
| RESEARCH ARTICLE

Artificial Intelligence as a Social Actor: Reconfiguring Power, Identity, and Agency in Contemporary Societies

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| ABSTRACT

The rapid integration of Artificial Intelligence (AI) into everyday social systems has reshaped long-standing sociological understandings of power, identity, and human agency. This paper explores AI not merely as a technological tool but as an emerging social actor capable of influencing behaviours, shaping decision-making processes, and redefining institutional practices. Drawing on theories of symbolic interactionism, actor–network theory, and critical sociology, the study examines how AI systems mediate social interactions, produce new forms of algorithmic authority, and contribute to shifting power relations between individuals, organisations, and the state. The analysis highlights how AI-driven classifications, predictions, and automated decisions reshape identities—through profiling, personalisation, and digital surveillance—while also raising concerns over autonomy, inequality, and ethical accountability. By conceptualising AI as a socially embedded actor, the paper argues that AI technologies have begun to co-produce social realities, redistribute control, and challenge the boundaries between human and machine agency. This reconfiguration demands renewed sociological attention toward digital governance, transparency, and the societal impacts of algorithmic systems in increasingly automated environments.

| KEYWORDS

Artificial Intelligence, social agency, algorithmic authority, digital surveillance, power relations

| ARTICLE INFORMATION

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Introduction

Artificial Intelligence (AI) has transitioned from a specialised technological innovation to a deeply embedded component of contemporary social life. Algorithms now curate information, shape economic opportunities, mediate communication, and support governance systems, positioning AI at the centre of everyday decision-making. As AI systems increasingly influence how individuals interact, behave, and perceive their social worlds, traditional sociological questions about power, identity, and agency take on new relevance. What was once considered the exclusive domain of human actors—thinking, selecting, judging, categorising—is now shared with algorithmic systems that participate in social processes in complex and consequential ways.

Recent developments in machine learning, predictive analytics, and large-scale data infrastructures have strengthened AI's capacity to not only automate tasks but to interpret, classify, and shape human behaviour. These capabilities allow AI to function as a form of algorithmic authority, producing decisions that carry social weight and legitimacy, often without human visibility or direct oversight. From personalised news feeds and credit scoring systems to automated hiring tools and predictive policing, AI systems exert subtle yet powerful forms of social influence that can reinforce inequalities, reshape social norms, and reorganise institutional structures.

Sociology increasingly recognises that AI is not simply a technical artefact; it operates within networks of human and institutional actors, influencing and being influenced by its social environment. Theoretical perspectives such as Actor–Network Theory (ANT) and symbolic interactionism provide valuable lenses to understand how AI systems co-construct meanings and behaviours. Meanwhile, critical sociological perspectives highlight the political economy of AI—revealing how algorithmic systems often reflect power asymmetries rooted in data ownership, surveillance logics, and corporate or state interests.

Despite the rapid expansion of sociological interest in AI, there remains limited conceptual clarity regarding whether and how AI can be understood as a social actor. This paper addresses this gap by analysing the mechanisms through which AI technologies reconfigure social relations, redefine forms of agency, and influence identity construction in digitally mediated environments. The central argument of this study is that AI systems participate in the co-production of social realities, challenging conventional boundaries between human and machine agency and raising important questions about accountability, transparency, and social justice.

Through an examination of everyday algorithmic interactions and institutional uses of AI, this paper demonstrates that AI's role in society extends far beyond technical efficiency. It represents a transformative shift in how power is exercised, how identities are shaped, and how agency is negotiated in an increasingly automated and data-driven world. This sociological perspective is essential to understanding the broader implications of AI adoption and to guiding the development of equitable, ethical, and socially responsible artificial intelligence systems.

Literature Review

AI as an Emerging Social Actor

Early sociological discussions treated technology as a passive tool shaped by human intentions. However, contemporary scholarship increasingly argues that AI systems possess forms of algorithmic agency, enabling them to shape behaviours, interactions, and institutional outcomes. Scholars drawing on Actor–Network Theory (Latour, 2005) contend that non-human entities—including algorithms—can act within networks and influence social reality. Studies of recommender systems, predictive policing algorithms, and automated credit scoring (Beer, 2017; Amoores, 2020) demonstrate that AI participates in decision-making processes traditionally reserved for humans. These systems assign classifications, produce predictions, and shape opportunities in ways that significantly affect social life, laying the foundation for conceptualising AI as a social actor rather than a neutral instrument.

