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Research Article

Deciphering Investment decision-making: Unraveling Overreaction, Herding and Overconfidence bias through Serial Mediation Analysis

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Abstract:

The current study aims to examine the influence of overreaction on the decision-making processes of investors. Also, this study investigates how herding and overconfidence serially mediate the connection between overreaction and investors' decision-making. This study used a survey method to collect data using a structured questionnaire from 426 individual investors in the South Indian region. The proposed serial mediation model was analyzed using PLS-SEM. The findings of this study revealed that overreaction significantly affects investors' decision-making. Herding and overconfidence partially and serially mediate the connection between overreaction and individual investors' decision-making. These findings contribute to a deeper understanding of biases and their adverse effects on investment decisions, providing crucial insights for investors, financial advisors, and policymakers in the stock market. This study is the first to examine the role of herding and overconfidence in mediating the association between overreaction and the investment decisions of individual investors.

1. Introduction

The conventional financial theories include the Option Pricing Theory formulated by Black, Scholes, and Merton, the Capital Asset Pricing Model developed by Sharpe, Lintner, and Black, the Arbitrage Pricing Theory proposed by Modigliani and Miller, and the Markowitz Portfolio Theory, which focuses on efficient portfolio management [1]. These theories are built upon two assumptions; all investors behave rationally and the stock market is efficient [2–4]. However, in reality, empirical evidence reveals that investors often act irrationally when making investment choices, and the stock market is found to be inefficient, such as heightened volatility and sudden market fluctuations [3]. Conventional theories have proven inadequate in explaining fundamental phenomena, such as market crashes and bubbles [4,5]. The shortcomings of conventional finance theories are addressed by prospect theory, as proposed by Kahneman and Tversky [6], which argues that investors are affected by various psychological biases while making investment decisions [7–9]. This paradigm shift has driven the emergence of behavioral finance as a distinct and continuously evolving discipline within the field of finance. The integration of 'psychology', 'economics', 'sociology', 'anthropology' and 'finance' has laid the foundation for the development of behavioral finance [7,10]. Behavioral finance attempts to explain investor irrationality and stock market anomalies [11].

Many empirical studies in the field of behavioral finance have evidenced that behavioral biases have a substantial impact on investment decision-making [12–14]. According to Shefrin and Statman [15] reported that bias is fundamentally a predisposition to make errors in decision-making. Investors tend to be more susceptible to various behavioral biases [16]. During the COVID-19 pandemic, biases severely triggered irrationality in decision-making, leading to poor investment choices [17]. Behavioral finance literature posits that irrationality in investment decision-making stems from the influence of behavioral biases [18]. Several recent research studies have underscored the direct effect of behavioral factors on individual investors' decision-making processes [9,12,19]. However, the role of serial mediators, such as herding and overconfidence, in the relationship between overreaction and investors' decision-making remains unexplored. To address this gap, the present study aims to investigate these interconnected relationships, thus contributing to the existing body of knowledge in behavioral finance.

The structure of the current study is outlined as follows: the subsequent section delineates the literature review and hypothesis development, followed by a discussion of the research methodology, results, discussion, and conclusion. Finally, we address the study's limitations and propose avenues for future research.

2. Material and Methods

2.1 Literature review and hypothesis development

Theoretical background

The behavioral finance literature highlights how mental shortcuts and emotions shape investors' decision-making processes. Prospect theory, introduced by Kahneman and Tversky [6], was utilized in the current study. This theory emphasizes investors' decision-making process based on the potential risks they face. Herding theory by Graham [20] underlines that investors often follow the decisions of others. Many behavioral finance scholars have evidenced in the past that biases significantly affect judgement and decision-making [10, 21–24]. The present study covers the relevant literature on overreaction, herding, overconfidence, and their impact on the decision-making processes of individual investors.

