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Word-of-Mouth Engagement in Online Social Networks: Influence of Network Centrality and Density

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Abstract: This paper investigates the effect of network centrality and network density on the propensity to engage in positive and negative eWOM, using social networks usage as a moderating variable. The research method was Structural Equation Modeling, and the data were collected through a survey conducted on 436 respondents from Romania. Findings showed that centrality and density only affect negative eWOM intent, the relationship being stronger at higher levels of network usage. In consequence, influential network members are more readily inclined to produce unfavorable eWOM. Subsequently, companies should make continuous efforts to spot and turn around bad publicity online.

Keywords: e-WOM engagement; network centrality; network density

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1. Introduction

Online social networks have become a vital medium for social interactions and information sharing between users. Within these networks, users can post reviews of products and services, thereby influencing the decisions of other consumers [1]. Previous studies [2,3] have shown that users' network position and connections can play a critical role in shaping their online behavior. Therefore, it is important to understand how social network centrality and density can influence users' propensity to post positive or negative reviews. Recent studies [4,5] suggest that users who occupy central positions in social networks have a greater influence on the decisions and behavior of other users. They have access to a greater amount of information and can influence the opinion of others through their connections. It has also been found [6] that users who are part of high-density networks are more likely to be influenced by the positive or negative opinions and reviews of other users. The current research focuses on the influence of social network centrality and density on users' tendency to post positive or negative reviews about products or services, known as electronic Word of Mouth (eWOM). Additionally, this article examines whether social network usage can moderate the effects of centrality and density on the intention to post positive or negative eWOM.

In today's digital landscape, social networks have become an integral part of our daily lives, providing platforms for individuals to connect, share information, and express their opinions. The concepts of social network centrality and density play crucial roles in shaping individuals' behavior within these networks.

Social network centrality refers to an individual's position or importance within a social network. It is measured by factors such as the number and strength of connections, the ability to access information, and the influence on others. Research suggests that individuals with higher centrality are more likely to engage in eWOM activities, as they possess greater social capital and influence [7,8]. Social network density, on the other hand, refers to the extent to which connections exist within a network. Higher network density facilitates the flow of information, making it easier for eWOM messages to spread.

Electronic word-of-mouth (eWOM) refers to the sharing of opinions, experiences, and recommendations about products and services through online platforms. It has emerged as a powerful driver of consumer decision-making. Social network centrality and density significantly influence individuals' engagement in eWOM activities. Those with higher centrality are more likely to initiate and participate in eWOM conversations, as their opinions carry more weight within the network [9]. Additionally, the density of a social network enhances the reach and impact of eWOM messages, as information spreads rapidly among densely connected individuals [10].

Social network usage is strongly influenced by social network centrality and density. Individuals with higher centrality are more likely to spend more time on social networks, as they derive social and informational benefits from their connections. Moreover, the density of a social network positively affects the frequency and duration of usage, as individuals are exposed to a larger volume of content and interactions [11]. This mutually reinforcing relationship between social network usage and network characteristics further amplifies the impact of eWOM activities.

Although there have been scientific studies about each individual aspect, no study has taken into account the analysis of the relationships between social network centrality, social network density, social network usage, and eWOM. Taking into consideration all the above aspects, this article aims to investigate the interconnected relationship between social network centrality, social network density, electronic word-of-mouth (eWOM), and social network usage. The findings will be useful for the understanding of the dynamics of these factors to harness the power of social networks for effective communication and marketing strategies.

The study is based on a sample of social media users, and the data were collected through an online questionnaire. Data analysis was performed using a structural equation model. The results indicate that social network centrality and density have a significant effect on the intention to post-negative eWOM. In other words, users who occupy a central position in the social network and those who are part of a dense network are more likely to post negative reviews about products or services. This relationship is stronger among users who use social networks more frequently.

The goal of this study is to cover the gap regarding the influence of social network centrality and density on eWOM intention, taking into consideration the moderation effect of social network usage.

The paper has relevant contributions to the field of knowledge. Based on the results obtained from the analysis, this research suggests that influential members of social networks are more likely to post negative eWOM. This should be a concern for companies that are interested in maintaining a positive online image. In light of these findings, companies should pay special attention to identifying and changing negative online advertising. Regarding the moderation of the effects of centrality and density, the results indicate that social network use can moderate the effect of density on the intention to post negative eWOM, but not the effect of centrality. In other words, users who use social networks frequently are less likely to post negative eWOM, regardless of their position in the social network. However, this effect was not observed in the case of positive eWOM.

