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# Analyzing the Factors Influencing the Prediction of Virtual Media Audience Reactions Using Artificial Intelligence

**Abdollah Daraei[1], Ahmad Heidary-Sharifabad[2,*] , Seyd Mahmoud reza Mortazavi[1]**

[1] *Department of Communications, May.C., Islamic Azad University, Maybod, Iran*

[2] *Department of Computer Engineering, May.C., Islamic Azad University, Maybod, Iran*

**Abstract**

Understanding the type and level of reactions of virtual media audiences is of great importance, given the widespread adoption of these media in today's world. A review of the literature in this area indicates that not much research has been conducted in this field. Therefore, the present study aims to investigate and analyze the factors influencing the prediction of virtual media audience reactions using artificial intelligence. For this purpose, based on a population of all users of virtual media and social networks in Tehran, the Morgan table is used to determine the sample size due to the unlimited nature of the population. According to the Morgan table, 384 people are selected as the sample. A questionnaire was designed based on the extracted qualitative model from previous qualitative research and distributed among the statistical sample. Then, the model was validated using structural equation modeling. The findings showed that emotional factors influence communication factors by 44%, while the influence of this factor on economic factors is 23%, on temporal factors 24%, and on political factors 31%. On the other hand, the influence coefficients of the manifest variables are often higher than 0.8, which indicates the high power of influence of the manifest variables and their high validity.

**Keywords:** Influencing factors, prediction, virtual media audience reactions, artificial intelligence

## 1. Introduction

Today, social networks have become a center for users to express their opinions and existence, and for various reactions to political and social events at national and global levels (Nozari, 2023). The

* Corresponding Author
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emergence and occurrence of these events can lead to the formation of numerous positive and negative currents, sometimes, especially negative currents, completely escaping the control and containment of governments (Sun & Duan, 2025). The occurrence of negative events can be accompanied by reactions that sometimes manifest as civil protests in the virtual space and sometimes as street protests and riots, and this is not limited to a specific geography. Therefore, identifying how virtual media audiences react is considered an important matter, which, due to the novelty of the topic, has rarely been addressed in research literature so far, and a review of the literature shows that this field is at the beginning of its research path (Nozari, and Chobar, 2024; Aslam et al., 2025).

The issue that motivates research in the field of predicting the reactions of virtual media audiences has been the significant events of recent years, which have largely prompted many audiences to react in the virtual space, and these reactions in the country have led to some bitter events, such as the 2022 incidents. The root of the 2022 protests lies in events that provoked many reactions on social networks, followed by calls for gatherings in the streets and public spaces. Of course, the 2022 event is merely one type of politically motivated reaction, but many other examples can be provided where an incident led to reactions from users. Therefore, identifying these reactions and, in fact, predicting them is considered essential.

However, it is not easy to predict events and audience reactions in the virtual space unless behaviors can be discovered based on quantitative techniques and past data. In today's world, artificial intelligence is considered a suitable tool for predicting and classifying any phenomenon, and this tool can also be used in the field of predicting the behavior and reactions of virtual space audiences. Given that previous research has not yet presented a model for using artificial intelligence to predict the reactions of virtual media audiences, and the validity of this model has not been quantitatively examined, the present research quantitatively analyzes and examines the qualitative model designed in previous research in this field using structural equation modeling.

The structure of the present article is such that the next section provides a literature review in the studied field, followed by a description of the research methodology, then an analysis of the findings, and finally, conclusions and recommendations are presented.

## 2. Literature Review

The first research on the audience was conducted during the period of mass society and mass culture development, which placed a major emphasis on this concept in media theory. Fascist and totalitarian movements were the main characteristics of the socio-political arena in the 1920s and 1930s, and the media was the primary tool of power.

The main effects were influenced by industrialization and urbanization processes, which caused a major change in the demographic structure of urban areas and led to the destruction of political relations as well as the psychological and social strengths of modern human identity. The complete lack of inclination towards new living and working conditions led to a media culture that was

drawn into a world of imagination and entertainment, which was achieved with the help of bright and sweet content. The audience is considered a mass of uniform individuals who react to media content in a calculated and unified manner. This stage of audience research is marked by a behavioral paradigm, showing that there are three vital aspects to audience characteristics, which are as follows:

The audience is a mass of individuals, and the importance of belonging to different social groups is rejected.

