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Presenting the Knowledge Extraction Model of Users' Trust in Marketing Based on Information and Social Network Data

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ABSTRACT

This research aims to present a model for extracting knowledge on users' trust in marketing based on information and social network data. The study was applied in grounded theory. Cognitive framing was employed using various data collection methods such as library study, examination of specialized sources and texts, and semi-structured interviews. Using purposive sampling, 14 experts were interviewed in 2023. The interviews were coded using ATLAS.TI software. To validate the results, data were evaluated and analyzed based on triangulation. The findings indicate a model of 18 concepts and 59 initial codes with 6 main axes. The conditions for this model include 6 concepts, background conditions with 3 concepts (information & communication technology infrastructure in the country, emulation of solutions from top companies in social network marketing, & digital economy), intervening conditions with 3 concepts (society's general knowledge level about information & communication technology tools, society's inclination toward engagement in social networks, & environmental changes), strategies with 3 concepts (facilitating user interaction for exchange of opinions under advertisement, electronic word-of-mouth advertising, & education), and consequences with 3 concepts (trust in & acceptance of advertisements by users, customer satisfaction, and economic productivity). The results indicate that the user trust model in social network-based marketing fundamentally utilizes network communications and interactions to structure trust and confidence. **©authors**

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1. Introduction

The knowledge extraction model of users' trust in marketing leverages both information and social network data to understand and predict trust dynamics. Firstly, it integrates information-based features such as the content of marketing messages, product descriptions, and user reviews to gauge the credibility and reliability of the information provided to users. Natural Language Processing (NLP) techniques can be employed to extract sentiment, key topics, and linguistic cues that influence trust perception (Pandian & Praveen Kumar, 2024). Additionally, this model incorporates social network data, analyzing users' interactions, connections, and social behaviors within online platforms. By examining factors like social influence, network structure, and user engagement patterns, it discerns how interpersonal relationships and social context shape trust perceptions (Costa et al., 2023)

Secondly, the model employs machine learning algorithms to process the extracted features from both information and social network data (Liu, 2020; Waltenrath, 2024). These algorithms can range from traditional statistical models to more advanced deep learning techniques capable of capturing complex patterns and interactions. Through training on labeled data, the model learns to recognize correlations between various features and users' trust levels, thereby establishing predictive capabilities (Gupta, 2024). By iteratively refining its parameters based on feedback and new data, the model continuously improves its accuracy in forecasting trust dynamics in marketing contexts (Jiang, 2012; Bosisio, 2024).

Finally, the knowledge extraction model generates actionable insights for marketers to enhance trust-building strategies (Duan et al, 2021). By identifying influential factors and key drivers of trust, marketers can tailor their messaging, content, and engagement strategies to resonate better with their target audience. For instance, insights from the model might suggest emphasizing certain trust-building elements in marketing campaigns or leveraging specific social network channels where trust formation is more pronounced (Hu et al, 2022). Moreover, the model enables marketers to monitor trust trends over time, adapting their strategies dynamically to evolving consumer preferences and market dynamics. Ultimately, by leveraging both information and social network data, this model empowers marketers to foster stronger and more authentic connections with their audience, leading to enhanced trust and loyalty (Hu et al, 2021).

Consumer trust in the virtual space is one of the critical issues in today's digital world (Quach et al., 2023). This trust in what is presented on social networks, websites, and other virtual spaces is crucial (Tamilmani et al., 2021; Soleimani, 2022). Consumers seek experiences that influence trust and honesty in organizations, brands, and various content. Consumer trust in these spaces is influenced by various factors, including content authenticity, social interactions (Kafilaleh et al., 2021; Kargirwar, 2023), user feedback and opinions, organizational or brand history, as well as the level of transparency and alignment with consumer values and expectations (Cannon, 1999; Giertz et al., 2016; Adam et al., 2020; Bethapudi et al, 2024). In the virtual space, a decrease in trust may lead to a reduction in revenue, sales, and an increase in consumer dissatisfaction (Carter et al., 2014; Hawlitschek et al., 2018). Therefore, many organizations and brands strive to enhance consumer trust through various strategies, including providing credible and valuable content, active engagement with audiences, offering transparent and trustworthy information, and using customer feedback and positive reviews to increase trust in their brand and products (Guo et al., 2018; Qi et al., 2022). Consumer trust in the virtual space can play a fundamental role in the success of an organization or brand and significantly impact purchasing decisions and customer interactions (Chiu et al., 2019).

User trust in social networks is one of the fundamental and influential factors in the success and sustainability of these networks (Hollebeek et al., 2016; Simon et al., 2018).

