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Behavioral Biases and Retail Investor Decision-Making in the Era of Social Media Trading: A Qualitative Study

[1]Shamsa Naheed
[*2]Dr. Suleman Amin
[3]Asia Rahman Khan Lodhi
[1]PMS (Management) Finance, University of Agriculture, Faisalabad
[*2]Lecturer, Department of Economics, University of Peshawar (UoP), Peshawar, Pakistan
[3]Director, Ministry of Information & Broadcasting, Islamabad
[1]Shamsace01@gmail.com, [*2]suleman.research@gmail.com, [3]asia.khan.lodhi@gmail.com

Abstract

The inclusion of the social media platform in the financial market has essentially transformed the behavioral pattern of retailing investment. Online community platforms like Reddit, X (once Twitter), Tik Tok, Discord and YouTube become decentralized information structures where financial stories, speculation, and sentiment are shared at an unprecedented rate. Although the previously mentioned cognitive biases have been traditionally listed in behavioral finance literature such as herd behavior, overconfidence, confirmation bias, anchoring and loss aversion, the experiential aspects of the biases and their exacerbation in digitally mediated trading settings have been relatively unstudied. In this research, the qualitative approach that will be used is interpretivism to explore how behavioral biases influence the decision-making process of retail investors in social media-based trading communities. Twenty-five retail investors who are active participants of the online trading forums were interviewed using semi-structured interviews. A thematic analysis shows that the social media settings increase classical cognitive biases in the following ways: algorithmic filtering, apparent social validation parameters, narrative framing, and emotionally charged group engagement. The results show that perceived collective intelligence enhances herd behavior; overconfidence is also socially reinforced in ways that depend on engagement mechanisms; confirmation bias is aggravated by personalization through algorithms; impulsive decision-making is fueled by the feeling of missing out; and trust is becoming disinterred and decentralized to peer networks and influencers. The contribution of the study to the literature on behavioral finance is that the psychological biases are placed in the context of digital sociotechnical systems and provides implications to monetary education, regulatory control, and platform regulation in modern markets.

Keywords: Behavioral finance; Retail investors; Social media trading; Herd behavior; Algorithmic amplification; Fear of missing out (FOMO)

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Corresponding Authors*

Dr. Suleman Amin

Introduction

Financial participation has greatly changed its structure over the last ten years. Traditional financial media, financial advisors, and brokerage firms are of little use to retail investors anymore, who now exist in a digital world of real-time information flow, content curation algorithms, and decentralized networks of discussion. The able-to-trade-free applications on mobile platforms have lowered the entry barriers in the structure and has increased the participation in the trading by younger and technologically proficient groups in large numbers (Eaton et al., 2022). Financial markets do not only depend on the institutional players; digitally networked individuals are becoming more and more influential on the price dynamics, volatility patterns, and sentiments formation.

The 2021 GameStop short squeeze has demonstrated the strength of digitally organized retail investors, casting fundamental doubts on market rationality, price discovery, and information efficiency (Eaton et al., 2022). Classical finance theory and especially the Efficient Market Hypothesis (EMH) presupposes the existence of rational participants that process the available information in the most optimal way and that this information is reflected in asset prices. In the given paradigm, systematic mispricing is supposed to be infrequent and temporary. Nonetheless, behavioral finance has shown time and again that rationality is systematically violated by investors as they make use of cognitive shortcuts, emotional impulses, and the social forces (Kahneman and Tversky, 1979).

The Prospect Theory states that people calculate based on the outcomes in relation to psychological reference points and have a loss aversion in which losses are more significant than similar gains (Kahneman and Tversky, 1979). Following studies have reported overconfidence bias in investment (Barber and Odean, 2001), herd behavior in the face of uncertainty (Banerjee, 1992), confirmation bias in information processing (Nickerson, 1998) and the sentiment driven market fluctuations (Barberis et al., 1998). However, these underlying behavioral paradigms formed are mostly created in the pre-digital informational context, where information access was less swift, consensus markers less apparent, and algorithmic amplification did not order content exposure.

