Uncovering the Role of Weak Ties in Implicit Networks of Influence: A Network Analysis on Recommendation Algorithms' Neighborhood

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Abstract

Purpose – In the contemporary postmodern context, consumers are often portrayed as liberated from social ties, fostering an environment conducive to individualism. Algorithmic artifacts, such as recommendation algorithms (RAs), are contributing to this paradigm by functioning as anti-link tools: they establish implicit social links among individuals with similar preferences, giving rise to clusters termed neighborhoods. These neighborhoods facilitate the provision of personalized suggestions based on shared interests, paradoxically fostering social connections amid the backdrop of individualism. RAs actively generate implicit networks of influence characterized by users sharing analogous preferences, thereby enhancing the predictability of user behaviors. Despite extensive research on explicit networks of influence and the impact of RAs on decision-making, there remains a scarcity of evidence on how users influence others within these implicitly generated networks, and the roles they play in shaping the flow of information across such implicit networks.

Design/methodology/approach – This study, drawing on the strength of weak ties theory, analyzes with a social network analysis a real-world network of 37,427 users and 1,300 products facilitated by RAs on an e-commerce platform.

Findings – The results contribute to literature on word-of-mouth (WOM) by clarifying the inherent characteristics and interconnections within implicit influence networks driven by recommendation agents (RAs). The findings identify the key users responsible for accelerating recommendations diffusion within these networks and reveal significant implications for scholars and marketers seeking to comprehend the effects of product recommendations in e-commerce contexts and refine their targeting strategies.

Research limitations/implications – The results contribute to the existing literature by highlighting the inherent characteristics and connections of implicit networks of influence facilitated by recommendation agents (RAs), identify the key users who facilitate the flow of the information inside the networks.

Practical implications – The paper shed light on substantial implications for WOM scholars and marketers aiming to understand the effects of product recommendations in an e-commerce setting and targeting processes.

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Originality/value – To the best of authors' knowledge, this study represents the first investigation into the implicit networks of influence facilitated by Ras.

Keywords Recommendation agents, Word-of-mouth, Implicit network of influence, Social network, Weak ties, Neighborhoods

Paper type Research paper

Introduction

Within the postmodern zeitgeist, consumers are frequently portrayed as not confined to any specific form of relationship and liberated from the constraints of social bonds (Payne *et al.*, 2017; Cova, 1997). The traditional social aggregates disperse to facilitate the unfolding of individualism (Skandalis *et al.*, 2016; Kozinets *et al.*, 2010; Cova, 1997) and algorithmic artifacts – such as recommendation algorithms (RAs) – contribute to this dynamic by serving as anti-link tools that may exacerbate individual instances (Ansari *et al.*, 2000).

However, to amplify the individual's realm of choice through recommendations tailored to users' interests, RAs necessitate the derivation of implicit social links among individuals sharing similar preferences to predict the users' future behaviors and influence choices (Gai and Klesse, 2019; Ansari *et al.*, 2000). Consequently, they aggregate individual instances in clusters of consumers with akin preferences – known as neighborhoods (Zhang *et al.*, 2020) – and furnish personalized suggestions based on other unknown like-minded users belonging to said group (Gai and Klesse, 2019; Aggarwal 2016; Ricci *et al.*, 2021; Ansari *et al.*, 2000). In this algorithmic process, individualism is paradoxically capable of fostering new and implicit social connections.

This discernible shift carries noteworthy implications for social influence processes. Nowadays, when an unfamiliar user – resembling to another in terms of purchased products, clickstream and page views – exhibits a novel behavior in the virtual sphere, the system automatically suggests a new item to buy, a combination of items "frequently purchased together" or a product they "may also like" to neighbor users who have manifested similar behaviors (Gai and Klesse, 2019; Aggarwal, 2016; Ricci *et al.*, 2021).

Therefore, to address individual instances, RAs generate implicit networks of influence – characterized by users sharing analogous preferences – to enhance the predictability of the user's future behaviors (Ansari *et al.*, 2000). They operate as explicit anti-link tools augmenting individualism to maximize the functional utility of individuals, while implicitly connecting users forming pertinent, but imperceptible social groups. While explicit forms of social influence and connections have been extensively discussed (Meyners *et al.*, 2017, Sridhar and Srinivasan, 2012, Kozinets *et al.* 2010; Wang and Benbasat, 2007; Hanson *et al.*, 2019; Hoskins *et al.*, 2021), in the contemporary landscape influenced by the emergence of RAs, there is an additional presence of implicit networks of influence that individuals encounter on a daily basis, concurrently coexisting with explicit forms. Nevertheless, marketing scholars have predominantly concentrated on explicit networks of influence and on RAs by exploring their impact on the consumer decision-making process (Wang and Benbasat, 2007; Xiao and Benbasat, 2007) and associated computational methods (Gai and Klesse, 2019; Xiao and Benbasat, 2007). To the best of our knowledge, there is still limited empirical evidence on how users influence others within these implicitly generated networks, and the roles they play in shaping the flow of information across such implicit networks. Given that most of service providers such as Amazon, Google, Meta, Netflix, Spotify and TripAdvisor, currently offer user recommendations generated by RAs and invest significantly in such systems (International Data Corporation, 2022), these social implications pertain to the entire digital existence of users.

Drawing on Granovetter's (1973) theory of the strength of weak ties, we propose that, much like in offline social networks, the implicit relationships formed through recommendation agents (RAs) also lie along a continuum – from strong to weak – each playing a distinct role in shaping how information spreads. Strong ties allow for the efficient sharing of information but tend to circulate familiar, overlapping content within cohesive "small worlds". In contrast, weak ties bridge disparate social clusters, introducing heterogeneous, novel information from otherwise inaccessible sources (Granovetter, 1973). In our idea, weak ties play a pivotal role within RA-driven networks by serving as bridges that connect distinct user neighborhoods and facilitate the diffusion of product recommendations to otherwise disconnected user clusters, thereby significantly amplifying the overall reach of the network.

We investigated these dynamics by analyzing behavioral data from 37,427 users across 1,300 products and exploring the structure and topology of the algorithmically generated network, with particular attention to the contrasting roles of weak and strong ties in the dissemination of information.

The results contribute to the word-of-mouth (WOM) literature by unveiling the underlying structures and characteristics of implicit influence networks facilitated by recommendation agents (RAs); identifying key users – particularly those connected through weak ties – who serve as critical conduits for information diffusion across user communities; and offering actionable insights for marketers by showing how certain users, especially those loosely embedded across multiple communities, can substantially amplify the reach of targeted messages through RA-driven algorithms.

Our findings challenge the long-standing perspective that strong ties are inherently more persuasive or impactful (Koo, 2016). Instead, in RA-enabled networks, weak ties – especially those bridging communities or linked to influential actors – can be equally, if not more, effective in disseminating information (Chiu *et al.*, 2014; Wirtz *et al.*, 2019; Lee and Kronrod, 2020). Specifically, in service contexts where the informational content of an interaction is of primary importance, weak ties may demonstrate superior effectiveness. By providing access to novel, detailed, diverse and less redundant sources of information, weak ties can exert a disproportionate influence on decision-making processes, thereby exceeding the persuasive utility of strong ties in settings where informational value constitutes the central determinant of impact.

The study further contests the notion that influence stems primarily from WOM explicitly connected to interpersonal communication within visibly connected social networks (Kozinets *et al.*, 2010). In RA-mediated contexts, influence occurs implicitly through algorithmic matchmaking based on behavioral similarity, thereby generating new forms of connection not accounted for in conventional models of coproduction (He *et al.*, 2021). Finally, our results refine the belief that dissemination effectiveness is determined mainly by the number of ties. Rather, they show that the quality and structural positioning of ties – measured through eigenvector centrality, PageRank and bridging positions – are decisive for enabling cross-community diffusion (Granovetter, 1973; He *et al.*, 2021).

The remainder of the article is organized as follows:

- an introduction to the conceptual background regarding AI-based customization agents, their significance in the decision-making process and their ability to improve implicit social connections;
- the presentation of the study's results;
- discussions on these findings; and
- an exploration of practical and theoretical implications.

Conceptual background

Recommendation algorithms and users' neighborhoods, the constitutional elements of implicit influence

RAs play a crucial role in maximizing individual functional utility while minimizing the risk of unsatisfactory decisions, reduce search costs and increase the likelihood of finding products aligning with users' interests and preferences (Hofacker *et al.*, 2016). They typically take the form of "You may also like […]" or "People who like this also like […]" sections, but they can also alter the positions of items in search results, or the items users are exposed to in their social network feeds (Gai and Klesse 2019).

Platforms, such as Amazon, Facebook, Instagram, Netflix and Spotify use this approach by collecting user preferences and matching individuals with similar ratings to provide tailored recommendations (Ansari *et al.*, 2000; Gai and Klesse, 2019; Aggarwal, 2016; Ricci *et al.*, 2021). To collect user preferences, RAs rely on either implicit or explicit elicitation methods (Gai and Klesse, 2019; Aggarwal, 2016; Ricci *et al.*, 2021). Implicit elicitation involves deducing users' preferences through their interactions within the e-commerce ecosystem, such as analyzing page views, browsing history and past purchases (Zhang *et al.*, 2020). On the other hand, explicit elicitation requires users to actively provide evaluations of their preferred features, categories and items, often occurring during account setup phases, as seen in platforms like Netflix (Aggarwal, 2016).

Following the elicitation process, a cohort of consumers sharing analogous preferences, referred to as a neighborhood, is formed (Ning *et al.*, 2015). Subsequently, when a member of this neighborhood initiates a behavior, the corresponding item linked to that behavior is automatically recommended to other users within the same neighborhood who share similar preferences (Ansari *et al.*, 2000). The underlying assumption is that a concealed companion with similar interests can exert a lasting influence on the customer journey of their neighbors (Ansari *et al.*, 2000). Indeed, these agents emulate traditional recommendations by using the opinions of like-minded individuals in the neighborhood to generate automated suggestions about products and services (Ansari *et al.*, 2000; Guttman *et al.*, 1999).

The concept of neighborhood has been extensively discussed in WOM literature (Muniz and O'Guinn, 2001) to classify groups of individuals that are inhomogeneous compared to other groups but similar within the cluster, with a reduced sense of we-ness, linked by temporary interests, few ties and define themselves in contrast to another community (Muniz and O'Guinn, 2001).

Similarly, given their implicit nature, we argue that algorithmic neighborhoods generated by recommendation agents (RAs) do not rely on a shared sense of we-ness, as they are formed and evolve over time based on user purchases rather than conscious group affiliation (Ning *et al.*, 2015; Table 1). RAs connect users – often without their explicit awareness – through demonstrated preferences, enabling individuals to become part of an implicit influence network. Within this network, users automatically generate behavioral insights and transmit marketing messages by initiating behaviors and receive recommendations by RA triggered by the actions of others in their neighborhood (Dellarocas, 2003). A foundational principle that mirrors the transformation in information search processes facilitated by technology and underscores that numerous consumers have now become an implicit source for product information (Hamilton *et al.*, 2021).

