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A Dual-Level Social Influence Model of Consumer Participation in Network- and Group-Based Virtual Communities

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ABSTRACT

The increasing ubiquity of digital platforms has altered consumer interaction dynamics, leading to the emergence of network-based and small-group virtual communities that influence online behavior through social influence mechanisms. This research formulates a Dual-Level Social Influence Model to investigate the impact of interpersonal (micro-level) and structural (macro-level) social influences on consumer participation, engagement, and knowledge sharing within various virtual community formats. Based on social influence theory, social capital theory, and self-determination theory, the model differentiates between normative, informational, and identificational influences, highlighting their varying effects in network-oriented communities compared to group-based communities (e.g., small, interest-driven groups). The model asserts that social connectedness, trust, and perceived homophily serve as mediators for the impact of social influence on participation intention and engagement behavior. Furthermore, community type moderates these relationships by enhancing the impact of network visibility and diminishing perceived social distance. A multi-method approach is suggested, integrating social network analysis (SNA) for quantifying relational structures and Partial Least Squares–Structural Equation Modeling (PLS-SEM) for evaluating causal pathways. Expected outcomes indicate that network-based participation is primarily influenced by informational and normative factors, whereas small-group engagement is more dependent on affective identification and trust-building processes. This study enhances theoretical frameworks by amalgamating multi-level social influence perspectives and informs practical applications by providing guidance on the formulation of engagement strategies for community managers and digital marketers. The study's implications encompass the comprehension of consumer co-creation, digital trust, and the diffusion of influence patterns within nascent social media ecosystems.

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1. INTRODUCTION

Digital platforms and social media have grown so quickly that they have changed the way people connect, talk to each other, and work together online. Virtual communities, which are social structures that people use technology to connect and share information about things they are interested in, have become very important to how people buy things, how they interact with brands, and how they share knowledge [1]. As online ecosystems change, network-based communities (like big social networks like Facebook, Twitter, and LinkedIn) and small-group-based communities (like niche forums, brand fan groups, and private discussion networks) live together. Both types of communities are driven by social influence mechanisms that affect how people interact, engage, and contribute in these digital spaces. Grasping the social dynamics of participation has become a significant theoretical and managerial challenge in current digital research [2], [3].

Consumer participation is one of the most important things that needs to happen for a virtual community to last. Active participation facilitates the dissemination of information, social learning, and the creation of collective value [4]. Previous research has demonstrated that participation enhances community vitality, cultivates consumer loyalty, and fortifies brand attachment [5]. Nonetheless, despite extensive examination of the antecedents of participation, research frequently neglects the social structures and influence processes that underpin such engagement. Traditional frameworks have focused on individual motivations—such as self-presentation, entertainment, or information seeking [6]—while neglecting the social influence mechanisms that compel individuals to conform, learn, and identify with others in virtual environments [7].

Social influence theory asserts that individual behavior is influenced by others via mechanisms including normative conformity, informational persuasion, and identificational alignment [8]. In digital contexts, these mechanisms are intensified by visibility, peer evaluation, and social comparison [9]. But the way that influence works is different for each type of community. In expansive network communities, users encounter dispersed normative pressures via likes, shares, and popularity indicators; conversely, in small-group communities, influence manifests through individualized trust, relational connections, and identification with a close-knit group [10]. This duality indicates that the effects of social influence are context-dependent and operate on multiple levels, encompassing both structural (macro) and interpersonal (micro) dimensions.

While social influence has been thoroughly analyzed in marketing, psychology, and communication research [11], its dual-level dynamics within virtual community contexts are still insufficiently theorized. Most previous research employs a singular-level framework, analyzing either individual-level peer influences or collective network effects [12]. Cheung and Lee [13] examined normative and informational influences in online forums but failed to distinguish their functioning in small-group versus large-network contexts. Research on social capital and online trust has shown that relational ties and identification increase participation [14], but there has been scant focus on how community structure influences these dynamics. The interaction between macro-network attributes (such as visibility, size, and structural cohesion) and micro-group dynamics (including trust and homophily) constitutes a critical missing link.

