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Third-Person Perception and Corrective Behaviors Toward Health Misinformation in Algorithm-Recommended Environments

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Abstract. During the outbreak of the novel coronavirus, the information environment has undergone tremendous changes, and the research on the spread of health misinformation has become very urgent. This study uses the third-person effect (TPE) theory and algorithmic literacy (AL) as an analytical framework to explore how users perceive the impact of health error information in the context of algorithmic recommendation, and whether individuals are willing to actively correct behavioral intentions. Therefore, this study combines third-party perception theory and algorithm literacy to explore the formation mechanism of users' corrective behavior intention. In this study, a national online questionnaire survey was conducted through the professional research institution Questionnaire Star, and a total of 208 respondents were collected. SPSS is used for statistical analysis of data and empirical testing of research hypotheses. The study found that respondents were more likely to think they were more susceptible to health misinformation than others. The traditional third-person perception theory does not show strong explanatory power in the health error information propagation scenario in the algorithm recommendation environment. The user's intention of corrective behavior may be mainly derived from the judgment of the degree of influence on others, and more related to the individual's understanding of the algorithm, the evaluation of corrective behavior, the influence of social norms and other factors. This study provides a new perspective for understanding the behavior mechanism and user cognition in the dissemination of health error information in the algorithmic environment.

Keywords: algorithmic health misinformation, third-person perception, recommendation, algorithm literacy

1. Introduction

In fact, before the outbreak of COVID-19, the academic community and public health departments had noticed the spread of health misinformation. Later, the great changes brought about by the epidemic to the information environment made the study of this problem more urgent. It was against this background that Chen and Fu conducted a study [1]. They take the third-person effect (TPE) as the core framework and integrate the theory of planned behavior (TPB) to build a process model to explain why individuals take the initiative to participate in corrective actions. Their research results

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show that when people are faced with misinformation from the healthy class, there is a common cognitive bias that they tend to think that the information is more harmful to others than to themselves. This cognitive bias is Third-Person Perception (TPP), and positively predicts the intention of individual reporting, comment reminding and other corrective behaviors through two intermediary paths of attitude and perceived behavior control [1].

There are two aspects of the theoretical contribution of this research that deserve special attention. First, it extends the behavioral consequences of the third-person effect investigation from the common support for media censorship in the past to the spontaneous error correction behavior of ordinary users, which just responds to the reality that the public role is changing in the social media era. Second, with the help of the three core concepts of the theory of planned behavior, it preliminarily reveals the cognitive mechanisms behind the third-party perception and influences the intention of behavior, and no longer just describes the direct relationship between the two. However, the data collection point of this study was the stage when the COVID-19 pandemic had just broke out in China in February 2020. At that time, users mainly searched for health information, forwarded it in Moments or browsed relevant websites. Individuals still retained a certain initiative in this information contact process. Five years later, the information environment has undergone structural changes, which has brought an unverified theoretical problem to the core mechanism of the third-person effect. Nowadays, short video platforms represented by TikTok and WeChat video accounts have become the main channel for Chinese netizens to obtain health content. This kind of platform is different from the traditional information environment, and content distribution is completely based on algorithm recommendation. The content seen by the user is actively pushed by the platform after analyzing the portrait of his historical behavior data. The user has changed from the person who actively searches for information to the recipient of the content that is continuously analyzed by the data and fed in a targeted manner. This situation to some extent echoes the relevant discussions in the academic community about the dataization of individuals and the mediumization of survival.

This change prompts people to re-examine the psychological basis of the third-person effect. The fundamental reason why the third-person effect exists stably is that individuals generally overestimate their own information judgment level and determine that others are more susceptible to false information interference. Users' understanding of the operation mechanism of social media algorithms, personalized recommendation logic based on behavioral data, and the potential impact of algorithm recommendations on information contact are defined as algorithmic literacy. At present, there is no empirical research on the relationship between the concept of algorithm literacy and the theoretical framework of third-party effects.

