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BEYOND THE NUMBER OF FOLLOWERS
Measuring Social Media Resonance Based on Direct Interactions

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ABSTRACT

In the context of the digital attention economy, the following analysis presents SlimScore, a method for assessing the resonance of content in social networks, focusing on direct interactions. To test the effectiveness of the tool, a study is carried out focusing on the social network X, based on a sample of 345,000 messages from more than 17,000 nodes (profiles). Through a comparative analysis with the Ayzenberg Social Index metric, it is shown how this approach provides more accurate results in measuring the virality of messages in social networks.

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1. Introduction

In the rapidly evolving landscape of the digital care economy, social networking sites (SNS) have emerged as critical platforms for shaping public discourse, cultural trends and individual behaviour. . Analysis of these platforms offers invaluable insights into the dynamics of information dissemination, engagement and influence. However, the complexity and breadth of social media data requires sophisticated approaches to accurately assess the impact of visual content and other forms of communication. This analysis introduces a novel method that focuses on direct interactions (sharing, mentioning and liking) to assess resonance, providing a deeper understanding of the influence of content in the digital environment.

In this context, it is crucial to distinguish between resonance, salience and influence. Resonance refers to the depth of engagement and emotional connection that content creates with its audience, often generating meaningful interactions. While salience is related to visibility, it does not necessarily mean positive engagement, often resulting from controversy or sensationalism. Influence encompasses the ability to influence perceptions, behaviours or decisions based on both the quality and quantity of engagement (Kaplan and Haenlein, 2010; Cha et al., 2010). The combination of these concepts can lead to misunderstandings about the true impact of social media content, highlighting the need for clear distinctions and robust analytical frameworks.

Furthermore, the rise of artificial intelligence and automated systems to generate hoaxes on social networks poses additional challenges and complicates the task of distinguishing genuine engagement from manipulated metrics (Ferrara et al., 2016). The proliferation of bots and fake accounts can inflate engagement statistics, misleading content creators and analysts about the true resonance of their content. There is therefore an urgent need for standardised methods that can distinguish authentic interactions from artificially generated rumours, ensuring the integrity and usefulness of social media analytics.

As digital platforms evolve, they play a critical role in shaping public discourse, cultural norms and political landscapes. This importance is underscored by the sheer volume of data generated by users around the world, providing a rich tapestry of human interaction and information exchange. In addition, there is a growing need for standards to distinguish between organically generated rumours and artificially amplified content in order to maintain the integrity and authenticity of online discourse.

With the rise of sophisticated algorithms and artificial intelligence in the selection and promotion of content on social media, there is growing concern about artificial rumours and echo chambers, where users are increasingly exposed to homogenised content (Pariser, 2011; Sunstein, 2017). This trend not only distorts perceptions of public opinion, but also undermines the democratic potential of social networks by limiting exposure to diverse viewpoints. There is therefore an urgent need for standards and mechanisms that can distinguish between content that truly resonates with human users and content that is artificially amplified for ulterior motives, such as political manipulation or commercial gain (Lazer et al., 2018).

1.1. Resonance, Notoriety and Influence

Critical examinations of social media highlight its role as a double-edged sword, facilitating democratic participation and community building, but also enabling the spread of misinformation and the manipulation of public opinion (Tufekci, 2017; Woolley & Howard, 2018). This duality highlights the importance of analysing the mechanisms of resonance, notoriety and influence within these platforms.

Distinguishing between resonance, notoriety and influence in the context of social networks is essential to understanding the nuanced dynamics of digital communication and social behaviour. Resonance refers to the degree to which a message or idea resonates within a community, amplified by the structural characteristics of the network and the relevance or emotional impact of the content (McQuail, 2010). It signifies the depth of engagement and the degree of amplification of the message, without necessarily implying a positive or negative evaluation.

Notoriety is a form of recognition or fame that often carries negative connotations and highlights the visibility that results from controversial, unusual or socially deviant actions or characteristics (Flynn et al.2017). While celebrity can increase the prominence of an individual or idea, it does not inherently imply persuasiveness or the ability to directly change the behaviour or beliefs of others.