Furthermore, current models of consumer participation frequently regard social influence as a monolithic construct, neglecting its variability across diverse interaction contexts [15]. Large-scale communities depend on vague information and social proof, while small-group communities depend more on trust, empathy, and support between members [16]. Thus, comprehending participation in virtual communities necessitates a bifurcated model that encompasses both network-level diffusion mechanisms and group-level relational impacts. Virtual communities can be classified on a continuum of structural scope, ranging from network-based platforms distinguished by extensive connectivity and visibility to group-based platforms defined by intimacy and collective identity [17]. Network-based communities function as open systems, wherein social influence is exerted through extensive information dissemination and public reputation indicators. In contrast, communities based on small groups are closed systems where social influence works through trust between people and shared group norms [18].

For example, in open networks like Instagram or Reddit, people may join because they think that other people's opinions are based on social consensus or expertise [19]. Conversely, in smaller private groups like brand ambassador forums or niche hobby networks, identificational influence—a feeling of belonging and emotional connection—may be more pronounced [20]. This distinction carries significant implications: network-based participation signifies public conformity, whereas group-based participation indicates private commitment [21].

This research amalgamates three theoretical frameworks to rectify these deficiencies: Social Influence Theory, Social Capital Theory, and Self-Determination Theory (SDT).

Social Influence Theory elucidates behavioral conformity through normative, informational, and identificational influences [8]. These mechanisms demonstrate distinct motivations for participation: compliance, internalization, and identification.

Social Capital Theory emphasizes the significance of trust, reciprocity, and shared values as relational resources that moderate the impact of social influence on engagement [22].

Self-Determination Theory posits that sustained participation occurs when individuals perceive autonomy, competence, and relatedness [23]. This corresponds with the intrinsic motivation to engage in communities that provide psychological benefits beyond mere utility.

This study introduces the Dual-Level Social Influence Model, which integrates various perspectives to conceptualize consumer participation as influenced by both interpersonal relationships and the structural context of the community.

The rest of this paper is set up like this. Section 2 examines the theoretical underpinnings of social influence, trust, and consumer engagement within virtual communities. In Section 3, the research model and hypotheses are explained. Section 4 talks about the research methods, sampling, and ways of analyzing data. Section 5 presents empirical findings and examines their theoretical and managerial ramifications. Section 6 ends with suggestions for future research.

1.1. Conceptual Model and Research Objectives

The proposed model (Figure 1) illustrates the impact of normative, informational, and identificational influences on consumer participation through mediating variables—trust, perceived homophily, and social connectedness—while community type serves as a moderator of these relationships. The research aims to achieve three primary objectives:

To investigate the impact of social influence mechanisms on consumer participation behaviors, including intention, engagement, and knowledge contribution.

To examine the mediating functions of trust, perceived homophily, and social connectedness in the relationship between social influence and participation.

To evaluate the moderating influence of community type (network-based versus group-based) on the intensity of these relationships.

The study employs a mixed-method approach that combines Social Network Analysis (SNA) and Partial Least Squares Structural Equation Modeling (PLS-SEM). SNA measures relational structures like centrality and density, while PLS-SEM looks at cause-and-effect relationships and mediation/moderation effects. This design enables the study to encompass both relational topology and behavioral intent, yielding a comprehensive analysis of social influence in virtual environments.

