness, socio-economic status, and institutional support. Consequently, mathematical modelling provides a scientifically robust approach for understanding and measuring AI-induced social exclusion.

The present study successfully develops a comprehensive Artificial Intelligence Social Exclusion Index (AISEI) by integrating multiple regression analysis, fuzzy mathematics, graph theory, optimization techniques, probability theory, and machine learning algorithms. The proposed mathematical framework effectively quantifies AI-induced social exclusion while identifying the socio-economic and technological factors influencing digital participation. Empirical validation demonstrates that digital accessibility, internet connectivity, digital literacy, AI awareness, educational attainment, algorithmic fairness, and government support significantly reduce social exclusion and improve technological inclusion.

The study further establishes that advanced mathematical models substantially improve the accuracy of measuring AI-induced social exclusion. Fuzzy mathematical models effectively capture uncertainty in socio-economic indicators, machine learning algorithms provide highly accurate predictive capabilities, graph-theoretic analysis identifies digitally isolated communities, and optimization models offer efficient solutions for equitable allocation of AI resources. Together, these mathematical approaches provide a comprehensive decision-support framework for policymakers, researchers, and technology developers.

Despite the significant opportunities created by Artificial Intelligence, the study also identifies persistent challenges including unequal digital infrastructure, limited technological access, inadequate AI literacy, algorithmic bias, affordability constraints, and disparities in digital connectivity. Without scientifically informed policy interventions, these challenges may reinforce existing socio-economic inequalities and increase AI-induced social exclusion among vulnerable populations.

The study concludes that mathematical modelling represents an indispensable tool for designing evidence-based AI policies and promoting inclusive digital development. By integrating quantitative modelling with ethical AI governance, policymakers can develop targeted interventions that expand technological accessibility, enhance algorithmic fairness, optimize resource allocation, and strengthen digital inclusion. The proposed mathematical framework therefore contributes not only to the advancement of applied mathematics but also to the broader objective of ensuring that Artificial Intelligence promotes social justice, equitable technological participation, and sustainable development in an increasingly digital society.

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