

To What Extent Can Mathematical Modelling Capture the Complexity of Human Behaviour?

Question 5

Palak Akhil Samani

Prabhavati Padamshi Soni International Junior College

Introduction

Attempts at modelling human behaviour mathematically rest on the premise that there are regularities in human behaviour that can be precisely specified (Grindrod, 2018).

Mathematical models are often inaccurate when modelling human behaviour. Consciousness is not computable, the dynamics of social and economic systems are fundamentally chaotic and human interpretation is irreducible to measurement and computation. Mathematical models can be used only as representations of patterns that became evident, but they cannot explain and anticipate human behaviour.

The Allure of Mathematical Precision

Mathematical models of human behaviour have proven effective in many cases.

Psychometric models facilitate optimal interventions for specific objectives (NTT Corporation, 2024). Game theory with Nash equilibria provides results in auctions and oligopolies. The Black-Scholes model abstracts risk-taking behaviour and future discounting, creating the first automated financial options market (Black & Scholes, 1973). However, such models are insufficient. Nash equilibrium forecasts behaviour only when people already know it. Mathematical models have limited usefulness with set parameters, while human behaviour develops dynamically. The Black-Scholes model's predictions deviated by over 30% during the 1987 crash, precisely when human panic behaviour dominated mathematical assumptions, revealing models work only when human behaviour conforms to their constraints. The Lucas Critique points out that policy changes alter behavioural relationships, making past data unreliable for prediction (Lucas, 1976). This shows that mathematical models assuming static behaviour cannot fully anticipate human responses, highlighting the contextual sensitivity and adaptability of human decision-making.

Formal precision through utility maximization excludes preference changes, social considerations and contextual meaning, achieving coherent models at the expense of explanatory force regarding actual human action.

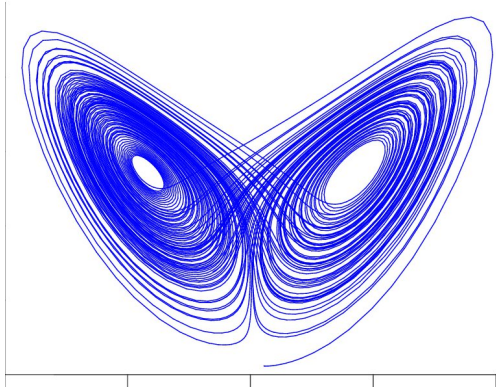


Fig 1: The Lorenz attractor: a deterministic system exhibiting chaotic behaviour. Even with perfectly defined rules, its trajectory never repeats, illustrating the limits of mathematical models in fully capturing complex, unpredictable systems like human behaviour.

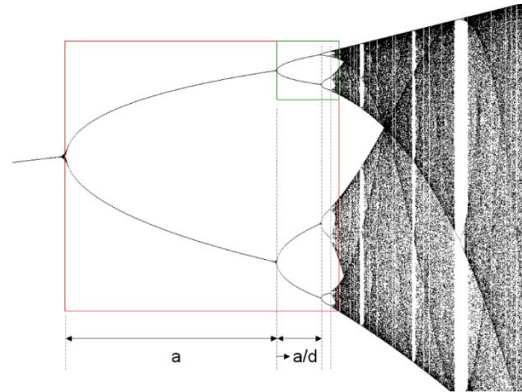


Fig 2: Bifurcation diagram of the logistic map illustrating how small changes in initial conditions can lead to vastly different outcomes, akin to the unpredictable nature of human behaviour.

Why Human Behaviour Resists Mathematical Modelling

Mathematical models cannot capture the qualitative dimensions of human behaviour, including meaning, intentionality, and ethical action (Husserl, 1913). Chaos theory, while itself a branch of mathematics, shows that deterministic systems can behave unpredictably due to sensitivity to initial conditions (Fractal Foundation, 2025). Ariely (2008) demonstrated that irrelevant anchoring numbers changed purchasing decisions by up to 400%, illustrating extreme sensitivity to initial conditions. Human behaviour exhibits similar sensitivity, compounded by consciousness and meaning-making, which makes mathematical modelling fundamentally limited. Tiny mood variations from irrelevant environmental cues cascade into large decision outcome differences (Loewenstein & Lerner, 2003). Whether to invest, marry or change careers may depend on small neurochemical differences, magnified through nonlinear cascades within consciousness. The behavioural field increasingly accepts that chaos theory better explains behaviours than linear mathematical models (PMC, 2024).