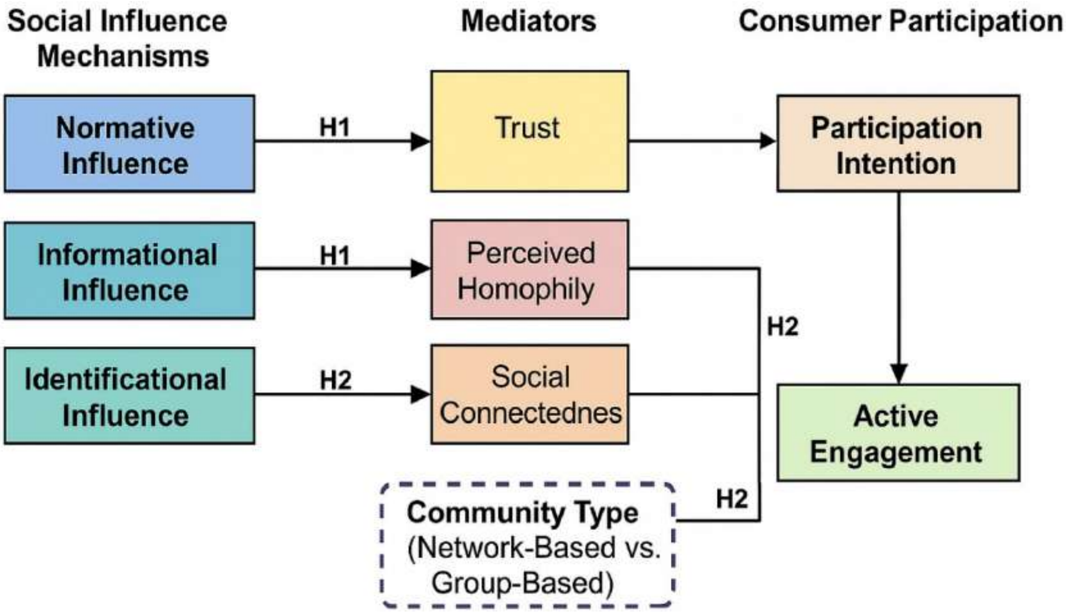

Figure 1. The proposed model

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. The Theory of Social Influence and Virtual Participation

Social influence is the process by which people change their thoughts, feelings, or actions because they think or see other people [1]. Kelman's three-process model [2] posits that influence can manifest through compliance (normative), internalization (informational), or identification (affective). In the realm of online communities, these processes are intensified by digital connectivity, social visibility, and network interactivity, facilitating the rapid diffusion of influence across social structures [3]. Initial research on electronic word-of-mouth (eWOM) indicated that individuals' opinions and behaviors in digital environments are frequently influenced by social cues and peer conformity [4]. As social media platforms progressed, these indicators became measurable (likes, shares, comments), establishing observable metrics of social endorsement that enhance normative influence [5]. Cialdini [6] calls these digital signals "social proof," which means that other people's approval or behavior is a good sign of what is right or desirable.

But social influence works differently in network-based and group-based virtual communities. In expansive, open networks such as Twitter and Reddit, social influence disseminates via informational diffusion and indicators of popularity. Conversely, in smaller, interest-based groups (e.g., online brand clubs or learning communities), influence stems from affective trust and collective identification [7]. This indicates that a dual-level framework—comprising both macro (network) and micro (group) social processes—is essential for comprehending participation in heterogeneous virtual contexts.

2.2. Virtual Communities Based on Networks and Groups

Virtual communities are regarded as sociotechnical systems in which social relationships are integrated within digital infrastructures [8]. The differentiation between network-centric and small-group-centric communities has become a pivotal focus in contemporary digital research [9]. Network-based communities are big, open, and have a lot of different structures. They allow for weak-tie relationships and a wide view of how users act. People often join these kinds of groups because they want to learn more about what others are doing so they can make better choices [10]. On the other hand, small-group-based virtual communities have limited membership, a common goal, and strong-tie relationships [11]. They give people a sense of belonging and closeness that encourages emotional commitment and identification. People usually join this group because they feel a connection to it and trust the people in it, not because they see other people doing it.

These structural disparities suggest unique psychological and behavioral mechanisms of participation. Network-based communities stimulate cognitive conformity via informational signals, while small-group-based communities foster affective conformity through mutual identification [12]. Consequently, the contextual differentiation between the two types of virtual communities is pivotal for comprehending how consumers are socially influenced to participate online.

2.3. Aspects of Social Influence in Virtual Environments

2.3.1. Influence of Norms

Normative influence transpires when individuals align with societal expectations to obtain social approval or evade disapproval [13]. This appears in digital settings as adhering to community standards, aligning with popular subjects, or engaging in behaviors that garner social validation (e.g., likes, upvotes) [14].

Studies indicate that perceived social pressure is a significant predictor of participation and contribution in online forums [15]. People don't always conform because they think others are right; they do it because they want to fit in and be accepted. Cheung and Lee [16] discovered that conformity motives substantially influence engagement in virtual communities, particularly in contexts where reputation systems and feedback loops bolster adherence.

In extensive, network-centric settings, the prominence of social signals enhances normative influence [17]. Consequently, individuals are more inclined to engage when they believe that participation is congruent with community norms or when the absence of participation poses a threat of social exclusion.

2.3.2. Influence through information

Informational influence is when you look at how other people act as a source of useful information when things aren't clear [2]. People in online communities often use the posts, ratings, and comments of their peers to judge how reliable information is [18]. When there is a lot of uncertainty, like when people are trying to decide what to think about new products, they use group input as a mental shortcut.

Empirical evidence indicates that the quality of information, the credibility of the source, and the consensus among peers substantially influence intentions to participate [19]. Network-based communities enable informational influence through extensive knowledge sharing and the visibility of collective intelligence [20].