From the neighborhoods to the development of implicit networks of influence

The concept of the implicit network of influence has been introduced by Hamilton *et al.* (2021) to emphasize the impact of others and emerging technologies, such as intelligent agents, on reshaping the idea of social closeness. They recognized that social entities,

Table 1. Comparison between neighborhoods and communities by characteristics

Characteristics	Neighborhood	Community
We-ness	Low	High
Links	Temporary	Durable
Consciousness of kind	Low	High
Perceived membership	Low	High
Feeling of connection	Low	High
Rituals	Absent	Present

Source(s): Authors' own work

referred to as "traveling companions," can influence users either implicitly or explicitly. Implicit influence occurs when the focal customer perceives a recommendation without any intentional effort from the social entity (i.e. neighborhoods), while explicit influence involves the sender's deliberate intent to guide the receiver's actions (Hamilton *et al.*, 2021; Argo and Dahl, 2020).

Prior research has extensively focused on the explicit influence occurring in communities and neighborhoods and managers have consequently adopted their marketing techniques to stimulate such communities (Mouritzen *et al.*, 2024; Wallace *et al.*, 2017; Risselada *et al.*, 2014; Katona *et al.*, 2011). Using a three-level process, Kozinets *et al.* (2010) pointed out that recommendations can be organic, when individuals recommend items to help others, alert them to poor service or communicate a status (i.e. organic interconsumer influence model) (Kozinets *et al.*, 2010); activated by opinion leaders who are seen as friends recommending tested and reliable products rather than sellers trying to dispose of goods (i.e. linear marketer influence model) (Nair *et al.*, 2010; Kozinets *et al.*, 2010); and, formed by consumer networks, groups and communities in which consumers actively co-produce value and new shared meanings within their community (Kozinets *et al.*, 2010), often outside the control of marketers (i.e. network coproduction model).

Other authors found evidence that informational influence (i.e. explicit) can influence consumers' decisions (Sridhar and Srinivasan, 2012), that geographic proximity can increase the salience of social ties and make it more likely that individuals will interact with and learn from others in their vicinity (Todri *et al.*, 2022; Dubois *et al.*, 2016; Meyners *et al.*, 2017) or examined how the explicit influence varies depending on the type of brand, the type of source and the reviewer's characteristics (Hoskins *et al.*, 2021). On the other hand, some authors have focused on the explicit influence on physical neighborhoods. Muniz and O'Guinn's (2001) seminal work on brand communities introduced a novel perspective on consumer-brand relationships, investigating the traditional notion of geographically bound communities (i.e. neighborhood). The authors observed that neighborhoods exhibit a low sense of shared consciousness, absence of rituals, traditions, values and norms. Nevertheless, they serve as a sphere of influence for the exposed consumers.

In the context of recommendation agents (RAs), implicit influence includes individuals with shared preferences who form neighborhoods based on demonstrated behaviors. The resulting implicit network is continually shaped by individuals' actions (Ning *et al.*, 2015) in a feedback-feedforward process, i.e. the RA discriminates the role of users based on the volume of feedback from individuals. This implies that when a user modifies his/her behavior, the system tends to link him/her with new neighborhoods, particularly if the current one has not exhibited similar novel behaviors. This continual movement signifies a persistent quest for homeostasis within the system and the development of implicit social bonds driven by the demonstrated behaviors of individuals (Ning *et al.*, 2015).

However, the extant literature on WOM has not investigated how the manifestation of new behaviors from the users, as collected by RAs, affects the process of implicit influence within algorithmic networks. When they change their behaviors or buy new products, the internal mechanisms of the influence process among users in implicit algorithmic networks, the strength of the resulting social ties and its effects on the dissemination of the information, are still unclear.

The strength of ties in implicit networks of influence

To examine how the internal mechanisms underlying the manifestation of new behaviors affect the influence process among users within implicit algorithmic networks – and to assess the strength of resulting social ties and their impact on information dissemination – we draw on Granovetter's (1973) theory of the strength of weak ties, a framework previously applied across diverse consumption contexts.

The theory posits that social relations are embedded in three types of ties – strong and weak – with varying levels of strength. Strong ties involve high levels of trust, collaboration and mutual respect and are embedded in cohesive networks where members are tightly connected. These "small circles" facilitate trust and communication but restrict exposure to novel or diverse knowledge. The dense connectivity of such networks results in redundant ties – multiple connections conveying similar information – thereby reducing the likelihood of encountering non-redundant insights.

For example, within LEGO ideas – a platform where fans submit original LEGO set concepts – frequent contributors often form strong ties with one another through repeated collaboration, mutual feedback and shared participation in themed contests. These long-time members may focus on similar design aesthetics or fan-favorite genres (e.g. space, architecture) and they tend to comment on and promote each other's submissions. While this community structure supports rapid feedback and skill refinement, it can also result in creative echo chambers, where most designs reflect prevailing trends and fail to push stylistic or thematic boundaries.

In contrast, weak ties often carry unfamiliar information, offering advantages such as greater access to novel insights and new partnerships. These ties are more likely to introduce external influences into a network and disseminate information widely (Goldenberg *et al.*, 2001). Returning to the previous example, weak ties – such as occasional engagement from new users or fans with interests outside of the core themes – connect the community to diverse perspectives. For instance, a long-time LEGO ideas user might come across a submission by a newcomer inspired by kinetic sculpture or contemporary art – areas not typically explored in mainstream LEGO sets. This weak tie introduces a novel design philosophy, sparking conversations and adaptations among more established creators. Thus, while strong ties promote efficient but redundant information exchange, weak ties act as bridges to heterogeneous information, fostering innovation.

One might reasonably ask whether a strong tie – despite being embedded in a dense and homogeneous network – can nonetheless acquire and transmit new information to its peers. While this is certainly possible, the structural and contextual characteristics of strong ties inherently reduce the likelihood and diversity of such knowledge (Granovetter, 1973). Members of tightly-knit groups often share similar backgrounds, environments and informational sources; therefore, even when one of them encounters a new idea, it is likely to be aligned (or even redundant) with or adjacent to what is already circulating within the group. In effect, the novelty is diluted by pre-existing cognitive and social overlap. Strong ties are excellent vehicles for reinforcing and deepening shared understanding and for transmitting complex, high-trust knowledge, but they tend to generate informational redundancy rather than diversity. Even when a user is newly introduced to a neighborhood, the recommendations they receive from strong ties reflect behaviors already dominant within the group. This occurs because the algorithm clusters users based on inferred preferences, not prior exposure. Thus, the perceived redundancy stems from the internal homogeneity of the constituted neighborhood rather than the individual's consumption history. For newcomers, this results in immediate exposure to a consistent and patterned set of behaviors reflective of the group's prevailing habits. Although the content may be new to the user, it is often repetitive within the network, reinforcing established trends rather than introducing alternatives. By contrast, weak ties connect individuals across different social or professional domains, serving as bridges to information pools that are not easily accessible through close-knit networks. This bridging function increases the probability of encountering genuinely novel and heterogeneous content, which can expand the individual's cognitive and informational capital. Therefore, although strong ties may occasionally introduce new knowledge, it is predominantly through weak ties that radically different and innovative information becomes accessible – especially information that challenges existing group norms or introduces unfamiliar perspectives.

Brown and Reingen (1987) emphasized the bridging function of weak ties, which enable information to traverse otherwise disconnected components of a social system. Without weak ties, networks become fragmented into isolated clusters, inhibiting broad information dissemination. Although weak ties are less influential in decision-making than strong ties (Yang *et al.*, 2023; Umashankar *et al.*, 2017; Koo, 2015; Ellison and Fudenberg, 1995; Brown and Reingen, 1987), Koo (2016) found that in electronic WOM (e-WOM) contexts, their impact can rival that of strong ties when paired with high recommender expertise. The study revealed that message credibility mediates the relationship between tie strength and expertise, suggesting that expertise can offset the influence gap associated with weak ties. Moreover, Koo (2015) showed that negative e-WOM from weak or no-tie sources can exert stronger influence on attitudes toward credence services than positive messages from strong ties, highlighting how weak ties can amplify risk perception and disrupt normative behaviors. This challenges the assumption that strong ties are inherently more persuasive and highlights the contextual effectiveness of weak ties – especially in service settings where informational value is paramount.

Supporting this, Lee and Kronrod (2020) found that weak ties can be more influential than strong ties when accompanied by consensus language, which RA are able to interpret and use. Because weak ties span broader and more diverse networks, they are associated with perceptions of widespread agreement, which strengthens the persuasiveness of messages. Importantly, such perceptions do not require consumers to be consciously aware of the underlying network structure; rather, they are often algorithmically simulated through cues such as consensus-oriented language ("people who bought this also liked […]", "frequently recommended by our community"), popularity framing ("bestseller in your area", "trending now among users like you") or numerical reinforcement ("over 10,000 users purchased this in the last month"). These signals create an impression of broad support that enhances influence, even in the absence of direct social awareness (Lee and Kronrod, 2020). Wirtz *et al.* (2019) added that online environments minimize metaperceptive concerns, empowering weak ties through a "digital disinhibition effect" and increasing their referral influence – a phenomenon particularly relevant in algorithmically mediated platforms like e-commerce. Further advancing this perspective, He *et al.* (2021) demonstrated that integrating weak and strong ties within algorithmic recommender models significantly enhances recommendation diversity and novelty, although at a minor cost to precision. Their hybrid PageRank approach improved the diversity of recommendations by over 20% in some cases, affirming that weak ties introduce non-redundant, peripheral items that enrich user exposure beyond mainstream preferences. In addition, Chiu *et al.* (2014) revealed that while strong ties foster trust, weak ties are vital for information bridging in digital spaces, particularly when messages contain hedonic cues.

In our study, we predict that both strong and weak ties can be observed in the implicit structures facilitated by recommendation agents (RAs). While prior work (Armstrong *et al.*, 2022; Yang *et al.*, 2023; Abrantes *et al.*, 2013; Friedkin, 1980; Weimann, 1983) has explored the role of weak ties in consumption contexts – often using hypothetical scenarios, small-scale experiments or static data –this is, to our knowledge, the first empirical analysis of a large-scale RA-enabled network that operationalizes tie strength from user behavior. See the Table 2 below for an extended literature review on the topic.

We posit that RAs construct networks by grouping consumers into subnetworks based on behavioral similarity, with strong ties forming within these clusters through recurring shared actions. Connections between subnetworks, however, arise through behavioral differences across users (Aggarwal, 2016). In such systems, when a strong tie – such as a frequently interacting neighbor – adopts a new behavior, that choice is automatically recommended to others within the neighborhood (Aggarwal, 2016; Ricci *et al.*, 2021):

H1. Weak ties are more likely to propagate a greater volume of recommendations across a wider range of implicit neighborhoods than strong ties.

H2. Strong ties are more likely to circulate fewer recommendations within a single implicit neighborhood, reinforcing established behavioral patterns.

Research

Data collection

To delineate the structure of implicit networks of influence facilitated by recommendation agents, we used a publicly available Amazon data set from 2018, encompassing 233.1 million transactions. Subsequently, we extracted a targeted subset of gift card items, totaling 147,194 users. Users not associated with any recommendations were excluded from the study, resulting in a matrix of 37,427 individuals and 1,300 products. The selection of the gift card data set enabled the quantification of network measures due to its suitable size for the conducted analysis, and gift cards are among the most frequently purchased items on the platform.

The choice of the Amazon data set was motivated by the platform's widespread and ongoing use of item-to-item collaborative filtering, a proprietary method Amazon formally introduced in 2003 and continues to use as a core recommendation logic today. While Amazon has since integrated more advanced AI techniques such as deep learning and generative models, the fundamental mechanism – recommending items based on co-purchase patterns and behavioral similarity – remains intact.