This trust is based on the relationships and interactions that users have with each other and with the system in these spaces. These relationships and interactions form the essential foundation for building user trust in the accuracy and security of information, the honesty of content, and the value that a social network provides (Islam et al., 2016; Jin & Youn, 2021; Xing et al, 2024). User trust in these networks has a direct impact on activities, interactions, and even the growth and expansion of these networks. In virtual communities, user trust plays a significant role in promoting information dissemination, exchanging opinions, and creating constructive spaces. When users trust to share their information and engage in interactions, a social network becomes a dynamic and valuable space for exchanging knowledge, experiences, and ideas (Srivastava et al., 2018; Jiang et al., 2019).

User trust also plays an important role in attracting new users; as individuals who trust a social network may also attract others to that network (Li et al., 2015; Kapoor et al., 2018). Additionally, user trust in a social network can have profound effects on business activities (Liu et al., 2012; Pentina et al., 2018). Users who trust a social network are more responsive to advertisements and content presented on it (Mao & Yuan, 2018; Shumanov & Johnson, 2021). This trust can lead to increased sales, improved advertising effectiveness, and even enhance the credibility and recognition of brands and organizations in the market. In today's world, where the virtual space and social networks are recognized as one of the most important marketing tools, building user trust in content and brands in this space is vital (Geissinger et al., 2016; Mirkovski et al., 2019).

One of the major challenges in this area is providing a comprehensive model for user trust in social media marketing. Contradictions and lack of transparency in content presentation, the influence of individuals and companies who can undermine trust with false information or deceptive advertising, and the absence of a uniform standard for evaluating trust, all point to the main challenge in this field (Cheung et al., 2019; Kar, 2021; Guhl et al, 2024). In this scenario, presenting a model that can consider various parameters and measure and predict user trust in content and brands on social networks is of great importance. This model should be able to recognize credible and influential content, consider factors such as the number of followers, user interactions, information authenticity, etc., and calculate trust based on them. Developing a model capable of predicting and evaluating trust in content and brands can help users make better decisions about engaging and participating in the online space. This modeling, in addition to increasing user trust, can also help companies and brands to have better approaches in social media marketing and establish more effective communication with their customers.

2. Literature Review

User Trust

User trust in social networks refers to individuals' confidence in the reliability, integrity, and trustworthiness of a social network or online platform (Luhmann, 2018). This trust is typically built upon past experiences, current interactions, and personal evaluations through which users gain assurance regarding the accuracy and security of content, information, and processes within a social network (Leckie et al., 2016; Khan et al., 2019). This type of trust in the social network's ability to safeguard users' privacy and information integrity, honesty in content and information presentation, and effective responsiveness and interaction with users (McKnight, 2005; Sun, 2010). User trust is essentially constructed from a combination of technical, security, and user experience factors that ensure users' confidence and satisfaction with the use of a social network (Tomlinson et al., 2020; Seyedin et al., 2021). This type of trust not only has a direct impact on users' behaviors and activities but also plays a significant role in the growth and sustainability of social networks; individuals who trust a network may engage more

actively in it and also attract others to it (Algharabat et al., 2018).

Knowledge Extraction

The knowledge extraction model is a sophisticated framework designed to sift through vast amounts of data, extracting meaningful insights and patterns (Nismi et al, 2023). It utilizes advanced techniques from fields like machine learning, natural language processing, and social network analysis to distill actionable knowledge from disparate sources. In essence, the model serves as a bridge between raw data and actionable intelligence, transforming complex information into understandable and useful insights (Tiwari et al, 2021). By leveraging this model, organizations can unlock hidden opportunities, mitigate risks, and make informed decisions. For example, in the context of users' trust in marketing, the model can uncover key factors influencing trust perception, such as the credibility of information and the social dynamics within online communities. This understanding enables marketers to refine their strategies, tailor their messaging, and engage with their audience more effectively, ultimately fostering stronger trust relationships and driving business success (Wang and Chen, 2020).

The knowledge extraction model operates as a sophisticated analytical framework capable of delving into diverse datasets to uncover nuanced insights (Sun and Loparo, 2019). Drawing upon techniques such as machine learning, natural language processing, and network analysis, it sifts through structured and unstructured data sources to distill actionable knowledge. Through this process, it converts raw data points into understandable patterns, trends, and correlations that can inform decision-making and strategy development (Ratner et al, 2016).This model is particularly powerful in domains like marketing, where understanding user behavior, preferences, and trust dynamics is paramount. For instance, in analyzing users' trust in marketing, the model can dissect various elements such as the tone and sentiment of customer reviews, the influence of social connections on purchasing decisions, and the impact of brand reputation on trust levels. By synthesizing these insights, marketers gain a comprehensive understanding of what drives trust among their target audience. Consequently, they can optimize marketing campaigns, refine product offerings, and tailor communication strategies to better resonate with customers, ultimately fostering deeper trust and loyalty. In essence, the knowledge extraction model empowers organizations to unlock the latent value within their data, driving more informed and effective decision-making processes across various domains (Shi et al, 2021).