Influence involves the ability to affect the opinions, behaviours or decisions of others by using mechanisms of persuasion, social proof and authority (Hennig-Thurau et al., 2010). Influence in social networks can be exerted through both resonance and salience, but specifically denotes an effect on change, be it attitude, perception or action.

The interplay between these concepts is complex. Resonance can generate influence when content that deeply engages a community also persuades members to adopt new beliefs or behaviours. Awareness can generate attention and facilitate influence, but it may not generate the positive engagement or agreement that resonance implies. The key difference lies in the quality of engagement and the outcome of the engagement process. While resonance and salience contribute to visibility and engagement, influence is the fundamental ability to drive change within that visibility.

1.2. The Concept of Resonance in Literature

In the digital age, social networks have become critical spaces for disseminating ideas, shaping public opinion and facilitating widespread influence. The concept of social media resonance refers to the degree to which content, ideas or messages resonate and amplify within these digital communities, profoundly affecting the dynamics of persuasion and influence. This phenomenon takes advantage of the networked nature of social media, where information can spread virally and reach far beyond its original audience.

Resonance in social networks is deeply intertwined with theories of persuasion and influence, building on foundational concepts such as the Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986) and Social Influence Theory (Cialdini, 2001). The ELM suggests that messages can persuade individuals via a central or peripheral route, depending on the audience's motivation and ability to process information (Petty and Cacioppo, 1986). In the context of social networks, resonance can enhance the peripheral route of persuasion by using social cues and the apparent popularity of ideas to influence attitudes and behaviour.

In addition, the principles of social influence theory, which include conformity, compliance and obedience (Cialdini, 2001), are manifested in the way messages resonate and spread through social networks. The visibility of others' endorsements, likes and shares serves as social proof, a powerful influence mechanism that guides individuals' perceptions and actions in line with perceived social norms.

The concept of resonance is also related to the theory of diffusion of innovations (Rogers, 2003), which examines how new ideas, practices or products spread within a community or society. In social networks, resonance can accelerate the diffusion process because highly resonant messages can quickly reach a "tipping point" (Gladwell, 2000) where their adoption spreads rapidly throughout the network.

In analysing the resonance of messages in social networks, researchers also consider the role of network structure, including the strength of weak ties (Granovetter, 1973) and the importance of influencers within network groups (Katz and Lazarsfeld, 1955). These structural elements of social networks have a significant impact on the flow of information and the potential for messages to resonate and influence at scale.

Resonance within social networks is a multifaceted phenomenon that is critical to understanding the dynamics of information dissemination, engagement and influence in the digital age. Unlike mere exposure or visibility, resonance implies a deeper level of interaction between content and its audience, characterised by emotional engagement, shared values and the reinforcement of community identities. This engagement is not merely passive; it actively shapes audiences' perceptions, beliefs and ultimately actions by aligning content with their personal and collective narratives.

At its core, resonance is about connection. It occurs when content resonates with people, echoing their experiences, aspirations or fears, thereby fostering a sense of community and shared understanding. For example, Slater (2007) analyses narrative persuasion and suggests that stories that are closely aligned with an individual's narrative identity are more likely to resonate and have a greater persuasive effect. This alignment between the narrative structure of the content and the self-concept or worldview of the audience is a critical aspect of resonance in digital communities.

Digital platforms amplify resonance through algorithms that select content based on users' preferences, behaviours and social connections (Pariser, 2011). This algorithmic curation can create echo chambers where resonant content is more likely to circulate within ideologically homogeneous networks, reinforcing the sense of resonance among like-minded people (Sunstein, 2017). The role of algorithms in shaping resonance highlights the interplay between technology and social dynamics, where digital architectures facilitate the amplification of resonant messages.

Furthermore, the concept of resonance extends beyond individual psychological processes to collective behaviours. The viral spread of memes, hashtags and movements on social media illustrates how resonance can mobilise communities around common causes or cultural moments (Milner, 2013). These instances of collective resonance demonstrate the power of social media not only to reflect, but also to shape social norms and public discourses.