Social media sites present new amplification effects which can radically transform the expression of cognitive biases. Engagement algorithms are based on emotionally resonant and high-interaction content whereas visible popularity metrics such as likes, shares, comments and trending tags are heuristic signs of credibility and consensus. Such structural features are likely to contribute to the increased psychological biases instead of reflecting them. Quantitative research has associated the social media sentiment with short-term stock returns and stock volatility (Bollen et al., 2011; Sprenger et al., 2014), but this research does not give much understanding of the lived experience by retail investors who are using these digital ecosystems.

Although the role of social media in the financial markets is increasingly recognized, very little qualitative research has been conducted on how retail investors perceive, internalize and rationalize the influence of online information in financial markets. To generalize the behavioral finance theory to digitally mediated settings, it is important to understand the subjective processes that lie behind trading decisions. The paper is thus a research on how behavioral biases are manifested, bargained, and enhanced through retail investors who are actively involved in social media trading communities.

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Research Aim

The first objective of the study is to investigate the effect of behavioral biases in the decision-making process of retail investor in the context of social media trading, as well as how the digital platform architecture can enhance or transform these biases.

Research Objectives

In a bid to attain this goal, the research seeks to meet the following objectives:

1. To determine the behavioral biases of the most active retail investors that trade within social media trading communities.
2. To explore how algorithmic curation, engagement capabilities, and viral content as platform characteristics affect investor cognition and emotional reactions.
3. To examine the rationales of online social effects on retail investors decision to trade.
4. To determine the reconfigurations in trust in financial information in peer-based digital communities.
5. To make a contribution to the theoretical body of behavioral finance by incorporating the knowledge of digital sociology and platform governance.

Research Questions

The guiding research question of this research is the following:

What are behavioral biases and how they affect retail investor decision-making during social media trading?

In the context of answering this main question, the study will also examine the following sub-questions:

1. What types of cognitive and emotional biases are the most salient among social media-active retail investors?
2. What are the effects of algorithmic filtering and visible engagement metrics in terms of perceived credibility and risk?
3. How do online communities influence confidence, urgency, and trust of investors in sources of information?
4. What reflective and rationalizing actions do investors undertake regarding decision making under the influence of social media interactions?

Through the answers to these questions, the study aims to apply behavioral finance to the context beyond the conventional market and investor psychology to the changing conditions of digitally networked financial involvement.

Literature Review

Behavioral finance questions the rationality of economic actors considering the psychological research in the process of financial modeling. Prospect Theory is still fundamental, which shows that risk-behind decision-making is reference-dependent and averse to losses (Kahneman and Tversky, 1979). Reference points can become dynamic in the context of social media trading when it comes to the exposure of highly visible stories of quick wealth acquisition.

Herd behavior occurs when people act in a manner that is dictated by other people in the situation of uncertainty (Banerjee, 1992). The social media sites increase the visibility of the collective action and therefore, consensus is more visible on the social media than in the traditional market. This increases cascades of information.

Overconfidence bias causes investors to overrate their predictive skills, which causes overtrading and less money made (Barber and Odean 2001). The likes and shares of a post can increase this bias through the social validation mechanism.

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Confirmation bias is the prejudice to believe-consistent information (Nickerson, 1998). The selective exposure is enhanced through the algorithmic personalization that filters and filters out content that is consistent with the history of prior involvement. Fear of missing out (FOMO) is the anxiety due to the perceived non-participation in rewarding experiences (Przybylski et al., 2013). This emotional pressure is increased in trading settings by viral success stories.

Although it has strong theoretical grounds, small qualitative studies have dwelled on the interaction of these biases with platform architecture. This research addresses this gap.

Methodology

A qualitative design that assumes the use of the interpretivist approach was taken in order to reflect subjective experiences of the retail investors. Purposive sampling was used to recruit twenty-five participants who fulfilled the criterion of active social media trading and had at least one-year experience of trading. Interviews were carried out through the video conferencing lasting about 60-75 minutes. Theoretic analysis was employed to analyze the data by transcribing them word-to-word and examining them by thematic analysis (Braun & Clarke, 2006). The inductive approach was used to code data inductively and subsequently in a sequence in order to find patterns in social influence, emotion as well as cognition. Member checking, audit trail documentation and reflexive journaling were used to assure trustworthiness.

