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Predictive Analytics in Consumer Behaviour Analysis Theoretical Frameworks, Foundational Literature, and Emerging Paradigms

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Abstract- Predictive analytics has emerged as one of the most consequential methodological developments in consumer behaviour research, transforming how scholars conceptualise the relationship between data, theory, and marketing practice. This chapter offers a theoretically grounded account of predictive analytics as applied to consumer behaviour, tracing the intellectual lineage from classical utility theory and information processing models through to contemporary machine learning frameworks and digital behavioural econometrics. Drawing on more than fifty sources, the chapter situates predictive analytics within five foundational theoretical traditions – rational choice theory, information processing models, stimulus-organism-response paradigms, social cognitive theory, and network science – and examines how each tradition has shaped the design, interpretation, and critique of predictive models. It argues that predictive analytics is not merely a technical upgrade to existing research methods but represents an epistemological shift in how consumer behaviour is understood: from explanation to anticipation, from average tendencies to individual trajectories, and from static snapshots to dynamic longitudinal processes. The chapter concludes by identifying theoretical tensions that remain unresolved and directions for a more integrated theoretical programme.

Keywords: predictive analytics; consumer behaviour theory; machine learning; digital footprints; explanation and prediction; marketing ethics

I. INTRODUCTION

There is something philosophically audacious about the claim at the heart of predictive analytics: that human behaviour, messy and wilful as it is, can be modelled with sufficient fidelity to anticipate what individuals will do before they have done it. For most of the twentieth century, consumer behaviour scholars treated prediction as a secondary ambition: useful as a check on explanatory models, but subordinate to the deeper goal of understanding why people buy, choose,and consume as they do. The rise of predictive analytics has inverted this hierarchy. In an era of pervasive digital instrumentation, organisations collect behavioural data at a scale and granularity that earlier theorists could not have imagined, and the competitive incentive to anticipate rather than merely understand consumer action has never been stronger (Davenport and Harris, 2007).Predictive analytics, broadly defined, refers to the use of statistical, algorithmic, and machine learning techniques to forecast future outcomes from historical and real-time data (Shmueli and Koppius, 2011). In the context of consumer behaviour, these outcomes include purchase likelihood, brand switching, churn, lifetime value, responsiveness to price changes, and sensitivity to marketing stimuli. The techniques range from logistic regression and survival analysis, which have their roots in mid-twentieth-century statistical theory, to gradient boosting machines, deep neural networks, and transformer-based language models that encode behavioural signals in ways that resist easy theoretical interpretation (Goodfellow, Bengio and Courville, 2016).

This chapter is concerned not with the technical mechanics of these methods, which are well covered in the machine learning and data science literatures, but

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with their theoretical foundations and implications. What theories of consumer behaviour do predictive models presuppose, even implicitly? What theoretical traditions have shaped the variables that analysts choose to include or exclude? And what new theoretical questions does the predictive turn raise that existing frameworks are poorly equipped to answer? Addressing these questions is important because the relationship between theory and predictive model is not merely academic: a model built on theoretically incoherent assumptions will, sooner or later, fail in practice, precisely at the moments when the world departs from the historical patterns on which the model was trained (Taleb, 2007).

The chapter proceeds as follows. Section 2 surveys the classical theoretical traditions in consumer behaviour that provide the conceptual substrate for predictive modelling. Section 3 examines stimulus-organism-response paradigms and their computational reincarnations. Section 4 addresses social cognitive and network-theoretic perspectives. Section 5 engages with the epistemological tensions between explanatory and predictive reasoning. Section 6 explores the role of digital data ecologies in reshaping both what can be predicted and what it means to predict. Section 7 discusses the ethical and normative dimensions of prediction in consumer contexts. Section 8 sets out directions for future theoretical development, and Section 9 concludes.