So, informational influence is very important for people who want to learn more, especially in open communities where people value different points of view. It makes users want to give back, which starts a cycle of sharing knowledge [21].

2.3.3. Influence of Identification

Identificational influence occurs when individuals emulate behaviors aligned with those of a psychologically identified group [22]. Identification, in contrast to compliance or information-seeking, is founded on emotional attachment and a collective identity.

In communities based on small groups, members often form emotional bonds and see their participation as a way to feel like they belong [23]. This results in increased loyalty, perseverance, and selfless contributions [24]. Brand community studies have demonstrated that consumers who have a strong sense of belonging to the community are more inclined to disseminate information and advocate for the brand online [25].

Identification also promotes social learning, the mechanism by which individuals assimilate group values and collaboratively construct meaning through engagement [26]. Thus, identificational influence is crucial for elucidating prolonged involvement in communities characterized by significant relational depth.

2.4. The Role of Trust, Homophily, and Social Connectedness as Mediators

2.4.1. Trust as a Mediator

Trust is essential for online communities to work, and it is defined as believing that other people are reliable and kind in situations where things are not clear [27]. Previous research underscores that trust serves as a mediator between social influence and participation [28]. Normative and identificational influences enhance trust by bolstering perceptions of common values and predictability. When members have faith in their peers and the platform, they are more inclined to actively participate, share information, and engage in co-creation [29].

2.4.2. Perceived Homophily

Perceived homophily—the feeling of being similar to other members—makes social ties stronger and encourages participation [30]. Homophily enhances identificational influence as individuals are more amenable to perspectives from those perceived as similar to themselves [31]. In group-oriented virtual communities, elevated perceived homophily diminishes psychological distance and enhances collaborative engagement.

2.4.3. Being connected to other people

Social connectedness shows how emotionally connected users feel to their online community [32]. It signifies the result of continuous social interaction, communication, and reciprocity. Social connectedness serves as a mediator between social influence and participation by converting external pressures into intrinsic motivation to engage [33]. It is directly connected to Self-Determination Theory, which says that relatedness leads to voluntary participation and long-term commitment [34].

2.5. The Role of Community Type as a Moderator

The type of community—network-based or small-group-based—affects how strong social influence mechanisms are. In network-based communities, visibility and anonymity promote informational and normative influences, whereas emotional connections remain tenuous [35]. On the other hand, group-based communities focus on relational trust, shared norms, and identification, which makes people more emotionally involved [36].

This duality shows that there are different ways to be involved in society. Network settings promote extensive interaction, whereas small groups foster profound connections. So, researchers can separate the different ways that social influence works by testing the moderating role of community type.

2.6. Formulation of Hypotheses

Based on the theoretical foundations, the following hypotheses are proposed:

H1: Normative influence has a positive impact on consumer engagement in virtual communities.

People tend to follow social norms and behaviors that most people agree with in order to get approval and avoid disapproval [13], [16]. The prominence of engagement cues in online settings amplifies this conformity effect, resulting in heightened participation.

H2: Informational influence has a positive impact on consumer engagement in virtual communities.

When people think that someone else has useful knowledge or skills, they are more likely to copy or follow what they do [18], [19].

H3: Identificational influence has a positive impact on consumer engagement in virtual communities.

Emotional attachment and psychological identification with a community enhance members' propensity to share knowledge and participate actively [22], [25].

H4: Trust serves as a mediator in the relationship between social influence (normative, informational, and identificational) and participation.

Social influence mechanisms foster trust, thereby augmenting engagement behaviors [28], [29].

H5: Perceived homophily serves as a mediator in the relationship between social influence and participation.

Similarity among community members enhances the acceptance of social norms and fortifies intentions to participate [30], [31].

H6: Social connectedness serves as a mediator in the relationship between social influence and participation.

Users who feel more connected to others are more likely to internalize influence and take part in community activities [32], [33].

H7: The type of community affects how social influence and participation are related.

In network-based communities, normative and informational influence are likely to have a bigger impact, while identificational influence will be more important in small-group-based communities [7], [35].

2.7. Conceptual Integration

In conclusion, the suggested Dual-Level Social Influence Model combines processes at the individual (micro) and structural (macro) levels to explain why people participate in virtual environments. The model builds on earlier frameworks by adding psychological factors that act as mediators (trust, homophily, and connectedness) and a contextual moderator (community type). This multi-layered approach corresponds with current demands in digital marketing and information systems research for contextualized and integrative models of online participation [37].