This research highlights the importance of centrality and density in relation to posting negative eWOM. Companies should consider these findings when developing their online marketing strategies and focus on identifying and changing negative online advertising.

The remainder of the paper is organized as follows: the Section 2 presents the main concepts and the research hypotheses development. Then, the Section 3 describes the sample used in this research, while the Section 4 presents the relevant data obtained during the analysis process. Based on the results of the analysis, the Section 5 highlights the main contributions of this research. Finally, the Section 6 presents the managerial implications, the limitations of the study and the future research directions.

2. Literature Review

The main focus of our research takes into consideration the e-WOM in both types (positive e-WOM and negative e-WOM), social network centrality, social network density, and social network usage.

2.1. Positive e-WOM

Positive electronic word-of-mouth (eWOM) is an increasingly important area of research in marketing, as it plays a crucial role in shaping consumer opinions and behaviors [12]. Positive eWOM refers to positive comments, reviews, recommendations, and other forms of electronic communication that consumers share about products or services through social media platforms, online review sites, forums, and blogs [13]. In the specialized literature [14], it is considered that eWOM is a very relevant component because the ideas and answers published in online media are the results of rational thoughts and not the result of a passing emotion.

Moreover, established authors [15] found that there is a notable difference between the concepts of WOM and eWOM because WOM is based on the credibility between two participants who know each other a priori, while in the case of eWOM, the interaction takes place between participants who know each other very little or not at all.

The content of positive eWOM can also vary, depending on the type of product or service being discussed, the platform used, and the purpose of the communication. Some common characteristics of positive eWOM include:

- Authenticity: Positive eWOM is often seen as more authentic and trustworthy than traditional advertising, as it comes from real people who have used the product or service [16].
- Reach: Positive eWOM has the potential to reach a large audience, as it can be shared and amplified through social media platforms and other online channels [17].
- Engagement: Positive eWOM can lead to engagement and interaction between consumers and brands, as consumers may respond to or share positive comments about a product or service [18].
- Permanence: Positive eWOM can have a long-lasting impact, as it can remain online for an extended period of time and be accessed by future consumers [19].

Positive e-WOM is a form of online communication where consumers share their positive experiences with a particular product, service, or brand. It is a powerful tool that can significantly influence consumer behavior and drive sales. One of the main benefits of positive e-WOM is that it can increase brand awareness and attract new customers [20]. When consumers share their positive experiences online, they are essentially promoting the brand to their friends, family, and social media followers. This can create a ripple effect that can reach a large audience and generate interest in the brand.

Positive e-WOM can also help build a strong and loyal customer base. When consumers share their positive experiences, they are essentially endorsing the brand and creating a positive association with it. This can lead to a sense of loyalty among consumers and can encourage repeat purchases. Moreover, positive e-WOM can enhance the brand's reputation and credibility. Consumers are more likely to trust recommendations from their peers than traditional advertising. When consumers share their positive experiences online, it can help build trust and credibility for the brand.

However, it is important to note that positive e-WOM is not always genuine. Companies may engage in astroturfing, a practice where they create fake positive reviews to manipulate consumer perception [21]. This can ultimately backfire and harm the brand's reputation. Therefore, it is important for companies to encourage genuine positive e-WOM through exceptional customer service, high-quality products, and ethical business practices. Companies can also incentivize consumers to share their positive experiences through referral programs or social media campaigns.

Positive e-WOM is a powerful tool that can significantly influence consumer behavior and drive sales. It can increase brand awareness, build a loyal customer base, and enhance the brand's reputation and credibility. However, companies must ensure that positive e-WOM is genuine and not artificially generated [22]. By focusing on providing exceptional customer experiences and ethical business practices, companies can encourage genuine positive e-WOM and reap the benefits that come with it.

2.2. Negative e-WOM

Negative e-WOM refers to the online communication of consumers' negative or unpleasant experiences with a particular product, service, or brand. It is a form of negative feedback that can affect a company's reputation and ultimately its sales [23]. There are several reasons why people choose to share their negative experiences online. One of these is the lack of other feedback options. People may want to share their experience with a product or service with others but do not have a direct way to do so [24]. In these cases, posting a comment online may be the only option. Posts have a major impact on both merchants and the user community from different fields. In the specialized literature [14,25,26], the impact that eWOM posts have on Yelp, TripAdvisor, or Reddit ecosystems was analyzed.

Another reason is that people believe that their negative feedback can help other consumers make a better decision [27]. By sharing their negative experience, they hope to prevent other consumers from making the same mistake.