Table 1: ***Participant Demographic Overview***

Variable	Category	Frequency (n=25)
Age Range	21–25	6
	26–30	8
	31–35	6
	36–45	5
Gender	Male	17
	Female	8
Experience in Trading	1–2 years	9
	3–5 years	11
	5+ years	5
Primary Platforms Used	Reddit	18
	X (Twitter)	14
	TikTok	10
	Discord	9

Findings

Thematic analysis has also determined the patterns that were common and showed a consistent and theoretically coherent shared feature by the participants, important to mention though is that not only within the social media trading ecosystems behavioral biases are found, but they are also structural forces of the digital architecture. The data point at the design characteristics of the platform, namely, algorithmic curation, the visible action of engagement measurement, the rapidity of information stating, and the performative action in the community, serves as the amplification mechanisms of the classical cognitive distortions introduced in the literature on behavioral finance.

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The most dominant and common one was the herd behavior. It was also usual that participants would begin trading upon noticing a high level of engagement on particular stocks in the multiple threads of Reddit or on hashtags or an extremely popular Tik Tok clip. The presence of thousands of users publicly expressing virtually the same sentiment created what we now call and participants feel as a collective certitude or crowd-backed certitude. Reliability was also used interchangeably with popularity to mean that the social consensus was to be substituted by due diligence that is independent. The same thing happens to this effect and informational cascade theory (Banerjee, 1992) where people make rational inferences by observing other people and their behavior. In case of digital trading, cascades are expedited due to algorithms of ranking whereby content with high engagement is considered.

Interestingly, the respondents stated that they became less uncertain when they saw numbers of consensus, i.e. the number of upvotes or the amount of reposts. It means that the indicators of engagement are mental shortcuts, which require less analytical processing and rely on heuristic processing. The behavioral model is one that is condoned by this kind of pattern wherein the indecisiveness creates the reliance on social signs (Hirshleifer and Teoh, 2003). These cues in the digital spaces are not accidents but are made to make sure that the most number of users are able to interact with the product and thereby is in a systematic manner upgrading herd behavior.

On the same note, social reinforcement processes boosted overconfidence bias. The respondents answered that they made the most confident post when other posts made by them were well-responded or that they made the most confident post when their predictions were proved by other participants. Engagement metrics, such as likes, comments, shares, supported the view of social competence and encouraged social proof. This is a self attribution bias in which a success is attributed to the inside aspect and a failure to the outside aspect (Barber and Odean, 2001). Part of the respondents admitted that they had been upgrading the rate of trade following the public confirmation, which exhibits the association of behavior between confidence and amount of trading that had been analyzed in the preceding research.

In this regard investing is performative. The formation of the social image of the successful trader increases the compliance with the earlier verdicts and the lack of readiness to admit a failure. Traces of overconfidence thus changes to a cognitive perversion that is internally held onto an externally validated behavior pattern. Digital affirmation technologies create feedback mechanisms, which promote aggressive predictive behavior and discourage prudence, which align with the theory of narrative economics, which concentrates on the virality of convincing financial stories (Shiller, 2017).

In interviews, there was confirmation bias that was algorithm-based. The respondents continually acknowledged that their feeds were displaying an increasing number of content related to their past trades and searches. Others revisited the process of active silencing or unfriending of opposing voices, which further diminished the informational exposure. Coherent streams of content through belief were thereby boosted that enhanced cognitive entrenchment through algorithmic personalization. Though the idea of confirmation bias is not novel to the psychological literature (Nickerson, 1998), the web environment does allow the self-reinforcement processes to operate on automatic settings whereby biased exposure is institutionalized.

The respondents stated that they thought that everybody supported them even though they later on recognized that there was likely to be conflicting information that would be presented in the lower part of the algorithmic feed. This means that personalization systems can result in artificial homogeneity of opinion, which creates bubbles of followers that reinforce opinion and reduce disapproval. Such dynamics can be explained by the current studies on the social transmission bias where any information that has an emotional or socially accepted emotional appeal spreads faster (Han et al., 2020).

Emotional urgency was high as a result of fear of missing out (FOMO). The exposure to viral screenshots of unbelievable gains raised perceptions of the lost opportunity. The reason why the participants cited regret avoidance frequently is that they were concerned about not doing it immediately because they were worried about end-permanent marginalization. This comes in line with the Prospect Theory which predicts that the expected regret can induce an individual to have a risk-seeking behavior (Kahneman and Tversky, 1979). In comparison to the domain of conventional investment, digital platforms expose an exposure to the highly salient gain narratives, re-setting psychological reference points in an enhanced direction.