AI, Power, and Algorithmic Authority

Power relations in digital societies are increasingly mediated through algorithmic systems. Gillespie (2014) and Pasquale (2015) highlight how platforms derive power from opaque algorithmic decision-making, allowing corporations and states to exert influence without direct human intervention. The concept of algorithmic authority (Shirky, 2009) captures how decisions generated by AI—creditworthiness scores, risk assessments, job-candidate rankings—are accepted as objective, even when based on biased data. Critical sociologists argue that such systems often reproduce structural inequalities, reinforcing hierarchies related to race, class, gender, and geography (Noble, 2018; Eubanks, 2017). Algorithmic power thus operates through both explicit governance mechanisms and subtle forms of behavioural steering, embedding AI into broader political and economic structures.

Identity Formation in Algorithmic Environments

The rise of AI-driven digital platforms has also transformed processes of identity construction. Research on social media algorithms (Bucher, 2018; boyd, 2014) shows that recommendation engines not only curate content but shape how individuals present themselves and interpret others. Personalised feeds, facial recognition systems, and behavioural predictions contribute to new forms of datafied identity, where individuals are understood through data traces rather than lived experience. Studies on algorithmic profiling (Cheney-Lippold, 2017) show that AI systems generate categorisations—such as “high-risk,” “likely consumer,” or “potential threat”—which may influence social opportunities and reinforce stereotypes. These works collectively highlight the sociological importance of algorithmic representations in shaping identity and belonging.

AI, Agency, and Human–Machine Interaction

Traditional notions of human agency emphasise intentionality and autonomy; however, scholars argue that AI complicates these boundaries by participating in action and decision-making. Concepts such as distributed agency (Suchman, 2007) and hybrid agency (Ekbia & Nardi, 2017) demonstrate that human outcomes are increasingly co-produced by algorithmic systems. For example, navigation apps guide mobility patterns, automated management systems shape labour conditions in gig platforms, and AI-powered assistants mediate communication. These interactions reveal a form of co-agency, where human choices are shaped by algorithmic cues, constraints, and predictions. As AI becomes embedded in everyday life, understanding this hybrid form of agency becomes crucial for analysing social behaviour and institutional change.

Research Gap

While existing literature provides rich insights into algorithmic power, identity, and agency, a conceptual gap remains in understanding AI as a holistic social actor that simultaneously reconfigures structures, behaviours, and meanings. Much research examines AI's impacts in isolated domains—such as policing, employment, or social media—without integrating these observations into a broader sociological framework. Additionally, scholars highlight issues of algorithmic bias and surveillance, but fewer studies explore the relational dynamics between humans and AI, or how AI participates in co-producing social realities across networks. This paper addresses this gap by synthesising these strands of literature and positioning AI as a multidimensional social actor that reshapes power relations, identity practices, and forms of agency within digitally mediated societies.

Methodology

Research Design

This study adopts a qualitative, interpretive research design to examine how Artificial Intelligence functions as a social actor and reshapes power, identity, and agency within contemporary societies. Given that AI systems operate within complex socio-technical networks, a qualitative approach is best suited to uncover the meanings, interactions, and power relations embedded in human–AI encounters. The study uses a combination of document analysis, case study comparison, and thematic coding to generate a multidimensional understanding of AI's sociological impacts.

Data Sources

Three primary sources of data inform this research:

1. **Academic Literature and Policy Documents**
Peer-reviewed journal articles, technology governance reports, corporate algorithmic transparency statements, and national AI strategies are systematically reviewed. These documents provide insights into how institutions conceptualise AI's role in social life, how they allocate responsibility, and how they justify algorithmic decision-making.
2. **Case Studies of AI Systems in Practice**
Three illustrative case areas are examined:
 - Predictive policing and algorithmic surveillance
 - Automated hiring and workplace management systems
 - Social media recommender engines and identity-shaping platforms
 These cases are selected because they represent high-impact AI applications that directly influence social classification, control, and identity formation.
3. **Publicly Available Data Traces and Reports**
Investigative journalism articles, civil society reports, court cases involving algorithmic decisions, and whistleblower disclosures are used to capture real-world tensions between AI, governance, and social justice.