Social Network

A social network refers to any type of online structure or platform that enables users to establish connections, share information, and facilitate social interactions and content and idea exchange through its tools and capabilities. These platforms allow users to create personal profiles, send and receive messages, share photos and videos, establish and manage communication networks, and participate in various groups and pages (Mozafari et al., 2015).

Social networks are widely present on the internet and include websites and applications such as Facebook, Twitter, Instagram, LinkedIn, YouTube, and many other platforms. These networks provide individuals with the opportunity to connect with others from around the world, share perspectives, ideas, and content, as well as to recognize and engage with brands, organizations, or different communities (Alalwan et al., 2019).

Social networks play a very important role as virtual spaces for information exchange, social interactions, and influencing social and commercial processes. They are used as tools for establishing meaningful and extensive connections in modern societies (Chatterjee et al., 2021; Koivisto et al., 2018).

Information data

Information data refers to any data related to the content, context, or characteristics of the information exchanged within a system

or platform. In the context of marketing, this can include product descriptions, reviews, promotional messages, and user-generated content. Information data can be analyzed using various techniques such as Natural Language Processing (NLP) to extract insights like sentiment, key topics, and linguistic patterns. Understanding the quality, credibility, and relevance of information is crucial for shaping users' trust perceptions in marketing interactions (Qi et al, 2022)

Social network data, on the other hand, encompasses the data generated by users' interactions and connections within social platforms (Martinez-Rodriguez et al, 2018). This includes information such as friendship connections, likes, shares, comments, and user engagement metrics. Social network data provides valuable insights into the relational dynamics and social influence within online communities. Analyzing social network data can uncover patterns of influence, community structure, and user behaviors, which are essential for understanding how social context shapes trust formation and decision-making processes in marketing (Qiao et al, 2021).

Continuing, the following research will delve into both domestic and international studies aligned with the research objectives.

Fetais et al. (2023) conducted a study titled "Does Social Media Marketing Activity Enhance Brand Loyalty? An Empirical Study on Luxury Brands," which demonstrated positive relationships between community engagement, brand love, and brand loyalty. Azhar et al. (2023) presented a research titled "The Impact of Social Media Marketing on Online Travel Purchasing Behavior after COVID-19 and the Mediating Role of Brand Trust and Brand Loyalty." The findings indicated that social networks have a significant and favorable impact on brand trust and loyalty, influencing purchasing intention. Aramburu et al. (2023) proposed a multidimensional data quality model for analyzing social media. The results showed that the exchange between quantity and quality for social media data is concentrated on a small percentage of engaged users. Therefore, data filtering can be easily achieved by ranking posts based on specified quality criteria using the proposed method.

According to the findings, the beneficial influence of brand trust and loyalty on the intention to purchase for arranging travel on social media platforms was discovered. Additionally, it was also confirmed that brand trust and loyalty mediate the relationship between social networks and trust. Therefore, social media significantly impacts the intention to purchase online travel by increasing brand trust and loyalty. Algharabat et al. (2021) presented a study titled "Social Commerce in Emerging Markets and Its Impact on Online Community Interaction." The results showed that the components of social commerce positively affect social support, community members' trust, and social presence. Moreover, it was found that social support and social presence have a positive impact on community members' trust. Furthermore, community members' trust positively influences flow, while both community members' trust and flow have a positive effect on community interaction. Xu et al. (2017) presented a study titled "Context-Aware Mobile Social Network Service Recommendation." They demonstrated that trust can reduce the risk of interacting with unknown entities and prevent malicious attacks. In the mentioned paper, an algorithm for recommending services based on trust in social networks was proposed, which considers the similarity of users and familiarity of friends when calculating trustworthy neighbors of target users.

Dilmaghani et al. (2021) presented a study titled "The Impact of Perceived Electronic Trust on the Willingness to Use Social Networks: A Case Study of WhatsApp Users in Tehran City." The findings of this research indicate that the constituent dimensions of electronic trust, including perceived information quality, security, and privacy preservation, influence the willingness to use social networks. Among these dimensions, perceived security has the greatest impact on users, while privacy preservation has the least impact on the adoption of social networks. Safiri et al.

(2018) presented a study titled "Exploring the Relationship between Interpersonal Trust and Sense of Social Security in Virtual Social Networks." They demonstrated that as the level of interpersonal trust among students on virtual social networks increases, they will experience a greater sense of security. Otherwise, a lack of security will prevail among them. Karampour et al. (2020) conducted research titled "Modeling Customer Behavioral Intention Based on Social Commerce Dimensions with an Emphasis on User Trust (Case Study: Telegram Social Network)." They showed that social commerce dimensions directly and indirectly, through user trust, influence customer behavioral intentions. Safaei et al. (2019) presented a study titled "Investigating the Impact of Social Dependency on Customer Trust in Social Networks." The results of this study showed that among the predicted factors, only the frequency of a customer checking their Instagram page has a significant effect on their trust level when making purchases from business pages.