This 2018 data set is, to date, the most recent publicly available data set that retains the structure of these collaborative filtering signals, specifically through the "Customers who bought this item also bought" and "Consumers who bought this item also bought" features. For instance, if a consumer receives a recommendation for a specific PC cover while purchasing a PC, it indicates that previous consumers who bought a PC also acquired a PC cover. This implies that a user buying product X would also likely purchase product Y because past users exhibited this behavior. These embedded signals are essential for reconstructing the algorithmic pathways through which users receive recommendations.

Table 2. Prior research on recommendation agents, e-WOM and online ties

Author(s)	Main findings	Investigated variables	Sample size
He *et al.* (2021)	Integrating strong and weak ties into PageRank improved recommendation diversity and novelty, though with a small loss in accuracy, showing a trade-off in recommender design	Accuracy, diversity, novelty	$n = 3{,}759$
Koo (2016)	Strong ties increase credibility and purchase intention, but experienced weak ties can be equally persuasive; message credibility mediates these effects	Tie strength, experience, credibility, intention, involvement, familiarity, service type	$n = 302$
Abrantes *et al.* (2013)	Experiential learning drives out-of-group e-WOM but not in-group, suggesting weak ties are key for sharing novel information; other motivations vary by context	Mood enhancement, experiential learning, escapism, social interaction, e-WOM In-Group, e-WOM out-group	$n = 302$
Koo (2015)	The impact of e-WOM depends on tie strength, service type and valence: negative no-tie reviews strongly affect credence services, while positive ties matter more for search/experience services	Valence, tie strength, service type, attitudes, intention	$n = 616$
Chiu *et al.* (2014)	Strong ties build trust, weak ties bridge groups; utilitarian vs. hedonic appeals align with cognitive versus affective involvement; blogs enhance trust more than email	Message context, message source, channel	$n = 363$
Wirtz *et al.* (2019)	Online environments reduce social concerns, allowing weak ties to exert greater influence through the digital disinhibition effect	Incentives, communication environment, tie strength, metaperception, referral likelihood	$n = 209$
Lee and Kronrod (2020)	Weak ties using consensus language increase persuasion by evoking broader group agreement and perceived diversity, outperforming strong ties in some contexts	Consensus language, tie strength, perceived group size, perceived diversity, validity, persuasion	$n = 1{,}522$
Our research	First study of RA-enabled networks shows weak ties – especially those linked to influential nodes – are critical for cross-community diffusion, while strong ties reinforce messages within communities	Tie strength, dissemination power, centrality metrics, embeddedness, participation coefficient	$n = 37{,}427$

Source(s): Authors' own work

In our study, we correlated the recommendations featured in the "Consumers who bought this item, also bought" section with each User ID to unveil the recommendations received by users and the similarities with recommendations conveyed to other users.

Methods

To scrutinize the extensive data set, we used social network analysis (SNA) methodologies (Burt, 1992; Granovetter, 1973). Data preparation was executed in Python, and processing and analysis were performed using packages such as "igraph" (Csardi and Nepusz, 2006), "sna" (Butts, 2015), "ape" (Paradis, 2019), "dnet" (Fang and Gough, 2014), "Network Toolbox" (Butts, 2015) and "bipartite" (Dormann *et al.*, 2008) in R Core Team (2017) (refer to Appendix). To handle the network's large size and matrices, a virtual machine equipped with R was established through the AI platform provided by Google Cloud Platform.

Given that all users received a set of recommendations, we computed a two-mode matrix. The columns included the total number of gift cards recommended by Amazon, while the rows represented users. Each cell within the matrix indicated the number of times a product was recommended to a user (refer to Figure 1).

After transposing the matrix, we obtained a one-mode user-user matrix of dimensions 37,427 * 37,427. In this matrix, each cell represents the number of times two users were exposed to the same recommendations. To eliminate self-loops, the diagonal of the adjacency matrix was set to zero (refer to Figure 2)

Subsequently, to identify potential neighborhoods around the recommended products, we used the Multilevel community detection algorithm (Blondel *et al.*, 2008). This algorithm determines communities based on modularity [1], assigning a distinct community to each node initially and then moving nodes to the community where they contribute most positively to modularity. This iterative process continues until the highest modularity for the community is achieved (Yang *et al.*, 2016). The resulting partition emphasizes numerous edges within communities and minimal connections between them. A higher number of links between two individuals increases the likelihood of them belonging to the same community. According to this algorithm, when two consumers are frequently exposed to the same recommendations, they are grouped into a community. The method is particularly suitable for large networks due to its computational complexity [O(N log N)], which is not quadratic (Xie *et al.*, 2013). To evaluate the significance of each neighborhood, two types of degrees were computed for each node: degrees based on neighbors within the community itself and

	B00BXLVZZE	B00IGYPALG	B00FTGTM5E	B075SHPN2P	B00FTJI60I	B079GCLTZM	B00FTGEXZI	B071DTXNHG
A3F44KCZ816GN2	1	1	1	1	1	1	1	1
A3M31G4GJ9066T	0	0	0	0	0	0	0	0
A35DVVHF5D00MP	0	1	1	0	1	0	0	0
A2P7PQ3G6TE8GT	0	1	1	0	0	0	0	1
A3L7FALBSLA3S	0	1	1	0	0	0	1	0
A21FCCP98J6YDU	0	1	1	0	1	0	0	1
A2I3RXUUF0J33N	0	1	1	0	0	0	0	1
A3VV44Y6WL297Q	0	1	1	0	1	0	0	0
A3O6MA878FRRRW	0	0	0	0	0	0	0	0
A2WRWI1U801TVQ	0	0	0	0	0	0	0	0

Figure 1. Matrix with UserIDs * recommended product ASINs
Source: Authors' own work

	A2HSD47KF0HII	AK7JS2ASR7LFF	ABGVLESCLQX85	ABQFTT7Z5OXQH	A2LL58UGFLH3PB	A32OUYZCN0QWTP
A2HSD47KF0HII	0	9	7	11	61	10
AK7JS2ASR7LFF	9	0	43	54	9	53
ABGVLESCLQX85	7	43	0	47	7	38
ABQFTT7Z5OXQH	11	54	47	0	11	54
A2LL58UGFLH3PB	61	9	7	11	0	10
A32OUYZCN0QWTP	10	53	38	54	10	0

Figure 2. Matrix with User * User and corresponding times they were exposed to the same recommendation
Source: Authors' own work

degrees based on neighbors outside the community. Subsequently, two-sample Wilcoxon tests were performed on these degrees to determine their significance.

In addition, to comprehend the role and characteristics of individuals and their ability to disseminate marketing messages, we developed a matrix to assess dissemination efficacy. The dissemination efficacy matrix reflects how often a product purchased by a particular user is recommended within the communities. The outcome is a matrix with dimensions Nusers * Ncluster, where each cell captures the instances when a product bought by users was shared in other neighborhoods. Furthermore, in a subsequent stage, a matrix incorporating various centrality and community-based metrics for each user was calculated. The matrix columns encompass measures assessing the user's position within the network and their capacity to disseminate recommendations within established neighborhoods. The 32,427 users by 7 measures matrix underwent testing using Pearson's correlation to determine if significant associations existed among the measures. In our idea, reduced centrality degrees were linked to diminished recommendation influence, indicating strong ties. Conversely, elevated degrees suggested weaker ties and greater recommendation influence.

To deal with the large data set we drawn on Efron's (1979) bootstrap method as a resampling technique. The bootstrap is suitable for quantifying the uncertainty associated to an estimator allowing for the computing of confidence intervals based on multiple samples (Efron, 1979). After generating 100 random bootstrap sample with replacement X*1, X*2,… X*100 of n = 1,000 observations each we replicated the Pearson's correlation coefficient statistics for each bootstrap sample.

Consequently, we generated numerous estimates of the Pearson's correlation coefficient, forming our bootstrap distribution. A subset of the 100 bootstrap replications is presented in Table 3, and the distribution is visualized in Figure 3. Subsequently, the bootstrap distribution was used to determine the empirical estimate, standard deviation, confidence interval and standard error, following the methodology proposed by Efron (1979). To address skewness observed in some bootstrap distributions, the bias-corrected and accelerated (BCa) bootstrap interval method was implemented (Figure 3) (Efron 1979).

Finally, to address the normality assumption, we applied Fisher's z-transformation (Silver and Dunlap, 1987) to all bootstrap distributions. This transformation enabled us to conduct a one-way ANOVA, evaluating whether significant differences existed among the subsamples. The number of samples served as a categorical variable, allowing us to explore variations in the assumed dependent variables across each level of the factor.

Network measures

Centrality measures. The set of centrality measures has been used to discover the role of individuals within the network, the neighborhoods and their relative importance. The simplest

Table 3. Number of significant neighborhoods available in the network and related measures

#Neighborhood	Size	Density	Significance	Modularity
1	980	0.990	***	0.048
2	4,983	1.000	***	0.048
3	579	1.000	***	0.048
4	2,083	1.000	***	0.036
5	5,933	1.000	***	0.036
6	5,005	0.999	***	0.036
7	1,148	1.000	***	0.036
8	6,847	0.999	***	0.046
9	116	1.000	***	0.046
10	2,160	1.000	***	0.046
11	1,365	1.000	***	0.046
12	234	1.000	***	0.046
13	5,917	1.000	***	0.046
14	77	1.000	***	0.000

Source(s): Authors' own work

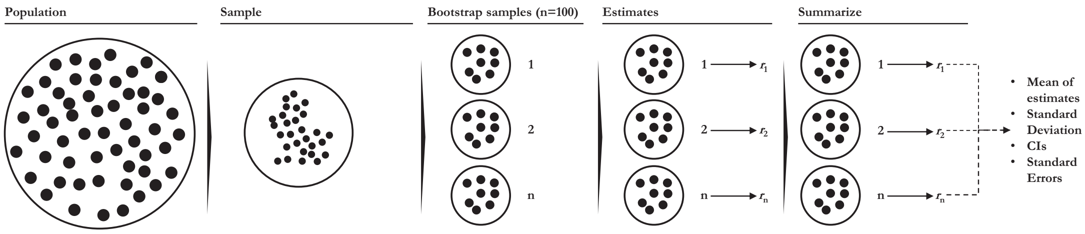

Figure 3. Bootstrap method
Source: Efron, 1979

degree centrality has been assessed to count the connections of the individuals (i.e. edges) (Bolland, 1988; Shaw, 1954).

Also, the eigenvector centrality has been measured to assess the quality of the connections of the actor (Freeman, 1978). A higher eigenvector centrality defines those nodes who are connected to most popular nodes in a network (Bonacich, 1987).

Furthermore, the betweenness centrality has been computed to discover the times a node is connected to the shortest path between two vertices. The higher the presence of an actor in these paths, the higher the power to control communication since several links are passing through those paths. Nodes that are present on many paths are more relevant in the communication process (Freeman, 1978).

Similarly, the closeness centrality has been outlined to represent the average distance, or average shortest path, to all other vertices in the network (Bavelas, 1948). A central actor would be close, on average, to other vertices in the network. The measure allows to evaluate if a central vertex is "close" to other nodes. At the end, the PageRank (Brin and Page, 1998, Page, 1998) index has been involved to assesses the relevance of nodes in the network modelling the probability that a "random" node who starts at a random position in the network and continues following links, will connect to a vertex in the network.

In our perspective, lower centrality degrees are associated with a decrease in recommendation influence, signifying strong ties. Conversely, higher degrees indicate weaker ties and a higher level of recommendation influence.