Adding random factors to equations doesn't encapsulate chaos, it expresses uncertainty. Human consciousness and its creative agency, transcends both determinism and randomness.

Limits of Mathematical Modelling

Mathematical models do not encompass meaning, purpose, intent, and qualitative experiences (Husserl, 1913). Numbers quantify, while human action involves qualitative value, worth, and meaning, which resists quantification. Reinforcement Learning “provides a framework for sequential decision-making” and “mathematically describes how decisions are paired with outcomes over time” (Oxford Academic, 2021). However, human behaviour includes the ability to do everything contrary to what is prescribed. The ability to act ethically, aesthetically, or for an existential cause is the most critical detail omitted.

Empirical evidence demonstrates these boundaries. Viktor Frankl (1946) noted that, in the Nazi concentration camps, people systematically violated models based on reward maximization and punishment minimization. Models assume certain universals in behavioural description, but human behaviour is necessarily cultural and temporally specific. The mathematical notion of time preference presupposes stability in discounting future rewards, but cultural beliefs about time differ radically (Hall, 1983). Linear and cyclical views of time cause different behavioural dispositions which can only be described in mathematical models by use of culturally-defined parameters thus negating claims of universality.

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

Fig 3: Q-learning update equation. Mathematical models can precisely quantify reward-based learning but fail to capture the qualitative, intentional, and ethical dimensions of human behaviour.

Neural Complexity and Behaviour

Computational methods in social neuroscience enable scientists to answer such questions as where in the brain specific computations, as inferred by behavioural models, are being done. Neural activity correlates with behaviour, but correlation does not imply causation. For example, identical neural firing patterns can produce different subjective experiences depending on context and attention (O'Regan & Noë, 2001).

The "hard problem of consciousness" (explaining how subjective experience arises) remains unsolved. Mathematical models may describe neuron activity, but they cannot account for why this activity produces intentional, conscious behaviour (Grindrod, 2018). Brain plasticity further undermines models, as neuronal connections continuously change in response to experience, invalidating fixed assumptions (Doidge, 2007).

The Social Emergence Problem

Mathematical models attempt to capture "social dynamics and cultural evolution" through agent-based approaches. But social reality has emergent properties that cannot be reconstituted into individual behavioural rules no matter how complex. Mathematical models can represent linguistic patterns statistically but not how meaning transpires through social interaction (Wittgenstein, 1953). Social institutions illustrate how reductionist mathematical modelling has failed. Akerlof's theory of the market for lemons shows how hidden information can collapse markets (Akerlof, 1970). In modelling human behaviour, this highlights that models fail if they ignore trust, perception, and information structures. Social and institutional context is essential for predicting realistic outcomes. Property rights, democratic governance and scientific communities are products of complex historical processes of contingent events, cultural meanings, and creative institutional design.

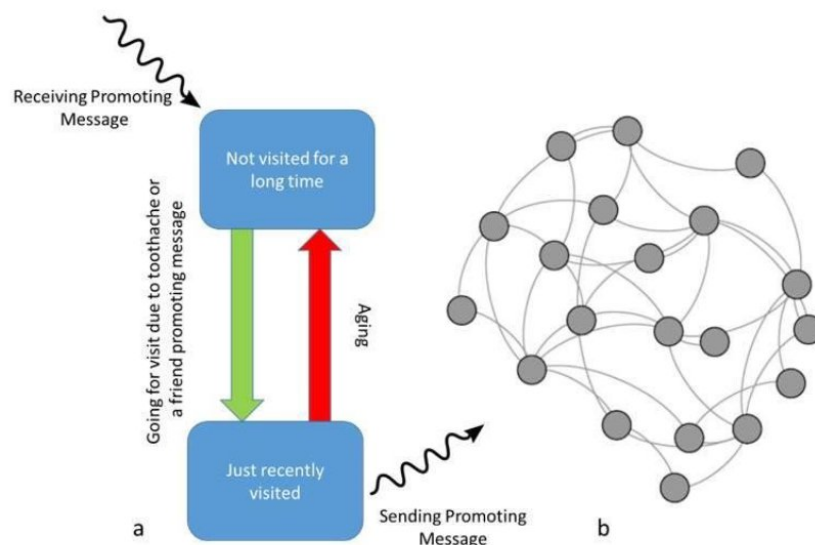


Fig 4: Schematic of an agent-based model illustrating how individual behaviours and interactions can lead to emergent social patterns, highlighting the challenges in modelling complex human systems.