Shir Khodayi et al. (2017) presented a study titled "Examining the Impact of Social Media on Brand Trust and Loyalty Formation in Brand Communities (Case Study: Instagram Social Network)." The results of this study indicate a significant and positive influence of individual and social identity on brand communities on social networks. Additionally, brand communities on social networks have a significant and positive impact on brand community engagement. Regarding the joint influence of brand community engagement on social interaction and brand usage, it was found that it was not the only mediator between social commitment and meaningful social interaction. Social interaction and brand usage also affect brand trust. Finally, the significant and positive impact of brand trust on brand loyalty was confirmed.

User trust models in social media marketing are among the most important tools used in analyzing user behavior and their impacts on marketing. These models are created to gain a deeper understanding of individuals' behavior and their trust in content, brands, and their peers in the digital space. One of the most important user trust models is the "Sender-Receiver" model. This model focuses on the influence of content senders (endorsers) on content receivers (endorsed). It demonstrates that user trust in content, brands, or individuals is shaped based on the roles and influence of individuals in social networks. In another model called the "Multidimensional Trust Model," various factors such as competence, honesty, and predictability of users' future behaviors are considered. This model provides a more detailed assessment of user behavior in the digital space by distinguishing between different dimensions of trust.

Moreover, trust models in social networks address the recognition of user behavioral patterns based on trust in others, the influence of content, and social activities. These models are important tools for analyzing and predicting user behaviors in the digital space and improving social media marketing strategies.

3. Methodology

The current research is considered to be applied in terms of research objective and qualitative in terms of methodology, employing a grounded theory approach with the Strauss and Corbin (1998) framework. In this study, methodological triangulation was utilized through various data collection methods such as library research, examination of specialized sources and texts, as well as semi-structured interviews. Data triangulation, involving the control of consistency across different data sources, was also a focus of the researchers and multiple data sources were utilized. Potential participants included all stakeholders, experts, elites, and marketing managers in the year 2023.

The sampling method was purposeful, and individuals from this group were selected for the qualitative part of the research and participated in the interview process. Purposive sampling was used to determine the samples in this research and select this group of experts. In this study, the primary sources of data were interviews, conducted in an exploratory and descriptive manner.

Gradually, after each interview, interview coding was performed, and theoretical codes emerged through constant comparative analysis. Similarly, coding was performed for 14 interviews, and sub-categories and main categories emerged. It should be noted that the saturation of core categories was achieved based on theoretical sampling so that the research continued until the concepts became dense and rich. For example, with the first 8 interviews, the core category became saturated, while for other categories such as results and implications, the data were insufficient, so interviews continued based on theoretical sampling until the desired category was saturated. It is worth mentioning that theoretical sampling for interviews was not based on the number of interviewees but on their role in densifying the categories. The interviews reached theoretical saturation after 14 interviews. The duration of each interview ranged from 30 to 50 minutes. ATLAS.ti software was used for qualitative data analysis, employing three stages: open coding, axial coding, and selective coding. The following questions were asked to the selected individuals in the qualitative sample during the interviews:

1. Is the use of social networks important for your business?

2. What do you think are the factors that build trust in users towards your brand or products in the virtual space?

3. Has the experience of other users with your brand on social networks been effective in gaining your trust?

4. What actions can help strengthen users' trust in your business in the virtual space?

5. Have changes in the way you communicate with customers on social networks affected their trust in your business?

6. How do you ensure that your communications on social networks increase users' trust?

7. Have your continuous communications and activities on social networks had any impact on users' trust in your brand or products?

8. How do you manage negative feedback or criticisms in the virtual space to maintain users' trust?

9. Has increasing users' trust through social networks had any impact on sales or acquiring new customers?

10. What role do you see for content and information published on social networks in building and strengthening users' trust?

4. Findings

A statistical description of the characteristics of field participants is presented in Table 1.

Table 1. *Demographic Characteristics of Interview Participants*

Demographic Characteristics	**Category**	Frequency	Frequency
gender	Female	6	43%
	Man	8	57%
education	Masters	10	71%
	PhD and above	4	29%
work experience	15-20	5	36%
	20-25	7	50%
	25 and above	2	14%
Age	30-40	6	43%
	40-50	6	43%
	50 and above	2	14%

For the purpose of open coding, all interviews were entered into the Atlas.ti software, and necessary analyses were conducted to extract the desired codes. The

coding labels were assigned based on the interviews conducted, and the researcher attempted to adhere to the participants' insights regarding their responses to prevent any potential unintentional bias as much as possible. Throughout the entire coding process, the researcher remained committed to the theoretical sensitivity derived from the principles of grounded theory, aiming to enrich the research as much as possible. Table 2 provides a sample of the coding of the conducted interviews.