Overreaction and investment decision-making

Investor overreaction has remained a pivotal and extensively debated topic in behavioral literature for decades. The groundbreaking work of De Bondt and Thaler [25] demonstrates that investors often overreact to unanticipated market news and events, resulting in significant fluctuations in stock prices. They assert that investors place a great value on historical performance while disregarding its mean-reversion tendencies. Researchers have previously shown that investors' decisions are strongly influenced by their overreaction to favorable earnings announcements [10]. Chiao and Hueng [26] conclude that book-to-market ratio and firm size are inadequate to comprehensively explain returns, so they propose overreaction as a risk factor that better accounts for stock returns. Kausar and Taffler [27] found that investors tend to overreact to positive market news. According to Lakonishok et al. [28] companies with high book-to-market equity, earnings-to-price ratios, and cash flow-to-price typically have weak historical earnings and growth. These results indicate that the market's overreaction to prior growth leads to mean reversion, indicating that stocks with historically poor performance demonstrate the potential for higher future returns. A recent study by Metawa et al. [29] has provided further evidence that overreaction impacts individual investors' decision-making. Therefore, the proposed hypothesis of this study is:

H_1: Overreaction significantly affects the investors' decision-making in the Indian stock market.

The impact of overreaction on investment decision-making through herding bias

Herding bias refers to investors' tendency to imitate the actions of other investors while making investment decisions, regardless of their own ability to bear risk [1,30]. Kengatharan and Kengatharan [31] identified a notable positive impact of herding bias on investors' decision-making. Similarly, Lee et al. [32] observed that individual investors exhibit a stronger tendency toward herding behavior compared to institutional investors. This behavior causes investors to limit their own decisions and instead replicate the actions of others in the market [33]. According to Zahera and Bansal [3], in the stock market, investors tend to align their decisions with those of others, which leads to price volatility that diverges from the asset's intrinsic value and ultimately results in lower returns. It has been documented that herding behavior is more pronounced in both bull and bear markets [34]. Previous studies have also highlighted that herding exerts a substantial impact on investors' decision-making [35,36]. Overreaction and herding behavior diverge from the principles of market efficiency, leading to price distortions [25,37]. Investors often exhibit overreaction to new information, which subsequently triggers herding behavior. Hence, the proposed hypothesis of this study is:

H_2: Herding serves as a mediator between overreaction and investors' decision-making in the Indian stock market.

The impact of overreaction on investment decision-making through overconfidence

Pompian [38] defined overconfidence bias as a tendency in which individuals exhibit "unwarranted faith in their own intuitive reasoning, judgments, and/or cognitive abilities". Overconfidence is the predominant bias influencing individual investors' investment decisions, leading to market inefficiencies [30]. Overconfident investors rely more on their own information than on market information [39]. Abhijith and Bijulal [40] demonstrated that overconfidence bias is a primary driver of deviations from rational decision-making processes. Ritter [41] reported that men are more likely to be overconfident than women. Odean [42] revealed that excessive trading by overconfident investors leads to diminished returns. Researchers have further concluded that overconfidence is the most prevalent among the behavioral biases affecting individual investors' decision-making [43]. Tekçe and Yilmaz [44] found that young investors with lower portfolio values, lower incomes, and from less educated regions are more susceptible to overconfident behavior. Maheshwari et al. [45] corroborated the prevalence of overconfidence among retail Indian investors. Previous studies have indicated that overconfidence bias affects the investment decision-making of individual investors [2,13,36,46,47]. Overconfident investors often believe in their predictive abilities and place undue emphasis on recent market events, thus amplifying overreaction. Thus, the proposed hypothesis of this study is:

H_3: Overconfidence serves as a mediator between overreaction and investors' decision-making in the Indian stock market.

The serial mediating effect of herding and overconfidence

The researchers identified overconfidence bias as the most influencing behavioral bias influencing individual investors' decision-making processes [19]. Overconfidence bias is particularly prevalent in the Indian stock market [48]. Herding behavior has a substantial effect on the investment decisions of individual investors in the context of the Indian stock market, as evidenced by Kumar et al. [49]. It has also been observed that, in the Vietnamese stock market, herding notably influences investors' decision-making [36]. Das and Panja [10] studied behavioral factors, including Under- and over-reaction, overconfidence, and self-attribution, and concluded that these factors positively influence the investment decisions of individual investors. Jabeen et al. [50] found that herding behavior and overconfidence mediate the connection between emotion and investment decisions. Jain et al. [51] concluded that the association between financial literacy and investment choices is serially mediated by herding behavior and overconfidence. As a result, there is no conclusive evidence examining the interaction between overreaction, herding, overconfidence, and investment decisions. Hence, the proposed hypothesis of this study is:

H_4: Herding and overconfidence serve as serial mediators between overreaction and investors' decision-making in the Indian stock market.