Measuring resonance on social networks often relies on quantitative metrics such as 'likes', 'shares' and comments, which can provide information about the depth of engagement and dissemination of content. However, these metrics only scratch the surface of the emotional and cognitive processes that underlie resonance. Qualitative analyses, including sentiment analysis and thematic analysis of user interactions, provide a richer understanding of how and why particular content resonates within communities (Jenkins et al., 2013).

In addressing the challenges of resonance, researchers have raised concerns about the potential for misinformation, polarisation and the reinforcement of harmful stereotypes through resonant content (Allcott & Gentzkow, 2017). These challenges highlight the need for a nuanced understanding of resonance that considers both its positive and negative impacts on society.

1.3. Social Index and its Limits on Resonance Measurement

The Ayzenberg Earned Media Value (EMV) Index, often referred to as the Social Index, has become a fundamental standard within the public relations industry for evaluating earned media (Dwyer, 2007). This tool provides companies with a quantitative framework for evaluating the performance of their earned media efforts by providing a structured method for assigning monetary values to various social media interactions, including likes, shares and comments. The valuation derived from these interactions facilitates a comprehensive understanding of the return on investment (ROI) of social media campaigns (Chung & Koo, 2015) and enables the identification of trends on key platforms such as X, Snapchat, Instagram, Facebook and YouTube.

Beyond its core functions, the Social Index serves as a critical dataset for decision making, enabling the comparison of EMV data across time periods and the identification of underlying trends in digital marketing strategies. This capability underlines the Index's role in demonstrating the tangible impact of social media initiatives on brand awareness and engagement.

While the Social Index is a valuable tool for measuring media performance, it is recommended that it be used in conjunction with other EMV analytics tools to gain a holistic view of a campaign's effectiveness. The core metrics of influencer marketing (Manthiou et al., 2016), including reach, impressions, engagement rate, conversion and sales, and sentiment analysis, complement the insights provided by the Social Index and provide a multifaceted perspective on digital marketing effectiveness.

The application of EMV methodologies, such as the Ayzenberg Social Index, is critical in assessing the importance of content in relation to brand marketing efforts (Ahuja, 2012). By using a formula that measures the impact of digital marketing strategies against other outreach efforts, the EMV method provides a valuable benchmark for evaluating the effectiveness of organisational marketing efforts in the digital realm, particularly in sectors such as Spanish tourism marketing, which is increasingly using influencers to improve brand engagement.

In critically evaluating the Ayzenberg Earned Media Value Index, it is important to recognise its inherent limitations, in particular its reliance on the number of followers to estimate impressions and engagement. This approach may not accurately represent the depth and quality of engagement, as a larger number of followers does not necessarily equate to more meaningful interactions (Kaplan and Haenlein, 2010). Furthermore, the index's primary focus on monetising social interactions may not fully align with the broader goals of digital marketing strategies, which often aim to cultivate long-term brand loyalty, improve customer satisfaction and encourage active community participation - outcomes that go beyond simple monetisation (Hoffman and Fodor, 2010).

While the Ayzenberg EMV index provides valuable insights into the economic impact of social media campaigns, its emphasis on quantitative metrics such as follower counts and its goal of translating engagement into dollar values can obscure the qualitative benefits of such strategies (Lovett & Staelin, 2016). This highlights the need to integrate quantitative and qualitative evaluations to gain a comprehensive understanding of a campaign's success and its impact on brand and consumer relationships (Culnan et al., 2010).

2. Hypothesis

In the digital landscape where social media platforms dominate the public sphere, understanding the true impact of content has become both a challenge and a necessity. Traditional metrics for measuring the success and reach of social media content often rely on follower counts and engagement metrics that can be manipulated or do not accurately reflect the depth of audience connection. This discrepancy highlights a gap in our ability to authentically assess content resonance, leading to the need for a refined analytical lens. The following hypotheses are proposed to explore alternative metrics that prioritise direct interactions over follower counts and economic incentives, with the aim of providing a clearer picture of true resonance and influence on social networks. This approach challenges the status quo and seeks to uncover a more organic understanding of content impact, free from the distortions of economic bias and the superficiality of follower metrics that can be artificially manipulated.