However, negative e-WOM can have a negative impact on companies and brands. Some studies showed that an increase in negative feedback can lead to a significant decrease in sales [28]. Negative feedback can affect a company's reputation and lead to a loss of consumer trust in its product or service.

There are several ways in which companies can manage negative feedback online. One of these is to respond to feedback and try to address the issues raised by consumers [29]. By resolving issues, companies can demonstrate that they respect their consumers and take their feedback seriously. This can help restore consumer trust in the brand.

Another approach is to use negative feedback as an opportunity to improve the product or service [30]. Companies can use negative feedback to identify problems and deficiencies in the product or service and then correct them. This can lead to significant improvements in the product or service and can help build a better reputation for the brand. Negative e-WOM is an important aspect of consumer feedback in the digital age. Companies must consider negative feedback and try to manage it effectively in order to protect their reputation and maintain consumer trust in the brand.

2.3. Social Network Centrality

Social Network Centrality is a concept that appeared before social networks based on IT technologies. This concept was analyzed already 20 years ago by [31] in scientific research that took into account the position of children in the social networks of study classes. Thus, the social position within such a network is based on three distinct concepts: having friends, occupying a central position in the network of friends, and being liked or disliked.

With the unprecedented proliferation of social networks such as Facebook, Twitter, and Linkedin, more and more individuals, colleagues, and organizations are interconnected through a social network. With the emergence of these online social networks, it becomes increasingly important to identify the node with the greatest influence [32]. Thus, centrality indicates the most important node in a network or a subgroup of a network, and the measurement of centrality becomes an essential task for research in the field of influence management. They are of the same opinion [33] who show that in the modern world, the theory of social networks is becoming more and more important in the social sciences, and the determination and measurement of centrality is a landmark that is the basis of this developing theory. Centrality is a reference index because it indicates which node occupies the most important and influential place in a network. Thus, central positions are associated with leadership, a good reputation in the network, or popularity with a high degree of influence.

According to the research carried out by [34], social network analysis algorithms must first take into account the nature of interactions between nodes. Thus, PageRank or Alpha-Centrality algorithms can determine the elements that can constitute central nodes in a social network. The dissemination of information to network nodes depends on several factors such as the position of the central node, its connections with other influential nodes and the methods of data transmission.

Authors from the specialized literature [35] have also taken into account models of social networks organized on several layers which in turn generate the concept of multi-layer centrality. At the scientific level [36], several specific methods have been developed for determining and calculating the centrality within a social network, reaching the concept of distributed computing. This concept takes into account the scalability of the approach, making calculations more efficient in the case of large data sets in the case of social networks.

The analysis of centrality in social networks has an important impact in several economic and social fields. Thus, for example, in the case of the tourism sector, Ref. [37] used SNA (Social Network Analysis) techniques to analyze the structural properties of participants from different tourist destinations in correlation with the indicator of centrality within the network. In this way, each actor/participant is characterized by a specific indicator related to indegree and outdegree. Thus, it was concluded that there is a direct relationship between the relational dynamics within the social network and the development of tourist destinations. Another interesting result was obtained by [38] who analyzed the relationship between urban vitality and street centrality based on data from social networks in China. In the same line of ideas, Ref. [39] obtained relevant results regarding the relationship between the interregional movements of the population in South Korea and the centrality at the level of urban localities. Regarding centrality in social networks, Ref. [40] analyzed the role that this concept has in various fields such as smoking and alcohol consumption. According to the research carried out by [41], centrality in social networks has a major role in terms of the speed and manner of spreading information within the network. This has a significant impact on the propagation of economically impactful messages in networks such as Twitter or Bitcoin. Thus, the contagion effect is one that can be modified due to nodes with a high degree of centrality.

Based on the previous results from the literature, we hypothesized that

H1a. *Social Network Centrality has a significant influence on Positive eWOM Intention*.

H1b. *Social Network Centrality has a significant influence on Negative eWOM Intention*.

2.4. Social Network Density

Recent research in the specialized literature [42] revealed that informational influence can be modified within a network through two main methods: promoting a reduced number of nodes with increased centrality, respectively increasing the overall density of the network. The mathematical results established that higher informational efficiency is obtained when using the method that involves increasing the overall density of the network. These results are especially true for random networks, as most social networks actually are.

Interesting research was carried out by [43] who also analyzed the role that social bots can play in social networks. If the social network consists only of human participants, the central participant of the network determines the final consensus in approximately 65% of the cases, depending on the degree of centrality and the density of the network. But, somewhat paradoxically, the participation in the social network of 2–4% of social bots can cause the reversal of the consensus in two-thirds of the cases. This result actually draws attention to the ease with which fake information and perceptions can spread in the case of a reasonably dense social network through eWOM generated by bots.