2.2 Methodology

This research employed a survey method, utilizing a structured questionnaire to collect data from individual investors across the southern Indian states of Andhra Pradesh, Tamil Nadu, Karnataka, Kerala, and Telangana. In this study, the snowball sampling was employed. The unavailability of investor-specific details, coupled with brokers' reluctance to disclose information due to internal policy constraints [10], posed a significant challenge in data collection. To address this limitation, the study adopted a snowball sampling approach [52].
A pilot study was carried out with 60 participants to assess the questionnaire's validity and reliability. After reaching the necessary threshold values for validity and reliability, we began the final phase of data collection. The questionnaire was shared on several social media platforms, including Facebook, Instagram, and WhatsApp. Between September 2024 and November 2024, the data was collected. Out of the 451 questionnaires that were given to investors, 426 valid responses were obtained and considered for the data analysis.
In this study, the G*power software was employed to determine the sample size, which recommended a minimum required sample size of 119 [53]. In this calculation, four predictors were included, and the alpha level was set at 0.05. Next, we chose a medium effect size of 0.15 and a power level of 0.95. G*power was selected due to its robust accuracy in performing power analyses for advanced statistical techniques such as structural equation modeling (SEM) [54]. The questionnaire used in this study was adopted from the prior research studies of Sarwar and Afaf [55], Jain et al. [56], and Das and Panja [10]. The questionnaire was organized into two sections. The first section included demographic information such as age, gender, occupation, annual income, and stock investment experience. The second section focused on obtaining responses related to the four latent constructs examined in the study. This section covered 18 items categorized under four constructs: overreaction, herding, overconfidence, and investment decisions. Each construct was measured using a 5-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree."
The study's research hypotheses were tested using "partial least squares structural equation modeling" (PLS-SEM) with SmartPLS 4. For analyzing complex relationships, PLS-SEM is widely regarded as an appropriate technique [57]. Therefore, PLS-

SEM was employed to examine the serial mediation in this study.

3. Results and Discussions

3.1 Demographic profile of the respondents

Among the 426 participants surveyed, 328 were male, while the remaining 98 were female. Nearly half of the respondents, accounting for 49.77% of the total sample, belonged to the 26–35 age bracket, followed by 30.52% within the 36–45 age range. The majority, specifically 34.98%, reported earning between Rs. 2.5–5 lakhs in annual income. Regarding stock market experience, 53.17% of the participants indicated having 2–5 years of involvement in stock investments. Table 1 provides an overview of the key demographic characteristics of the respondents.

Table 1. *Demographic profile*

Variables	Category	Frequency	Percentage (%)
Gender	Male	328	77
	Female	98	23
Age	≤ 25	46	10.80
	26 - 35	212	49.77
	36 - 45	130	30.52
	Above 46	38	8.92
Income	≤ 2,50,000	137	32.16
	250,001–500,000	149	34.98
	500,001–750,000	85	19.95
	750,001 – 1,000,000	31	7.28
	Above 1,000,000	24	5.63
Investment experience	2 - 5	355	83.33
	5 - 10	41	9.62
	Above 10	30	7.04

Notes: Sample size = 426
Source: Authors' elaboration.

3.2 Common method bias

Researchers using PLS-SEM in behavioral studies must be highly aware of the potential for common method bias [58]. Common method bias (CMB) occurs when data is obtained using a single instrument, making it crucial to verify the absence of CMB issues [59]. In this research, CMB was evaluated using Harman's one-factor test. The results suggest that a single factor accounts for 46.35% of the total variance, which is below the recommended threshold of 50% [60]. Therefore, we conclude that CMB does not present a concern in this research.