H1: Traditional social network rankings, such as the Ayzenberg Social Index, are predominantly based on follower counts and are directly influenced by the number of followers, which may not accurately reflect the actual resonance and influence of the content.
H2: Measurement approaches that only consider direct interactions (shares, likes and mentions) will provide more accurate and realistic results for assessing the resonance of social media content, avoiding the bias introduced by follower counts.
H3: Current ranking mechanisms are overly influenced by engagement metrics, which can be artificially inflated by monetary investment, distorting the perception of content's organic resonance. A novel approach that prioritises direct interactions over engagement metrics influenced by economic factors will provide a more authentic measure of content impact and cultural resonance.

These assumptions form the basis for a thorough examination of existing metrics against a proposed methodology that focuses on direct interactions as the primary indicator of content resonance. The distinction between follower-based metrics and direct interaction metrics highlights the potential mismatch between perceived resonance (often influenced by economic factors) and organic resonance. By highlighting the importance of direct interactions, this study aims to propose a more reliable and authentic framework for understanding the dynamics of social media content and its impact on audiences, beyond the limitations of follower counts.

3. Methodology

This study uses a quantitative, big data-based approach to analyse the resonance of social network content within a dataset of 345,000 posts from 17,074 nodes (unique authors) on social network X, collected during May 2023. The analysis contrasts Ayzenberg's EMV index with our newly formulated SlimScore Composite Resonance Index, providing a multi-faceted understanding of the dynamics of social media engagement.

3.1. Analytical Framework

3.1.1. Analysis of the Ayzenberg EMV Social Index

The Ayzenberg EMV Social Index quantifies the monetary value of user interactions, including likes, shares, and comments. While this index primarily measures the value of engagement (placing an economic value on interactions), it is recognised that an account's number of followers can indirectly influence EMV. Accounts with a higher number of followers potentially have a greater reach, which could increase the visibility and impact of interactions, thus affecting earned media value. While focusing on the value of engagement, Ayzenberg's model recognises the broader context of reach and efficiency of engagement as contributing to the overall valuation of social networking activity.

3.1.2. SlimScore Analysis

In contrast, the SlimScore emphasises the importance of direct social interactions (shares, likes and mentions) as indicators of content resonance, without direct monetary valuation.

The development of this methodology is based on previous studies on social media influence (Lamirán, 2022), which have shown their effectiveness in detecting viral content and identifying the most influential profiles.

This methodology establishes a quantitative framework for assessing the salience of X accounts during election campaigns, using a composite metric that weights different types of social interactions: retweets, mentions and likes. The weights assigned reflect the hypothesis that retweets imply a higher degree of influence than mentions and mentions imply a higher degree of influence than likes.

Social media resonance is an important indicator of public participation and engagement, especially during major events such as election campaigns. Traditionally, influence is measured by the number of followers or the frequency of posts. However, these metrics do not fully capture meaningful interaction. Therefore, a Z-score based methodology is proposed to normalise and weight social influence indicators: retweets, mentions and likes.

The indicator was developed along the following lines:

a) Data collection: Data is collected from Twitter accounts using relevant keywords. The number of retweets, mentions and likes for each account over a given period is then extracted.
b) Normalisation of the indicators: The values of each indicator are normalised using the Z-score to standardise the data. The Z-score is calculated as $Z= (X- \mu)/\sigma$, where X is the indicator value, μ is the mean of the indicator values and σ is the standard deviation of the indicator values.
c) Weighting of the indicators: Weights are assigned to each normalised indicator based on its perceived impact on social influence: retweets (3), mentions (2) and likes (1).
d) Calculation of the composite resonance index: A composite index is calculated by adding the weighted Z-scores of the three indicators for each user: SlimScore=3 Zretweets+2 Zmentions+1 Zlikes.
e) Statistical analysis: Composite indices are analysed to identify trends and patterns of influence. Finally, statistical methods are used to assess the significance of differences between social network X accounts.