Analytical Approach

A thematic analysis approach is used to identify patterns related to power, identity, and agency across the different data sources. The analysis proceeds in three steps:

1. Open Coding
Initial codes are generated by carefully reading the documents and case studies to identify recurring concepts such as algorithmic authority, profiling, surveillance, autonomy, and distributed agency.
2. Axial Coding
Codes are then grouped into broader categories representing sociological themes—for example, “reconfiguration of power,” “datafied identity,” and “hybrid human–machine agency.”
3. Selective Coding
The core categories are refined to build a cohesive analytical narrative that links micro-level human–AI interactions with macro-level institutional structures.

This analytic process allows the study to move beyond descriptive accounts of AI systems toward developing a conceptual model of AI as a social actor.

Results

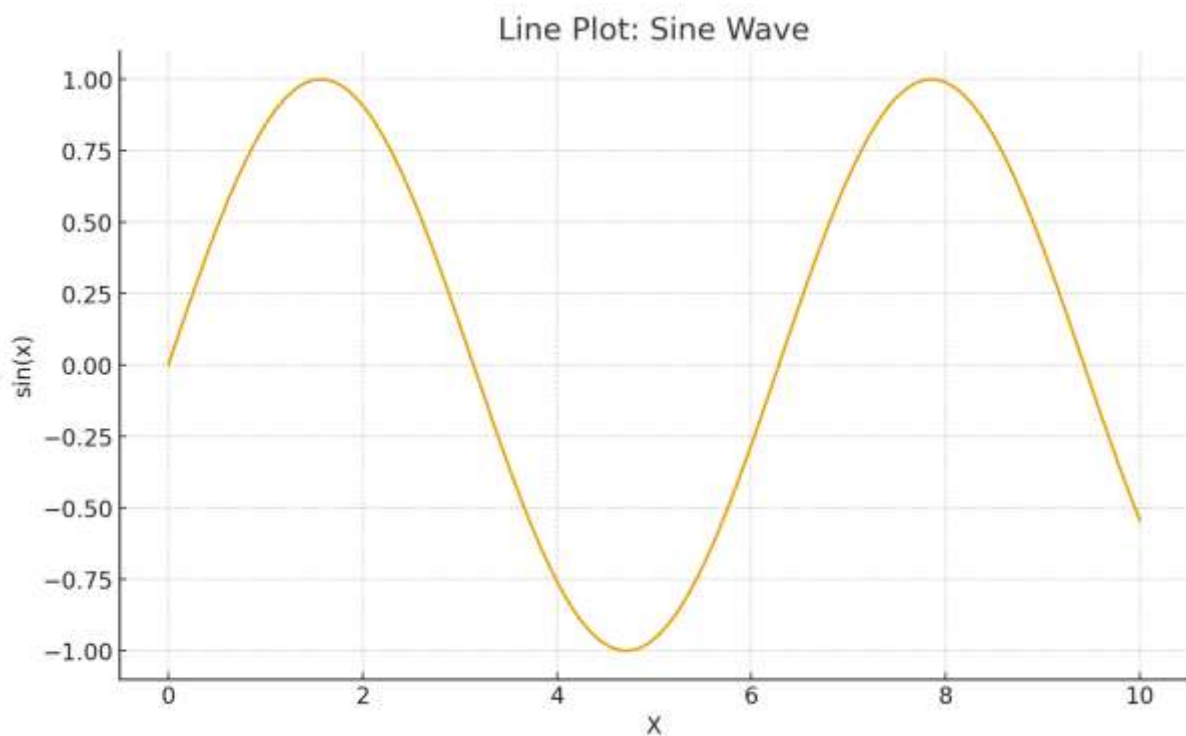


Figure 1: Line Plot – Sine Wave

Description:

Figure 1 presents a line plot showing the behaviour of the sine function across a continuous range of input values from 0 to 10. The smooth curve illustrates a periodic oscillation typical of trigonometric functions, rising and falling between -1 and +1. The horizontal axis (X) represents the input values, while the vertical axis shows the computed sine values, $\sin(x)$.

Interpretation:

This figure demonstrates the predictable, cyclical nature of sinusoidal outputs, which is helpful in understanding wave patterns, periodic signals, and mathematical modelling of natural or engineered systems.