3.3 Measurement model assessment

First, we started assessing the measurement model to evaluate its validity and reliability of the model. Table 2 depicts the measurement model results. This study includes five latent variables: overreaction, herding, overconfidence, and individual investors' investment decisions. In the measurement model, to evaluate indicator reliability, internal consistency reliability, convergent validity, and discriminant validity [57]. In this study, all outer loadings exceed the 0.708 threshold, ensuring indicator reliability [61]. As shown in Table 2, Cronbach's alpha (α) and Composite reliability (CR) for all constructs exceed the recommended value of 0.7 [61]. Thus, confirming the internal consistency reliability. For evaluating the convergent validity, AVE was employed. The AVE should exceed 0.5 or higher [57]. It is observed from Table 2, that all constructs for AVE surpassed the threshold value, hence, convergent validity was also achieved.
We further evaluated the constructs' discriminant validity using the "Fornell-Larcker criterion" and the "heterotrait-monotrait (HTMT) ratio" [62]. Following the Fornell-Larcker criterion, the square root of each construct's AVE should be greater than its correlations with the other latent constructs [57]. This criterion was met, as shown in Table 3. For all constructs, the HTMT ratio values should remain below 0.9 [63]. As presented in Table 4, all HTMT values were below the threshold of 0.9, thus confirming the discriminant validity of the constructs.

3.4 Structural model assessment

After achieving the measurement model, the structural model was then examined. First, we assessed the collinearity issues of predictor variables in the model using the Variance inflation factor (VIF) before gauging the structural model in this study. Collinearity issues in any model are mainly caused by the high intercorrelation among variables [64]. Collinearity is not considered an issue within the model when VIF values are below 5 [65]. In the present study, the absence of collinearity concerns within the model is confirmed by VIF values lower than 5. Next, we test the hypotheses using a Bias-Corrected and accelerated (BCa) bootstrapping approach with 10,000 resamples [57]. The hypothesis results are presented in Table 5 and the structural model is shown in Figure 1. The study's results exhibit that overreaction has a direct impact (β = 0.344, t = 5.064) on individual investors' investment decision-making, supporting H1. Next, the evaluation of mediation effects was conducted in

Table 2. *Measurement model results*

Constructs	Items	Outer loadings	Cronbach's alpha	rho a	CR	AVE
Overreaction	OR 1	0.904	0.861	0.862	0.915	0.782
	OR 2	0.892				
	OR 3	0.857				
Overconfidence	OC 1	0.782	0.878	0.895	0.916	0.733
	OC 2	0.916				
	OC 3	0.851				
	OC4	0.868				
Herding	HD 1	0.917	0.847	0.847	0.897	0.686
	HD 2	0.850				
	HD 3	0.876				
	HD 4	0.783				
Investment decisions	ID 1	0.772	0.924	0.928	0.940	0.691
	ID 2	0.899				
	ID 3	0.846				
	ID 4	0.848				
	ID 5	0.876				
	ID 6	0.732				
	ID 7	0.833				

Source: Authors' elaboration.

Table 3. *Discriminant validity: Fornell-Larcker criterion*

	Herding	Investment decisions	Overconfidence	Overreaction
Herding	**0.858**			
Investment decisions	0.797	**0.831**		
Overconfidence	0.803	0.754	**0.856**	
Overreaction	0.758	0.765	0.639	**0.884**

Notes: The square root of the AVE is shown in bold values. **Source:** Authors' elaboration.

Table 4. *Discriminant validity: HTMT ratio*

	Herding	Investment decisions	Overconfidence
Investment decisions	0.880		
Overconfidence	0.899	0.830	
Overreaction	0.867	0.852	0.711

Source: Authors' elaboration.

accordance with the guidelines specified in [65–67], and the strength of mediation was further assessed using the Variance Accounted For (VAF) method, as proposed by Nitzl et al. [67]. The calculation of the VAF involves dividing the indirect effect by the total effect for each relationship, the values of VAF are presented in Table 5. A VAF below 20% signifies the absence of mediation, a VAF ranging from 20% to 80% indicates partial mediation, and a VAF greater than 80% suggests full mediation [67]. The results show that herding partially mediates the association between overreaction and individual investors' investment decisions (β = 0.264, t = 5.879, VAF = 47.08%), supporting H2. Overconfidence was also identified as a partial mediator in the connection between overreaction and individual investors' investment decision-making (β = 0.061, t = 2.487, VAF = 35.17%), thus confirming H3. Finally, we tested the serial mediation and found that herding and overconfidence partially and serially mediate the connection between overreaction and individual investors' investment decisions (ß = 0.025, t = 2.581, VAF = 23.56%), affirming H4. Furthermore, the R^2 for this model was calculated by incorporating the exogenous variable (overreaction) and the serial mediators, namely herding and overconfidence. The R^2 value indicates that the model accounts for 73% of the variance in investment decisions made by individual investors, highlighting its strong explanatory power [68].