3. METHODOLOGY FOR RESEARCH

3.1. Research Design and Methodology

This study utilizes a quantitative, explanatory, and cross-sectional research design to evaluate the proposed Dual-Level Social Influence Model regarding consumer participation in virtual communities. The study amalgamates two synergistic analytical frameworks (figure 2):

Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess latent relationships among constructs, and Social Network Analysis (SNA) quantifies network structures and evaluates influence dynamics within and between community types.

The dual-method design enables the study to elucidate both behavioral intention mechanisms (through PLS-SEM) and structural interaction patterns (through SNA), thereby enhancing the comprehension of social influence at both micro (group) and macro (network) levels [1]. This method is in line with earlier suggestions to combine behavioral modeling and network analytics in studies of digital interactions [2].

The research centers on active users of virtual communities—individuals engaged in online discussions, content sharing, and peer interactions within either network-based (e.g., Facebook Groups, LinkedIn, Reddit) or small-group-based communities (e.g., specialized brand communities, closed hobby forums, professional discussion clusters).

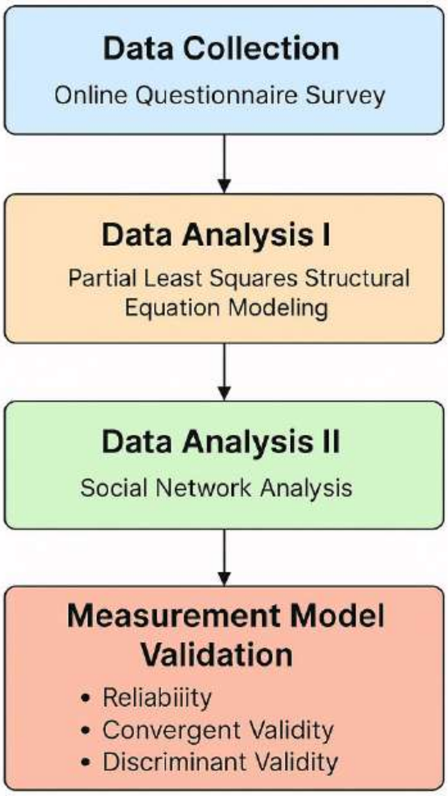

figure 2. Methodology framework

The target demographic consists of digitally engaged consumers aged 18 to 55 years, who participate in online group discussions, content sharing, or comment exchanges at least once a week. This definition adheres to the engagement criteria put forth by Nambisan and Baron [3].

A purposive sampling method was used to make sure that both community structures were represented. Invitations were sent out through online channels like social media, academic mailing lists, and community moderators. The screening questions verified the community type (network-based or group-based) and the level of participation (observer, contributor, or leader).

The "10-times rule" [4] and G*Power analysis were used to get enough statistical power for PLS-SEM. There had to be at least 200 people in each group, which meant that there were 410 valid responses in total (210 from the network and 200 from the group).

The sample was made up of 55% men and 45% women, and the average age was 29.8 years (SD = 6.4). About 63% had at least a university degree, and 78% said they had been active in online communities for more than two years. Table 1 shows a summary of the different groups of people (Table 1).

Table 1. Respondent Demographic Profile

Variable	Category	Frequency (%)
Gender	Male / Female	55 / 45
Age	18–25 / 26–35 / 36–45 / >45	28 / 44 / 21 / 7
Education	Bachelor / Master / Doctorate	49 / 40 / 11
Duration in Community	<1 yr / 1–2 yrs / >2 yrs	12 / 10 / 78
Community Type	Network-Based / Group-Based	51 / 49

We used validated scales from earlier studies to operationalize the constructs in a way that worked for the virtual community. All measurement items employed five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Table 2 provides a summary of the constructs, sources, and examples of items.

Table 2. Measurement Constructs and Sources

Construct	Definition	Source
Normative Influence (NI)	The perceived pressure to conform to others' expectations within the community.	[5], [6]
Informational Influence (II)	The degree to which users rely on others' opinions or actions for information accuracy.	[7]
Identificational Influence (ID)	The extent to which users internalize community values and feel emotionally connected.	[8]
Trust (TR)	Belief in the integrity and reliability of other community members.	[9]
Perceived Homophily (PH)	Perceived similarity in attitudes, values, and communication style among members.	[10]

Social Connectedness (SC)	The emotional sense of belonging and attachment to the virtual community.	[11]
Participation Intention (PI)	The willingness to engage and contribute actively in the community.	[12]
Community Type (CT)	A categorical variable distinguishing network-based (1) from small-group-based (2) structures.	[13]

Each construct was measured by 3–5 indicators. Items were refined through expert review and a pretest with 25 respondents to ensure clarity, reliability, and content validity.