The density of the social network has an important influence on the way information is transmitted within the network. Thus, the study carried out by [44] highlighted the fact that the activity of information transmitters is positively influenced by the density of the network. According to [45], although usually the density of social networks is quite easy to estimate within established platforms, this concept can also be analyzed if the communication process takes place via email. Thus, social network density becomes a relevant indicator for measuring and evaluating the cohesion of an official group or an ad hoc group.

Recent studies [10] have highlighted the fact that social network density has an important effect on user behavior at the group level in that one generation of consumers can significantly influence the behavior and consumption appetite of the next generation of customers. In this way, social network density determines how users come to consider social networks as providers of social services. By contrast, the analysis carried out by [46] on the Yelp network generated interesting results that in high-density social networks, influencers (e.g., people with high centrality) do not always generate positive reactions through eWOM on the other participants in the network. Specifically, influencers with many connections within a dense network may reduce eWOM intention in certain periods of time.

From a chronological point of view, Ref. [47] demonstrated that companies' efforts to influence consumers through eWOM took into account the aspect of network density. Thus, during the last 10 years, studies in the specialized literature have increasingly focused on determining the influence of the density of social networks on eWOM. As proof of this, Ref. [48] highlighted the fact that within social networks, consumers can generate both positive and negative eWOM. Negative eWOM is mainly shared through special messages with group members, while positive eWOM is shared mainly on companies' social media accounts. In these situations, network densities play a major role in terms of the speed of message distribution and their final global impact. Based on the identification of lexical change, [49] tried to predict negative word-of-mouth in social media so that company managers could anticipate a possible wave of non-friendly messages that would affect the business image. In this context of analysis, density has a strong negative correlation.

Based on the previous results from the literature, we hypothesized that

H2a. *Social Network Density has a significant influence on Positive eWOM Intention.*

H2b. *Social Network Density has a significant influence on Negative eWOM Intention.*

2.5. Social Network Usage

Recent research in the field of communication through social networks [50] has demonstrated that nowadays consumers have an increasing power to influence purchase decisions through eWOM (electronic Word-of-Mouth). The use of social networks has a direct impact on eWOM and generates significant changes in purchasing behavior.

Using social networks to promote sales through electronic Word-of-Mouth has various valences. Thus, Ref. [51] showed that positive eWOM can be influenced by stimulating social network users who play games and who receive various financial or virtual incentives to promote messages through the distribution of advertisements to other participants. In the same line of ideas, the study carried out by [52] highlighted that the intensity of the use of social networks has both a direct and indirect influence, through eWOM, on the consumption and promotion of products in the online environment.

In the modern economy based on strong competition, companies must communicate intensively on social networks to succeed in conveying their messages and influence customers. According to [53], this is due to the fact that an important part of consumers makes purchase decisions based on social media referrals. Ref. [54] showed that in certain situations, unlike men, women rely more on family members and eWOM from social networks to obtain product referrals, generally having more positive opinions about products and services promoted through eWOM.

The use of social networks has a significant influence in various economic fields. Thus, according to [55], the tourism industry is one of the main beneficiaries of eWOM advantages when social networks are used intensively because both tourists and hotels end up communicating directly or indirectly to share information and opinions. In the same tourism industry, Ref. [56] found that the quality and quantity of information are the predominant factors that can influence eWOM behavior when using social networks.

Regarding eWOM for Corporate Social Responsibility, Ref. [57] found that the corporate image can cause social network users not to spread eWOM to their friends list. In the air transport industry, Ref. [58] analyzed social media usage characteristics that influence eWOM and found that personality and informational characteristics have a determining role. According to the results obtained by [59], the field of higher education is one that continuously adapts and is forced to use the advantages offered by social network usage to promote eWOM to the target audience from present and future students. Regarding electronic commerce, Ref. [60] found that eWOM has a strong influence if the source has high credibility within the social network and if the information provided is integrated. The use of social networks also has implications for eWOM in the banking sector as well, where customers need trusted opinions and positive experiences to continue the relationship with the institutional financial partner [61]. Banks' communication through social networks has a positive influence on customer loyalty, and eWOM has a mediating effect in this relationship; information made by banks through social networks about their CSR activities generates an emotional attraction from customers [62], leading to a positive feeling of reciprocity that produces increasing loyalty and a sense of attachment to bank's brand.

eWOM communication through social network usage has a number of influencing factors such as the strength of ties and reciprocity, according to research carried out by [63]. Also, social network usage has influence on eWOM, but this influence is impacted by different cultural orientations and social relationships [64].