3.5 PLSpredict analysis

The current study evaluated the model's predictive relevance using the Q^2 value and the PLSpredict analysis [69]. Table 6 reveals that all Q^2 predict values for investment decision items exceed zero. When employing the PLSpredict procedure, if the prediction errors of PLS MV for endogenous constructs are non-symmetric, it becomes necessary to compare the partial least squares mean absolute error (PLS MAE) with the linear regression model mean absolute error (LM MAE) for each indicator to determine the model's predictive relevance [69]. We identified non-symmetric PLS MV prediction errors in this analysis. Therefore, we compared the values of PLS MAE with the LM MAE values for all investment decision indicators. These results are illustrated in Table 6. The results showed that, for the majority of indicators, PLS MAE values were lower than LM MAE values, indicating that the model exhibits a moderate degree of predictive relevance [69].

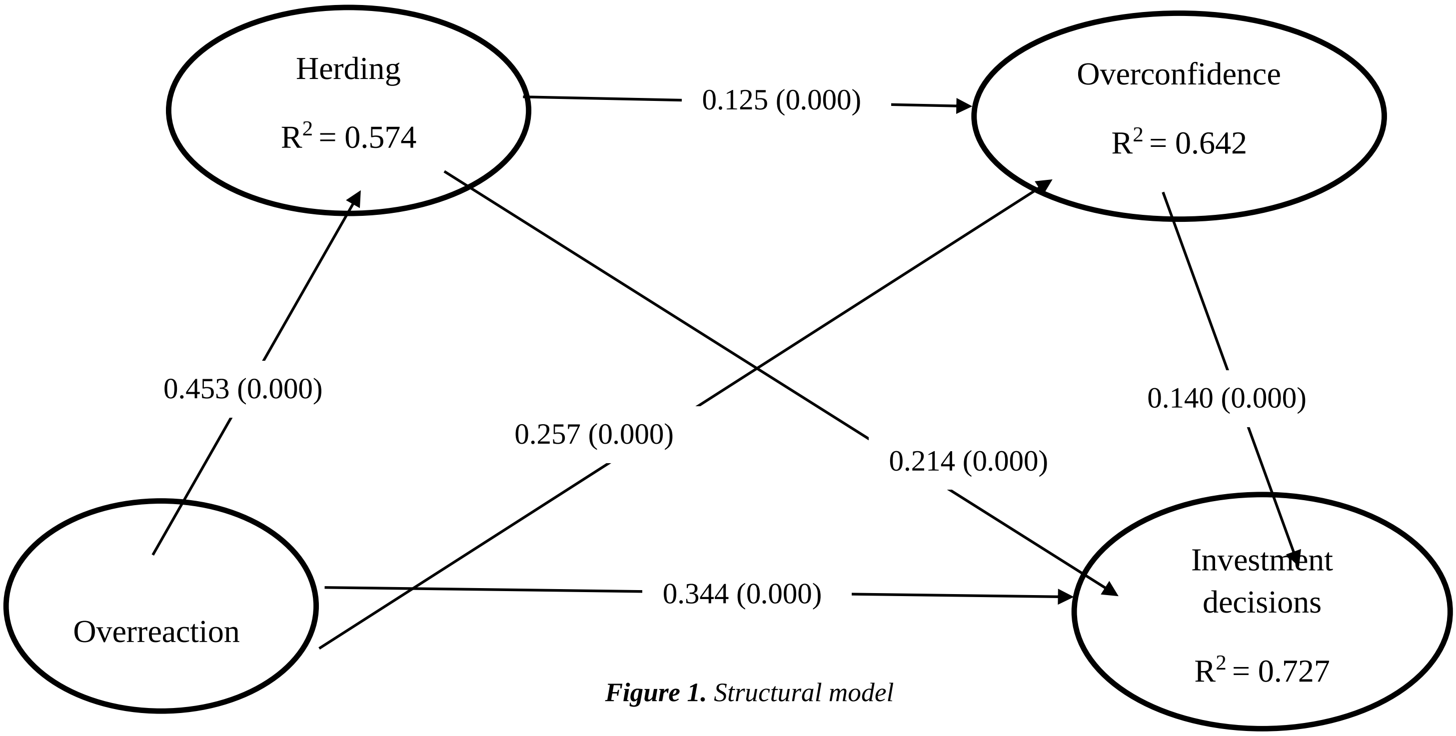

Figure 1. *Structural model*

Table 5. *Hypothesis testing results*

Hypothesis	Path	Path coefficient	T statistics	P value	VAF	Decision
H1	OR -> ID	0.344	5.064	0.000	-	Supported
H2	OR-> HD-> INV	0.264	5.879	0.000	47.08%	Supported
H3	OR -> OC -> INV	0.061	2.487	0.000	35.17%	Supported
H4	OR-> -HD->OC -> INV	0.025	2.581	0.000	23.56%	Supported

Table 6. *PLSpredict results*

Indicator	PLS Q²predict	PLS-SEM MAE	LM MAE
ID 1	0.312	0.629	0.715
ID 2	0.227	0.781	0.754
ID 3	0.447	0.527	0.578
ID 4	0.267	0.732	0.753
ID 5	0.412	0.565	0.571
ID 6	0.024	0.776	0.764
ID 7	0.056	0.718	0.725

3.6 Discussion

The present research aims to examine the influence of overreaction on individual investors' investment decisions. Further, this study also attempts to investigate the role of herding and overconfidence in mediating the connection between overreaction and individual investors' investment decisions through serial mediation analysis. The study's results demonstrate that overreaction has a significant and positive impact on investors' decision-making. Investors tend to overreact to recent information and events related to a particular stock while ignoring the fundamentals, which in turn influence their stock investment decisions. This finding aligns with the previous research [10,29].

In the mediation analysis, herding partially mediated the association between overreaction and individual investors' investment decisions.

Herding behavior intensifies market overreaction, as the collective tendency of investors to engage in massive buying or selling heightens price volatility, thereby disrupting market equilibrium. Overconfidence partially mediated the connection between overreaction and individual investors' decision-making.

Overconfident investors amplify the effects of overreaction by placing excessive emphasis on their perceived ability to predict market movements. Consequently, this decision-making can lead to significant fluctuations in the stock market. This study uncovers a novel finding, demonstrating that overconfidence and herding partially and serially mediated the association between overreaction and investors' decision-making.