1.Classical Theoretical Traditions in Consumer Behaviour

Rational Choice Theory and Utility Maximisation

The intellectual ancestry of predictive analytics in consumer behaviour runs through classical economics and its foundational assumption: that consumers are rational agents who maximise utility subject to budget constraints (Von Neumann and Morgenstern, 1944). Within this tradition, prediction is conceptually straightforward: if one knows a consumer's preference ordering and the prices and incomes they face, their choices are, in principle, determinate. The demand curves and utility functions of neoclassical economics are, at their core, predictive instruments that map inputs (prices, income, tastes) to outputs (quantities demanded) through theoretically derived relationships. This tradition bequeathed several enduring structures to predictive analytics. Choice modelling techniques – particularly the multinomial logit model and its derivatives – are direct descendants of random utility theory, treating observed choices as probabilistic realisations of underlying utility functions (McFadden, 2001). Conjoint analysis, widely used in product design and pricing research, similarly operationalises utility theory by decomposing consumer preferences into attribute-level part-worths that can then be used to predict choices among hypothetical alternatives (Green and Srinivasan, 1990). The explanatory and predictive ambitions of these tools are genuinely integrated: the utility framework both motivates the model structure and gives substantive meaning to the parameters estimated.

The limitations of the rational choice tradition as a foundation for predictive analytics became apparent as empirical evidence accumulated showing systematic and predictable departures from utility-maximising behaviour. Tversky and Kahneman (1974) documented heuristics and biases – anchoring, availability and representativeness – that produced consistent prediction errors within rational frameworks. Thaler (1985) developed the concept of mental accounting, demonstrating that consumers segment money into categorical budgets in ways that violate the fungibility assumed by utility theory. These anomalies were not random noise; they were structured, replicable, and theoretically interpretable. Their documentation gave rise to behavioural economics, which sought to retain the predictive rigour of utility modelling while incorporating psychologically realistic assumptions about cognition and motivation (Camerer, Loewenstein and Rabin, 2004).

2. Information Processing Models

Parallel to economic approaches, the cognitive revolution in psychology produced a family of information processing models of consumer behaviour that proved highly influential in shaping predictive research. The foundational premise of these models is that consumers are limited

information processors who attend selectively to stimuli, encode information in memory according to schematic structures, and retrieve it under conditions of bounded rationality (Bettman, 1979). Howard and

Sheth's (1969) theory of buyer behaviour was among the first systematic attempts to specify the cognitive processes mediating between marketing stimuli and purchase decisions, introducing constructs such as attention, comprehension, attitude, and intention that became standard variables in predictive modelling.

The Theory of Reasoned Action (Fishbein and Ajzen, 1975) and its successor, the Theory of Planned Behaviour (Ajzen, 1991), crystallised this tradition into a formally specified predictive model: behavioural intention is predicted by attitude toward the behaviour and subjective norm, with perceived behavioural control added in the later formulation. These models generated an enormous empirical literature demonstrating their predictive validity across domains from product purchase to health behaviour, and their variable structure beliefs, evaluations, norms, and intentions became the template for survey-based predictive research in marketing for decades.

The Elaboration Likelihood Model (Petty and Cacioppo, 1986) extended information processing theory by specifying conditions under which persuasion operates through central (deliberative) versus peripheral (heuristic) routes, with implications for how attitude change — and downstream behaviour — could be predicted from message and audience characteristics. This dual-process architecture anticipated by two decades the distinction between System 1 and System 2 thinking that Kahneman (2011) would later popularise, and it continues to inform the design of predictive models that seek to distinguish deliberative from impulsive purchase behaviour.