Table 2. *Coded Interviews*

Codes (Symbol of interviews)	Concept
A_1, B_4, E_6	Pages and pages that deny users the possibility of commenting have established a kind of one-way and ineffective communication.
A_2, B_9, G_5, K_1	Experience has shown that advertising of well-known brands receives more visitors and likes.
A_3, B_1, F_8, I_7	Young and teenage generations have a strong role model of social media advertising.
A_4, F_2	Choosing the wrong media or page can weaken the brand.
A_5, E_4, J_1	All the efforts of the advertising industry are to arouse the sense of search in the audience.
G_{10}, K_2	The advertising solutions of the world's top companies are the best models in the field of digital marketing.
A_6, C_{10}, I_4	If businesses have already branded themselves, their advertisements on social media will attract more attention.

In Figure 1, the word cloud of identified codes is presented based on the specified frequency.

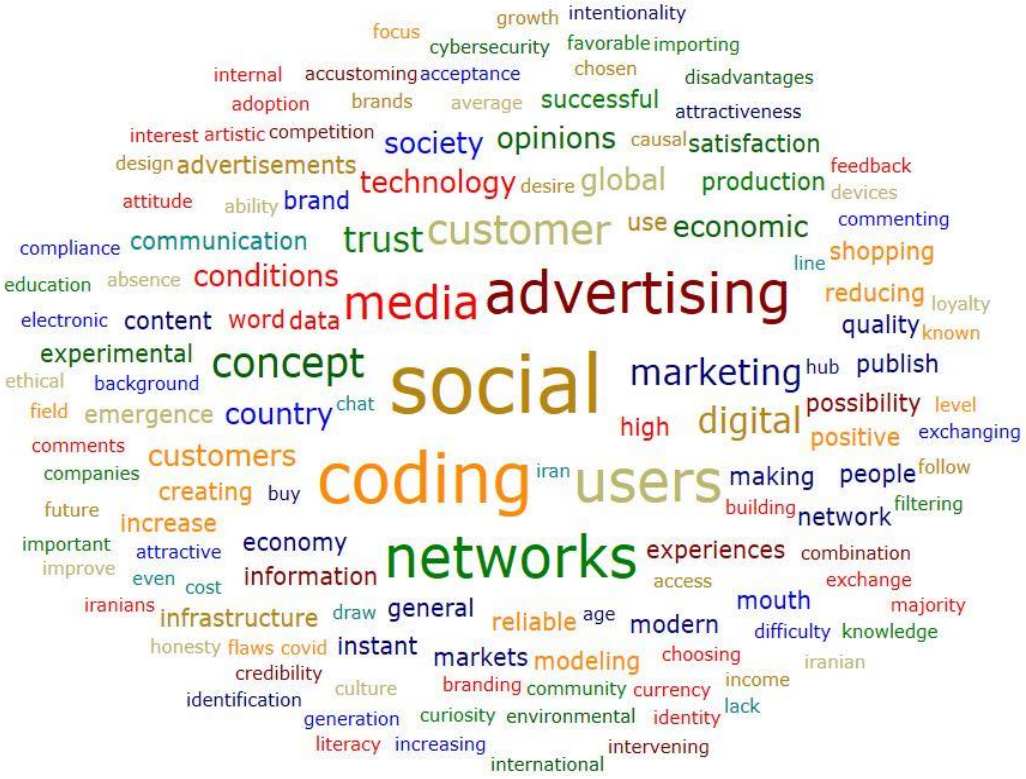

Figure 1. *Common Codes in the Software*

Continuing, based on the dimensions of the grounded theory model by Strauss and Corbin (1998), the categorization of identified codes is specified in Tables 3 to 7.

Table 3. *Open Coding of Qualitative Data (Causal conditions)*

Selective encoding	Category (Axial coding)	Concept (open coding)
Causal conditions	The general interest of the society in using social networks	Membership of the majority of people in social networks
		The favorable situation of Iran in terms of social networks
	Creating attractive content for advertising	The importance of the art of content production
		Curiosity, follow-up and even the desire to buy
		The quality and attractiveness of the advertising message
	Compliance with ethical principles in advertising design	The importance of honesty in advertising
		Users' understanding of the truthfulness or intentionality of advertisements
		Absence of unethical competition
	Using the power of the brand to win the trust of users	The importance of branding
		Promotion of well-known brands, with high feedback
		The importance of a strong brand in reducing the flaws and disadvantages of advertising
	Using reliable and specialized media to publish advertisements	The fit between the product/service and the media or page that is chosen to publish the ad is very important.
		The importance of media credibility
		The importance of choosing the type of media

Causal conditions play an essential role in creating a research model, and in the above table, the causal factors were identified separately based on codes in four categories.