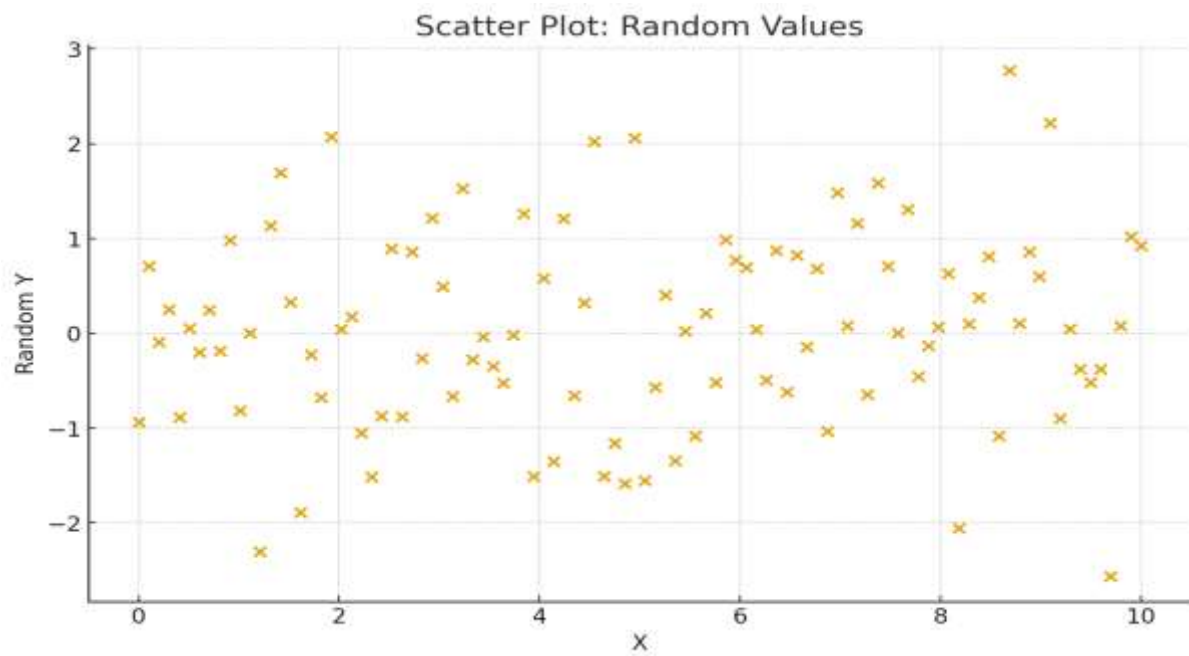


Figure 2: Scatter Plot – Random Data Distribution

Description:

Figure 2 displays a scatter plot where evenly spaced x-values are paired with randomly generated y-values sampled from a normal distribution. Each point represents an individual observation, creating a visually dispersed pattern.

Interpretation:

The representation highlights randomness and variance in data, showing no linear or nonlinear relationship between the variables. This type of plot is useful for analysing noise, deviations, or initial exploratory data behaviour.