3.1.3. Comparative Analysis

The study compares the results of the Ayzenberg EMV Social Index and the SlimScore Index, highlighting the different perspectives on the impact of social media content. This comparison sheds light on the nuances between evaluating engagement and direct interaction metrics, providing insight into the different facets of social media resonance.

In this study, we use Pearson's correlation coefficient, a statistical measure that assesses the linear relationship between two continuous variables. Pearson's correlation coefficient (denoted as r) ranges from -1 to +1, where +1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship and 0 indicates no linear relationship. This coefficient thus quantifies the degree to which two variables are linearly related.

3.2. Data Collection

The dataset was systematically extracted using the API of social network X, ensuring a broad representation of user interactions during the specified period.

3.2.1. Data Structure

Data was collected from the X API, focusing on specific key performance indicators (KPIs) relevant to social media engagement: retweets, likes, mentions, impressions and followers. These metrics were chosen for their importance in measuring user engagement and reach on the platform. In addition, we calculated the SlimScore index and the Ayzenberg index for each user to capture the overall engagement and influence of X's accounts.

3.2.2. Data Normalisation

Given the different scales of the KPIs, we normalised the data to ensure comparability between metrics. Normalisation was performed using the Min-Max scaling technique, which rescales the data to a range [0, 1]. This step ensures that each KPI contributes equally to the analysis, eliminating bias due to differences in scale.

3.2.3. Correlation analysis

We calculated Pearson's correlation coefficient to examine the relationship between the SlimScore index and each KPI (retweets, likes, mentions, impressions, followers), and between the Ayzenberg index and the same set of KPIs. The aim of this analysis was to find out how these indices, which represent aggregate measures of social network performance, relate to the individual engagement metrics commonly used to measure user interaction and reach on X.

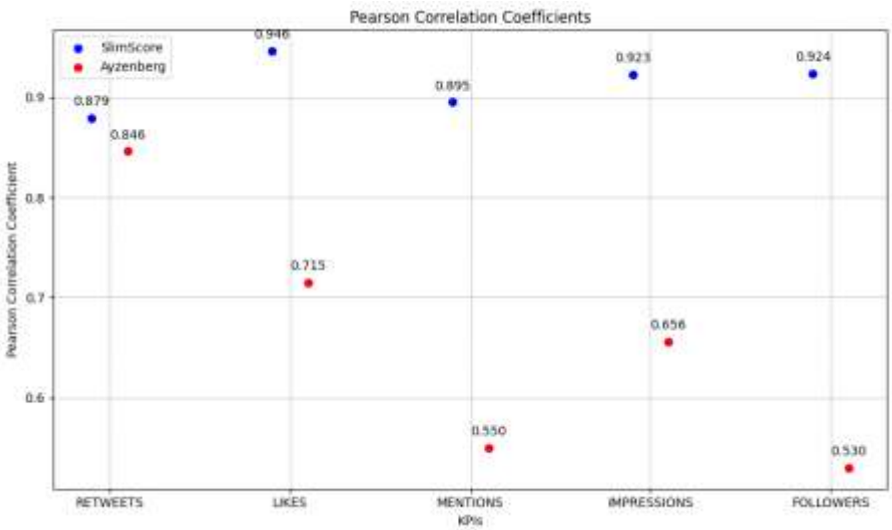
4. Results

The results of this analysis are described below.

4.1. Pearson's Correlation:

Analysis of the X data using Pearson's correlation coefficient provided insight into the relationship between aggregate social network performance indices and specific engagement metrics. In particular, the SlimScore index showed a strong positive correlation with key performance indicators such as retweets, likes, mentions, impressions and followers, suggesting that accounts with higher indices are associated with higher user engagement and broader reach on the platform. Similarly, while the Ayzenberg Index also showed positive correlations with these KPIs, it showed a slightly lower degree of correlation, indicating differences in how different indices capture aspects of social media influence. These findings underscore the interconnectedness of social network performance measures and highlight the potential of the SlimScore to reflect the multifaceted nature of user engagement on X.