Community-driven measures. While the prior measures are nodes-specific, a set of community-driven indicators have been adopted to discover the structure of communities and the role of individuals within them. In network analysis, a community relies on densely connected nodes and shared properties, such as friendship, like-minded individuals or a frequent exchange of communication (Palla *et al.*, 2007). A relevant measure that can be used to highlight relevant nodes in the community is the embeddedness (Palla *et al.*, 2007), defined as the ratio between the internal degree (the number of connections to other vertices within the community) and the total degree (all connections, including ones with vertices outside the community).

Similarly, the participation coefficient has been computed. A vertex with edges exclusively in its own community has a participation coefficient of 0. To compute the participation coefficient the WalkTrap algorithm has been used (Pons and Latapy, 2005) and if two nodes i and j are in the same community, the probability to get to a third node k located in the same community through a random walk should not be very different for i and j. Values closer to 1 suggest greater within-community connectivity and values closer to 0 suggest greater between-community connectivity.

All the previously mentioned metrics are designed to comprehend the user's placement within neighborhoods, the extent of connections with others and the strength of these ties.

Results

Network properties and neighborhood detection

Our analysis initially focused on the main structure of the network (Table 4). The overall diameter of the graph, which is the length of the longest path between a pair of nodes (Wasserman, 1994), is equal to 2, with an average number of steps between two nodes equal to 10,082 (i.e. mean distance). These results illustrate a densely interconnected network of users, connected by the recommendations they encountered during their shopping activities. Indeed, a total of 694,560,660 connections were identified within a network of 37,427 users and 1,300 products, resulting in an overall density of 0.9917. Graph density is assessed on a scale from 0 to 1, indicating a spectrum from no connections to all actors being interconnected. In this scenario, most users are linked, albeit with varying degrees of strength, implying that, in accordance with the rationale behind the RAs, diverse relationships exist among users based on the extent to which they were jointly exposed to certain recommendations. Indeed, subsequent graph measures elaborate on this observation.

The average degree of each node is 37,118, signifying the distinct number of nodes that each user interacts with. This implies that each user has a 99% probability (i.e. 37,118/37,427)

Table 4. Network measures

	Nodes	Weighted edges	Diameter	Mean distance	Density	Avg. degree	Avg. strength	Avg. participation coefficient	Avg. betweenness centrality
Network graph	37.427	694,560,660	2	10,082	0.9917	37.118	1,018,888	0.5003	17,774.08

Source(s): Authors' own work

of being connected to another user through the messages conveyed by RAs. It suggests that the majority of users are linked to all other nodes due to their shared exposure to at least one recommendation.

Despite the highly interconnected nature of Amazon's network, where all users have a 99% probability of being connected to another, a measure of relationship strength has been incorporated to determine the extent to which two or more users are exposed to the same implicit network of influence facilitated by the RA. Specifically, the average strength of each node, denoting the number of edges from one node to another, stands at 1,018,888 distributed among the previous 37,118 average links in varying degrees. This indicates that User1 and User2 may have been connected 100 times, while User1 and User3 only 2 times. According to the measure involved (i.e. the participation coefficient), greater the weight of the connection between two users, the more instances they have been exposed to the same message. This would provide clarity on the exact number of connections between two users and their respective positions within the neighborhood.

Indeed, the average participation coefficient, representing the strength of a node's connections within its community, is precisely 0.5003, with a minimum of 0.5 and a maximum of 0.501. This suggests that a portion of users frequently shares the same messages and is deeply integrated within communities, while another segment tends to connect with different neighborhoods, indicating lower within-community connectivity. However, considering 1 as an indicator of higher within-community connectivity and values closer to 0 as a measure of increased between-community connectivity, RAs-enabled communities trend toward 1. This result also elucidates the structure of RAs-enabled implicit networks, predominantly combining users within neighborhoods.

Moreover, the average shortest paths between two nodes passing through a specific node (i.e. betweenness centrality) stand at 17,774, signifying that, on average, a node finds itself in the middle of the path between two other nodes 17,774 times. These findings affirm that users within the network are closely interconnected, potentially owing to product variety or users' ability to convey messages similarly. However, distinctions in the strength of ties are apparent based on the participation coefficient and average strength indicators. This hints at the existence of additional substructures within the network, with users playing distinct roles within them.

In this context, to delve deeper into the network's structure and individual connections, we used the Multilevel community-detection algorithm to evaluate the presence of communities based on modularity (Blondel *et al.*, 2008). The identified communities consist of individuals who are more interconnected within their community and less connected to other communities. In addition, the density within a community, influenced by the average strength of links among individuals, is expected to surpass the overall density of the entire network.

As depicted in Figure 4, we discovered 14 densely connected neighborhoods, each exhibiting an overall density higher than that of the entire graph. For each community in the graph, two types of degrees for each node were computed: degrees based on links within the community itself and degrees based on the members available in the graph. Subsequently, two-sample Wilcoxon tests were conducted on these two types of degrees to determine the significance level. The outcome revealed that all neighborhoods are statistically significant at the $p < 0.001$ (***) level (Table 3).

Upon examining the 14 neighborhoods, we observe prominent connections among actors in the majority of these neighborhoods, along with a recurring presence of peripheral users within each subgraph. These nodes, owing to their peripheral roles, may have fewer connections with members of the community, making them potential conduits for linking

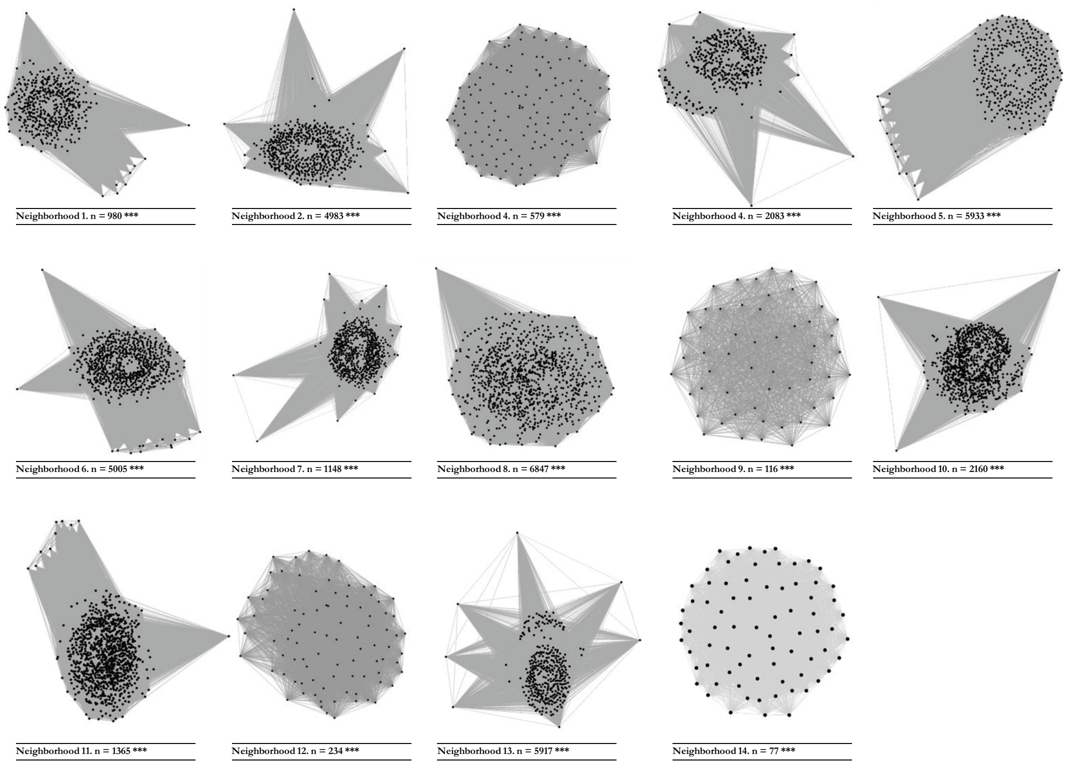

Figure 4. Number of significant neighborhoods available in the network
Source: Authors' own work

with external users in other communities. These individuals could engage with nodes in different networks, facilitating the transfer of information from external contexts to the internal environment (Vikatos *et al.*, 2020; Corradini *et al.*, 2020; Granovetter, 1973; Burt, 1992). They might function as bridges, spreading marketing messages across a greater number of communities, while users embedded within their communities are more likely to generate redundancy in message reception and delivery, repeatedly sharing the same messages within their community (Granovetter, 1973).

Nodes' measures and dissemination efficacy

To examine whether peripheral positions are correlated with higher levels of recommendation dissemination in line with our hypothesis, we systematically gathered centrality and community-driven measures for each individual user. These metrics served multiple purposes:

- testing our hypothesis;
- characterizing the position of each user within the network; and
- determining their role in disseminating recommendations among other users and neighborhoods.

As outlined in the *Methods* section, we used bootstrap-based resampling techniques (Efron, 1979) to evaluate the Pearson's correlation coefficient estimate between dissemination efficacy and other measures across 100 samples, each consisting of $n = 1{,}000$ observations.

The bootstrap distribution for coefficients in each subsample, along with the corresponding confidence intervals, is presented in Table 5.

Subsequently, we proceeded computing the 95% CIs and the standard errors of all bootstrapped distributions using the BCa bootstrap interval (Efron, 1979). Hence, through the procedure we obtained the 95% CIs for each measure with the associated standard errors and the average estimate (Figure 5 and Table 6).

In a further test, we analyzed the mean differences of the estimates among the 100 subsamples through a one-way ANOVA after adopting the Fisher's Z-transformation for each distribution to respond to the normality assumption. As shown in Table 7, all p-values are not statistically significant, indicating that coefficients do not vary significantly across the level of the categorical variable.

As a result, the r eigen centrality estimate reported a mean of 0.41, a value that is included in the 95% of the samples since the CI's lower level is equal to 0.403 and the upper level is equal to 0.417. Similarly the embeddedness ($Mr_{embeddedness}$ = −0.45; [LL: −0.482; UL: −0.423]), participation coefficient ($Mr_{\mathrm{participationcoefficient}}$ = −0.46; [LL: −0.500; UL: −0.430]), degree centrality ($Mr_{\mathrm{degreecentrality}}$ = 0.39; [LL: 0.395; UL: −0.401]), closeness centrality ($Mr_{\mathrm{closeness\ centrality}}$ = 0.43; [LL: 0.418; UL: 0.456]), betweenness centrality ($Mr_{\mathrm{betweenness\ centrality}}$ = 0.472; [LL: 0.470; UL: 0.473]) and PageRank (Mr_{PageRank} = 0.508; [LL: 0.500; UL: 0.515]) do not vary significantly across the bootstrapped samples and all the reported means are contained in the 95% of them.