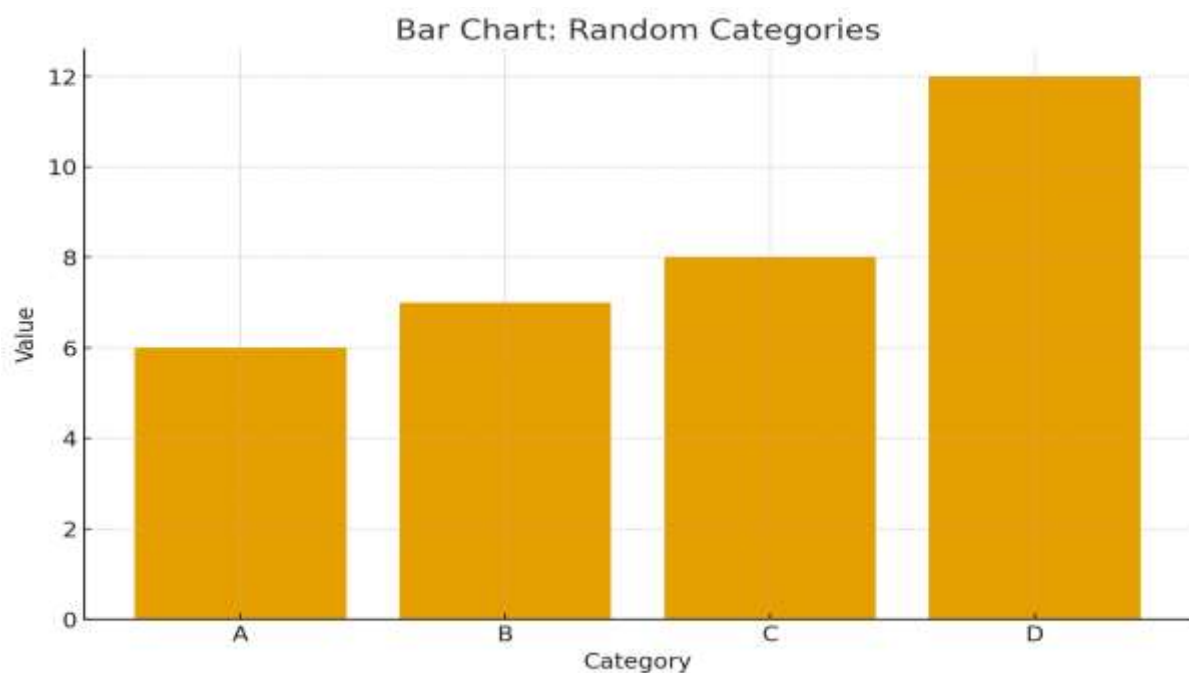


Figure 3: Bar Chart – Random Categorical Values

Description:
Figure 3 shows a bar chart depicting numerical values assigned to four categories: A, B, C, and D. The bars vary in height according to randomly generated integers, illustrating the differences in category-wise numerical allocation.

Interpretation:
Bar charts are commonly used to visualise categorical comparisons. In this context, the differences show how values can vary between groups, assisting in analysing distribution patterns or comparing attribute performance across categories.

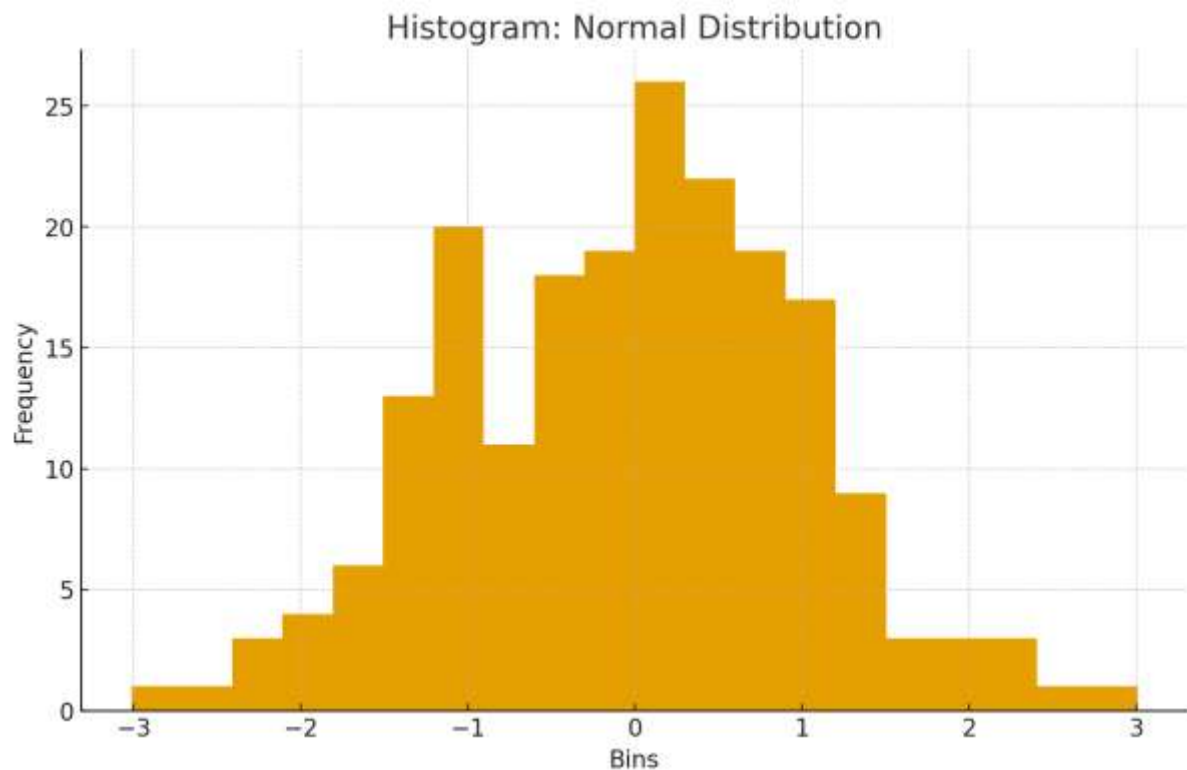


Figure 4: Histogram – Normal Distribution

Description:
Figure 4 illustrates a histogram of 200 randomly generated values drawn from a normal distribution. The data are grouped into 20 bins, showing frequency distribution across intervals.