According to the participants, there was less time spent on decision-making, as they typically made trades a few minutes after going through trending content. Perhaps, emotional contagion was quite viral, and celebratory expressions, emojis, and urgency clues were present in comment boxes. FOMO was thus not only an internal anxiety system, but socially disseminated. The popularity and speed of success stories appear to be the drivers of the phenomenon of time compression in decision-making, to deliberate less and to act more now.
The re-organization of trust is a strange discovery. The participants had doubts of institutional analysts, financial media, and traditional advisory constructions. Peer networks were perceived to be more real, transparent and in accordance with the interests of retailing. Simultaneously, though, this democratization of information predisposed people to a higher level of misinformation, coordinated hype, and speculation by the influencers. Trust was not killed but merely stripped off credential authority and credibility of popularity.

This transfer is suggestive of wider sociological transformation in digital space in terms of epistemic power. The monetary authority is disaggregated out of the institutional expertise and is rejoining the engagement visibility. These forces are beyond the boundaries of the entertainments and investments advice and are problematic in terms of the regulation of influencer marketing and unresolved conflicts of interest. All the outcomes are that social media sites are not mere sources of information but mental addicts, which are inherent in the market interactions. Digital affordances structure classical behavioral biases such as herding, overconfidence, confirmation bias, FOMO, and loss aversion. The platform architecture is used to communicate with human cognition in an attempt to shape investor perception, emotional response, and behavioral response.

Rather than viewing behavioral biases as individual cognitive errors, the current paper defends a sociotechnical perspective according to which technology can be used to manipulate cognitive situations. Combining an algorithm design and psychological disposition forms a greater volatility of the market and rapid sentimental cascades. Platform architecture then must become a context variable in the behavioral finance theory, and an influence on the extent of decision-making and speed.

Table 2: ***Thematic Coding Summary***

Theme	Empirical Pattern Observed	Theoretical Foundation
Amplified Herd Behavior	Trades triggered by trending posts and visible engagement	Informational cascades (Banerjee, 1992)
Socially Reinforced Overconfidence	Increased trade frequency after public validation	Overconfidence bias (Barber & Odean, 2001)
Algorithmic	Homogeneous content exposure	Confirmation bias

Theme	Empirical Pattern Observed	Theoretical Foundation
Confirmation Bias	reinforcing positions	(Nickerson, 1998)
FOMO-Induced Impulsivity	Rapid trade execution due to viral gain narratives	Prospect Theory (Kahneman & Tversky, 1979)
Reconfiguration of Trust	Credibility assigned based on engagement rather than expertise	Narrative economics (Shiller, 2017)

Table 3: ***Integrated Bias Amplification Model***

Classical Bias	Traditional Manifestation	Digital Structural Amplifier	Behavioral Outcome
Herd Behavior	Following market trends	Real-time consensus metrics	Rapid collective entry into volatile assets
Overconfidence	Self-attribution of gains	Public affirmation feedback loops	Excessive trading frequency
Confirmation Bias	Selective reading of financial news	Algorithmic personalization	Echo chambers & cognitive entrenchment
Loss Aversion	Avoidance of realized losses	Viral display of extreme gains	Risk-seeking to avoid regret
FOMO	Social comparison within peer group	Continuous exposure to trending success narratives	Impulsive, short-term trading

Implications

The findings suggest that the models of behavioral finance must be formulated in such a way that the system of digitally mediated amplification should be taken into account. Both are classical images of the cognitive processes of the person, although the new generation of the investor activity is founded on the frames of algorithm that defines the priorities of perception, distribution of attention, and the level of emotion.

Firstly, one should have digital cognitive bias awareness in financial literacy programs. The investors must be educated to view the engagement measures as measures of popularity as opposed to accuracy. The curricula should include algorithms filters, emotional contagion and social validation dynamic modules.

Second, there can be behavioral safeguards that are built on the brokerage platforms. The tendency to be impulsive could be countered by letting the footing settle and then making volatile trades. The over-confidence can be eradicated by the visualization of the portfolio risk tools. The herd behavior can be minimized using a reflective prompt which would lead one to do independent verification.