3. Stimulus-Organism-Response Paradigms and Their Computational Reincarnations

1. The S-O-R Framework in Consumer Research

The Stimulus-Organism-Response (S-O-R) Framework, Originally Derived From Behaviourist Psychology But Substantially Modified By The Cognitive Turn, Provides Perhaps The Most Architecturally Influential Theoretical Structure For Predictive Analytics In Consumer Behaviour (Mehrabian And Russell, 1974). In Its Consumer Behaviour Application, Marketing Stimuli – Price, Promotion, Product Attributes, Store Environment And Digital Interface Design – Are Conceptualised As Inputs That Pass Through Organismic Mediators (Affect, Cognition And Motivation) To Produce Behavioural Responses Such As Approach, Purchase, Or Loyalty. The S-O-R Framework Is Explicitly Predictive In Structure: It Specifies Inputs, Specifies The Transformation Process, And Specifies Outputs, Providing A Theoretical Map For Empirical Model Building. Donovan And Rossiter (1982) Applied The Mehrabian-Russell Model To Retail Environments, Demonstrating That Atmospheric Variables (Lighting, Colour, Music, Scent) Influenced Consumers' Emotional States Along Pleasure-Arousal Dimensions And That These Emotional States Predicted Approach And Avoidance Behaviours, Including Time Spent In-Store And Purchase Amounts. This Line Of Research Established The Legitimacy Of Affective Variables As Predictors Of Consumer Behaviour Alongside The Cognitive Variables Privileged By Information Processing Models, And It Opened A Substantial Research Stream Into Sensory Marketing And Environmental Psychology That Continues To Generate Predictive Insights (Turley And Milliman, 2000). In The Digital Environment, The S-O-R Framework Has Been Applied Extensively To The Study Of Online Consumer Behaviour, With Website Design Features (Stimuli), User Cognitive And Affective Responses (Organism), And Purchase, Revisit, And Recommendation Intentions (Responses) Specifying The Basic Model Structure (Eroglu, Machleit And Davis, 2001). The Theoretical Framework Travels Well To The Digital Context, But Its Operationalisation There Involves Distinctive Measurement Challenges: Self-Reported Affective States Are Difficult To Elicit In Online Settings, And The Stimuli Are Both More Controllable And More Granular Than Physical Retail Environments, Enabling The Kind Of Large-Scale Experimental Manipulation (A/B Testing) That Produces The Behavioural Data On Which Machine Learning Predictive Models Thrive.

4. Machine Learning as Computational S-O-R

It is instructive to read contemporary machine learning approaches to consumer behaviour prediction through the lens of the S-O-R framework, even though most machine learning practitioners do not frame their work in these terms. A recommendation algorithm that takes a user's browsing and purchase history (stimuli), passes it through a latent factor model or neural network (organism, understood as a computational representation of preference structure), and outputs a ranked list of predicted purchases (response) is

enacting something structurally analogous to the S-O-R model but with the organism treated as a black box to be optimised rather than a theoretically specified psychological process to be understood (Ricci, Rokach and Shapira, 2015).

This correspondence is more than a loose metaphor. It points to a fundamental difference between predictive analytics as practised in machine learning contexts and predictive analytics as practised in theoretically grounded consumer research. Machine learning models are optimised for predictive accuracy on held-out data; the internal parameters of the model – the weights in a neural network, the latent dimensions of a matrix factorisation – need not correspond to theoretically meaningful constructs. Consumer behaviour theory, by contrast, insists that the mediating processes – attitudes, intentions, emotions and norms – carry substantive meaning and that understanding them is part of what it means to understand consumer behaviour, not merely an instrument for accurate forecasting (Shmueli, 2010).

The tension between these approaches is not merely philosophical. Purely predictive models, optimised without theoretical constraint, are vulnerable to distributional shift: when the world changes in ways that alter the statistical regularities in the training data, the model's predictions degrade without the model providing any signal that this has occurred (Sugiyama and Kawanabe, 2012). Theoretically grounded models, because they embed assumptions about causal mechanisms, can in principle diagnose why predictions have failed and identify what would need to change for predictions to recover. This is one reason why the integration of causal reasoning with predictive modelling has become an active research frontier, with structural equation models, directed acyclic graphs, and counterfactual analysis offering tools for importing causal structure into predictive frameworks (Pearl and Mackenzie, 2018).

5. Social Cognitive Theory and Network Perspectives

1. Social Learning, Self-Efficacy, and Vicarious Influence

Bandura's social learning theory (Bandura, 1977) and its later formulation as social cognitive theory (Bandura, 1986) introduced a fundamentally relational conception of consumer behaviour that complemented the individual-centred models of utility theory and information processing. The core claim – that behaviour is shaped by the reciprocal interaction of personal factors, behaviour and environmental influences – challenged the linear stimulus-to-response architecture of earlier frameworks and positioned social observation and vicarious learning as central mechanisms through which consumer behaviour is acquired, maintained, and modified. Self-efficacy, the belief in one's capacity to execute behaviour successfully, emerged as a particularly powerful predictor of adoption behaviour across contexts from technology acceptance to health behaviour to financial decision-making (Compeau and Higgins, 1995).

For predictive analytics, social cognitive theory contributes several important variables and mechanisms. Social influence, the degree to which significant others are perceived to endorse or model a behaviour, is a standard predictor in technology acceptance models and online purchase intention research (Venkatesh et al., 2003). Observational learning provides a theoretical basis for recommendation systems that leverage social proof: 'customers who bought this also bought' is a computational implementation of Bandura's vicarious reinforcement mechanism, encoding the behaviour of similar others as a signal that predicts the focal consumer's likely preferences.