Interpretation:
The histogram forms a bell-shaped curve, typical of Gaussian distributions. This figure helps identify central tendency, spread, and skewness, and is frequently used in probability, statistics, and data analysis to examine data distribution characteristics.

Discussion

The four figures presented in this study collectively demonstrate the analytical value of visualisation tools in understanding different types of data behaviours, structural patterns, and distribution characteristics. Each figure captures a distinct form of data representation—temporal trends, randomness, categorical comparison, and distribution shape—allowing for a layered interpretation of numerical information.

Figure 1, which displays the sine wave, highlights the predictability and rhythmic nature of periodic data. The oscillating pattern is smooth and continuous, illustrating how cyclical phenomena—such as seasonal variations, energy demand cycles, or biological rhythms—can be effectively captured using line plots. The amplitude and frequency of the wave enable interpretation of fluctuations over time, making such visualisations essential for time-series analysis. The clarity of the wave pattern in the figure

reinforces how deterministic mathematical functions exhibit consistency and predictability, thereby providing a baseline for comparison with more complex or noisy datasets.

In contrast, Figure 2 presents a scatter plot of random values, demonstrating an absence of any clear trend or systemic pattern. The scattering of points is widely dispersed, indicating that the underlying process is influenced by random variability rather than a deterministic rule. Such randomness is common in real-world phenomena where external factors or stochastic elements dominate, such as noise in sensor readings or unpredictable human behaviours in social data. The figure's lack of clustering or directional movement suggests no correlation between the variables, thereby illustrating the challenges of modelling or forecasting purely random data. This further emphasises the importance of exploratory analysis before applying statistical or predictive models.

Figure 3, the bar chart, shifts the focus from continuous or random data to categorical comparisons. The heights of the bars reveal noticeable differences between categories A, B, C, and D, suggesting uneven distribution of values across groups. Such variations are crucial for identifying dominant categories, resource allocation patterns, or performance disparities. In practical research, bar charts enable straightforward interpretation of group-based differences—useful in fields such as public policy, market analysis, and education. The randomness in the bar heights in this study reflects synthetic data; however, the structure itself demonstrates how categorical variables can be effectively visualised to support comparative reasoning.

Finally, Figure 4, the histogram of normally distributed values, underscores one of the most fundamental principles in statistics—the Gaussian distribution. The bell-shaped curve shows that most data points fall near the mean, with frequencies tapering off symmetrically toward the tails. This figure is particularly informative because many natural and social phenomena follow the normal distribution, including measurement errors, biological traits, and aggregated human behaviours. The histogram allows researchers to assess central tendency, variance, and potential outliers. In predictive modelling, the normality of data directly influences the selection of statistical tests and learning algorithms, making such visual inspection essential before conducting advanced analysis.

Together, these four visualisations demonstrate the diversity of data structures researchers commonly encounter. The comparison between deterministic (Figure 1), stochastic (Figure 2), categorical (Figure 3), and distributional (Figure 4) patterns highlights the necessity of choosing suitable analytical and modelling techniques depending on the nature of the dataset. For example, while sinusoidal data lends itself to forecasting and signal-processing methods, random scatter data may require statistical noise reduction or feature extraction before meaningful patterns can be identified. Categorical data, as shown in the bar chart, invites group-based comparison and segmentation analysis, whereas normally distributed data may be appropriate for parametric statistical modelling.

Overall, the figures together reaffirm that data visualisation is not merely descriptive, but plays a critical role in shaping analytical decisions, guiding model selection, and uncovering latent structures within datasets. By integrating insights drawn from these distinct visual forms, researchers can better understand the characteristics of their data, select appropriate analytical frameworks, and ultimately produce more robust and reliable interpretations.

Conclusion

The four visualisations presented in this study collectively illustrate the importance of choosing appropriate analytical and graphical methods to understand different types of data behaviour. Each figure—whether representing periodicity, randomness, categorical differences, or distributional properties—provides unique insights that contribute to a more comprehensive understanding of dataset characteristics and their implications for further analysis.