The media text is a stimulus through which the audience reacts uniformly, meaning the complexity of the potential meanings of the text is ignored. The focus is on the function of media, which is observed in the propaganda function of media (Omeish et al., 2024; Keihani, 2025).

Social media actors strive to create an attractive identity to achieve social status and audience attention. The focus is on establishing individual identities by showcasing skills and expertise. Others may design group identities by positioning themselves within social groups and emphasizing a sense of "us." This is crucial for mainstreaming a peripheral group. A clear group identity affirms group value and attracts others with similar mindsets, thus creating an effective space for the group to expand. The performance of group identities can energize social media audiences, which is necessary to direct broad social attention to the peripheral group. Right-wing groups have a strong tendency to implement group identities. Right-wing hate groups contrast their in-group transcendence and grievances against out-group perishability, which is a strategy for in-group member belonging and educates the public about out-groups. Additionally, messages from right-wing networks on social media are highly focused and coordinated, indicating possible group changes (Shahzad et al., 2024).

According to social identity theory, individuals are obligated to in-group members and expect in-group reciprocity regarding resources and interactions. Social media provides individuals with an opportunity to network directly and communicate with in-group members, creating social cohesion. Individuals on social media can react to the actions of others. This occurs in various ways, from direct liking, sharing, and commenting to more complex reactions. This presence is valuable and sought after by all types of actors, such as:

- Social media platforms
- Social media influencers
- Journalists
- Politicians

Promoters promote information that has desirable implications and avoid information that has negative implications. In social networks, promoters only select positive life events and choose desirable personal information to share with their social network friends. In contrast, scrutiny drives individuals to seek confirmation of existing concepts. Scrutiny can include both negative and positive aspects of oneself. The key difference between scrutiny and promotion is related to

the readiness for existing negative information. When evaluating behavior, the motivations for specific behavior are not present. For example, when an individual posts a positive self-presentation, we do not know whether this post is motivated by the need for self-promotion or the need for self-scrutiny. Since positive scrutiny and promotion are expressed in terms of online behavior, when evaluating scrutiny-like behavior, the focus is solely on examples of negative scrutiny. The transmission of valuable personal behaviors and attitudes is called self-indulgence (Okeleke et al., 2024).

The most important theories related to the present research are theories such as reception theories, uses and gratifications theory, and expectancy-value theory, which fall under audience-centric theories. Another type of important theories related to the present research are media and semantic theories, the most important theories falling under this general concept being representation theory, encoding and decoding theory, and McLuhan and Innis's theory.

The third type of theories that can be related to audience reactions are macro-sociological theories of communication, the first of which is John Thompson's theory, based on media and modernity. The second theory concerning the sociology of communication is Habermas's theory of media and the public sphere, and the third theory includes Williams's theory of technology and cultural form. Communication theory includes the fourth type of sociological theories of communication.

There are also theories in the field of technology and artificial intelligence that are completely aligned with the objectives of the present research. The most important theory under artificial intelligence and technology theories is the behavioral data mining theory. Regarding the prediction of employee behavior, there are also some models, with the perception of intention model in social media being considered the first model in this regard. Social media audience manipulation models are considered the second category of prediction models.

This section presents a literature review in the studied field. The conducted research pertains to the last three years and is mostly focused on employee behavior in social media and its prediction and classification. Liao (2024) investigated the determinants of social media in encouraging environmental behavior and gained insights based on social impact theory and planned behavior theory. Zareie and Sakellariou (2024), focused on maximizing fuzzy effect in social networks. Mehrabioun (2024), presented a multi-theoretical approach to user continuance intention in social networks. They combined the planned behavior theory, confirmation model, and consumption values. Wang and Li (2024), predicted behavior and understood the consumption intention of e-commerce users in social networks. Racek et al. (2024), examined the Russian war in Ukraine based on user reactions in virtual social media. Sun and Duan (2025), predicted user intention and its reaction in human-computer interaction. Aslam et al. (2025), predicted user personality based on tweets sent through machine learning techniques. Ruan et al. (2025), designed a digital media recommender system based on user behavior analysis and emotional feature extraction. Jiang and Ferrara (2025), modeled large-scale user behavior using language models and social network data.