Drawing on these results, a positive significant association between dissemination efficacy and eigen centrality has been assessed (r = 0.41, CI [0.403; 0.417]. It indicates that the higher is the connection of a vertex with most influential nodes, the higher is the ability to spread a recommendation in more neighborhood after the purchase. Conversely, there is a negative correlation between the dissemination efficacy of a user and the embeddedness in a neighborhood ($r_{embeddedness}$ = −0.45; [LL: −0.482; UL: −0.423]). These results suggests that a user with strong ties in a community tend to spread less messages than users with a low level of embeddedness, indicating that a more peripheral position (i.e. weak ties) in the neighborhood enhance the ability to spread the recommendation to a greater number of communities. Similarly, the participation coefficient, which measure the strength of a node's connection within its community, is negatively correlated to the dissemination efficacy ($r_{\mathrm{participationcoefficient}}$ = −0.46; [LL: −0.500; UL: −0.430]). The higher is the within-community connectivity, the lower is the ability of a user to spread the message across different neighborhoods. On the other hand, users with an high degree centrality in the network are more likely to spread recommendations more than users with a low degree ($r_{\mathrm{degreecentrality}}$ = 0.39; [LL: 0.395; UL: −0.401]). It indicates that the ability to spread a message across different communities increase with the level of popularity (i.e. the number of edges) of a node. Moreover, a positive correlation coefficient has been found between dissemination efficacy and betweenness centrality ($r_{\mathrm{betweenness\ centrality}}$ = 0.472; [LL: 0.470; UL: 0.473]). Such measure, as described by Zhang *et al.* (2020), it is an indicator of bridging positions. However, users who often resides in the middle way of the shortest path of two other users, are those who have the highest probability to spread a product across different communities. Similarly, a positive correlation has been found between the closeness centrality and the dissemination efficacy ($r_{\mathrm{closeness\ centrality}}$ = 0.43; [LL: 0.418; UL:0.456]). It indicates that users with the shortest distance to other users, on average, tend to be more influential in spreading a recommendation across the entire network. Finally, the positive correlation between PageRank and dissemination efficacy (r_{PageRank} = 0.508; [LL: 0.500; UL: 0.515]) confirms a user linked to parsimonious vertex highly connected with relevant vertex is more able to spread the information across different neighborhoods (Figure 6). F6

Table 5. Bootstrap distribution of each network measure and the corresponding mean of correlation coefficients

Bootstrap sample	*r*_EigenCentrality	*r*_Embeddedness	*r*_ParticipationCoefficient	*r*_DegreeCentrality	*r*_ClosenessCentrality	*r*_BetweennessCentrality	*r*_PageRank
1	0.44 [0.39, 0.50]	−0.61 [−0.66, −0.55]	−0.39 [−0.45, −0.33]	0.40 [0.34, 0.47]	0.55 [0.49, 0.62]	0.47 [0.41, 0.54]	0.54 [0.48, 0.60]
2	0.40 [0.34, 0.46]	−0.56 [−0.62, −0.5]	−0.23 [−0.29, −0.17]	0.38 [0.32, 0.44]	0.56 [0.50, 0.62]	0.47 [0.41, 0.53]	0.50 [0.44, 0.56]
3	0.48 [0.34, 0.46]	−0.37 [−0.62, −0.5]	−0.34 [−0.43, −0.28]	0.41 [0.37, 0.47]	0.57 [0.50, 0.62]	0.47 [0.41, 0.53]	0.58 [0.52, 0.63]
…	…	…	…	…	…	…	…
50	0.42 [0.36, 0.48]	−0.57 [−0.63, −0.51]	−0.37 [−0.44, −0.31]	0.40 [0.33, 0.46]	0.45 [0.39, 0.52]	0.48 [0.41, 0.54]	0.53 [0.47, 0.59]
51	0.36 [0.30, 0.42]	−0.39 [−0.46, −0.33]	−0.42 [−0.52, −0.31]	0.40 [0.33, 0.46]	0.36 [0.30, 0.52]	0.47 [0.40, 0.53]	0.46 [0.40, 0.52]
…	…	…	…	…	…	…	…
99	0.42 [0.38, 0.50]	−0.11 [−0.17, −0.05]	−0.41 [−0.47, −0.35]	0.38 [0.28, 0.40]	0.34 [0.40, 0.52]	0.47 [0.40, 0.54]	0.50 [0.44, 0.56]
100	0.42 [0.36, 0.48]	−0.44 [−0.50, −0.38]	−0.42 [−0.48, −0.36]	0.39 [0.32, 0.45]	0.36 [0.33, 0.45]	0.48 [0.41, 0.54]	0.51 [0.45, 0.56]

Source(s): Authors’ own work

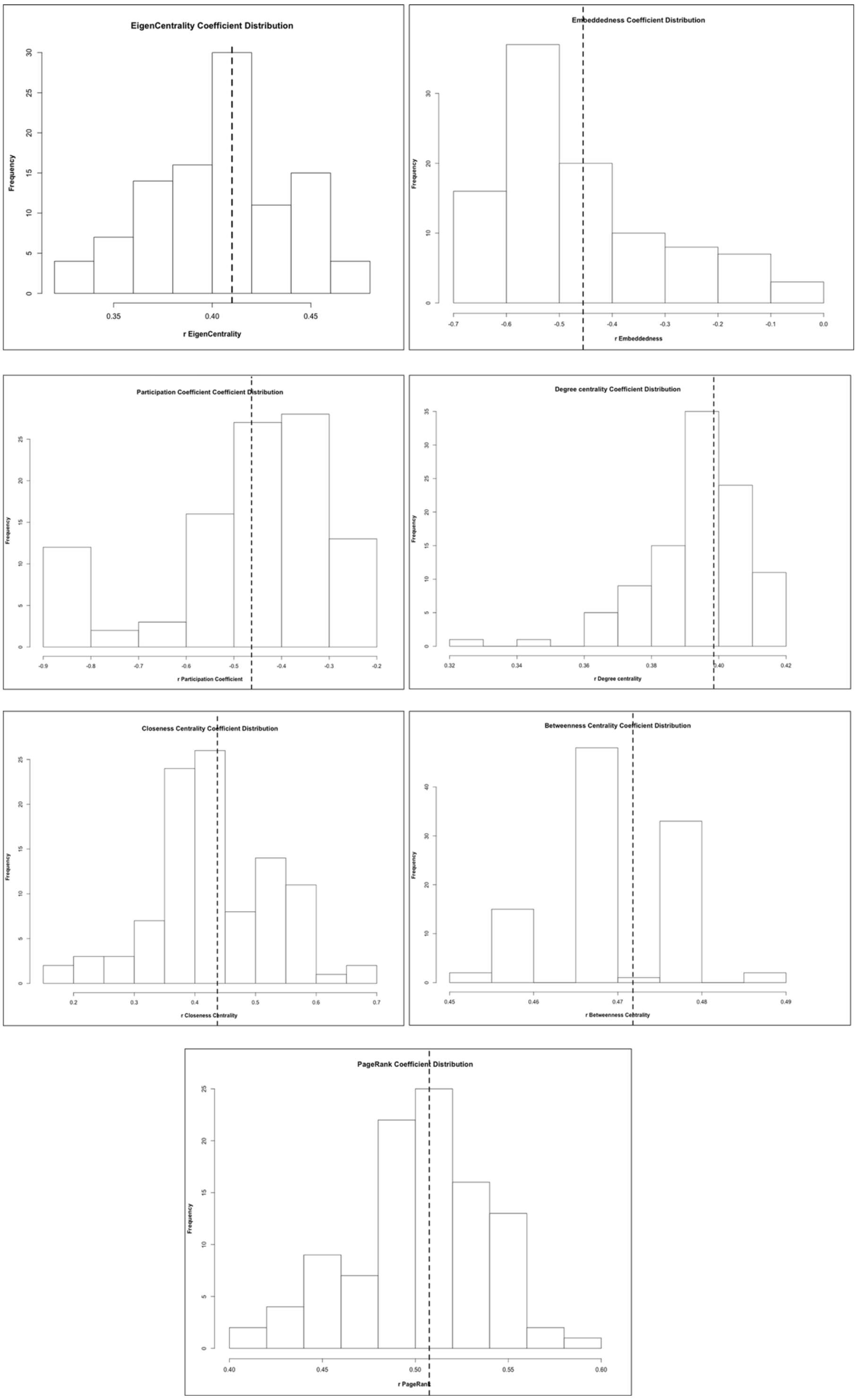

Figure 5. Bootstrap distribution of each network measure and the corresponding mean of correlation coefficients

Source: Authors' own work

Table 6. Mean of estimates and CIs

	*r*_EigenCentrality	*r*_Embeddedness	*r*_ParticipationCoefficient	*r*_DegreeCentrality	*r*_ClosenessCentrality	*r*_BetweennessCentrality	*r*_PageRank
Estimate (SE)	0.41 (0.003)	−0.45 (0.015)	−0.46 (0.018)	0.39 (0.002)	0.43 (0.010)	0.472 (0.001)	0.508 (0.004)
CI	[0.391; 0.414]	[−0.482; −0.423]	[−0.500; −0.430]	[0.395; 0.401]	[0.418; 0.456]	[0.470; 0.473]	[0.500; 0.515]

Source(s): Authors’ own work

Table 7. Results of one-way ANOVA

	*r*_EigenCentrality	*r*_Embeddedness	*r*_ParticipationCoefficient	*r*_DegreeCentrality	*r*_ClosenessCentrality	*r*_BetweennessCentrality	*r*_PageRank
SS	0.005	0.0004	0.028	0.0002	0.0017	0.0001	0.0029
MS	0.005	0.0004	0.027	0.0002	0.0017	0.0001	0.0029
F	2.946	0.014	0.508	0.849	0.143	1.704	1.817
p	0.08	0.90	0.47	0.359	0.70	0.19	0.18
Df	(1;99)	(1;99)	(1;99)	(1;99)	(1;99)	(1;99)	(1;99)