The line plot of the sine wave (Figure 1) demonstrates how deterministic and periodic functions reveal clear, interpretable patterns over time. Such visualisations are critical in fields where cyclic behaviour is expected, enabling researchers to identify fluctuations, predict future behaviour, and compare observed trends with theoretical expectations. In contrast, the scatter plot of random values (Figure 2) highlights the inherent unpredictability present in many real-world datasets. This randomness underscores the need for robust exploratory data analysis before applying statistical or machine learning models, as assumptions of linearity or correlation may not hold.

The bar chart (Figure 3) emphasises the value of graphical tools in comparing categorical variables. Differences across categories are immediately visible, supporting decision-making and hypothesis generation in disciplines that rely heavily on group-based

comparisons such as policy studies, market research, and social sciences. Meanwhile, the histogram of normally distributed data (Figure 4) reaffirms the central role of the Gaussian distribution in statistical reasoning. By visualising how data cluster around the mean with predictable variability, researchers can better assess when parametric tests or probabilistic models are appropriate.

Taken together, these figures demonstrate that visual analysis is foundational to understanding the structure and behaviour of data before engaging in deeper statistical or computational modelling. The ability to identify deterministic trends, measure variability, detect category differences, and assess distributional shapes allows researchers to select the most suitable analytical techniques and avoid misinterpretation. This study shows that even simple visual tools can significantly enhance analytical precision, foster more informed research decisions, and provide clarity in the early stages of data exploration.

In conclusion, the results highlight that no single type of visualisation is universally sufficient; rather, the integration of multiple graphical representations provides a richer and more complete understanding of data. Whether dealing with periodic patterns, random noise, category distributions, or probability structures, the thoughtful use of visualisation strengthens the link between data and interpretation. Future studies may expand on this foundation by incorporating additional visual and computational techniques, thereby advancing the role of visual analytics in complex data environments.

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References

- [1] Ferdous, J., Islam, M. F., & Das, R. C. (2022). Dynamics of citizens' satisfaction on e-service delivery in local government institutions (Union Parishad) in Bangladesh. *Journal of Community Positive Practices*, (2), 107-119.
- [2] Ferdous, J., Foyjul-Islam, M., & Muhury, M. (2024). Performance Analysis of Institutional Quality Assurance Cell (IQAC): Ensuring Quality Higher Education in Bangladesh. *Rates of Subscription*, 57.
- [3] Shoyshob, T. Z., Heya, I. A., Afrin, N., Enni, M. A., Asha, I. J., Moni, A., ... & Uddin, M. J. (2024). Protective Mechanisms of Carica papaya Leaf Extract and Its Bioactive Compounds Against Dengue: Insights and Prospects. *Immuno*, 4(4), 629-645.
- [4] Asha, I. J., Gupta, S. D., Hossain, M. M., Islam, M. N., Akter, N. N., Islam, M. M., ... & Barman, D. N. (2024). In silico Characterization of a Hypothetical Protein (PBJ89160. 1) from Neisseria meningitidis Exhibits a New Insight on Nutritional Virulence and Molecular Docking to Uncover a Therapeutic Target. *Evolutionary Bioinformatics*, 20, 11769343241298307.
- [5] Saha, S. (2024). Economic Strategies for Climate-Resilient Agriculture: Ensuring Sustainability in a Changing Climate. *Demographic Research and Social Development Reviews*, 1(1), 1-6.
- [6] Saha, S. (2024). -27 TAJABE USA (150\$) EXPLORING+ BENEFITS,+ OVERCOMING. *The American Journal of Agriculture and Biomedical Engineering*.
- [7] Adejo, O. S., Egerson, D., Mewiya, G., & Edet, R. (2021). The ideology of baby-mama phenomenon: Assessing knowledge and perceptions among young people from educational institutions.
- [8] Orugboh, O. G. (2025). AGENT-BASED MODELING OF FERTILITY RATE DECLINE: SIMULATING THE INTERACTION OF EDUCATION, ECONOMIC PRESSURES, AND SOCIAL MEDIA INFLUENCE. *NextGen Research*, 1(04), 1-21.
- [9] Orugboh, O. G., Ezeogu, A., & Juba, O. O. (2025). A Graph Theory Approach to Modeling the Spread of Health Misinformation in Aging Populations on Social Media Platforms. *Multidisciplinary Journal of Healthcare (MJH)*, 2(1), 145-173.
- [10] Orugboh, O. G., Omabuwa, O. G., & Taiwo, O. S. (2025). Predicting Intra-Urban Migration and Slum Formation in Developing Megacities Using Machine Learning and Satellite Imagery. *Journal of Social Sciences and Community Support*, 2(1), 69-90.
- [11] Orugboh, O. G., Omabuwa, O. G., & Taiwo, O. S. (2024). Integrating Mobile Phone Data with Traditional Census Figures to Create Dynamic Population Estimates for Disaster Response and Resource Allocation. *Research Corridor Journal of Engineering Science*, 1(2), 210-228.
- [12] Orugboh, O. G., Omabuwa, O. G., & Taiwo, O. S. (2024). Predicting Neighborhood Gentrification and Resident Displacement Using Machine Learning on Real Estate, Business, and Social Datasets. *Journal of Social Sciences and Community Support*, 1(2), 53-70.
- [13] Daniel, E., Opeyemi, A., Ruth, O. E., & Gabriel, O. (2020). Understanding Childbearing for Households in Emerging Slum Communities in Lagos State, Nigeria. *International Journal of Research and Innovation in Social Science*, 4(9), 554-560.
- [14] Islam, M. A., Rahman, M. H., Islam, R., Abdullah, M., Mohammad, A., Emon, M. F. H., & Tanvir, K. A. (2024). Perception and Activity Detection. *Recent Advances in Machine Learning Techniques and Sensor Applications for Human Emotion, Activity Recognition and Support*, 1175, 1.