Constrained Success

Machine learning algorithms trained on massive behavioural datasets can predict consumer purchases, political preferences, and relationship outcomes with surprising accuracy: political preferences of Facebook users were predicted with up to 95% accuracy using only number of likes (Kosinski et al., 2013). However, these successes are statistical rather than understanding of choice or action. Effective applications of mathematics in modelling occur when behavioural complexity is limited. Ostrom demonstrated that communities manage shared resources through context-dependent norms and rules (Ostrom, 1990). This shows that human behaviour is shaped by culture and institutions, which cannot be universally quantified. Mathematical models must consider these local and social factors to meaningfully represent behaviour. Financial derivatives pricing works where all traders are equally adept at math and institutions operate under same constraints.

While traditional mathematical models have limitations, approaches like phenomenology, auction theory and complexity theory emphasize context, culture, and emergent properties, offering complementary insight into human behaviour.

Conclusion

Mathematical modelling identifies predictable patterns but fails to reflect human complexities. Mathematical methods succeed in modelling aggregate patterns under controlled conditions but are systematically inadequate for addressing consciousness, meaning-making, social emergence and creative agency.

Human action includes qualitative dimensions beyond mathematical capture, reinforcing the limits of models. Mathematics remains useful for describing mass patterns, testing hypotheses under controlled conditions, and providing policy frameworks assuming behavioural stability. Still, the capacity of mathematical modelling to replicate human behavioural patterns remains inherently limited by the categorical distinction between quantitative mathematical representation and qualitative human experience. This underscores the need of developing methods appropriate to human reality. While pure mathematics cannot capture the full richness of human experience, integrating computational, phenomenological, and complexity-based approaches may offer the closest approximation to understanding the patterns underlying human behaviour.

Bibliography

- Akerlof, G. A. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84(3), 488–500.
- Alexander, J., Giesen, B., Münch, R., & Smelser, N. J. (1987). *The micro-macro link*. University of California Press.
- Anderson, C. (2008). The end of theory: The data deluge makes the scientific method obsolete. *Wired Magazine*, 16(7), 16-07.
- Ariely, D. (2008). *Predictably irrational: The hidden forces that shape our decisions*. HarperCollins.
- Arrow, K. J. (1951). Social choice and individual values. *Yale University Press*.
- Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637-654.
- Brentano, F. (1874). *Psychology from an empirical standpoint*. Routledge & Kegan Paul.
- Britannica, T. Editors of Encyclopaedia (2021, July 20). Chaos theory. *Encyclopaedia Britannica*. <https://www.britannica.com/science/chaos-theory>
- Camerer, C. F. (2003). *Behavioural game theory: Experiments in strategic interaction*. Princeton University Press.
- Capra, F. (1996). *The web of life: A new scientific understanding of living systems*. Anchor Books.
- Chalmers, D. J. (1995). Facing up to the problem of consciousness. *Journal of Consciousness Studies*, 2(3), 200-219.
- Complexity Digest. (2024). *Social dynamics and cultural evolution*. Retrieved from <https://www.complexitydigest.com>
- Dennett, D. C. (1991). *Consciousness explained*. Little, Brown and Company.
- Dilthey, W. (1883). *Introduction to the human sciences*. Princeton University Press.
- Doidge, N. (2007). *The brain that changes itself*. Viking.