Source(s): Authors' own work

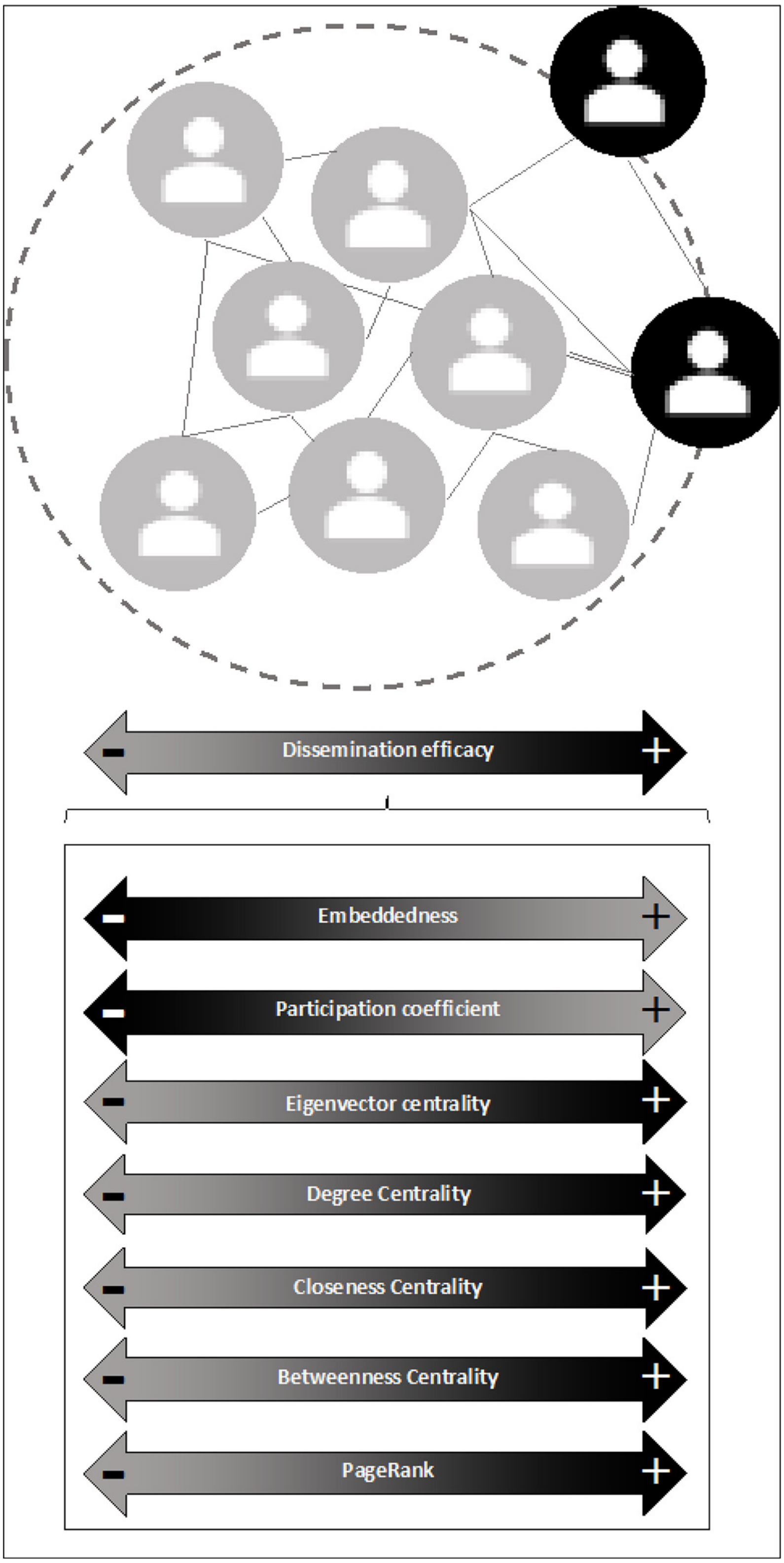

Figure 6. Dissemination efficacy according to the network measures
Source: Authors' own work

These associations reflect a structural continuum within the network, where users range from highly embedded community members (strong ties) with limited cross-community influence, to peripheral or bridging individuals (weak ties) whose positioning enables broader dissemination across substructures. Such substructures reveal differentiated user roles, from in-group communicators to inter-group connectors, offering strategic entry points for targeting recommendation flows. In addition to highly embedded and peripheral users, a subset of users emerged who occupy intermediate structural positions – neither fully central within a community nor completely marginal. These users often demonstrate moderate values of centrality, embeddedness and participation coefficient, placing them in a liminal zone between cohesion and outreach. Functionally, they may serve as boundary spanners, facilitating selective information transfer between clusters while retaining credibility within their home communities. Their position enables context-sensitive recommendation dissemination, making them valuable for bridging semi-related neighborhoods where full integration may be less effective. This role is especially relevant in cases where subtle content tailoring or domain-specific expertise is needed for cross-community influence.

Discussion

The results indicate that the recommendation-enabled network is not only extremely dense, with almost every user connected to nearly all others, but also structured in ways that reveal different patterns of interaction and influence. With over 37,427 users and 1,300 products generating nearly 695 million connections, the graph shows important variations in tie strength and in the roles played by individual users. Community detection uncovered fourteen statistically significant neighborhoods, each more internally cohesive than the network as a whole, but also populated by peripheral users who act as bridges to other communities. These peripheral actors are crucial for the transfer of information across groups, while highly embedded users tend to reinforce messages within their own community, leading to redundancy rather than broad dissemination. Measures of centrality and connectivity further clarify these dynamics: users who are closer to influential nodes, who occupy positions along the shortest paths between others or who maintain a higher degree of overall connections are more effective in spreading recommendations across the system. In contrast, users whose activity is concentrated within their own neighborhood, indicated by high embeddedness or strong within-community participation, have less impact on cross-community diffusion. Together, these findings suggest that recommendation networks operate along a continuum of roles: at one end, highly embedded actors serve as in-group communicators, ensuring repeated exposure within their communities; at the other, peripheral or bridging users extend the reach of recommendations beyond community boundaries, amplifying their spread. Between these extremes, some individuals emerge as boundary spanners who are neither fully central within their group nor entirely marginal, but strategically positioned to transfer information selectively while retaining trust and relevance within their own cluster. Such differentiated roles underscore the dual nature of recommendation networks, which simultaneously foster cohesion within communities and enable the circulation of messages across them, with important implications for understanding how influence, redundancy and novelty are distributed in large-scale digital environments.

Theoretical implications

Our study builds on prior research on weak ties and the literature on WOM (He *et al.*, 2021; Koo, 2016; Chiu *et al.*, 2014; Wirtz *et al.*, 2019; Lee and Kronrod, 2020) by applying strength of weak ties theory (Granovetter’s, 1973) to reframe how recommendation agents create connections – not through direct social interaction, but through patterns of behavioral similarity.

First, this study represents a meaningful departure from traditional WOM theory (Kozinets *et al.*, 2010) by revealing how RA-enabled networks operate and how they transform the dynamics of WOM. Rather than relying on explicit communication within peer networks, RA systems silently and implicitly orchestrate influence through algorithmic matchmaking. These implicit networks redefine coproduction (Kozinets *et al.*, 2010) by creating a dynamic system in which influence is distributed, reactivated and perpetuated through user behaviors (e.g. clicks and page views). As users respond to personalized recommendations, they contribute to a self-sustaining loop of algorithmic influence and behavioral alignment. Whereas traditional coproduction emphasized peer influence within explicit communities, where individuals shaped each other's consumption through direct communication (Kozinets *et al.*, 2010), RA-driven systems are algorithmically mediated: shared behaviors, rather than direct social interactions, become the foundation of influence. Users receive personalized recommendations derived from behavioral similarity with others, and by responding to these suggestions, they enter a cycle of mutual influence that reactivates the system. In this new model, users do not need to communicate directly to influence one another, marking a significant evolution of WOM theory: the recommender engine functions as an intermediary, a meta-layer of implicit ties formed silently through shared behaviors such as purchase history, browsing patterns and preference similarity.

As illustrated in Figure 7, RA systems thus redefine the classic WOM process. What was once constrained by physical proximity and explicit communication is now governed by behavioral resemblance, network structure and algorithmic logic. The social fabric of influence has shifted: weak ties, once valued primarily for their bridging potential in traditional networks, now extend their reach through algorithmic matchmaking and play a central role in the digital marketplace.

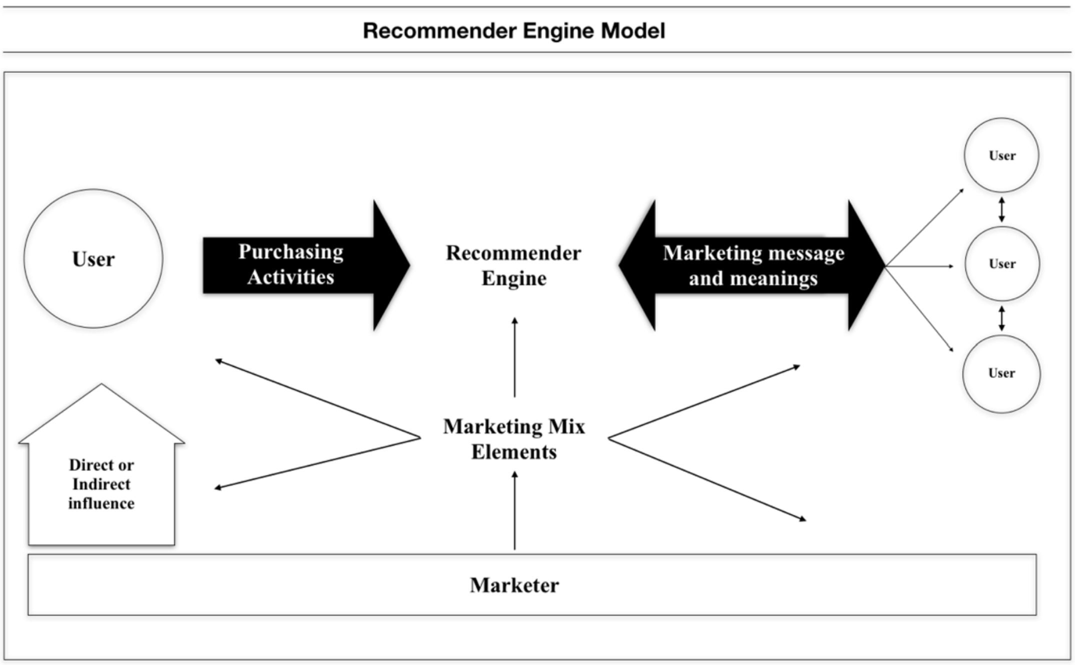

Figure 7. Recommendation process enabled by RAs
Source: Authors' own work

Second, this study adds to the WOM literature by focusing on the specific role of each user within RA-enabled implicit networks. While previous studies have explored tie strength in traditional e-WOM and recommendation effectiveness, few have considered the algorithmic construction of ties in digital environments. For example, He *et al.* (2021) emphasized the benefits of incorporating both strong and weak ties to enhance diversity and novelty in recommender systems, though at the cost of some accuracy. Their findings suggest that weak ties are relevant for accessing long-tail items and expanding recommendation reach. Our study further contributes by showing that weak ties not only diversify exposure but also enhance the spread of recommendations.

Third, this study extends our insight into weak ties, highlighting the importance of their quality in addition to their strength. While Koo (2016) found that strong ties enhance credibility and purchase intention in e-WOM, experienced weak-tie recommenders can be equally persuasive, our findings indicate that dissemination efficacy is not solely a function of tie strength or connection count, but also depends on the quality of those connections. Users with high eigenvector centrality – those connected to influential actors within the network – exerted disproportionate influence in spreading recommendations. Similarly, PageRank confirmed that users linked to high-value nodes had significantly greater dissemination potential. These results add nuance to the role of weak ties: weak-tie users connected to key influencers can become particularly powerful vectors of diffusion.

Chiu *et al.* (2014) showed that weak ties in digital environments facilitate bridging and utilitarian communication, while Wirtz *et al.* (2019) demonstrated that weak ties gain greater influence online due to reduced metaperceptive concerns and digital disinhibition. These findings align with our argument that RAs create implicit networked environments in which weak ties are not only possible but structurally empowered to influence a broader audience.

Furthermore, Lee and Kronrod (2020) observed that weak ties using consensus language on social platforms can surpass strong ties in persuasive impact, as they are perceived as more diverse and broadly connected. This resonates with our findings that RA-mediated weak ties link users across heterogeneous communities, enabling broader exposure and more effective dissemination.

Practical implications

To enhance the practical relevance of our research, we conducted interviews with senior managers from two of the world's top six technology companies (Forbes, 2025) – specifically, a major e-commerce platform and a leading streaming service. These discussions confirmed the timeliness and importance of our study, as it addresses a pressing concern for online marketplaces that rely on recommendation agents (RAs) to foster user engagement. The managers emphasized that increasingly stringent privacy regulations are limiting RAs' access to third-party data, forcing digital platforms to increasingly rely on first-party data. As a result, many RAs now produce repetitive, less diverse recommendations, creating a critical need for strategies that can enhance recommendation diversity without compromising user privacy. In light of this challenge, companies may benefit from adopting a hybrid recommendation approach – one that balances diversity with specialization. Such a strategy can promote the discovery of novel content, maintain a sense of personalization and boost overall user engagement.