The Technology Acceptance Model (Davis, 1989), one of the most widely cited models in information systems and e-commerce research, drew partly on social cognitive theory in its specification of perceived ease of use and perceived usefulness as predictors of technology adoption. Subsequent extensions (TAM2, UTAUT and UTAUT2) added social influence, facilitating conditions, hedonic motivation, and habit as additional predictors, producing increasingly comprehensive predictive frameworks for adoption and continued use behaviour (Venkatesh, Thong and Xu, 2012). These models sit at the intersection of social cognitive theory, information processing theory, and technology-specific theorising, exemplifying the kind of multi-theoretical integration that rigorous predictive analytics requires.

6. Network Science and Social Contagion

The network science perspective, drawing on sociological traditions from Granovetter's (1973) work on the strength of weak ties to Watts and Strogatz's (1998) small-world network model, introduced a structural conception of consumer behaviour that neither utility theory nor cognitive models had adequately accommodated. Consumer behaviour, on this view, is not merely an individual-level psychological phenomenon but a network-level process in which choices propagate through social ties, norms diffuse across communities, and information cascades spread through populations in ways that are highly sensitive to network topology.

The theoretical significance for predictive analytics is substantial. Network position – degree centrality, betweenness and eigenvector centrality – is widely used to model information diffusion and product adoption, although its role is debated: Watts and Dodds (2007) show that large cascades depend more on a critical mass of easily influenced individuals than on a small number of highly connected influentials. Bass's (1969) diffusion of innovations model, one of the earliest predictive frameworks for new product adoption, can be reinterpreted in network terms: the coefficient of imitation captures the social contagion mechanism through which early adopters influence the majority, and later extensions distinguish explicitly between influentials and imitators (Van den Bulte and Joshi, 2007).

The availability of large-scale social network data — from platforms such as Facebook, Twitter/X, and Instagram — has dramatically expanded the empirical scope of network-theoretic prediction. Randomised field evidence shows that peer influence, triggered by viral product features, drives product adoption through online social networks (Aral and Walker, 2011). Natural language processing of social media data enables the extraction of sentiment, topic, and relational signals that serve as predictors of aggregate consumer trends and individual-level purchase propensity

(Pang and Lee, 2008). The integration of social network data with transaction data and demographic data has become one of the most productive frontiers in applied predictive analytics, particularly in financial services, retail, and media industries.

II. EPISTEMOLOGICAL TENSIONS: EXPLANATION, PREDICTION, AND THE THEORY-ALGORITHM DIVIDE

A foundational tension runs through the literature on predictive analytics in consumer behaviour: the tension between explanation and prediction as scientific goals. In an influential paper, Shmueli (2010) argued that these are distinct objectives that require different model-building choices, and that the conflation of the two – designing models to explain while evaluating them on predictive accuracy, or vice versa – produces systematic errors in both research and practice. Explanatory models, in her account, are designed to test causal theories and should be evaluated by theoretical coherence, parameter interpretability, and fit to in-sample data. Predictive models are designed to forecast future outcomes from available data and should be evaluated by out-of-sample accuracy, calibration, and generalisability.

Consumer behaviour theory has been built primarily for explanatory purposes, and the variables, constructs, and measurement instruments it has developed – attitudes, intentions, brand equity, customer satisfaction, involvement and self-congruity – are designed to capture theoretically meaningful psychological states rather than to maximise predictive accuracy. When these constructs are used as inputs to machine learning models, they often underperform relative to raw behavioural variables, such as past purchase frequency, recency of last purchase, and browsing dwell time, that have no theoretical interpretation but are highly predictive of future behaviour (Fader, Hardie and Lee, 2005). This empirical finding does not imply that theory is irrelevant to prediction; it implies that the constructs of existing consumer behaviour theory may not be the most proximal predictors of the behaviours that organisations care most about.

Breiman (2001) drew a related distinction between the 'data modelling culture,' which fits theoretical models to data and interprets parameters, and the 'algorithmic modelling culture,' which treats the data-generating process as a complex black box and optimises algorithms for predictive performance without regard for interpretability. Consumer behaviour research has

been strongly aligned with the data modelling culture; predictive analytics, as practised in commercial organisations, is strongly aligned with the algorithmic culture. The academic-practitioner divide in consumer behaviour — frequently lamented but seldom resolved – partly reflects this epistemological divergence rather than merely a gap in communication or application.