- Fractal Foundation. (2025). *Chaos theory*. Retrieved from <https://fractalfoundation.org/resources/what-is-chaos-theory/>
- Frankl, V. E. (1946). *Man's search for meaning*. Beacon Press.
- Friedman, M. (1953). *Essays in positive economics*. University of Chicago Press.
- Geertz, C. (1973). *The interpretation of cultures*. Basic Books.
- Grindrod, P. (2018). On human consciousness: A mathematical perspective. *Network Neuroscience*, 2(1), 23-40. https://doi.org/10.1162/NETN_a_00030
- Guess, D., & Sailor, W. (1993). Chaos theory and the study of human behaviour: Implications for special education and developmental disabilities. *The Journal of Special Education*, 27(1), 16-34.
- Hackman, J. R. (1962). *Mathematical models in the behavioural sciences*. Prentice-Hall.
- Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behaviour and Human Performance*, 16(2), 250-279.
- Hall, E. T. (1983). *The dance of life: The other dimension of time*. Anchor Press.
- Heidegger, M. (1962). *Being and time*. Harper & Row.
- Hofstede, G. (1980). *Culture's consequences: International differences in work-related values*. Sage Publications.
- Hull, J. C. (2018). *Options, futures, and other derivatives*. Pearson.
- Husserl, E. (1913). *Ideas: General introduction to pure phenomenology*. Macmillan.
- Iyengar, S., & Lepper, M. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, 79(6), 995-1006.
- James, W. (1890). *The principles of psychology*. Henry Holt and Company.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrical*, 47(2), 263-291.
- Kant, I. (1785). *Groundwork for the metaphysics of morals*. Cambridge University Press.

- Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behaviour. *Proceedings of the National Academy of Sciences*, 110(15), 5802-5805.
- Lieberman, M. D., Eisenberger, N. I., Crockett, M. J., Tom, S. M., Pfeifer, J. H., & Way, B. M. (2021). Putting feelings into words: Affect labelling disrupts amygdala activity in response to affective stimuli. *Psychological Science*, 18(5), 421-428.
- Loewenstein, G., & Lerner, J. S. (2003). The role of affect in decision making. *Handbook of Affective Sciences*, 619-642.
- Logothetis, N. K. (2008). What we can do and what we cannot do with fMRI. *Nature*, 453(7197), 869-878.
- Lucas, R. E. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy*, 1, 19–46.
- Maguire, P., Moser, P., Maguire, R., & Griffith, V. (2018). Mathematical model of consciousness proves human experience cannot be modelled on a computer. *arXiv preprint arXiv:1801.00012*.
- Mathematical Consciousness Science. (n.d.). *AMCS - Association for Mathematical Consciousness Science*. Retrieved from <https://amcs-community.org/mathematical-consciousness-science/>
- Mauss, M. (1925). *The gift: Forms and functions of exchange in archaic societies*. Cohen & West.
- Merleau-Ponty, M. (1945). *Phenomenology of perception*. Routledge.
- Milgrom, P. (2004). *Putting auction theory to work*. Cambridge University Press.
- Nash, J. (1950). Equilibrium points in n-person games. *Proceedings of the National Academy of Sciences*, 36(1), 48-49.
- North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press.
- NTT Corporation. (2024). *Psychometric models for optimal interventions*. NTT Technical Review.

- O'Regan, J. K., & Noë, A. (2001). A sensorimotor account of vision and visual consciousness. *Behavioural and Brain Sciences*, 24(5), 939-973.
- Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press.
- Oxford Academic. (2021). Reinforcement learning: An introduction to the computational approach to learning optimal behaviour. *Philosophical Transactions of the Royal Society B*, 376(1819), 20190382.
- PMC. (2024). *Behavioural field research and chaos theory applications*. PubMed Central. Retrieved from <https://www.ncbi.nlm.nih.gov/pmc/>
- Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, 10(2), 59-63.
- Resnicow, K., & Page, S. E. (2008). Embracing chaos and complexity: A quantum change for public health. *American Journal of Public Health*, 98(8), 1382-1389.
- Sapir, E. (1921). *Language: An introduction to the study of speech*. Harcourt, Brace and Company.
- Sartre, J. P. (1943). *Being and nothingness*. Philosophical Library.
- Schroeder, M. (1991). *Fractals, chaos, power laws: Minutes from an infinite paradise*. W.H. Freeman.
- Simon, H. A. (1955). A behavioural model of rational choice. *Quarterly Journal of Economics*, 69(1), 99-118.
- Strotz, R. H. (1955). Myopia and inconsistency in dynamic utility maximization. *The Review of Economic Studies*, 23(3), 165-180.
- Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behaviour & Organization*, 1(1), 39-60.
- Weber, M. (1922). *Economy and society*. University of California Press.
- Wittgenstein, L. (1953). *Philosophical investigations*. Macmillan.