The research conducted by [58] showed that social media usage characteristics have a significant impact on eWOM intent. Moreover, [65] proved that involvement in social networking sites is a positive eWOM trigger. In the light of these results, it is reasonable to consider network usage as a moderator in the relationship between centrality and density, on the one hand, and propensity to produce eWOM on the other hand. In consequence, we formulate the following hypotheses:

H3a. *Social network usage moderates the relationship between network centrality and positive eWOM intent. More specifically, the relationship is stronger under high network usage levels.*

H3b. *Social network usage moderates the relationship between network density and positive eWOM intent. More specifically, the relationship is stronger under high network usage levels.*

H4a. *Social network usage moderates the relationship between network centrality and negative eWOM intent. More specifically, the relationship is stronger under high network usage levels.*

H4b. *Social network usage moderates the relationship between network density and negative eWOM intent. More specifically, the relationship is stronger under high network usage levels.*

Based on the previous hypotheses, the proposed model is presented in Figure 1.

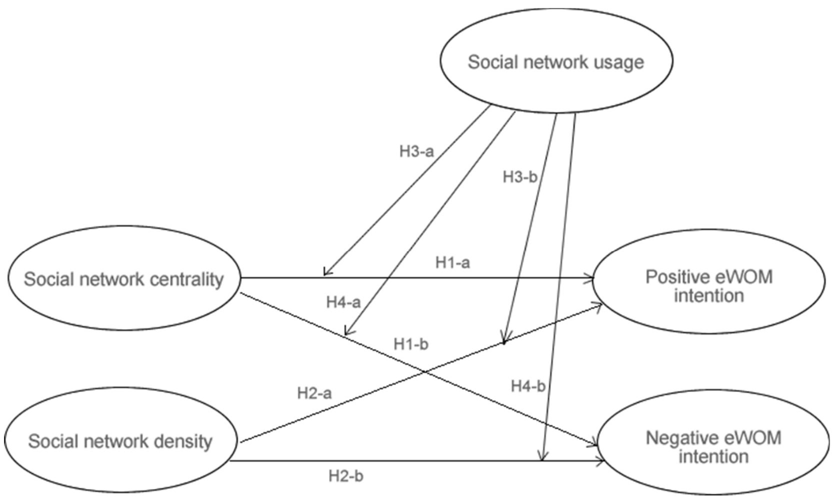

Figure 1. The research model.

3. Materials and Methods

The data for the present research were collected using an online questionnaire administered to a convenience sample of 436 Romanian students and young professionals. The questionnaire link was distributed to respondents via email or social media groups. To make sure that all questionnaires would be fully completed and to avoid issues related to missing data, all questions were made mandatory.

The respondents' ages were between 18 and 42 years, with an average of 21.18 years and a standard deviation of 2.47 years. About 67% of the respondents were female, while 33% were male.

The respondents were requested to ask twenty-one questions, divided into five scales. Each scale was used to measure a specific construct, namely: network centrality, network density, network usage, intention to provide positive word-of-mouth, and intention to deliver negative word-of-mouth.

To assess network centrality and density, the scales of [66] were employed. To measure social network usage we have used the scale devised by [67]. This scale considers not only the duration and frequency of social media usage, but also emotional relationships with the network and the integration of network usage into individuals' daily routines.

Finally, to assess respondents' propensity to provide positive or negative WOM in the online environment we have adapted the scale created by [68].

4. Data Analysis and Results

The first step of our data analysis process consisted of running an exploratory factor analysis (EFA) to ascertain whether the individual items are properly correlated with the associated constructs. EFA was performed using the IBM SPSS software, version 26. At the end, five items out of twenty-one were eliminated, because they presented high cross-loadings or poor loadings. More precisely, three network centrality items were removed, as well as one network usage item and one item of propensity to deliver positive eWOM. The Kaiser–Meyer–Olkin indicator for the last EFA model was 0.817, showing good factor adequacy. The Bartlett's sphericity test was statistically significant ($p < 0.01$).

During the second step, a confirmatory factor analysis (CFA) was performed, in order to assess the relationships between our latent constructs and their related items. The cutoff values used to estimate the goodness-of-fit of the measurement model were the following: for the comparative fit index (CFI)—0.900 [69], for the Tuckey–Lewis index (TLI)—0.900 [70], for the goodness-of-fit index (GFI)—0.800 [71], for the adjusted goodness-of-fit index (AGFI)—0.800 [67], for the root mean square error of approximation (RMSEA)—0.08 [69], and for the standardized root mean square residual (SRMR)—0.08 [70], for the χ^2/df ratio—between 1 and 5 [72].