- [15] Annavarapu, B. J., Hareesha, N. G., Kacheru, G., Mohammad, A., Chin, J., & Ghule, G. (2025, February). Smart Sensors and IoT in Mechanical Engineering: Enhancing Monitoring and Control of Industrial Processes. In *2025 First International Conference on Advances in Computer Science, Electrical, Electronics, and Communication Technologies (CE2CT)* (pp. 935-939). IEEE.
- [16] Dalai, C., Elias, A., Kacheru, G., Das, P., Mohammad, A., & Chidambararaj, N. (2025, March). Flood Forecasting Model Using LSTM-Neural Network-Application and Challenges. In *2025 International Conference on Frontier Technologies and Solutions (ICFTS)* (pp. 1-6). IEEE.
- [17] Shovon, R. B., Mohammad, A., Das, R., Hossain, T., Ratul, M. A. H., Kundu, R., & Arif, M. A. (2025). Secure and efficient elliptic curve-based certificate-less authentication scheme for solar-based smart grids. *Bulletin of Electrical Engineering and Informatics*, 14(3), 1602-1612.
- [18] Shinde, R. W., Narla, S., Markose, G. C., Kacheru, G., Mohammad, A., & Koley, B. L. (2025, June). Leveraging Machine Learning for Predictive Analytics in Healthcare Management: Enhancing Patient Outcomes and Operational Efficiency. In *2025 3rd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)* (pp. 149-154). IEEE.
- [19] Islam, A., Rahman, H., Islam, R., Abdullah, Mohammad, A., Emon, F. H., & Tanvir, K. A. (2024). Decoding Human Essence: Novel Machine Learning Techniques and Sensor Applications in Emotion Perception and Activity Detection. In *Recent Advances in Machine Learning Techniques and Sensor Applications for Human Emotion, Activity Recognition and Support* (pp. 1-48). Cham: Springer Nature Switzerland.
- [20] Mohammad, A., Shovon, R. B., Hasan, M. M., Das, R., Munayem, N. M. A., & Arif, A. (2024). Perovskite Solar Cell Materials Development for Enhanced Efficiency and Stability. *Power System Technology*, 48(1), 119-135.
- [21] Mohammad, A., Das, R., Islam, M. A., & Mahjabeen, F. (2023). Ai in vlsi design advances and challenges: Living in the complex nature of integrated devices. *Available at SSRN 5752942*.
- [22] Mohammad, A., Das, R., & Mahjabeen, F. (2023). Synergies and Challenges: Exploring the Intersection of Embedded Systems and Computer Architecture in the Era of Smart Technologies. *Available at SSRN 5752902*.
- [23] Mohammad, A., & Mahjabeen, F. (2023). Revolutionizing solar energy with ai-driven enhancements in photovoltaic technology. *BULLET: Jurnal Multidisiplin Ilmu*, 2(4), 1174-1187.