Zhang (2025) discovered anomalous user behavior in social networks based on graph neural networks.

Yang and Crespi (2025), provided a systematic review of the application of social media and social brain abnormalities. Nozari et al., (2025), analyzed and predicted the purchasing behavior of e-commerce users based on logistic regression models. Filippas et al. (2025), investigated production and consumption in social media.

## 3. Methodology

The present research is applied in terms of its objective, and descriptive-analytical in terms of data collection. In this research, based on an extracted model from previous research, which has been validated using a qualitative approach, the relationships between variables are examined. Figure 1 presents the conceptual model of the research.

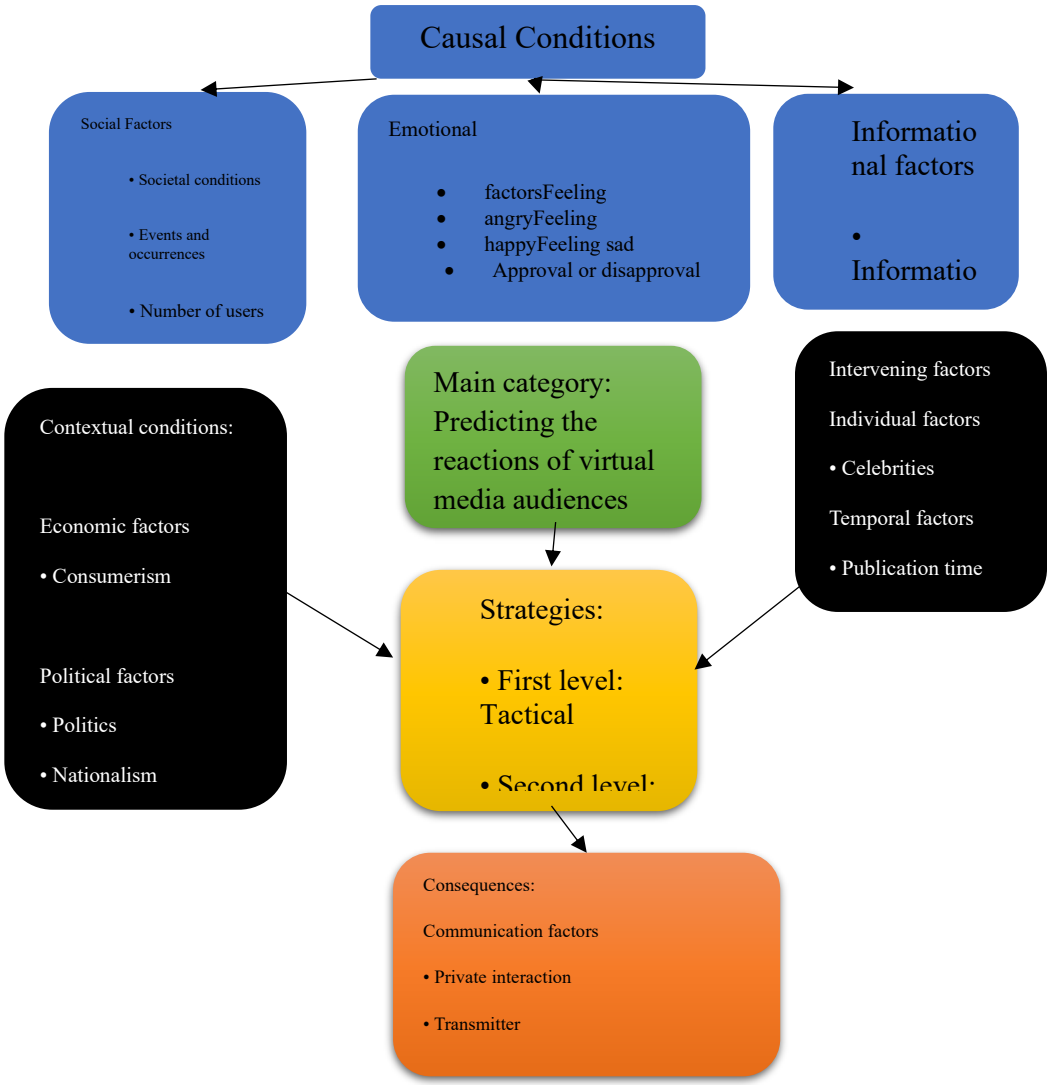


Figure 1: Conceptual Model of the Present Study

This model is derived from previous qualitative research, which has been converted into a structural equation model, and thus, the validity of the model is examined through this method. In the quantitative section, the statistical population includes all users of virtual media and social networks in Tehran. Given the unlimited nature of the population, Morgan's table is used to determine the sample size. According to Morgan's table, 384 people are selected as the sample, and the sampling method is random cluster sampling, meaning that random sampling is conducted from different areas of Tehran, and all individuals in the population have an equal chance of being selected as a sample.

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The data collection tool in the present study includes a questionnaire on a Likert scale, which covers the extracted components from the qualitative section and is considered the research indicators. These components are set up in a Likert scale format and distributed among the statistical sample in the quantitative section. The validity of these components is measured by factor loading analysis, and reliability is measured using Cronbach's alpha test. Several extracted indicators are presented in this section.

Data analysis in the present study is performed using the structural equation model, which is implemented in SmartPLS software.

### 3. Analysis Data

In this section, the model is quantitatively analyzed. For this purpose, structural equation modeling and factor loading analysis are used. In this section, the extracted model from the qualitative part is converted into a structural equation model in SmartPLS software, based on which the model's validity can be quantitatively measured.

