CHAPTER

TWENTYONE

RATIONAL BY DESIGN: THE EFFECTS OF SOCIAL MEDIA ALGORITHMS ON HUMAN BEHAVIOUR AND SELF-IDENTITY IN INDIA

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Rational algorithms exist all around us and are ingrained deeply in our lives. They claim to help us connect with people, information, and even our supposed future lovers. Although algorithms achieve most of their goals accurately, and humans benefit greatly from them, we as behavioural scientists cannot help but question- at what cost? We acknowledge that these algorithms have simplified human life by reducing choice overload, but sometimes they also lead people to unfavourable long-term outcomes. We theorise this to be a result of the algorithms being designed for the 'Homoeconomicus' rather than homo sapiens.

This paper identifies the interplay of social media algorithms, the social media influencers and their attempts at audience capturing. We then argue their mediation which leads to polarisation in the community. We summarise our position by identifying our concerns with this interplay when it raises ethical questions about

fairness, justice and long-term benefits in digital product consumption and policy-making for the next billion users.

Introduction

The neo-classical economic perspective speculates that people behave rationally in every decision-making moment to attain their goals. To maintain a uniform understanding of rationality, economists across the geographic region often assume these preferences represent people's true interests, as opposed to involving other socio-economic or psychological elements [7]. Rationality in economics is based on a set of seven assumptions, some of which are, 'humans are Bayesian information processors', 'have well-defined and stable preferences' and 'maximise their expected utility' [23]. The reason we draw attention to these assumptions is that they are not representative of humans and their desires but still create foundational blocks of various Artificial Intelligence (AI) and Machine learning (ML) models [10,21].

An established model of thinking in cognitive psychology states that Homo sapiens are governed by two differing and integrated systems of thinking. System 1 is for fast intuitive thinking, and System 2 is for a slow deliberate analytical approach (which requires greater cognitive effort) [31]. Considering the number of decisions humans may have to make in a day, these System 1 heuristics are useful but may lead humans to make systematic errors [28]. For example, when a person 'pulls' on a door when it says 'push' [20] or invests all of their savings in products endorsed by a prominent social media influencer [1], we should not assume that the person is acting in their best interest. This may reflect the combination of their actual preference and decision-making errors.

For this paper, we specifically focus on Recommender Systems in Machine Learning and their rational attempts to maximise product interaction. We also draw attention to the social media influencers and their attempts at audience capturing. Then, we argue the effects of their mediation that enable partisanship and polarisation in the identity construction of India.

Cognitive biases and the social media

We can attribute the rapid rise in people coming online from rural and urban India within the last decade to factors like cheaper data plans, marketable technology, and the Digital India Initiative [2]. Many of the users coming online have little or no knowledge of personal computers. The estimated number of social media users in India in 2020 was approximately 518 million and is estimated to grow to 1.5 billion by 2040 [3]. The democratised digital space has allowed people access to information and resources. We, first-hand, witnessed both the positive and negative social impact of these platforms during the Covid-19 crisis [32]. Platforms meant for personal messaging have become platforms for content consumption, curated by unsupervised moderators or editors. As we progress towards rapid digitisation of information, services and governance in developing countries, we emphasise the need for analysis and regulation of human interaction with the algorithmic models.

While a group of scholars choose to emulate human cognition, others aim to create intelligence with a lack of concern for human emotions [25]. Today's algorithms are designed for the 'Homo-economicus' (a rational decision-maker) [10]. We argue researchers should seek AI to understand human intelligence as a property of a socio-economic system rather than a specific human attribution [14]. This we theorise may be influential in designing better and more inclusive digital artefacts. AI models, like many human-designed systems, are bounded by rationality. The criterion for their achievement relies on the need to maximise the 'interaction' between the product and the consumer (in tune with the rational economic assumption that people always seek to maximise their expected utility). We can measure the interaction through a variety of proxies based on different contexts. For example, the number of clicks and daily engagement, to name a few. While we as authors understand the complexity and levels within each measure, for this paper we want to annotate these proxies under an umbrella to highlight their overall effect on triggering cognitive biases. Although the algorithmic systems ethically aim to aid people in making better decisions, sometimes they affect different people differently [8]. We assume that these asymmetric preferences between people often arise from the biases within the design of the models itself.