Third, the social media outlets must be made more transparent as far as the financial content amplification is concerned. It may be reduced by labeling sponsored financial content and clearer identification of the intention of influencers to reduce the risks of misinformation. The assistance of the algorithmic accountability mechanisms can also be helpful in the context of responsible dissemination of information.

Fourth, the regulators will be able to consider emerging regulations of digital financial promotion. Increased distance between entertainment and financial advice is becoming a necessity in the systems that are driven by influencers.

Lastly, the study identifies the significance of interdisciplinary integration. Behavioral finance must collaborate with digital sociology, communication studies, and computer science to examine the interaction between technological design and cognitive bias. The integrative changes of theory and regulation needed in markets are the social dynamics which platforms have mediated.

Limitations, Future Research and Recommendations

Despite providing thorough qualitative information about the behavioral biases in the social media trading situations, it should be kept in mind that there are many limitations the study is subjected to. The initial weakness is a limitation in statistical extrapolation due to the qualitative method and the sample size of 25 participants. Qualitative research findings do not depict behavioral trends at the population level whereas the nature of qualitative investigation is rather on depth than breadth (Braun and Clarke, 2006). Retail investor sample is heterogeneous in terms of experience, financial literacy, socioeconomic status and geographical location and, therefore, the themes developed below can be considered exploratory but not universal.

Second, there is also the problem of retrospective bias and social desirability bias since the data on the self-reported interview is being used. The participants may ultimately end up recreating past decisions without knowing and rationalising decisions to protect self-image. The fact that individuals usually reinterpret previous actions to gain cognitive consistency is an old research observation in behavioral finance (Hirshleifer, 2001). Due to this reason, some of the participants could have underreported impulsive behavior or overemphasized on rational deliberation. Although the member checking has been conducted to enhance the credibility, self-perception is never objective.

Third, this research did not involve a factual observation of the trading behavior or analysis of real transactions. The research would be an encapsulation of the perceived processes involved in the decision-making process versus the established and verified trading trends. The approaches of brokerage information or behavioral surveillance could be used in the future study to cross-examine the findings of the interview with the empirical evidence of transactions. Such mixed-method designs would provide a superior causal finding on the extent of amplification of bias.

The other limitation is the heterogeneity of the platform. The study did not allow comparison of differences in platform architecture even though the participants reported their participation in platforms such as Reddit, X (Twitter), Tik Tok, and Discord. Every platform features various algorithmic models and social norms. For example, Reddit is more about community management and discussion threads, while TikTok is more about short-form video content and instant algorithmic virality. Behavioral amplification can be influenced differently by manipulating the differences in structure. The influence of features of design on the acquisition of cognitive bias should be done through comparative studies with a platform in the future.

Moreover, part of the research was conducted in a specific regulatory and sociocultural environment. Financial behavior is also not purely driven by cognitive bias but institutional trust, regulatory frameworks, cultural norms on risk, and macroeconomic conditions are also contributors (Shiller, 2020). In this way, the findings may not be fully generalizable to markets with stronger investor protection laws, more stringent financial sector regulators, or varying levels of digital literacy. The research theory would be significantly stronger in the case of the cross-national study.

The future methodology should be expanded. In quantitative surveys perceived bias amplification can be quantitatively assessed in validated psychometric scales. It may apply experimental designs to model both simulated and algorithmically curated feeds to establish whether exposure to metrics of engagement has a direct positive influence in raising trading impulsiveness. Longitudinal studies could trace the temporal variation in investor cognition as individuals gain experience in digital ecosystems.

The network analysis of online trading communities is the other possible direction. The information patterns of diffusion can be plotted to ascertain how the cascades and dissipation of sentiment are constituted. The interactions between behavioral finance and computational social science would allow understanding the processes of digital amplification better (Han et al., 2020).

Neuroscientific and psychophysiological methods also have the possible contribution. An assessment of the intensity of the FOMO and loss aversion activation would be feasible in terms of the level of emotional arousal one experiences when being exposed to the content of the viral trading. Such new solutions to digital behavioral finance would be supported by these interdisciplinary solutions.