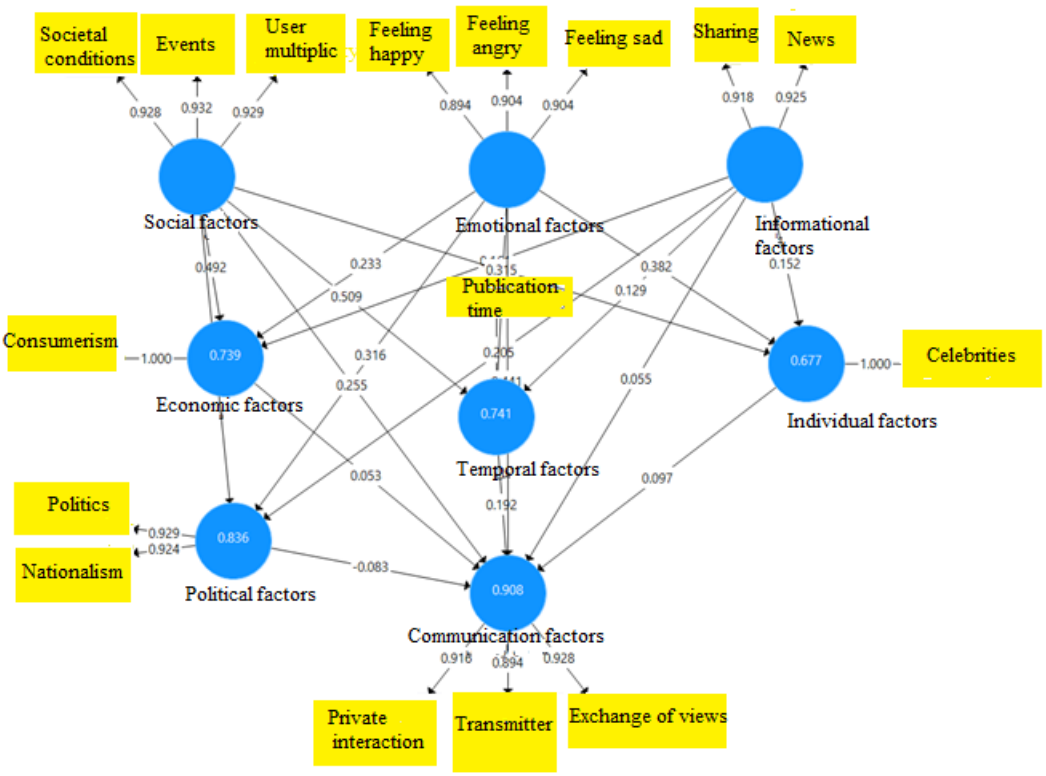


Figure 2: Structural equation model based on the path

Figure 2 presents the structural equation model of the current research, with the explanation that the above figure is based on path coefficients, which are the relationships between latent variables, and reveals the relationships between the main variables. Therefore, by looking at the above model, one can understand the level of intensity of relationships between variables in the current research.

Regarding the above structural equation model, it should be noted that this model is based on the obtained model and shows the relationships between factors. In the initial conceptual model, these relationships were merely assumed, but in the structural equation model, the relationships are statistically considered, and the arrows representing the relationships between variables carry the weight of their connection. The closer this number is to 1, the stronger the relationship, and the closer it is to zero, the weaker the relationship. Based on the above model, it is possible to measure whether causal factors truly influence outcomes and whether intervening and contextual factors genuinely play an intervening or contextual role.

On the other hand, based on the structural equation model, it can be understood whether independent variables truly play an influential role in the model. It should also be noted that the yellow boxes represent the items or indicators under each main variable that the structural equation model is capable of measuring. Through this model, it can be determined whether these indicators are fundamentally significant. Therefore, the presented model not only addresses the relationships between main variables but also measures the relationships between sub-variables or indicators.

The method of measuring these two types of variables is different, however. Main variables are measured based on regression, and sub-variables are measured based on factor loading analysis, whose characteristics will be described later.

The result obtained from the structural equation model presented in the current research indicates the significance of all relationships and, in fact, all hypotheses at a 95% confidence level. In fact, based on this, it can be said that the model has quantitative relationships. For example, the effect of independent or causal variables on outcomes can be examined, or the role of mediating and intervening variables can be confirmed based on the obtained structural equation model. Consequently, it can be shown that the presented model, based on the opinion of experts, has the necessary competence and can be considered as a model for measuring and explaining the reactions of virtual audiences.