Figure 1. Pearson's correlation coefficients



Source: Own elaboration

The strong correlation between followers and SlimScore might suggest that, while followers are not directly considered in the calculation of the index presented here, there are underlying factors that influence both the Index and the number of followers. For example, content quality or engagement levels (likes, retweets, mentions) could lead to a higher composite resonance index and an increase in followers.

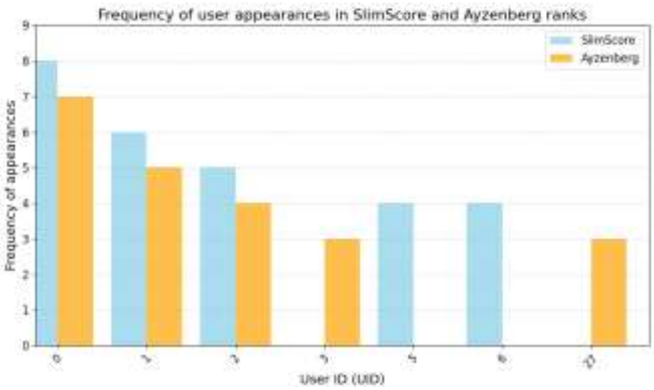
It is possible that factors included in the SlimScore index, such as retweets, likes and mentions, indirectly influence the number of followers. High engagement rates can increase a user's visibility on the platform, leading to a higher number of followers. Therefore, the correlation with followers can be an artefact of the relationship between engagement metrics and follower growth.

Comparison between the SlimScore and Ayzenberg indices in relation to the X KPIs reveals distinct correlation patterns that provide insights into their respective measures of social media performance. The strong correlations of the SlimScore index across all KPIs suggest that it is an integral reflection of overall engagement and reach. In contrast, the Ayzenberg index, with its varying correlation strengths, can offer a nuanced perspective, potentially emphasising the virality aspect of content (as indicated by its higher correlation with Retweets).

4.2. Messages with Greater Resonance

Figure 2 shows the frequency of appearance of users in the SlimScore and Ayzenberg scores, providing information on the prominence of users within each rank. Each bar represents the frequency of occurrence of a particular User ID (UID), with different colours distinguishing between the SlimScore and Ayzenberg scores.

Figure 2. Frequency of occurrence of users in the SlimScore and Ayzenberg rankings



Source: Own elaboration

We observe that certain user IDs have a higher frequency of occurrence compared to others within each rank. For example, in the composite rank, user IDs 0, 1 and 2 appear to be the most prominent, with relatively higher frequencies of occurrence compared to the rest. Similarly, in the Ayzenberg rank, the same user IDs maintain a notable presence, albeit with slightly lower frequencies.

Figure 3. Comparative table of frequency of users (UID), by KPI and by Index

	Composite Resonance Index	USUARIO	AYZENBERG	USUARIO.1	RETWEETS	USUARIO.2	ME GUSTA	USUARIO.3	MENCIONES	USUARIO.4	IMPRESIONES	USUARIO.5	SEGUIDORES	USUARIO.6
0	1.000000	0	0.801136	27	1.000000	4	1.000000	4	1.000000	34	1.000000	10	1.000000	13
1	0.981814	1	0.551136	18	0.890713	1	0.889057	6	0.386282	90	0.313474	53	0.459493	14
2	0.348745	2	1.000000	20	0.808639	5	0.618445	7	0.363016	91	0.491547	25	0.282838	15
3	0.323979	3	0.789773	21	0.690281	6	0.549209	5	0.237064	92	0.361300	27	0.218961	16
4	0.308838	5	0.778409	24	0.608639	3	0.524432	29	0.162493	93	0.316718	62	0.203576	63
5	0.225753	34	0.772727	17	0.410067	86	0.449283	65	0.154834	94	0.290973	65	0.151235	54
6	0.184151	73	0.687500	30	0.406811	42	0.255058	3	0.105094	95	0.175815	8	0.131568	41
7	0.180003	6	0.687500	22	0.399136	0	0.211425	78	0.092258	96	0.148756	72	0.124093	85
8	0.128944	4	0.647727	23	0.398704	29	0.194759	1	0.084236	82	0.120145	89	0.109235	77
9	0.095248	75	0.636364	25	0.386476	0	0.140124	86	0.070197	97	0.038843	50	0.104918	44
10	0.079937	27	0.630682	32	0.376674	7	0.129387	42	0.067389	98	0.049197	88	0.080731	43
11	0.040479	61	0.517045	19	0.241801	1	0.077632	0	0.044124	10	0.046842	6	0.053981	52
12	0.037898	82	0.378000	31	0.187473	0	0.040606	27	0.037804	72	0.043022	86	0.050430	48
13	0.037349	7	0.318182	26	0.166739	0	0.024639	0	0.030886	99	0.041320	58	0.046907	38
14	0.023549	87	0.289682	10	0.070842	2	0.017894	1	0.022062	2	0.040850	71	0.038753	69
15	0.018151	80	0.181818	33	0.049244	76	0.004542	0	0.017248	100	0.025526	4	0.038443	51
16	0.010726	53	0.142045	34	0.047516	2	0.004267	2	0.013638	87	0.014798	47	0.030932	48
17	0.006401	37	0.142045	34	0.031965	75	0.002475	58	0.013237	62	0.008992	5	0.014898	84
18	0.004439	88	0.130682	28	0.012095	1	0.000413	83	0.000401	101	0.000550	78	0.002352	57
19	0.000000	25	0.000000	29	0.000000	62	0.000000	67	0.000000	102	0.000000	35	0.000000	79