Our findings have also substantial implications for marketers aiming to amplify the spread of product recommendations on an e-commerce platform. When using recommendation agents (RAs), marketers must intricately understand the network dynamics and the distinct roles played by users within it. This necessitates a reevaluation of the targeting strategy, acknowledging that users exhibit different levels of recommendation dissemination and can be approached accordingly. By strategically targeting users with bridge roles to initiate product purchases and leveraging collaborative filtering within neighborhoods, marketers can effectively trigger recommendations to thousands of users across various neighborhoods.

However, for this automated influence mechanism to be activated, marketers must first identify and persuade the bridging user to purchase the product. If this specific user does not complete the purchase, the algorithmic chain reaction (e.g. "You may also like" or "Users who bought this also bought") will not be initiated, and the potential wide-scale dissemination across multiple neighborhoods will be lost. Conversely, if the bridging user does make the purchase, the recommendation engine automatically launches a silent, large-scale campaign, diffusing the product information to a far greater number of users than what could be achieved through traditional strong-tie pathways. This underscores the strategic imperative for marketers to recognize and convert these high-diffusion nodes as a first step in their campaign architecture.

To this end, in recent years, advancements in other domains have proposed measures to assist practitioners in recognizing users in bridge positions. For instance, Vikatos *et al.* (2020) explored the application of bridge-extraction algorithms on platforms like X and Foursquare, introducing metrics to characterize bridge participation based on users' peripheral positions situated between their own network and others. This insight also holds implications for e-tailers relying on RAs for product recommendations. Empowering brands to refine their user targeting choices by delineating users' roles in the community and offering automated bridge-extraction methods could enhance the experience for users in bridge positions by increasing their likelihood of receiving promotions or discounts; provide sellers with diverse targeting strategy options, granting more control over outcomes; and broaden e-tailers' business models by defining different pricing tiers based on the marketer's targeting approach.

Moreover, our findings suggest that the ideal tie strength to target depends heavily on specific marketing objectives. If the goal is to maximize reach and increase product exposure across multiple user clusters, weak ties are the most effective. Conversely, if the aim is to boost conversions by reinforcing product credibility and driving action within trusted groups, strong ties should be prioritized.

Importantly, beyond traditional marketing implications, our research highlights a transformative potential of weak ties in extending the marketing value chain. Weak ties, when effectively leveraged and valorized through RAs, enable marketers to access new and previously hidden target segments – long-tail audiences that often remain undetected through direct analysis. Ex post purchase data reveals these new "long tail" segments, allowing marketers to activate a virtuous cycle:

- RAs discover new weak ties;
- RAs deliver recommendations to these hidden segments;
- these segments gain awareness of products they previously did not know or consider, potentially appreciating their value if the algorithm functions well;
- companies pragmatically identify new customers with minimal prior connections to existing buyers; and
- traditional CRM and customer management strategies can then be deployed for these newly uncovered targets.

This cycle embodies a progressive growth model of the user base, moving consumers from weak, implicit ties toward more explicit, mild and eventually strong ties through engagement programs. Marketing for weak ties thus becomes a distinct approach – one that integrates commercial, organizational and operational elements – to navigate effectively across the customer journey, from broad awareness to deep engagement. This contrasts with one-size-fits-all recommendation strategies, emphasizing a calibrated balance: weak ties for top-of-funnel reach and strong ties for bottom-of-funnel conversion and retention. In addition, it expands marketers' ability to identify cross-selling and up-selling opportunities and to engage consumers in ways that were hidden or less evident in traditional frameworks. By bridging disparate user clusters, weak ties foster the emergence of new promotional avenues and richer engagement paths, effectively embedding the influence process deeper into the marketing value chain. In this sense, RA systems do not simply replicate existing WOM dynamics; they transform the very nature of marketing coproduction, creating a more fluid, dynamic and far-reaching ecosystem of consumer influence and value creation.

Along the spectrum of social others, there are then opportunities that extend beyond interactions with proximal individuals or AI-generated forms of interactions (Mazzù *et al.*, 2024). These opportunities involve distal individuals (Hamilton *et al.*, 2021), those connected through so-called weak ties. Increasing attention should be then given to these distant connections, prompting the emergence of a distinct approach referred to as marketing for the weak ties. Distal social others include broad audiences or society at large, people who are often anonymous, unfamiliar or absent from the consumer's immediate social environment. Despite their weaker connections, they play a crucial role in generating new behavioral insights and spreading information across social groups, thereby influencing other consumers' decision-making processes.

Thus, marketers should aim at developing a specific marketing for weak ties, that integrate commercial, organizational and operational elements to move effectively along the funnel and beyond a one-size-fits-all recommendation strategy. Instead, they must balance weak and strong ties according to their position in the funnel: weak ties for top-of-funnel reach and awareness, and strong ties for bottom-of-funnel conversion and retention. Future research and managerial applications may benefit from exploring how to calibrate this balance effectively, and from identifying optimal tie strengths that connect neighborhoods without diluting influence due to behavioral dissimilarity.

Limitations and future research

Our study presents several limitations that offer promising directions for future research. First, we relied on a 2018 public Amazon data set, which did not include users' sociodemographic information. Future studies could examine whether implicit neighborhoods evolve over time and whether bridging users maintain their structural roles or become absorbed into communities.

Second, our analysis focused on Amazon gift card transactions, raising the question of whether tie dynamics differ for high- versus low-involvement products. Prior research suggests that the influence of RAs varies by product type and expertise, and future work could examine how tie strength interacts with product and user characteristics to influence recommendation outcomes (Baccelloni *et al.*, 2025, Song *et al.*, 2025).

Third, our study emphasized the diffusion of recommendations rather than the conversion rate of the recommended products. Analyzing actual purchase behavior in response to recommendations would provide richer insight into the persuasive efficacy of RA-mediated networks (Hamilton *et al.*, 2021).

Finally, our research introduces and validates a structural framework that reconceptualizes how digital WOM emerges and spreads through RA-enabled implicit networks (Kozinets *et al.*, 2010). By identifying the roles of weak, strong and bridging ties in such environments, we provide both theoretical and practical insights that pave the way for future inquiry into the evolution, effectiveness and strategic utilization of algorithmically constructed consumer networks.

Note

[1.] Modularity is a measure of the structure of networks or graphs which measures the strength of division of a network into modules (also called groups, clusters or communities). Networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules.

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Further reading

Zhang, H. and Gong, X. (2021), “Consumer susceptibility to social influence in new product diffusion networks: how does network location matter?”, *European Journal of Marketing*, Vol. 55 No. 5, pp. 1469-1488.

Appendix. Script

#Dataset pre-processing in Python

In [ ]:

```
# Imports
import os
import json
import gzip
import pandas as pd
from urllib.request import urlopen
import numpy as np
```

In [ ]:

```
#Get "also buy" recommendation

metadata = pd.read_json('meta_Gift_Cards.json',lines=True)
metadata.head()

metadata = metadata[['also_buy','asin']]

metadata_object = []

for index, row in metadata.iterrows():
    new_object = {"asin":"", "also_buy":""}
    new_object["asin"] = row["asin"]
    new_object["also_buy"] = row["also_buy"]
    new_object["also_buy"].sort()
    metadata_object.append(new_object)
```

In [ ]:

```
#Append recommendation to ASINs

all_arrays = []

for row in metadata_object:
    all_arrays.append(row["also_buy"])


xt = np.concatenate(all_arrays)
asin_univoci = list(set(xt))
```

In [ ]:

```
#Get Reviewers/Shopper and associated ASIN
reviews = pd.read_json('Gift_Cards.json',lines=True)

reviews = reviews[['reviewerID','asin']]

reviews.head()

len(reviews)

reviewers_oggetto = []

for index, row in reviews.iterrows():
```

(*continued*)

```
    new_object = {"asin":"", "reviewerID":""}
    new_object["asin"] = row["asin"]
    new_object["reviewerID"] = row["reviewerID"]
    reviewers_oggetto.append(new_object)
```

In [ ]:

```
# Unique reviewers
all_reviewers = []

for row in reviewers_oggetto:
    all_reviewers.append(row["reviewerID"])

reviewer_univoci = list(set(all_reviewers))

df = pd.DataFrame(0, columns = asin_univoci, index=reviewer_univoci, dtype=object)
```

In [ ]:

```
#Match Reviewers/Shopper and recommendation received

for review in reviewers_oggetto:
    asin_da_trovare = review["asin"]

    found_product = {}
    for x in metadata_object:
        if x["asin"] == asin_da_trovare:
            found_product = x
            break
        else:
            x = None

    for product in found_product["also_buy"]:

        df.at[review["reviewerID"],product] =  df.at[review["reviewerID"],product] + 1
        print(review["reviewerID"], product)
        print("\n")
```

In [ ]:

```
#Data analysis in R
```

In [ ]:

```
# Libraries
library(igraph)
library(sna)
require(ape)
library(NetworkToolbox)
library(bipartite)
library(dnet)
library(bigalgebra)
```

In [ ]:

```
#load initial edgelist
network_csv <- read.csv("alllines.csv", header=FALSE)
```

In [ ]:

```
#Graph based on edglist + df removal
network_graph <- graph.data.frame(network_csv, directed=T)
rm(network_csv)
```

(continued)

In [ ]:

```
#Bipartite Graph User*Recommended item
V(network_graph)$type <- bipartite_mapping(network_graph)$type # Two-mode graph
V(network_graph)$color <- ifelse(V(network_graph)$type, "lightblue", "salmon")
V(network_graph)$shape <- ifelse(V(network_graph)$type, "circle", "square")
E(network_graph)$color <- "lightgray"
V(network_graph)$size <- 10
```

In [ ]:

```
#Incidence matrix - User-product
personproduct_matrix1 <- as_incidence_matrix(network_graph)
colnames(personproduct_matrix1) <- gsub(' ',",colnames(personproduct_matrix1))
```

In [ ]:

```
#remove unused dfs
rm(network_graph)
```

In [ ]:

```
# Adjacency matrix user*user + links within the cells
person_person_matrix <- (personproduct_matrix) %*% t(personproduct_matrix)
diag(person_person_matrix) <- 0
```

In [ ]:

```
# User*User graph
person_person_graph1 <- graph_from_adjacency_matrix(person_person_matrix,
mode="undirected", weighted = TRUE)
# Removal of isolated elements
Isolated = which(igraph::degree(person_person_graph1)==0)
person_person_graph <- igraph::delete.vertices(person_person_graph1, Isolated)
```

In [ ]:

```
rm(person_person_graph1)
```

In [ ]:

```
# Graph measures
#diameter is the length of the longest path (in number of edges) between two nodes
diameter(person_person_graph, directed=FALSE, weights=NA)
```

In [ ]:

```
#mean_distance is the average number of edges between any two nodes in the network
mean_distance(person_person_graph, directed=FALSE)
```

In [ ]:

```
#edge_density is the proportion of edges in the network over all possible edges that could exist
edge_density(person_person_graph)
```

In [ ]:

```
#reciprocity measures the propensity of each edge to be a mutual edge; that is, the probability
that if i is connected to j, j is also connected to i.
reciprocity(person_person_graph)
```

In [ ]:

```
#transitivity, also known as clustering coefficient, measures that probability that adjacent
nodes of a network are connected. In other words, if i is connected to j, and j is connected to k,
what is the probability that i is also connected to k?
igraph::transitivity(person_person_graph, type="global")
```

In [ ]:

```
#degree, the number of adjacent edges to each node. It is often considered a measure of direct
influence.
mean(igraph::degree(person_person_graph))
```

In [ ]:

(*continued*)