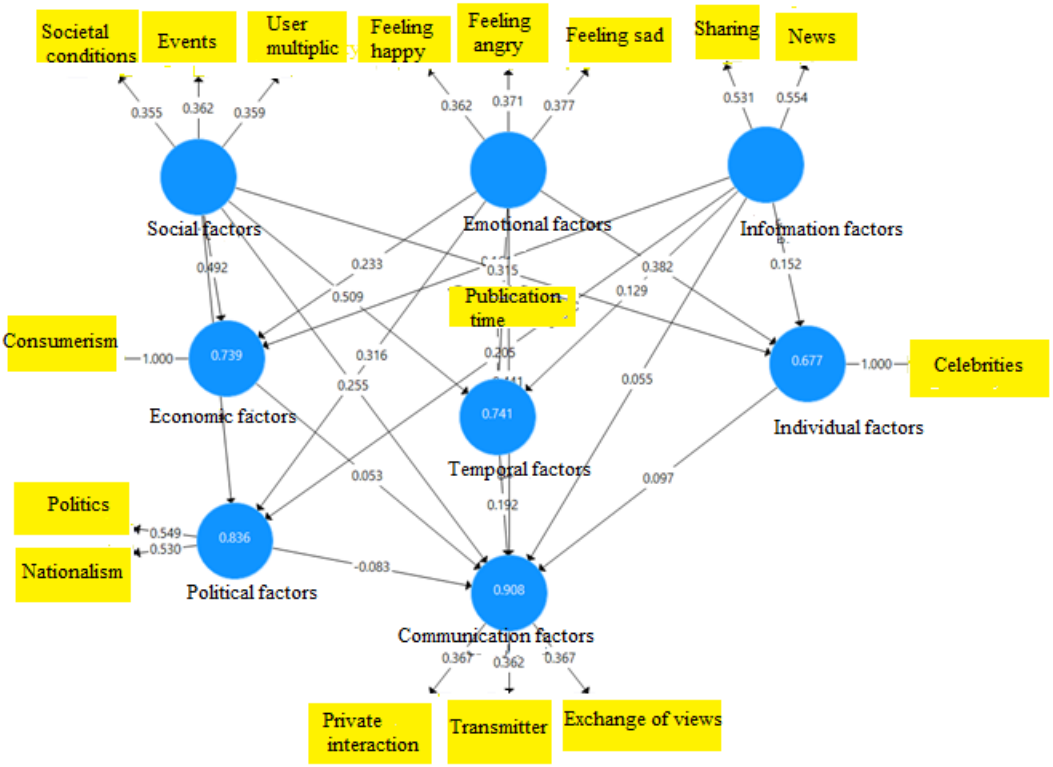


Figure 3: Structural equation model based on t-statistic

Based on Figure 3, it can be observed at what level the relationships between variables are based on the t-statistic. Based on this, the strength of the relationship between observed and latent variables can also be measured.

Next, the results of the path analysis are presented in Table 1.

Table 1: Path analysis

| Variables | Social factors | Communication factors | Information factors | Economic factors | Temporal factors | Political factors | Emotional factors | Individual factors |
|---|---|---|---|---|---|---|---|---|
| Social factors | | 0.255 | | 0.492 | 0.509 | 0.423 | | 0.315 |
| Communication factors | | | | | | | | |
| Information factors | | 0.055 | | 0.161 | 0.129 | 0.205 | | 0.152 |
| Economic factors | | 0.053 | | | | | | |
| Temporal factors | | 0.192 | | | | | | |
| Political factors | | 0.083 | | | | | | |
| Emotional factors | | 0.441 | | 0.233 | 0.248 | 0.316 | | 0.382 |
| Individual factors | | 0.097 | | | | | | |

Based on Table 1, it can be observed how strongly each variable affects another. In path analysis, the path between variables is shown, and the coefficients are explained based on the path taken. According to the table above, emotional factors influence relational factors by 44%, while their influence on economic factors is 23%, on temporal factors 24%, and on political factors 31%. The closer the influence value is to 1, the higher the strength, which, in the table above, results in approximately moderate.

Next, factor loading analysis is discussed. Factor loading analysis measures the items or indicators of a model; the closer it is to 1, the more validity it shows. The acceptable threshold in factor loading analysis is 0.4. Table 2 presents the results of the factor loading analysis for the proposed model.