Source: Own elaboration

A comparison between the SlimScore and Ayzenberg rating matrices (Figure 3) suggests nuances in the assessment of user salience. While both indices show similarities in the distribution of user frequencies, the SlimScore ranking appears to offer a slightly broader spectrum of user interactions, encompassing a wider range of user IDs with comparatively higher frequencies of appearance. On the other hand, the Ayzenberg ranking shows a more concentrated distribution, with fewer user IDs showing a higher frequency of occurrence.

5. Discussion

This quantitative research outlines a comparative overview between the SlimScore and Ayzenberg ranking indices, providing a critical insight into the complexity of user engagement in digital environments. The differences observed in the frequency distributions of users according to each index postulate divergent methodological approaches to quantifying the resonance of messages on social network X.

Based on a weighted average of shares, likes, and mentions, the SlimScore composite resonance index represents a multidimensional indicator of social media engagement. The higher frequencies associated with certain user IDs in the composite index imply a high level of visibility and potential influence, making it possible to identify users whose messages are most successfully disseminated on the network.

In contrast, Ayzenberg's index, which may be calibrated to assess specific metrics or criteria considered important contexts, shows a more delimited distribution of user frequencies. Although a cohort of user IDs occupies a prominent position in Ayzenberg's ranking, the scope of participation measures and their link to the monetary value of interactions may limit their ability to capture the totality of user interactions. However, the concentrated approach of the Ayzenberg index could be beneficial in contexts where niche metrics or different typologies of engagement are of primary importance.

The juxtaposition of the SlimScore and Ayzenberg indices highlights a strategic dichotomy between comprehensiveness and specificity in measuring user salience. The SlimScore index aligns with a broad range of engagement measures, while the Ayzenberg index provides a focused assessment that adheres to pre-defined engagement criteria. The choice between these dichotomous indices depends on the research objectives, as each offers a different view of the mechanics of user engagement.

In conclusion, the use of SlimScore in comparative analysis with the Ayzenberg Social Index has demonstrated its ability to provide more accurate results in measuring the virality of social media messages. This accuracy is crucial for unravelling patterns of content distribution and resonance, which in turn facilitates more informed and effective strategic planning by content creators, brands, and political organisations. By more accurately reflecting the active engagement of audiences, SlimScore is a useful tool for designing communication strategies that not only aim to extend reach, but also to deepen impact and encourage organic rather than artificially automated engagement.

The SlimScore study therefore makes a significant contribution to the field of digital communications and social network analysis. By offering a refined metric for assessing online resonance, it invites critical reflection on current measurement practices and points the way towards more holistic analyses that recognise the complexity of human interactions in the digital realm. Ultimately, the proposed index not only enriches academic understanding of social influence in the digital age, but also provides practitioners and strategists with more effective tools to navigate and shape the contemporary media landscape.