Along with the expansion of its strategies, artificial intelligence investment recommendation systems are another issue that should be investigated in the future research. The more the financial commentary produced by AI is authentic, the more difficult it could be to determine whether it was produced by the organic peer sentiment or enhanced by an automated mechanism. These studies into the interaction between AI-driven content and cognitive biases will be critical for understanding the dynamics of the future market.

Recommendations

The implications of this study for the weight of investors, teachers, platform designers, brokerage companies, and regulatory agencies are significant. The recommendations are categorized under five areas that are, investor education, platform governance, brokerage interventions, regulatory policy and development of academic research.

Firstly, financial literacy needs to be revised to address the amplification of digital cognitive bias. Traditional education to investors is grounded on diversification, risk taking and long term planning. However, contemporary digital trading requires the criticality of algorithm exposure and social validation processes. The training programs should specifically teach investors the herd behavior, the confirmation traps, the FOMO and the overconfidence in the social media setting (Barber and Odean, 2001; Nickerson, 1998). The digital information literacy modules should be designed to inform investors that measures of engagement are an indicator of popularity and not reliability.

Second, the social media platforms would require expanding the publication of financial material distribution. An algorithmic-based accountability programs may include disclosure labels showing when content is trending based on velocity of engagement and unverified financial analysis. The platforms can also be frictional to high-risk financial promotion, e.g. warning banners or prompts to conduct other independent research before proceeding to act on virally promoted investment claims.

Third, the platform of brokers could be developed by means of behavioral nudges, aimed at minimizing impulsive decision-making. As indicatively, the cooling-off of the timers before engaging in extremely volatile trades could be employed to aid in introducing some form of thinking. The overconfidence bias would be addressed with the help of the portfolio risk dashboards that would reveal the volatility exposure and concentration risk. The situation with short-term FOMO-induced actions can be alleviated by behavioral cues that bring investors on track of long-term objectives of their strategy.

Fourth, the development of the clear disclosure standards by the regulatory authorities should be in terms of financial influencers. The influencers can be very useful and it can be hard to draw the line between two worlds of amusement and financial consultation. The unsophisticated investors would be saved through open disclosure of sponsored content and disclosure of conflict of interest. The other avenue that can be explored by regulators is to trace organized campaigns of manipulations without curbing the normal operations in markets.

Fifth, policymakers will encourage the interdisciplinary collaboration of financial economists, psychologists, sociologists, and computer scientists. The behavioral finance must adapt to the digital mediated markets. Regulatory design will include sociotechnical analysis needed to ensure that the investor protection systems will not be out of place in the rapidly changing technological environment.

Finally, digital behavioral finance is recommended to be created as a research program in universities and research centers. Theory development will be improved by investing in interdisciplinary studies on algorithmic amplification, narrative economics, and investor psychology. Because the markets will always become digital, there will be a necessity to conduct active research to predict new care behavior weaknesses.

Conclusion

The classical cognitive biases, as well as technologically engineered magnification mechanisms, are met in the actions of retail investors in the social media trading systems. As demonstrated in this paper, herd behavior, overconfidence, and confirmation bias as well as the fear of missing out are not new but the intensity and speed of their development are radically enhanced by the constructions of online platforms. The indications of visible engagements that lead to heuristic shortcuts to credibility are present. The personalization using algorithms strengthens belief consistent information. Psychological lives are re-established through viral stories. The public validation strengthens confidence based on identity.

These tendencies pose a threat to the traditional ideologies of market rationality and investor autonomy. Behavioral finance must expand to cover the perspectives of digital sociology and platform governance in addition to individual cognition. Markets are not just the aggregation of rational or boundedly rational individuals, but are coded in algorithmically edited social spaces, which affect perception, feeling, and behavior.

Modern financial market is an area of study that cannot go without knowledge in psychology, economics, communications studies, and computer science. The investor protection strategies should be revised. In financial literacy education, awareness of digital bias should be included. The social media companies and the brokerage platforms must know that they are also adding to the escalated cognitive distortions. Regulators will also need to balance the issue of innovation, transparency and accountability.

As the financial interaction based on the digital landscape develops further, the understanding of human psychology and the technological design will be a crucial factor. It is not only access to markets that will turn retail investing of the future but the knowledge of behavioral forces that make the decisions of more and more networked and algorithm-driven systems.

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