Table 4. *Open Coding of Qualitative Data (Strategic Conditions)*

Selective encoding	Category (axial coding)	Conceptt (open coding)
Strategic	Making it possible for users to exchange opinions under the ad	The position of users' opinions
		The possibility of commenting
		The possibility of exchanging opinions
		positive comments
	Electronic word of mouth advertising	Artistic and positive advertising
		Ability to chat users
		The emergence of word of mouth marketing
	Education	Building public trust
		Training customers to use social media marketing tools
		Teaching media culture
		Adoption of social network marketing for customers

Strategies improve the category and model under investigation and finally it can be shown that the situation can be improved with the knowledge gained from the existing conditions with the suggested strategies.

Table 5. *Open Coding of Qualitative Data (Outcomes)*

Selective encoding	Category (axial coding)	Concept (open coding)
Outcomes	Trust in advertising and its acceptance by users	Instant trust of users
		Speed up instant shopping
		Customer satisfaction

	customer satisfaction	Improve customer attitude
		Increase customer loyalty
		Increasing the number of customers
	Economic productivity	Economic growth of the country
		Reducing the cost of the country
		Increase sustainable income
		Combination of traditional and modern system
		Identification of global markets
		Global customer focus

Based on the proposed strategies, possible results can be seen in the form of consequences, which in this model, with the correct implementation of the strategies, the consequences of the model are interpreted in this way.

Table 6. *Open Coding of Qualitative Data (Background Conditions)*

Selective encoding	Category (axial coding)	Concept (open coding)
Background Conditions	Information and communication technology infrastructure in the country	Reduce users based on filtering
		Poor quality of internal messengers
		The prevalence of mobile phone operators
	Modeling the solutions of top companies in the field of social network marketing	Using successful experiences
		Using international experiences
		Successful Iranian models
	Digital economy	Policy making based on experimental and experimental data
		cybersecurity
		Trusted digital identity
		Reliable digital data hub
		Public infrastructure for the digital economy

Background conditions play a fundamental role in creating strategies and establishing them. According to the background conditions, all strategies can be well managed to see the expected consequences correctly

Table 7. *Open Coding of Qualitative Data (Intervening Conditions)*

Selective encoding	category (axial coding)	concept (open coding)
Intervening Conditions	The general knowledge level of society about information and communication technology tools	High technological literacy of Iranians
		Accustoming people to social networking tools
		The average age of the community to use social networks
	Society's tendency to draw a line from social networks	Creating a subculture in society by social networks
		Modeling the young generation from social networks
		The origin of shopping in social networks
	environmental changes	Rapid changes in global markets
		The outbreak of the Covid-19 pandemic
		Economic sanctions
		The emergence of virtual currency and the uncertainty of its future
		Lack of access to modern production technology and the difficulty of importing devices

The Kappa index was higher than 0.7 and the reliability of the model was confirmed. After the completion of analysis and evaluation of various data, the final model of the study is presented as follows:

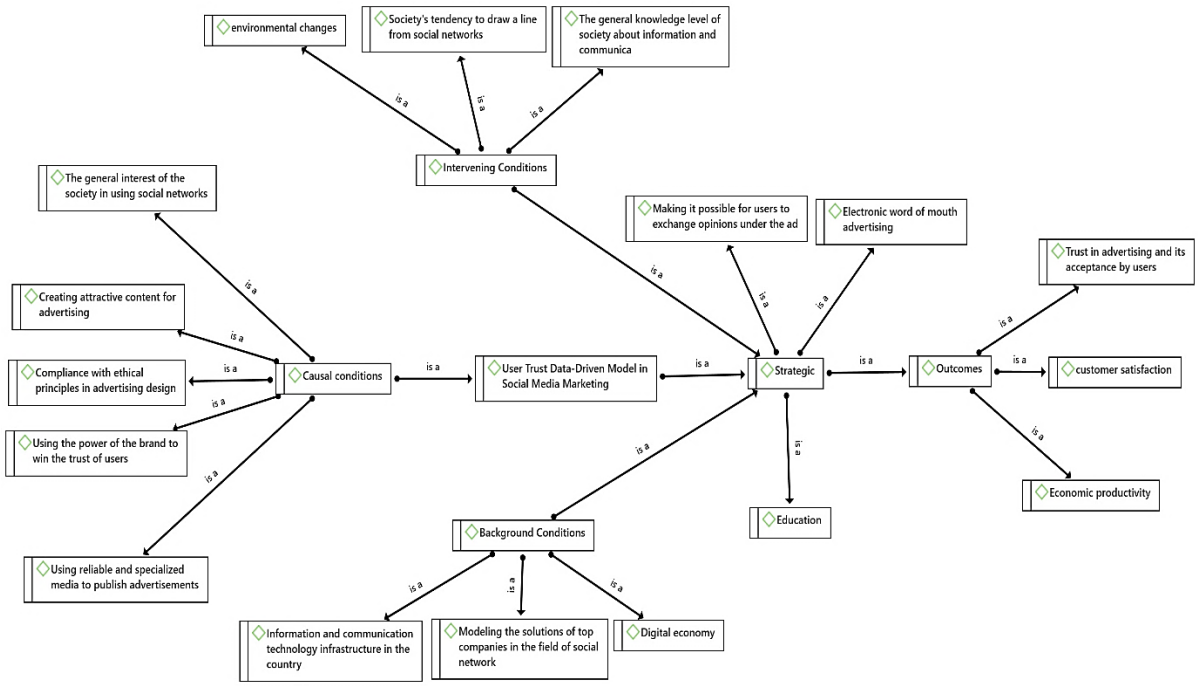

Figure 2. *The knowledge extraction model of users' trust in marketing based on information and social network data (ATLAS.TI Output)*

In Figure 2, based on Strauss and Corbin's model, in the form of a paradigm model, it was found that the category can be identified and the model can be proposed well based on the fit of the Kappa index.

5. Discussion

The aim of the research was to present the knowledge extraction model of users' trust in marketing based on information and social network data based on interviews conducted with stakeholders, experts, professionals, and marketing managers in the year 1402 (Hijri Solar calendar), using a data-driven approach. A paradigmatic model was proposed, comprising 18 constructs, 59 initial codes, and 6 main axes. The main objective, user trust in social media marketing, formed the core construct of the research Initial conditions, consisting of 6 constructs (general public interest in using social media, creating engaging content for advertising, adherence to ethical principles in advertising design, leveraging brand power to gain user trust, and using reputable and specialized media for advertising dissemination), background conditions with 3 constructs (information and communication technology infrastructure in the country, emulating strategies of top companies in social media marketing, and digital economy), intervention conditions with 3 constructs (public knowledge level about information and communication technology tools, societal inclination towards social media usage, and environmental changes), strategies with 3 constructs (facilitating user exchange of opinions under advertising, electronic word-of-mouth advertising, and education), and consequences with 3 constructs (trust in and acceptance of advertising by users, customer satisfaction, and economic productivity).

Based on the specified Initial conditions, it can be said that in the model of user trust based on social media networks, some key factors influencing the structure of trust have been designed. These include components such as the general public's interest in using social media, creating engaging content for advertising, adhering to ethical principles in advertising design, leveraging brand power to gain user trust, and using reputable and specialized media for advertising dissemination. The general public's interest in using social media can be considered as the main foundation for the trust structure. The existence of an active and widespread community that extensively uses social media provides an opportunity for exchange

of information and experiences among users, and these interactions can create and strengthen trust. Creating engaging content for advertising can be considered as a fundamental tool for attracting attention and building trust among users on social media networks. Engaging, useful, and creative content has the ability to establish a deeper connection with the audience, and if aligned with ethical standards, it enhances trust. Leveraging the power of the brand to gain user trust and using reputable and specialized media for advertising dissemination plays a crucial role in trust-building. Brands that increase their brand power through powerful strategies and providing credible content can earn user trust. Moreover, using reputable and specialized media for advertising ensures the credible and trustworthy transmission of messages to the audience. Research (Dilmaghani et al, 2021; Safaei et al, 2019; Mozafari et al, 2015; Cheung et al, 2019; Farajnezhad et al, 2022) has been consistent with the findings.

Based on the identified contextual factors, the model of user trust based on social media networks benefits from the combination of various technological factors and emerging marketing methods. Information and Communication Technology (ICT) infrastructures in countries play a crucial role in the creation and expansion of this model. These infrastructures include high-speed internet, easy access to smartphones, and advanced telecommunications technologies. These communication factors provide users with the ability to easily access social networks, share information, and improve their interactions with others. Research (Giertz et al, 2021; Farajnezhad et al, 2021; Soleimani, 2022; Quach et al, 2023) has been consistent with the findings.

Emulating strategies from top companies in the field of social media marketing is also of significant importance. Leading companies in this field have been able to implement models of customer acquisition, building relationships with audiences, and establishing trust in social media environments by using data analysis, artificial intelligence, and innovative marketing methods. Utilizing these patterns and successful experiences can assist other companies and users of these networks and can lead to considerable improvements in building user trust. Digital economy also plays a crucial role in shaping this trust model. Developments in the digital economy have facilitated the acceleration of information transfer and online transactions. This capability increases user trust in their communications and interactions in the virtual space and helps reduce informational and transactional barriers. The digital economy leverages easy access and assurance to enhance user trust in social networks. Based on the intervening conditions outlined, the model of user trust in social networks is heavily influenced by three important components that shape collectively. The level of general knowledge within society regarding Information Technology (IT) tools is of paramount importance. This level of knowledge may be determinant for trust in social networks because individuals who have sufficient awareness in this domain may be better equipped to understand the capabilities and risks associated with these networks and utilize them appropriately.