The research of Chen and Fu leaves a phenomenon that cannot be fully explained: the direct effect of TPP on subjective norms is not significant and contradicts the conclusions of most similar studies. The author attributed this to the social distance effect without empirical testing. Moving the research situation to the algorithmic medium environment may provide a new entry point for re-examining the path, which is not within the focus of this study.

Under the above research background, this study draws on the model framework of Chen and Fu to introduce a new variable of algorithm literacy, and transfers the research situation from the traditional media information environment to the contemporary social media platform based on algorithm recommendation. Focusing on this situation transfer, this study proposes three questions: in an environment where algorithm recommendations are normalized and filled with health error information, do users think that such information has a far more serious negative impact on others than on themselves; whether the third-person effect perception can trigger the user's behavioral intention to correct health misinformation; whether algorithm literacy is involved in shaping the

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third-person effect perception. The theoretical significance of the research is to promote the discussion of the applicable boundary of the third-person effect, and the practical significance is to provide a reference basis for platform governance and digital literacy education.

This study proposes H1: people think that the adverse effects of health false information on others are far greater than on themselves. H2: This perception of 'underestimating yourself and overestimating others' will lead to a willingness to act to correct health rumors. RQ3 is an exploratory question to examine the relationship between algorithmic literacy and third-party effect perception. The reason why there is no directional hypothesis is that high algorithm literacy may bring two opposite psychological changes: one is to realize that they are accurately pushed by the algorithm and put down the sense of superiority, so that the third-person perception is weakened. the other is to provoke psychological defense instead, insisting that they are not easy to be fooled, so that the third-person perception is enhanced [2, 3]. Both inferences are supported by literature, and the final conclusion is presented by data.

2. Research methods

This study collects data through a cross-sectional online survey. A cross-sectional design means that all variables are measured at a single point in time, which is suitable for exploration of this study, because it allows multiple path relationships between variables to be tested at a manageable cost. It should be noted that the cross-sectional data reveals statistical correlation rather than strict causal inference, and this limitation will be resolved in the discussion section.

2.1. Detailed methods

The target group is TikTok or WeChat users who are active every day in mainland China. The inclusion criteria are between the ages of 18 and 45, and use one of the platforms for at least 30 minutes a day. The questionnaire is distributed to eligible subjects through the "WJX" platform, and two screening questions are placed at the beginning to exclude subjects who do not meet the age or time requirements. The target effective sample size is set at about 100, which can provide sufficient statistical force for the analysis of the structural equation model.

2.2. Measures

All variables were measured with 7-point Likert scales, except that the anchors for correction behavior intention were different, as described below. The items were adapted from established instruments that had demonstrated good reliability in previous studies (Table 1), and only contextual adjustments were made to tailor them to the algorithmic recommendation setting and the topic of health misinformation.

• Frequency of exposure to algorithmically recommended content. This scale was adapted from the media attention scale developed by Ho, Liao, and Rosenthal in Environmental Communication, which originally measured public attention to internet environmental information [4]. The present study adjusted the context to the health information domain, kept three items, and used a 7-point scale from 1 (strongly disagree) to 7 (strongly agree). An example item is "I browse health-related content in the recommended feeds on Douyin or WeChat every day".

• Third-person perception (TPP). The operationalization followed the difference score method used by Chen and Fu [1], with items adapted from the scale by Schweisberger, Billinson, and Chock in Journal of Computer Mediated Communication [5]. The study set up two items to measure the

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impact of health false information on themselves and on general users. Both items were scored by 7 points, and the 'impact on others' score was subtracted from the 'impact on themselves' score. This difference is the operational index of third-person perception. The greater the difference, the stronger the third-person perception.

• Algorithm literacy. Referring to Dogruel et al.'s theoretical framework on Internet users' algorithmic capabilities [6], combined with health information dissemination scenarios and social media algorithm recommendation features, we set up four items to measure respondents' perceptions of platform push principles, differences in information received by different users, reasons for recommendation, and algorithmic content recognition capabilities. All questions used a seven-point scale, 1 for 'very disagree', 7 for 'very agree'. The average score of the four items constitutes the algorithm literacy variable. The higher the score, the higher the self-rated algorithm literacy level of the respondents.