#Strength is a weighted measure of degree that takes into account the number of edges that go from one node to another. In this network, it will be the total number of interactions of each character with anybody else.

```
mean(igraph::strength(person_person_graph))
```

In [ ]:

#Closeness measures how many steps are required to access every other node from a given node. It's a measure of how long information takes to arrive (who hears news first?). Higher values mean less centrality.

```
mean(igraph::closeness(person_person_graph))
```

In [ ]:

#Betweenness measures brokerage or gatekeeping potential. It is (approximately) the number of shortest paths between nodes that pass through a particular node.

```
mean(igraph::betweenness(person_person_graph))
```

In [ ]:

#participation coefficient

```
min(participation(person_person_matrix, comm = c("walktrap", "louvain"))$overall)
max(participation(person_person_matrix, comm = c("walktrap", "louvain"))$overall)
mean(participation(person_person_matrix, comm = c("walktrap", "louvain"))$overall)
```

In [ ]:

#degree distribution and vertex and edges count

```
ecount(person_person_graph)
vcount(person_person_graph)
```

In [ ]:

#community detection

```
kc <- multilevel.community(person_person_graph)
```

In [ ]:

#size of community detected

```
sizes(kc)
```

In [ ]:

 # modularity

```
modularity(kc)
```

In [ ]:

#Wilcoxon t-test

```
dCommSignif(person_person_graph,comm = kc)
```

In [ ]:

 # density network vs density neighborhood

```
graph.density(person_person_graph)
```

In [ ]:

#density communities

```
for (index in 1:length(kc)){
  ego.admin <- induced.subgraph(graph=person_person_graph, kc[[index]])
  print(graph.density(ego.admin))
  print(index)
}
```

In [ ]:

#nodes measures

```
persons_with_measures <- matrix(nrow = nrow(person_person_matrix), ncol = 9)
rownames(persons_with_measures) <- rownames(person_person_matrix)
colnames(persons_with_measures) <- c('EigenCentrality', 'Embeddedness (Transitivity)',
'ParticipationCoefficient', 'DegreeCentrality', 'ClosenessCentrality', "Authority",
"BetweennessCentrality","PageRank", "DiffusionPower")
```

(*continued*)

In [ ]:

```
# eigencentrality
persons_with_measures[,'EigenCentrality'] <- eigen_centrality(person_person_graph, directed =
FALSE, weights = NULL, options = arpack_defaults)$vector
```

In [ ]:

```
#closeness centrality
persons_with_measures[,'ClosenessCentrality'] <- igraph::estimate_closeness(person_person_graph,
mode = "all", cutoff=1)[1000:3000]
```

In [ ]:

```
# embeddedness
persons_with_measures[,'Embeddedness (Transitivity)'] <-
igraph::transitivity(person_person_graph, type='local')[1:2000]
```

In [ ]:

```
# participation coefficient
persons_with_measures[,'ParticipationCoefficient'] <- participation(person_person_matrix, comm =
c("walktrap", "louvain"))$overall
```

In [ ]:

```
# degree centrality
persons_with_measures[,'DegreeCentrality'] <- centr_degree(person_person_graph)$res
```

In [ ]:

```
#authority
persons_with_measures[,'Authority'] <-authority_score(person_person_graph)$vector
```

In [ ]:

```
#betweeness centrality
persons_with_measures[,'BetweennessCentrality'] <-
igraph::estimate_betweenness(person_person_graph,directed = FALSE, cutoff=2)[1000:2000]
```

In [ ]:

```
#Page Rank
persons_with_measures[,'PageRank'] <- page_rank(person_person_graph)$vector
```

In [ ]:

```
#Definition of recommendation diffusion indicator
```

In [ ]:

```
#Cluster*Sum of recommended products Matrix
cluster_product <- matrix(0L, nrow = length(kc), ncol = ncol(personproduct_matrix))
colnames(cluster_product) <- colnames(personproduct_matrix)


for (cluster_index in 1:length(kc)) {


  for (person in 1:length(kc[[cluster_index]])) {

    cluster_product[cluster_index,] <- array(cluster_product[cluster_index,]) +
array(personproduct_matrix[person,])

  }

}
```

In [ ]:

```
#Recommended products to a cluster
cluster_product[cluster_product==0] <- NA
```

(*continued*)

In [ ]:
```
#Products bought by each individual
product_purchases_matrix <- read.csv("acquisti.csv", row.names = 1)
product_purchases_matrix <- as.matrix(product_purchases_matrix)
cluster_product_purchase <- matrix(0L, nrow = length(kc), ncol = ncol(product_purchases_matrix))
colnames(cluster_product_purchase) <- colnames(product_purchases_matrix)
```
In [ ]:
```
for (cluster_index in 1:length(kc)) {


 for (person in 1:length(kc[[cluster_index]])) {

   cluster_product_purchase[cluster_index,] <- array(cluster_product_purchase[cluster_index,]) +
array(product_purchases_matrix[person,])

 }

}
```
In [ ]:
```
#Count of product bought by each individual in the cluster
```
In [ ]:
```
cluster_product_purchase[cluster_product_purchase==0] <- NA
```
In [ ]:
```
reccommended_buy_matrix <- matrix(0L, nrow = length(kc), ncol =
ncol(product_purchases_matrix))
colnames(cluster_product_purchase) <- colnames(product_purchases_matrix)

for (row in 1:nrow(cluster_product)) {
 for(column in 1:ncol(cluster_product)) {
   if(is.na(cluster_product[row, column]) == FALSE && is.na(cluster_product_purchase[row,
column]) == FALSE) {
     if (cluster_product[row, column] > 0 && cluster_product_purchase[row, column] > 0) {
       reccommended_buy_matrix[row, column] <- cluster_product[row, column]
     }
   }

 }

}
```
In [ ]:
```
#Count how many times a product has been purchased in a cluster
reccommended_buy_matrix[reccommended_buy_matrix==0] <- NA
```
In [ ]:
```
product_cluster_matrix_diffusion <- matrix(0L, nrow = nrow(person_person_matrix), ncol =
length(kc))
rownames(product_cluster_matrix_diffusion) <- rownames(person_person_matrix)
```
In [ ]:
```
#Matrix for recommendation diffusion - From one user to n clusters
for (person in rownames(product_cluster_matrix_diffusion)) {
 # prodotti acquistati dalla persona
 purchases <- colnames(product_purchases_matrix)[product_purchases_matrix[person,] > 0]
```
(*continued*)

```
  for (purchase in purchases) {
    for (cluster_index in 1:length(kc)) {
      #print(cluster_product[cluster_index,][purchase])
      if (is.na(cluster_product[cluster_index,][purchase]) != T) {
        #print(purchase)
        product_cluster_matrix_diffusion[person,cluster_index] <- 1
      }
    }
  }
}
```

In [ ]:

```
#Attach to matrix
product_cluster_matrix_diffusion[product_cluster_matrix_diffusion==0] <- NA
#rowMeans(product_cluster_matrix_diffusion, na.rm = TRUE)
#rowSums(product_cluster_matrix_diffusion, na.rm = TRUE)
colnames(product_purchases_matrix)[is.na(product_purchases_matrix) == FALSE]
colnames(product_purchases_matrix)
colnames(product_cluster_matrix_diffusion)
persons_with_measures[,'DiffusionPower'] <- rowSums(product_cluster_matrix_diffusion,na.rm =
TRUE)
```

In [ ]:

```
if(!require(psych)){install.packages("psych")}
if(!require(PerformanceAnalytics)){install.packages("PerformanceAnalytics")}
if(!require(ggplot2)){install.packages("ggplot2")}
if(!require(rcompanion)){install.packages("rcompanion")}
```

In [ ]:

```
#correlation among values per matrix
corr.test(persons_with_measures,
          use    = "pairwise",
          method = "pearson",
          adjust = "none")
```

In [ ]:

```
#Iterate 100 correlation matrices (with n=1000) using RMarkdown and get a report

library(knitr)
library(markdown)
library(rmarkdown)
library(stringr)

subsample <- c(1:100)

for(i in 1:length(subsample)){
  rmarkdown::render(
    input = "NetworkAnalysis-Markdown.Rmd",
    output_file = NULL,
    params = list(subsample  = subsample[i]))
}
```

In [ ]:

```
#Correlation table in APA format
```

(*continued*)

```
apa.cor.table(persons_with_measures, filename = paste0("Report_",Sys.time(),".rtf"))
```

In [ ]:

```
#All correlation tables have been combined through Excel and then processed in R again
```

In [ ]:

```
dataset <- read_excel("~/RTF/Coefficientsestimates.xlsx")
```

In [ ]:

```
#plot correlation coefficients distribution
hist(dataset$`1. EigenCentrality`, col="white", border="black", main="EigenCentrality Coefficient
Distribution", font.lab=2, xlab="r EigenCentrality")
abline(v=mean(dataset$`1. EigenCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$`1. EigenCentrality`)

hist(dataset$'2. Embeddedness', col="white", border="black", main="Embeddedness Coefficient
Distribution", font.lab=2, xlab="r Embeddedness")
abline(v=mean(dataset$`2. Embeddedness`),col="black",  lwd=3, lty=2)
mean(dataset$'2. Embeddedness')

hist(dataset$'3. ParticipationCoefficient', col="white", border="black", main="Participation
Coefficient Coefficient Distribution", font.lab=2, xlab="r Participation Coefficient" )
abline(v=mean(dataset$`3. ParticipationCoefficient`),col="black",  lwd=3, lty=2)
mean(dataset$'3. ParticipationCoefficient')

hist(dataset$'4. DegreeCentrality', col="white", border="black", main="Degree centrality
Coefficient Distribution", font.lab=2, xlab="r Degree centrality")
abline(v=mean(dataset$`4. DegreeCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$'4. DegreeCentrality')

hist(dataset$'5. ClosenessCentrality', col="white", border="black", main="Closeness Centrality
Coefficient Distribution", font.lab=2, xlab="r Closeness Centrality ")
abline(v=mean(dataset$`5. ClosenessCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$'5. ClosenessCentrality')

hist(dataset$'6. BetweennessCentrality', col="white", border="black", main="Betweenness
Centrality Coefficient Distribution", font.lab=2, xlab="r Betweenness Centrality")
abline(v=mean(dataset$`7. BetweennessCentrality`),col="black",  lwd=3, lty=2)
mean(dataset$'6. BetweennessCentrality')

hist(dataset$'7. PageRank', col="white", border="black", main="PageRank Coefficient
Distribution", font.lab=2, xlab="r PageRank ")
abline(v=mean(dataset$`8. PageRank`),col="black",  lwd=3, lty=2)
mean(dataset$'7. PageRank')
```

In [ ]:

```
#ANOVAs after Fisher's transformation
model <- aov(dataset$'Z-EigenCentrality'~dataset$'Sample', dataset)
model1 <- aov(dataset$'Z-Embeddedness'~dataset$'Sample', dataset)
model2 <- aov(dataset$'Z- ParticipationCoefficient'~dataset$'Sample', dataset)
model3 <- aov(dataset$'Z- DegreeCentrality'~dataset$'Sample', dataset)
model4 <- aov(dataset$'Z- ClosenessCentrality'~dataset$'Sample', dataset)
model5 <- aov(dataset$'Z-Authority'~dataset$'Sample', dataset)
model6 <- aov(dataset$'Z- BetweennessCentrality'~dataset$'Sample', dataset)
model7 <- aov(dataset$'Z- PageRank'~dataset$'Sample', dataset)
```

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