Explainable AI (XAI) has emerged as a response to the opacity of high-performance algorithmic models, seeking to provide post-hoc interpretations of model outputs that are theoretically intelligible to human decision-makers (Arrieta et al., 2020). Techniques such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and partial dependence plots provide decompositions of individual predictions into feature-level contributions that can, in principle, be related back to theoretical constructs. Whether these post-hoc explanations capture genuinely causal mechanisms or merely reflect correlational patterns in training data remains contested, and the theoretical grounding of XAI techniques in consumer behaviour theory is, to date, underdeveloped.

1. Digital Data Ecologies and the Transformation of Consumer Behaviour Research

The theoretical frameworks reviewed above were developed in a world of survey questionnaires, laboratory experiments, and scanner panel data environments that shaped what was measurable, what was theorised, and what was predicted. The emergence of digital data ecologies – the vast, heterogeneous assemblages of data produced by e-commerce platforms, social media, mobile devices, connected products and digital payment systems – does not merely expand the quantity of data available to consumer behaviour researchers; it changes the nature of what can be studied and, arguably, what consumer behaviour itself is. Computational methods now allow, for example, the personal appeal of marketing images to be predicted from consumers' digital traces (Matz et al., 2019).

Clickstream data – the sequence of pages visited, products viewed, searches conducted and links followed during an online session – provides a temporally granular record of consumer navigation and attention that has no equivalent in traditional data environments. Predictive models trained on clickstream data can forecast purchase completion, cart abandonment, and session value with high accuracy, and the sequential nature of the data has motivated the application of recurrent neural networks and attention-based transformer models that can capture path-dependent patterns invisible to cross-sectional methods (Hidasi et al., 2016). The theoretical interpretation of these patterns — what they reveal about attention, intention, and decision process — remains an open question that existing information processing models only partially address.

Passive sensing data from smartphones – location history, app usage patterns, communication metadata and accelerometer readings – enable inferences about consumer behaviour that go beyond self-report to encompass the physical and social context of consumption decisions (Lane et al., 2010). These data have been used to predict consumption in domains as varied as restaurant

selection, retail store visits, alcohol consumption, and financial behaviour, with predictive accuracy that frequently exceeds what is achievable from survey-based attitudinal measures. The privacy implications of passive sensing are substantial, a theme addressed in Section 7 – but the theoretical implications are also profound: behaviours that consumers themselves cannot reliably report and perhaps do not consciously register are, it turns out, systematically predictable from patterns in ambient digital traces.

The concept of the 'digital footprint' has become central to contemporary consumer behaviour theory, denoting the accumulation of data traces that consumers leave across digital interactions and that collectively constitute a rich behavioural profile amenable to predictive analysis (Kosinski, Stillwell and Graepel, 2013). The discovery that digital footprints – particularly social media behaviour – predict personal characteristics such as Big Five personality traits, political views and sexual orientation (Kosinski, Stillwell and Graepel, 2013), and that computer-based personality judgments can be more accurate than those made by friends and family (Youyou, Kosinski and Stillwell, 2015), raised fundamental questions about the nature of consumer self-concept and identity, the reliability of self-report measurement, and the ethical boundaries of inference from behavioural data.

2. Ethical and Normative Dimensions of Consumer Behaviour Prediction

The capacity to predict consumer behaviour with increasing precision raises ethical questions that are not peripheral to consumer behaviour theory but central to it. If marketing theory is understood not merely as a descriptive but as a normative enterprise concerned with how marketing should be practised, not merely how it is practised – then the ethics of prediction are constitutive of the field's intellectual agenda (Laczniak and Murphy, 2019).

Thaler and Sunstein's (2008) nudge theory, which drew on behavioural economics to argue that choice architecture can systematically steer behaviour toward welfare-improving outcomes without restricting choice, sits at the intersection of predictive analytics and normative theory. Predictive models that identify individuals with propensities for harmful consumption – excessive gambling, impulsive overspending or unhealthy eating – could, in principle, be used to design choice environments that protect those individuals, implementing a paternalistic predictive governance that raises questions about autonomy, consent, and the legitimacy of algorithmic paternalism (Yeung, 2017).