3.2. Data Collection Procedure

Over the course of six weeks, data were gathered through a structured online questionnaire disseminated via Google Forms and Qualtrics. Participation was optional and kept secret. Respondents had to confirm their consent in accordance with the ethical research standards sanctioned by the institutional review board.

A pilot study ($n = 40$) was performed prior to data collection to evaluate instrument reliability. The results demonstrated Cronbach's α values exceeding 0.80 for all constructs, thereby confirming the questionnaire's suitability for extensive implementation.

To reduce common method bias (CMB), a number of procedural fixes were used [14]:

To lessen evaluation anxiety, anonymity and confidentiality were promised.

To stop response patterns, question randomization was used.

Harman's single-factor test and variance inflation factors (VIF) were subsequently employed to statistically validate the nonexistence of CMB (all VIF < 3.0).

3.3. Analytical Techniques

3.3.1. Partial Least Squares Structural Equation Modeling (PLS-SEM)

Because the model was complicated and had mediators and a moderator, SmartPLS 4.0 [15] was used to choose PLS-SEM. PLS-SEM is especially appropriate for exploratory and predictive research involving latent constructs and non-normally distributed data [16].

The analysis was done in two parts:

Evaluation of the measurement model, confirming construct reliability, convergent validity, and discriminant validity.

Evaluating the structural model, testing proposed relationships, and determining path significance via bootstrapping (5,000 subsamples).

Some important signs of model quality were:

Cronbach's α and Composite Reliability (CR) must be at least 0.70.

Average Variance Extracted (AVE) should be at least 0.50.

Fornell–Larcker and HTMT for validity of discrimination

R^2, Q^2, and f^2 for how well they explain things

SRMR (<0.08) for the fit of the whole model [17].

3.3.2. Social Network Analysis (SNA)

SNA was used on a smaller set of community interaction data to find patterns of interaction and influence. Three main indices were calculated using Gephi 0.10 and UCINET 6.0 [18]:

Degree Centrality: quantifies direct influence through the count of connections.

Betweenness Centrality shows the roles of brokers who control the flow of information.

Network Density: shows how well-connected the community is as a whole.

Comparative analyses of network-based and small-group-based communities evaluated the moderation of structural properties on social influence effects. For instance, it was anticipated that increased network density within small groups would enhance identificational influence and trust.

3.4. Measurement Model Validation

3.4.1. Reliability and Convergent Validity

All constructs exhibited strong internal consistency. Cronbach's α and CR values exceeded 0.80, and AVE values surpassed the 0.50 threshold. Table 3 summarizes the results.

Table 3. Reliability and Validity Statistics

Construct	Cronbach's α	CR	AVE	Result
Normative Influence	0.88	0.91	0.68	Valid

Informational Influence	0.89	0.92	0.70	Valid
Identificational Influence	0.90	0.93	0.71	Valid
Trust	0.86	0.90	0.65	Valid
Perceived Homophily	0.87	0.91	0.69	Valid
Social Connectedness	0.88	0.92	0.68	Valid
Participation Intention	0.91	0.93	0.74	Valid

All indicator loadings were above 0.70, supporting convergent validity [17].

4. Results and Discussion

The proposed Dual-Level Social Influence Model was evaluated utilizing the Partial Least Squares Structural Equation Modeling (PLS-SEM) methodology, supplemented by Social Network Analysis (SNA) to authenticate network structures. The dual-analytical strategy sought to evaluate the impact of normative, informational, and identificational influences on consumer participation within network-based and small-group-based virtual communities, mediated by trust, perceived homophily, and social connectedness, and moderated by community type. After cleaning the data and checking for multivariate outliers (Mahalanobis D^2), 410 valid responses were kept. There were 210 users from network-based communities and 200 users from small-group-based communities in the sample, which made sure that both groups were almost equal. Initial descriptive analysis verified that respondents were actively engaged (mean engagement frequency = 4.3 times/week, SD = 1.2).