The values for our measurement model are CFI = 0.932, TLI = 0.911, GFI = 0.925, AGFI = 0.889, RMSEA = 0.071, SRMR = 0.066, and χ^2/df = 3.222. All indicators are within the cutoff values, so our model is a very good fit.

The main indicators of the measurement model are synthesized in Table 1. All factor coefficients are statistically significant ($t > 1.96$) and their standardized values are greater than 0.5. The average variance extracted (AVE) are also higher than 0.5, denoting a sound convergent validity. Additionally, all constructs have a good internal consistency (Cronbach's alpha values and composite reliabilities are greater than 0.7).

Further, to assess the discriminant validity of our measurement model, the construct squared correlations have been compared to the average variance extracted. As shown in Table 2, all the AVE values (in the main diagonal) are greater than the corresponding squared correlations, indicating a good discriminant validity.

Table 1. Summary indicators of the measurement model.

Constructs and Items	Beta	*t*-Value	SE	Alpha	Composite Reliability	AVE
Network centrality	-	-	-	0.728	0.706	0.604
I maintain daily contact with most people in my social network,	0.812	-	-	-	-	-
I can acquire information from other people quickly.	0.716	11.201	0.066	-	-	-
Network density	-	-	-	0.834	0.841	0.703
I am familiar with the members of my social network.	0.904	-	-	-	-	-
Members in my social network are familiar with me.	0.887	21.128	0.048	-	-	-
I often communicate with members of my social network.	0.628	14.281	0.053	-	-	-
Network usage	-	-	-	0.814	0.754	0.686
Social networks are part of my everyday activity.	0.556	-	-	-	-	-
I dedicate part of my daily schedule to social networks.	0.623	12.387	0.112	-	-	-
I feel out of touch when I haven't logged on to my social networks in a while.	0.653	9.492	0.157	-	-	-
I feel I am part of my social network community.	0.709	10.246	0.150	-	-	-
I would be sad if social networks shut down.	0.683	10.041	0.163	-	-	-
I am happy with the social networks, in general.	0.663	9.577	0.119	-	-	-
Positive eWOM intention	-	-	-	0.878	0.797	0.751
I would post positive things about the brand.	0.816	-	-	-	-	-
I would recommend this brand to the people in my social network	0.959	14.795	0.080	-	-	-
Negative eWOM intention	-	-	-	0.795	0.721	0.572
I would complain to the members of my social network.	0.809	-	-	-	-	-
I would discuss with the members of my social network about my frustrations.	0.808	15.110	0.070	-	-	-
I would say negative things about the brand in my social networks.	0.644	12.706	0.057	-	-	-

Table 2. Average variance extracted and squared correlations.

	Network Centrality	Network Density	Network Usage	Positive eWOM Intention	Negative eWOM Intention
Network centrality	0.604				
Network density	0.358	0.703			
Network usage	0.217	0.062	0.686		
Positive eWOM intention	0.068	0.037	0.106	0.751	
Negative eWOM intention	0.088	0.037	0.148	0.331	0.572

In the third step of our analysis, the causal model presented in Figure 1 was tested. In this model there are two types of effects: main effects (network centrality and density) and interaction effects (the moderating effects of network usage). Upon running the model, two interaction effects proved to be not significant. More specifically:

– the interaction effect of centrality and usage on the positive eWOM intention;
– the interaction effect of density and usage on the positive eWOM intention.

As a result, these interactions were removed from the model. The values of goodness-of-fit indicators for the final model were CFI = 0.999, TLI = 1.000, GFI = 0.998, AGFI = 0.986, RMSEA = 0.001, and SRMR = 0.015, $\chi^2/\mathrm{df} = 0.742$. These values indicate a very good model fit.

The path coefficients for the final causal model can be examined in Table 3. The coefficients of the removed paths are found in Table 4.

Table 3. Path coefficients of the causal model.

Hypothesis	**Path**	**Coefficient**	**t**	**SE**	***p***	**Result**
				Main effects		
H1a	Network centrality -> Positive eWOM intention	0.098	1.386	0.071	0.166	Not supported
H1b	Network centrality -> Negative eWOM intention	0.160	2.367	0.067	0.018	Supported
H2a	Network density -> Positive eWOM intention	0.055	0.902	0.061	0.367	Not supported
H2b	Network density -> Negative eWOM intention	0.006	0.110	0.058	0.912	Not supported
-	Network usage -> Positive eWOM intention	0.300	1.386	0.071	<0.001	-
-	Network usage -> Negative eWOM intention	0.380	7.420	0.051	<0.001	-
				Interaction effects		
H4a	Moderator 1 * -> Negative eWOM intention	0.124	2.826	0.044	0.005	Supported
H4b	Moderator 2 ** -> Negative eWOM intention	−0.109	−2.226	0.049	0.026	Supported

* Moderator 1 represents the interaction effect of network centrality and network usage. ** Moderator 2 represents the interaction effect of network density and network usage.