The societal inclination towards reliance on social networks is also of significant importance. When a society widely utilizes social networks, trust in these networks typically increases. This is because the daily and widespread use of these networks by individuals can increase attention to others' experiences and levels of engagement in these spaces. Environmental changes can also impact trust in social networks. These changes may include shifts in laws and regulations governing privacy, alterations in algorithms and information display methods on these networks, or even new events such as breaches or security incidents that may affect users' trust in these networks. Overall, these environmental changes can either weaken or strengthen users' trust in social networks, especially when these changes occur continuously and visibly.

The trust model based on social networks often utilizes a combination of factors to create a trustworthy platform. One of the most important factors in this model is the

possibility of user interaction. The existence of a space for conversation, sharing experiences, and opinions among users can foster mutual trust regarding discussed services or products. This capability can serve as an effective means to establish social trust.

Electronic word-of-mouth advertising is also a method that can contribute to trust-building in the social network model. The occurrence of such advertising happens directly through individuals and on a personal level. Due to the direct communication and greater trust established between individuals, this type of advertising can effectively enhance users' trust in a particular product or service. Education is another important component recognized in the social network-based trust model. Providing useful and practical educational content can help strengthen users' trust in a particular social network. The occurrence of this educational process enhances users' knowledge and abilities, consequently strengthening their trust in the social network.

6. Conclusion

Finally, based on the identified outcomes, it can be said that in the trust model based on social networks, three main components are examined: "trust in advertising and its acceptance by users," "customer satisfaction," and "economic efficiency." Trust in advertising and its acceptance by users examines the importance of users' trust in the advertisements and promotions introduced on social networks. Users must trust the content and information provided to the extent that they can experience its realization and authenticity. For example, if a product or service is introduced on a social network and users trust these advertisements, the likelihood of purchasing and using that product or service increases. Customer satisfaction pertains to how users interact with the content, products, or services offered on social networks.Customer satisfaction is considered a key indicator for evaluating the success or failure of an advertising program or advertising strategy. If the content or advertisements available on social networks meet the needs and expectations of users and lead to customer satisfaction, there is a higher likelihood of creating long-term relationships and increasing trust in the brand or product. Economic efficiency refers to the level of performance and profitability obtained from activities carried out on social networks. Advertising expenditure, financial returns, sales growth, customer acquisition, and improvement in customer relationships are among the factors that indicate economic efficiency. If strategies and advertising on social networks lead to improved profitability and economic efficiency, this component is highlighted as one of the key evaluations in the trust model. From the limitations of the research to its qualitative approach, it can be mentioned that the Foundation's data method examines the issue of users' trust based on network data only in one industry and society.

Also, this research has been reviewed in the environment of business professionals and in the form of an academic community, and the managers of Internet companies did not participate in this research, which can be seen in the use of the results. Based on the obtained results, researchers can examine the main issue in service and production industries and compare the results. It is also possible to check the situation of the main issue in Iran and advanced countries.Here are some practical suggestions for implementing a knowledge extraction model of users' trust in marketing based on information and social network data:

- Gather information from various sources such as product descriptions, user reviews, social media posts, and promotional messages. Employ Natural Language Processing (NLP) techniques to extract sentiments, key topics, and linguistic cues. Ensure to include both textual and visual content for a comprehensive understanding of the information landscape.
- Analyze the context in which the information is presented. Determine how factors like user demographics, cultural backgrounds, and temporal trends influence trust perceptions. Tailor the analysis to account for different contexts and ensure that

marketing messages align with users' expectations and preferences.

- Explore users' interactions, connections, and social behaviors within online platforms. Utilize social network analysis techniques to identify influential users, community structures, and information diffusion patterns. Understand how social influence and network dynamics impact trust formation and decision-making processes.

- Employ machine learning algorithms to process extracted features from information and social network data. Train predictive models to forecast trust dynamics based on historical data and user interactions. Continuously refine the models using feedback and new data to improve prediction accuracy over time.

-Identify key trust signals within the data that indicate credibility, reliability, and authenticity. These signals could include positive sentiment, user engagement metrics, social endorsements, and expert recommendations. Incorporate these signals into trust assessment algorithms to inform marketing strategies.

- Continuously monitor trust trends over time to identify emerging patterns and shifts in user behavior. Use real-time analytics to track changes in trust levels and adapt marketing strategies accordingly. Stay agile and responsive to evolving consumer preferences and market dynamics.

- Leverage insights from the knowledge extraction model to personalize marketing strategies for different user segments. Tailor content, messaging, and engagement tactics to resonate with users' trust preferences and social network dynamics. Implement targeted campaigns that address specific trust concerns and motivations.

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