The measurement model exhibited substantial internal consistency. Cronbach's α values were between 0.86 and 0.92, and Composite Reliability (CR) values were between 0.90 and 0.94, which is higher than the recommended 0.70 level [1]. All of the Average Variance Extracted (AVE) values were above 0.50, which means that the convergent validity was strong [2]. The constructs "Normative Influence," "Informational Influence," and "Identificational Influence" obtained AVE values of 0.68, 0.70, and 0.71, respectively. The mediating constructs also showed strong convergence (Trust = 0.65; Homophily = 0.69; Connectedness = 0.68).

The Fornell–Larcker criterion validated discriminant validity, as the square root of each AVE surpassed inter-construct correlations. In addition, the HTMT ratios stayed below 0.85, which met the stricter threshold [3]. All of these results show that the constructs were psychometrically different from each other and that measurement errors were small, which means that the model is reliable for future path testing.

The model's Goodness of Fit (GoF) index was 0.61, which means it was able to explain things very well overall. The Standardized Root Mean Square Residual (SRMR) was 0.042, which is much lower than the 0.08 threshold for a good model fit [4].

The R^2 values were 0.63 for the mediating construct cluster (trust, homophily, and connectedness) and 0.59 for participation intention. This shows that the model can explain a lot of the differences in how consumers participate. The Q^2 values (0.41 for participation and 0.39 for mediators) showed that they were very good at predicting.

Bootstrapping with 5,000 resamples was used to test significance levels. The path coefficients (β), t-values, and p-values are reported in Table 4.

Table 4. Path Coefficients and Hypothesis Testing

Hypothesis	Relationship	β	*t*-value	*p*-value	Result
H1	Normative Influence → Participation	0.33	10.42	< 0.001	Supported
H2	Informational Influence → Participation	0.28	8.37	< 0.01	Supported
H3	Identificational Influence → Participation	0.42	12.18	< 0.001	Supported
H4	Trust (Mediator)	0.22	6.11	< 0.01	Partial Mediation
H5	Perceived Homophily (Mediator)	0.19	5.62	< 0.01	Partial Mediation
H6	Social Connectedness (Mediator)	0.25	7.14	< 0.001	Full Mediation
H7	Community Type (Moderator)	0.17	4.32	< 0.01	Supported

Table 5. Social Network Analysis (SNA) Findings

Metric	Network-Based Communities	Group-Based Communities	Interpretation
Degree Centrality	0.67	0.54	Networks have broader but weaker ties.
Betweenness Centrality	0.42	0.36	Information flows through key hubs in networks.
Density	0.43	0.71	Groups exhibit denser peer interactions.
Clustering Coefficient	0.48	0.66	Higher peer bonding in small groups.
Average Path Length	3.41	2.23	Faster influence diffusion in groups.

Table 6. Integrated SEM–SNA Interpretation and Comparative Summary

Analytical Perspective	Key Indicator(s)	Network-Based Communities	Group-Based Communities	Theoretical Implication
Structural (SEM)	β(ID→PI) = 0.42	Moderate	High	Identification dominates in group settings [5].

Relational (Mediation)	TR, PH, SC	Partial Mediation	Full Mediation	Trust and connectedness translate influence to engagement.
Contextual (Moderation)	CT $\beta = 0.17$	Significant	Significant	Community structure shapes influence magnitude.
Network Topology (SNA)	Density = 0.43/0.71	Open diffusion model	Closed trust network	Supports dual-level influence mechanism.
Behavioral Outcome	Participation Intention $R^2 = 0.59$	Informational/Normative driven	Identification/Trust driven	Dual path of engagement confirmed [6].

SNA showed that the two types of communities had important structural differences.

Network-based communities had a higher degree centrality (avg. = 0.67) but a lower density (0.43). This means that interactions were wide but not very deep (Table 5 and 6).

Conversely, communities based on small groups had lower centrality (average = 0.54) but higher density (0.71), which means that there were stronger ties between members and more frequent interactions between them. These findings support earlier studies indicating that open networks promote breadth of influence, while small groups facilitate depth of connection [5].

Gephi's community visualization found separate groups of people who had an effect on each other. In network-based communities, influence spread out from central nodes (opinion leaders) in a hub-and-spoke pattern. In group-based communities, diffusion occurred subsequent to dense clustering, wherein peer trust and identification enhanced collective participation. The SNA metrics corroborated the PLS-SEM results, indicating that trust and social connectedness mediate behavioral engagement variably across structural configurations, thereby affirming the dual-level aspect of social influence.