Table 4. Coefficients of the removed paths.

Hypothesis	**Path**	**Coefficient**	***p***	**Result**
	Interaction Effects			
H3a	Moderator 1 * -> Positive eWOM intention	0.029	0.603	Not supported
H3b	Moderator 2 ** -> Positive eWOM intention	0.020	0.754	Not supported

* Moderator 1 represents the interaction effect of network centrality and network usage. ** Moderator 2 represents the interaction effect of network density and network usage.

The interaction effect of network centrality and network usage on negative eWOM intent is presented in Figure 2.

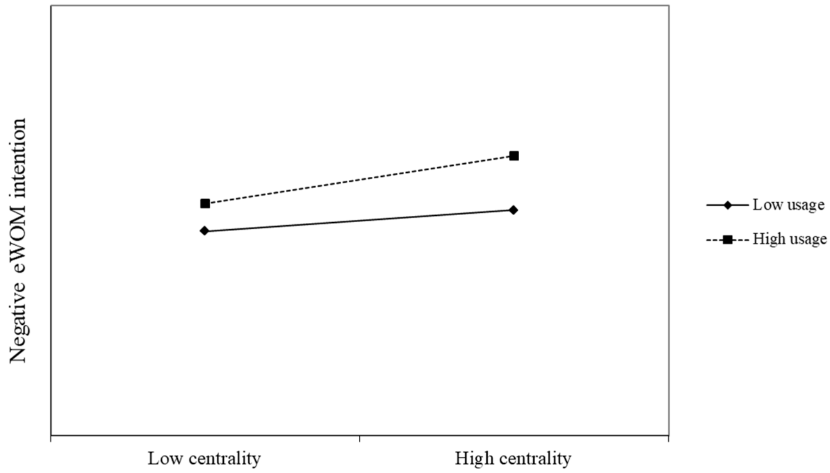

Figure 2. Interaction effect of network centrality and usage on negative eWOM intent.

It can be noticed that centrality has greater impact on eWOM intentions in the group that presents high network usage levels.

Furthermore, the interaction effect of network density and network usage on negative eWOM intent can be examined in Figure 3.

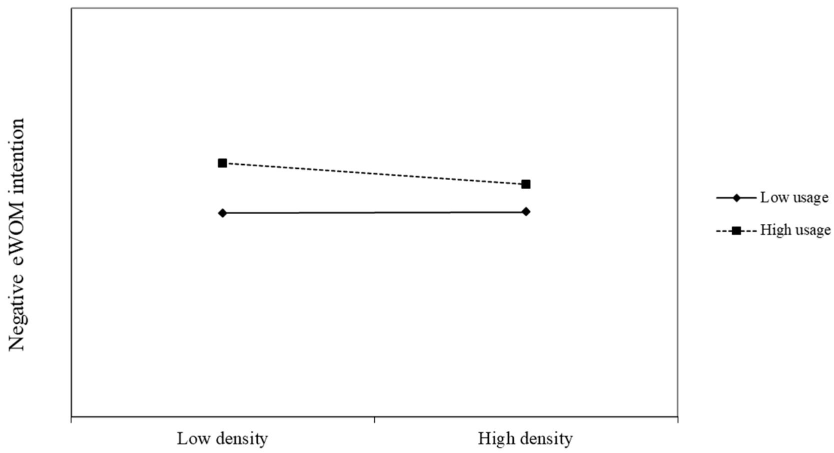

Figure 3. Interaction effect of network density and usage on negative eWOM intent.

In the group with low usage levels, density has no influence on negative eWOM intent. However, in the "high usage" group density has a negative impact on eWOM propensity: people with lower network density present stronger intentions to deliver negative eWOM.

These findings will be discussed in detail in the following section.

5. Discussion

In the first place, our study indicates that network centrality does not influence the inclination to deliver positive eWOM. Being popular in their social network, having a big influence and being perceived as an "opinion leader" is not enough to induce people to recommend products and services to other network members. As previous research shows, the propensity to generate positive eWOM is determined by factors like altruism, self-enhancement or economic incentives [9], satisfaction and brand loyalty [73], and tie strength and homophily [74]. In consequence, these variables (and similar ones) are the real triggers of positive eWOM intent, not the level of network centrality.