Various studies on the use of social media highlight the attentional capture of system 1 (emotion- driven) thinking. They elaborate on the diffusion of logic in consumers approaching content during

heavy discourse [18] [27]. Nadia Bahemia builds on this by elaborating how people think emotionally when choosing matches on dating platforms [19]. Verhults et al., in their study, assert that familiarity of traits activates pos-

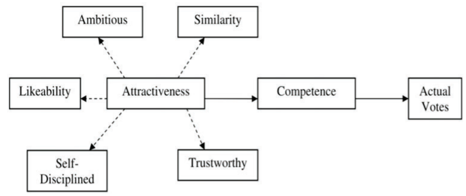

Figure 21.0.1: The halo effect around attractiveness and the causal path from attractiveness, through competence judgments to the actual vote shares for Senate elections [29]

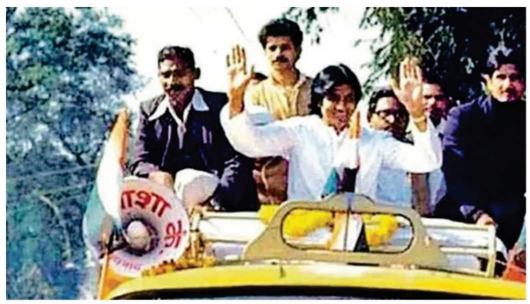

Figure 21.0.2: Amitabh Bachchan campaigning on Allahabad streets in 1984 (HT) [16]

itive feelings used for constructive judgement related to a person's competence, creating a Halo effect [29]. For example, Amitabh Bachchan's successful win in the 8th Lok Sabha elections against H. N. Bahuguna, the former Chief Minister of Uttar Pradesh can be attributed to his public appeal as a Bollywood superstar [16].

Similarly, as social media influencers themselves are users of the various platforms they alter their content to increase engagement with circles, they believe subscribe to the same perception. At the centre, consumers seek information that fits their existing beliefs. These together create unconscious filter bubbles known as confirmation bias [22].

As social animals, we like to conform to the expectations and beliefs of the group we most resonate with, called herding or the bandwagon effect. This very often leads to in-group and out-group biases. For primal human needs, the hedonic expectation of group comfort is necessary. As research indicates humans base decisions on group behaviour than performing a tedious cost-benefit analysis at an individual level [15] [4]. Although herding can have a positive effect and induce good social norms, it can, like other biases also lead to long-term preference reversal in one's well-being [30]. Research further elaborates that the lack of diversity in information sharing in social

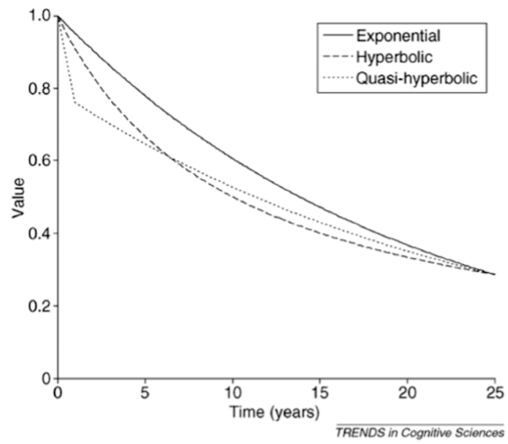

Figure 21.0.3: Exponential discounting assumes a constant rate of discounting, Hyperbolic discounting is generally greater for short time periods than long periods, Quasi hyperbolic follows a similar form as hyperbolic after the initial period [6].

interaction often distorts the population's perception of the community [11] [26]. The repeated exposure to misinformation or biased reporting creates an echo chamber which restricts people from electing the best possible outcomes. Literature helps us understand users are also likely to decide the authenticity of information based on similar assumptions of authority [12] [13]. For example, if a user regularly interacts with one-sided information on any topic in social media, the algorithm will learn and predict this as default need and further nudge polarisation [9].

The rational algorithm understands the user's preferences through pattern recognition. The models can assume the user's current choices (a deviation from a standard long-term preference) to be a true rational preference. For the models to do their job better, they tend to loop back these 'irrational' preferences in a much shorter duration to create quicker and more predictable feedback loops [24]. Simultaneously, this interaction between the algorithm and the user capitalises on the innate human tendency to discount future gains in seek of instant profit (in this case, a dopamine hit triggered by social media validation) [6]. We have noted this to have negative payoffs on the well-being and privacy of the users [5] [12] [26].

Conclusion

In conclusion, we as behavioural scientists argue that the capitalisation of rational algorithmic agents on cognitive biases of the users raises questions of fairness and justice when they lead to negative extremes [17]. Flyvbjerg further states that "political biases are a major challenge to any project, along with 'Strategic misinterpretation' which can distort or misinterpret information to secure more commitment" [13]. As authors, we do not say that digital transformation is necessarily bad, but that we should elicit preferences and systems that focus on the behavioural aspects of human nature.

Human interaction in digital space is a dense topic of discourse partly because it begs to question how much mediating power agents of algorithmic systems should have, and at what level policymakers should intervene. And, if governmental or private stakeholders should even make some of these decisions. We understand that 'choice architects' exist at every level of social communication, and one cannot completely avoid them or our own innate biases. But one way to navigate them on social platforms would be by nudging for a transparent framework of regulations and digital policy-making that takes into consideration the various socio-economic and psychological influences of the users.

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Citation

Singh, M., Khatri, D.A. (2023). "Rational by design: The effects of social media algorithms on human behaviour and self-identity in India." In S. De, A. Arya, M. Young, D. Ramesh, & J. Pal (Eds.) *Social media and society in India* (pp. 118–125). University of Michigan.