• Attitude toward correcting misinformation. The scale was taken from Zhao, Yin, and Song in Computers in Human Behavior [7], which originally measured social media users' evaluation of rumor refutation behaviors. The study kept four items and replaced the scenario with the correction of health misinformation. A sample item is "Correcting health misinformation on social media is a meaningful thing to do" and a 7-point scale was used.

• Subjective norm. The classic scale by Schifter and Ajzen in Journal of Personality and Social Psychology was adopted [8], which originally measured the perceived expectations of significant others in weight loss decisions. Three items were retained and adapted to the correction context. They asked participants about the extent to which their parents, relatives, and friends expected them to take corrective actions, using a 7-point scale.

• Perceived behavioral control. The scale from Zhao was also used, and three items were kept. These items measured respondents' subjective evaluation of their own ability to identify and correct health misinformation. An example item is "I can identify health misinformation on social media" and a 7-point scale was applied.

• Correction intention. The scale was taken from Lim in Journalism and Mass Communication Quarterly [9], which included five items. The anchors were adjusted to range from 1 (very unlikely) to 7 (very likely). The items covered specific behaviors such as commenting to remind others, reporting to the platform, forwarding fact-checking content, privately informing someone, and participating in discussions. A sample item is "I am very likely to report this health misinformation to the platform".

Before the formal survey, a pilot test was carried out with 36 participants who matched the target group characteristics. The main purpose was to check the comprehensibility of the algorithmic awareness scale items, and some wording was adjusted accordingly. The formal questionnaire was organized in the order of demographic information, frequency of algorithmic exposure, algorithmic literacy, third-person perception, the three TPB components, and correction intention. A minimum response time and logic check questions were included to filter out careless answers or automated responses. Most of the pilot participants were university students who had a certain understanding of algorithmic recommendations, so the results from these 36 responses showed a positive trend, with a tendency towards third-person perception. However, the small sample size might have been coincidental, and because the formal sample was more diverse, the focus was placed on the formal results.

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Table 1. Summary of measurement tools

Variable	Number of items	Response format	Source
Frequency of exposure to algorithm-recommended content	3	1-7 points	Ho, Liao & Rosenthal [4]
Third-person perception (TPP)	2(difference score)	1-7 points	Schweisberger, Billinson & Chock [5]
Algorithm literacy	4	1-7 points	Dogruel, L., Masur, P., & Joeckel, S [6]
Attitude toward corrective actions	4	1-7 points	Zhao, Yin & Song [7]
Subjective norms	3	1-7 points	Schifter & Ajzen [8]
Perceived behavioral control (PBC)	3	1-7 points	Zhao, Yin & Song [7]
Behavioral intention to engage in corrective actions	5	1-7 points	Lim [9]

Note: Except for behavioral intention to engage in corrective actions, all scales used a 7-point Likert format ranging from 1 (strongly disagree) to 7 (strongly agree). The intention scale used a 7-point format ranging from 1 (very unlikely) to 7 (very likely).

3. Results and discussion

3.1. Results

The questionnaire was organized in the sequence of demographic information, algorithmic exposure frequency, algorithmic literacy, third-person perception, the three TPB elements, and correction intention, with a minimum response time and logic check questions to screen out invalid responses. The formal survey collected 208 responses, and after removing those that did not meet the requirements, 196 valid responses were obtained.

A paired samples t-test was used to examine H1 by comparing the perceived influence of health misinformation on oneself and on others. The results showed that the respondents perceived a significantly stronger influence on themselves ($M = 5.31$, $SD = 1.289$) than on others ($M = 5.03$, $SD = 1.244$). Therefore, H1 was not supported, and the sample did not exhibit the traditional third-person perception but rather showed a pattern of first-person perception to some extent.

Based on the valid sample with no abnormalities and with all measurement items meeting normality assumptions, regression analysis showed that third-person perception was not significantly related to correction intention ($\beta = 0.025$, $p = 0.728$), so H2 was not supported. To explore the relationship between algorithmic literacy and third-person perception, a linear regression analysis was conducted, and the results indicated no significant relationship ($\beta = 0.055$, $p = 0.445$).