Nevertheless, centrality positively influences the propensity to provide negative eWOM. In networks with high centrality level, members maintain direct contact and can quickly acquire information from one another. As a result, a member who is deeply dissatisfied with a product or service will likely disseminate negative information about that product and warn other network members to stay away from it. One of the reasons of producing negative eWOM is venting negative feelings [9]. People may find it easier to express these feelings to network members they can contact on a regular basis and have an influence on.

Furthermore, the relationship between network centrality and the propensity to generate negative eWOM is moderated by network usage. As our model shows, this relationship is much stronger for individuals with high levels of network usage. The explanation is evident: people who spend more time on social networks and feel they are part of their network community are more likely to convey information about products and brands in those networks. For people who are not very active in social networks (like Facebook or TikTok, for instance), the relationship between centrality and negative eWOM intent is still positive, but weak. So, these people are less expected to share information about products and services they disliked. This result is confirmed by the findings of [75], who showed that network usage intensity positively influences negative eWOM.

Our research also shows that network density does not directly influence positive or negative eWOM intent. This is a surprising result because density reflects the degree of closeness among members and the communication frequency. However, it is possible that these aspects are not strong enough eWOM triggers. In the case of positive eWOM intent, the explanation may be the same as above: the stimuli of positive eWOM are satisfaction, brand loyalty, self-enhancement, altruism, and other personal factors. Hence, the degree of network density (i.e., the closeness of relationships between members) does not seem to have a decisive impact on positive eWOM inclination. Further research may be necessary here to clarify this point.

In the case of negative eWOM intent, our model reveals that the relationship between density and eWOM predisposition is moderated by network usage. For individuals with low social network usage, the relationship is very weak and practically insignificant. However, in the group of members that present high usage levels, we found a negative relationship between density and negative eWOM intention. Apparently, high-density networks discourage the spreading of unfavorable opinions about bad products. This is another unexpected finding, but it can be explained in the light of the theoretical perspectives introduced by [76]. As this author points out, networks with high density can constrain members' behavior, facilitating sanctions when the network rules and norms are broken. Talking badly about companies or brands could be considered inappropriate conduct in many of these networks. In consequence, members will likely avoid conveying negative information or to merely complain about their unpleasant experiences. This is even more true for members who use social networks intensively and are emotionally attached to their network (and would feel bad if they were excluded in one way or another). These members will abide by the network rules if these rules dissuade the spreading of negative eWOM.

6. Conclusions

This paper investigates the effects of network density and centrality on eWOM intent. It is the first study that considers these variables as eWOM predictors; other authors, like [77], have proposed models where they are introduced as moderators. From this perspective, the article is a definite contribution to the field of knowledge, being a solid starting point for future comparative research.

Social networks are interactive communication tools that let people share information with one another, including information about products and services [78]. Centrality and density, two important social network features, only influence the inclination to provide negative eWOM. They do not seem to have a significant impact on positive eWOM intent. So, people who maintain close contact with their network members and have a high influence on them manifest a tendency to complain about their negative experiences with purchases, post comments about bad products or services, leave negative reviews about the brands that dissatisfied them, and so on. This tendency is generally stronger for individuals who use social networks frequently and develop emotional relationships with their network.

However, our research indicates that the propensity to engage in negative eWOM activities could be limited in social networks with high-density levels. As [76] shows, high-density networks tend to control their members' behavior through norms and rules. If these norms tacitly disallow public complaints about products and brands, members could refrain from disseminating negative eWOM.

As a general conclusion, companies should do their best to control and even turn around (if possible) bad publicity online. That is because prominent social network members, with great popularity and influence, are particularly inclined to generate negative eWOM, as our study shows. Therefore, an effective response strategy should be developed. Companies should monitor all places where their customers gather, detect negative comments, and react quickly, providing solutions to the customers' issues. This strategy can significantly reduce the negative eWOM amount and its damage to the company's reputation.

This study has a few limitations. First, the convenience sampling method was used. This method could affect the generalization of our results, to some extent. Moreover, the sample is only composed of Romanian individuals, most of them students, aged under 30. We have selected mainly students because they are active in social networks and communicate very often with their peer members.

Further research could consider other moderating variables in the relationship between centrality and density, on the one hand, and eWOM propensity on the other hand. These moderators might be various positive and negative eWOM triggers ascertained in the literature (like customer satisfaction or dissatisfaction, for example). Building separate models for positive and negative eWOM and using appropriate moderators for each model type could also be helpful.

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