Table 2. Factor Loading Analysis

| Variables | Social factors | Communication factors | Information factors | Economic factors | Temporal factors | Political factors | Emotional factors | Individual factors |
|---|---|---|---|---|---|---|---|---|
| Feeling angry | | | | | | | 0.904 | |
| Feeling happy | | | | | | | 0.894 | |
| Feeling sad | | | | | | | 0.904 | |
| News | | | 0.925 | | | | | |
| Information sharing | | | 0.918 | | | | | |
| Celebrities | | | | | | | | 1.000 |
| Transmitter | | 0.894 | | | | | | |

| Variables | Social factors | Communication factors | Information factors | Economic factors | Temporal factors | Political factors | Emotional factors | Individual factors |
|---|---|---|---|---|---|---|---|---|
| Exchange of views | | 0.928 | | | | | | |
| Private interaction | | 0.916 | | | | | | |
| Multiple users | 0.929 | | | | | | | |
| Events | 0.932 | | | | | | | |
| Release time | | | | | 1.000 | | | |
| Politics | | | | | | 0.929 | | |
| Social conditions | 0.928 | | | | | | | |
| Consumerism | | | | 1.000 | | | | |
| Nationalism | | | | | | 0.924 | | |

Based on Table 2, it can be observed that the influence coefficients of the observed variables are often higher than 0.8, which indicates the high power of influence of the observed variables and their high validity. Additionally, the latent variables obtained a value of 1 with one observed variable, which is considered natural for the existence of an observed variable under latent variables.

Next, the predictive validity of the independent variables, which are causal in the present study, is assessed. For this purpose, R-squared is used. The closer this number is to 1, the higher the predictive power of the independent or causal variables in the present research model. The results are presented in Table 3.