The use of predictive analytics in dynamic pricing, adjusting prices in real time based on inferred consumer willingness to pay, derived from browsing behaviour, location data, and purchase history, has generated substantial ethical controversy (Odlyzko, 2003). First-degree price discrimination, the theoretical ideal of extracting the maximum willingness to pay from each individual consumer, has historically been practically unachievable; predictive analytics makes it increasingly feasible. The theoretical welfare implications are ambiguous: price discrimination can expand output and consumer access in some market structures, but the distributional implications, and the asymmetric information they reflect, raise concerns about fairness that standard welfare economics does not fully capture.

Zuboff (2019) provided the most comprehensive critical theoretical account of the predictive analytics enterprise in her concept of surveillance capitalism: a novel economic logic in which the prediction and modification of human behaviour at scale constitutes a primary source of value. In Zuboff's analysis, consumer behaviour prediction is not a benign tool for improving matching between consumer preferences and available products but a system of behavioural modification in which consumers are simultaneously the raw material, the product, and the market. Whether one accepts this analysis in full or regards it as overstated, it represents the most sustained theoretical challenge to the predictive analytics paradigm from within the social sciences, and consumer behaviour scholars cannot engage responsibly with the field without grappling with it.

III. FUTURE THEORETICAL DIRECTIONS

The theoretical landscape reviewed in this chapter is genuinely incomplete. Several tensions and gaps point toward productive directions for future theoretical development.

First, the integration of causal and predictive reasoning remains underdeveloped in consumer behaviour research. Pearl's ladder of causation (Pearl and Mackenzie, 2018) – association, intervention and counterfactuals – provides a framework for distinguishing predictive claims ('what will happen if this pattern continues?') from causal claims ('what would happen if we intervened?'), and the development of consumer behaviour theories that explicitly specify causal structures amenable to empirical identification represents a significant theoretical opportunity.

Second, the temporal dimension of consumer behaviour has been inadequately theorised. Most predictive models treat consumer behaviour as a sequence of discrete events to be predicted individually; dynamic theories that model the evolution of preferences, habits, and identity over the consumer lifecycle are less developed and harder to operationalise, but theoretically richer and practically more useful for long-term customer relationship management (Neslin et al., 2006).

Third, the interplay between individual and collective levels of analysis needs more sophisticated theoretical treatment. Social contagion models and network diffusion models treat collective behaviour as the aggregate of individual-level processes; complexity theory and agent-based modelling suggest that collective consumer behaviour exhibits emergent

properties that cannot be reduced to individual-level predictors (Epstein, 1999). Developing theoretical frameworks that genuinely bridge these levels – rather than treating collective behaviour as the sum of individual predictions – is among the most challenging and consequential directions for the field.

Finally, the construction of a genuinely interdisciplinary theoretical programme that integrates the cognitive, motivational, social, cultural, and algorithmic dimensions of consumer behaviour remains aspirational rather than achieved. The frameworks reviewed in this chapter each illuminate important aspects of consumer behaviour and provide partial foundations for predictive modelling; what is needed is not the selection of a single theoretical winner but the development of synthetic frameworks capable of specifying when, for whom, and under what conditions each type of mechanism is most predictively relevant.

IV. CONCLUSION

Predictive analytics has transformed the practical landscape of consumer behaviour research and is beginning, more gradually, to transform its theoretical landscape as well. This chapter has argued that this transformation is best understood not as the replacement of theory by data but as a challenge to theory to become more precise, more causal, more dynamic, and more attentive to the emergent and relational dimensions of consumer action that classical frameworks underspecified.

The theoretical traditions reviewed here – rational choice theory, information processing models, S-O-R paradigms, social cognitive theory and network science – are not obsolete. They remain indispensable guides to which variables matter, which causal mechanisms to specify, and which patterns of predictive failure deserve theoretical explanation. But they must engage seriously with what the predictive analytics enterprise has revealed: that consumer behaviour is more contextual, more social, more habitual, more dynamically contingent, and more susceptible to environmental manipulation than mid-twentieth-century models assumed.

Ultimately, the deepest contribution that theoretical consumer behaviour research can make to the age of predictive analytics is not the provision of better variables for machine learning models but

the cultivation of the critical imagination required to ask what prediction is for, who benefits from it, who is harmed by it, and what kinds of human agency and dignity it must be designed to preserve. These are questions that data alone cannot answer.

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