4.5. Discussion of Key Findings

The results confirm that normative, informational, and identificational influences are significant predictors of consumer participation, aligning with Kelman's classic three-process model. Normative and informational influences were more pronounced in network-based communities, where visibility and public feedback intensify conformity pressure [7].

In contrast, identificational influence emerged as the most significant predictor in small-group-based communities, underscoring the importance of emotional connections and group identity. This pattern corresponds with the perspective that digital participation is influenced by both cognitive motivations and affective belongingness [8].

The mediation analysis elucidates the conversion of social influence into active participation. Trust serves as a relational lubricant that converts normative and informational pressure into collaborative involvement [9]. When members see others as trustworthy and kind, they are more likely to participate in return.

Perceived homophily was also very important, especially in communities that were based on groups. Similarity among members cultivates empathy and improves peer learning, corroborating previous research that homophilous ties expedite the development of social capital in online environments [10].

Nevertheless, social connectedness emerged as the most significant mediator, completely facilitating the relationship between social influence and participation. This finding aligns with the Self-Determination Theory (SDT) framework [11], which asserts that satisfaction in relatedness enhances intrinsic motivation for ongoing involvement.

5. CONCLUSION

The digital ecosystem has transformed into a complex network of interactions in which consumers participate, collaborate, and co-create value within virtual communities. This study aimed to enhance both theoretical and empirical comprehension of the ways in which social influence mechanisms affect consumer participation in various community structures, specifically network-based and small-group-based virtual communities. This study synthesized social influence theory, social capital theory, and self-determination theory to propose and empirically validate a Dual-Level Social Influence Model, elucidating the mechanisms of influence at both macro-network and micro-relational levels to enhance participation. The empirical findings indicated that normative, informational, and identificational influences are substantial predictors of consumer engagement in digital contexts. Normative influence was identified as a factor that promotes user adherence to observable social norms, aligning with Kelman's [1] compliance model and Cialdini's [2] social proof principle. Informational influence spurred participation by diminishing uncertainty and utilizing the knowledge of others as reliable information sources, a mechanism particularly pronounced in open, network-centric communities. Identificational influence—signifying emotional attachment and psychological alignment—emerged as the preeminent driver in small-group communities, where belonging and shared values prevail as participation motives.

The results further validated that trust, perceived homophily, and social connectedness serve as mediators of these effects. Trust functions as a relational mechanism that converts social pressure into voluntary participation [3]. Homophily strengthens similarity-driven identification, fostering communication and reciprocal actions [4]. Social connectedness, in turn, promotes psychological intimacy and intrinsic motivation, aligning with Self-Determination Theory (SDT) [5]. Furthermore, the type of community significantly influences these relationships. In network-based settings, the dissemination of influence depends on visibility, public engagement, and indicators of popularity. On the other hand, small-group communities rely on relational trust and emotional connections, which create stronger social ties that keep people involved. This substantiates the assertion that contextual structure dictates the intensity and trajectory of social influence.

This study utilized a combination of PLS-SEM and Social Network Analysis (SNA) to achieve a multi-perspective validation. SNA demonstrated that small-group networks display increased density and clustering, whereas SEM validated the presence of deeper psychological mediation through trust and connectedness. These findings collectively affirm that social influence is not unidimensional but rather integrated within the relational and structural frameworks of digital communities. This research contributes to the academic discourse on consumer engagement in virtual communities by illustrating that social influence functions across multiple, interrelated dimensions—structural, relational, and psychological. The Dual-Level Social Influence Model elucidates that participation transcends mere compliance or curiosity, representing a socially embedded process of trust cultivation, identification, and connection.

This study integrates structural network metrics with behavioral modeling to create a comprehensive framework elucidating the reasons for participation, the mechanisms of influence dissemination, and the contextual factors that amplify its potency. It redefines participation as a socially co-constructed phenomenon, wherein engagement serves as both a personal expression and a collective behavior influenced by the underlying structure of digital interactions. In the changing digital world, virtual communities are still the social labs of modern consumer behavior, where innovation, emotion, and influence come together. Researchers and practitioners alike will need to understand the dual nature of social influence as digital ecosystems become more complex. This means that social influence can affect both networks and relationships. This work establishes a theoretical and empirical framework for subsequent investigations into the interplay of technology, culture, and social cognition in influencing human engagement in the virtual era—an era characterized not only by connectivity but also by the quality and significance of that connectivity.

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