Table 3. R-squared

| Dependent, mediating, and intervening variables | R-squared | Adjusted R-squared |
|---|---|---|
| Communication factors | 0.908 | 0.907 |
| Economic factors | 0.739 | 0.737 |
| Temporal factors | 0.741 | 0.739 |
| Political factors | 0.836 | 0.834 |
| Individual factors | 0.677 | 0.675 |

As shown in Table 3, the predictive power of the independent variables is at a high level, mostly above 0.7, which indicates that the independent variables have high predictive power.

This section measures the reliability of the variables. The quantitative reliability results of the variables are presented in Table 4.

Table 4. Reliability of variables

| Variables | Cronbach's Alpha | rho_A | Composite reliability | Average variance extracted |
|---|---|---|---|---|
| Social factors | 0.921 | 0.921 | 0.950 | 0.864 |
| Communication factors | 0.900 | 0.900 | 0.937 | 0.833 |
| Information factors | 0.822 | 0.823 | 0.918 | 0.849 |
| Economic factors | 1.000 | 1.000 | 1.000 | 1.000 |
| Time factors | 1.000 | 1.000 | 1.000 | 1.000 |
| Political factors | 0.835 | 0.836 | 0.924 | 0.859 |
| Emotional factors | 0.884 | 0.884 | 0.928 | 0.811 |
| Individual factors | 1.000 | 1.000 | 1.000 | 1.000 |

Based on Table 4, it can be observed that the reliability of the variables is at a desirable level, as it is above 0.8, indicating a high degree of agreement among the research respondents.

Goodness of fit is used to assess the overall structural equation model presented in the current research. The results are presented in Table 5.

Table 5: Goodness of fit

| **Fit Parameters** | **Saturated Model** | **Estimated Model** |
|---|---|---|
| SRMR | 0.034 | 0.034 |
| d_ULS | 0.156 | 0.160 |
| d_G | 0.442 | 0.447 |
| Chi-Square | 951.365 | 959.237 |
| NFI | 0.873 | 0.872 |

Table 5 presents various criteria for assessing model fit, with SRMR being the primary criterion. In the table above, model fit has been assessed using the SRMR criterion, and the results indicate model fit from the perspective of this criterion. The SRMR criterion should be less than 0.08, as shown in the table above; therefore, the model is in a suitable condition according to the SRMR criterion.

## 5. Conclusion

The present study aimed to quantitatively analyze the influential components in predicting audience reactions based on artificial intelligence. The results showed that the model is significant

at a 95% confidence level. Therefore, it can be said that the extracted model is a capable model for predicting audience reactions in social networks, and given that no similar model has been presented in the research literature, the model can be a good estimator for audience reactions, and all components are considered significant. Furthermore, factor loading analysis greatly assisted in assessing the significance of the extracted indicators in the qualitative section.

In fact, factor loading analysis can be considered a method for measuring observed variables. Observed variables are important because they form the items or indicators of a model. Of course, regarding questionnaires, it should be said that they form constructs or questions, and by assessing factor loading analysis, it can be determined whether a questionnaire has the necessary validity or not. However, regarding the present research model, the goal is to assess the validity of the indicators under the main variables. For example, in this model, it is measured whether factors such as "publication time" under "temporal factors" or "consumerism" under "economic factors" have the necessary meaning and validity. Otherwise, if the indicators under a variable lack validity and are less than 0.4 based on factor loading analysis, it can be said that the variable has no meaning.

For example, if "publication time" under "temporal factors" reached a figure less than 0.4, then "publication time" could not be confirmed, and consequently, "temporal factors" would not be considered a significant mediating or moderating variable. As a result, it can be said that factor loading analysis is an important method for assessing the validity of a model by measuring the validity of its underlying indicators. Given that in the present study, the indicators under a model are above 0.8, the validity of all variables can be confirmed because they are in a desirable state of validity and have a large distance from the threshold value, which is 0.4. In the present study, this has been achieved, and the validity of all indicators has been confirmed.

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