To further analyze the factors affecting correction intention, a multiple linear regression model was built with algorithmic literacy, attitude, subjective norm, and perceived behavioral control as independent variables and correction intention as the dependent variable. The overall model was statistically significant ($R^2 = 0.668$, $F = 96.128$, $p < 0.001$), and all four independent variables had significant positive effects on correction intention. Among them, attitude had the strongest influence

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(β = 0.302), followed by perceived behavioral control (β = 0.258), algorithmic literacy (β = 0.189), and subjective norm (β = 0.157).

3.2. Discussion

H1 predicted that users would perceive a greater influence of health misinformation on others than on themselves. However, the findings were the opposite (self-influence M = 5.31 > other influence M = 5.03), and respondents believed that they themselves were more likely to be affected, which reflects a first-person perception. In the algorithmic recommendation environment, the traditional third-person perception theory was not supported in the health misinformation context. One possible reason is that health information is personally relevant, and individuals naturally pay attention to their own health and disease risks rather than whether others might be affected. Another possible explanation is that within an algorithmic recommendation environment, the content users encounter is filtered and pushed through personalization, so users feel that the content is somewhat relevant to themselves [10]. However, this study did not directly measure users' perception of algorithmic personalization, and this explanation still needs to be verified by future research.

H2 predicted that third-person perception would influence an individual's intention to correct health misinformation. The results showed no significant effect (β = 0.025, p = 0.728). One possible explanation is that when users encounter health misinformation, they may think others are affected, yet they do not actively correct it. Third-person perception reflects a judgment about the target of influence, while the intention to correct is a more complex behavioral decision [11], and even if users believe health misinformation affects others, they may not necessarily take the initiative to correct it.

Algorithmic literacy discussed in this study did not significantly affect third-person perception (β = 0.055, p = 0.445). A possible explanation is that these two variables focus on different issues, as algorithmic literacy may weaken an individual's blind trust in health misinformation rather than strengthen the belief that others are more easily deceived than oneself.

After testing the research hypotheses, a supplementary regression analysis was conducted to further understand factors that might influence correction intention. The results showed that algorithmic literacy, attitude, subjective norm, and perceived behavioral control all significantly and positively predicted correction intention ($p < 0.001$), meaning that in this context, individual cognitive and capability factors may play a more direct role [12].

4. Conclusion

This study focused on the third-person perception phenomenon in the spread of health misinformation under algorithmic recommendations, and it examined whether users exhibited third-person perception and whether this perception would further influence their correction intention. Through the analysis of 196 valid responses, the study found that the traditional third-person perception had limited explanatory power in the context of health misinformation, and respondents tended to believe that they themselves were more affected. When health misinformation is disseminated, users pay more attention to how the information influences their own health judgments and behavioral decisions.

The analysis indicated that algorithmic literacy did not significantly affect third-person perception. Although users' understanding of algorithmic recommendation mechanisms differed, this difference did not significantly change their judgment about who was more likely to be affected by health misinformation. Third-person perception also did not significantly affect users' intention to

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correct misinformation, which suggests that even though users believed others were affected, their motivation to actively correct was not strong.

In contrast, algorithmic literacy, attitude, subjective norm, and perceived behavioral control all significantly promoted users' correction intention, with attitude showing the most noticeable impact. This indicates that a positive attitude and higher algorithmic literacy are more helpful in increasing users' willingness to actively correct health misinformation. It suggests that in an algorithmic recommendation environment, improving users' algorithmic literacy and their ability to discern health information may be more beneficial for health misinformation governance than simply focusing on third-person perception. In the process of health misinformation spread, whether users are willing to take corrective actions may depend more on their own judgment of the social environment, their assessment of the value of correction, and their perceived ability to carry out the behavior.

This study found that the traditional third-person perception has certain applicability limitations in the context of algorithmic recommendations and health misinformation, which shows that users' cognition and behavioral mechanisms regarding information influence may differ from those in traditional media environments. Although the third-person perception path was not verified, this study further identified other factors that can influence correction intention, and it provides a reference for understanding user information judgment and behavioral mechanisms in personalized communication.

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