3.7 Theoretical implication

The present study contributed to the existing behavioral finance literature by exploring the influence of overreaction on investment decisions, employing a serial mediation analysis to assess the roles of herding and overconfidence in the Indian stock market. Notably, prior research has not yet examined the role of herding and overconfidence as serial mediators in the connection between overreaction and individual investors' investment decisions, providing significant evidence to support the theoretical contribution.

3.8 Practical implication

This research is helpful for investors, investment advisors, and policymakers. First, investors will benefit from this study's novel findings, which contribute to the behavioral finance literature by highlighting the importance of avoiding reliance on market noise and making more informed and rational investment decisions, ultimately leading to a more profitable investment portfolio. Second, investment advisors can enrich their guidance to clients so that they may be able to make optimal investment decisions. Lastly, policymakers can organize educational workshops for investors to raise awareness about effectively dealing with market news and recent events. Decision-making is applied in different fields in the literature [70-76].

4. Conclusions

This study confirms the substantial impact of overreaction on individual investors' decision-making processes. It also attempts to analyze how overreaction influences investment choices by employing serial mediation analysis, focusing on herding behavior and overconfidence in the Indian stock market. The study's results show that herding and overconfidence partially and serially mediated the connection between overreaction and individual investors' decisions.

This study has certain limitations, which have been identified and suggested as avenues for further research in the area of behavioral biases. The current research used a cross-sectional design; therefore, future researchers in behavioral finance could focus on a longitudinal study to overcome the common method bias. Second, this study focused solely on respondents from the southern region of India, future investigations could include participants from both the northern and southern regions of India to identify patterns of similarities and differences. Third, behavioral biases (herding and overconfidence) were utilized in this study, future research might explore other biases that could be relevant for examining the mediating variables.

Author Statements:

- **Ethical approval:** Ethical approval was not required, as informed consent was obtained from all participants, and the collected data was fully anonymized.
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