References

Ahuja, V. (2012). Market Influence Analytics in a Digital Ecosystem. *International Journal of Online Marketing (IJOM), 2*(4), 42-53. https://doi.org/10.4018/ijom.2012100103

Allcott, H., & Gentzkow, M. (2017). *Social media and fake news in the 2016 election. Journal of Economic Perspectives, 31*(2), 211-236. https://doi.org/10.1257/jep.31.2.211

Cha, M., Haddadi, H., Benevenuto, F., & Gummadi, K. (2010). Measuring User Influence in Twitter: The Million Follower Fallacy. *Proceedings of the International AAAI Conference on Web and Social Media, 4*(1), 10-17. https://doi.org/10.1609/icwsm.v4i1.14033

Chung, N., & Koo, C. (2015). The use of social media in travel information search. *Telematics and Informatics, 32*(2), 215-229. https://doi.org/10.1016/j.tele.2014.08.005

Cialdini, R. B. (2001). *Influence: Science and practice* (4th ed.). Allyn & Bacon.

Culnan, M. J., McHugh, P. J., & Zubillaga, J. I. (2010). How large U.S. companies can use Twitter and other social media to gain business value. *MIS Quarterly Executive, 9(4),* 243-259.

Dwyer, P. (2007). Measuring the value of electronic word of mouth and its impact in consumer communities. *Journal of Interactive marketing, 21(2),* 63-79. https://doi.org/10.1002/dir.20078

Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM, 59*(7), 96-104. https://doi.org/10.1145/2818717

Flynn, D. J., Nyhan, B., & Reifler, J. (2017). The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. *Political Psychology, 38(*S1), 127-150. https://doi.org/10.1111/pops.12394

Gladwell, M. (2000). *The tipping point: How little things can make a big difference*. Little, Brown.

Granovetter, M. S. (1973). The strength of weak ties. American Journal of Sociology, 78(6), 1360-1380. https://www.jstor.org/stable/2776392

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2010). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing, 18*(1), 38-52. https://doi.org/10.1002/dir.10073

Hoffman, D. L., & Fodor, M. (2010, October 1). *Can You Measure the ROI of Your Social Media Marketing?* MIT Sloan Management Review. https://sloanreview.mit.edu/article/can-you-measure-the-roi-of-your-social-media-marketing/

Jenkins, H., Ford, S., & Green, J. (2013). *Spreadable media: Creating value and meaning in a networked culture*. NYU Press. https://www.jstor.org/stable/j.ctt9qfk6w

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons, 53*(1), 59-68. https://doi.org/10.1016/j.bushor.2009.09.003

Katz, E., & Lazarsfeld, P. F. (1955). *Personal influence: The part played by people in the flow of mass communications*. Transaction Publishers. https://doi.org/10.1007/978-3-658-21742-6_67

Lamirán, J. M. (2022). *La influencia en redes sociales durante los eventos deportivos:" Los casos de Twitter en los Mundiales de Ciclismo en Pista de Londres (Reino Unido) 2016, y Apeldoorn (Países Bajos) 2018"* (Doctoral dissertation, Universitat Politècnica de València). https://doi.org/10.4995/Thesis/10251/190811

Lazer, D., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., ... & Zittrain, J. L. (2018). The science of fake news. *Science, 359*(6380), 1094-1096. https://doi.org/10.1126/science.aao2998

Lovett, M. J., & Staelin, R. (2016). The role of paid, earned, and owned media in building entertainment brands: Reminding, informing, and enhancing enjoyment. *Marketing Science, 35*(1), 142-157. https://doi.org/10.1287/mksc.2015.0961

Manthiou, A., Rokka, J., Godey, B., & Tang, L. (2016). How Social Media Marketing Efforts Influence Brand Equity Creation and Its Consequences: The Case of Luxury Brands. In *Developments in marketing science: proceedings of the Academy of Marketing Science* (p. 561). https://doi.org/10.1007/978-3-319-11815-4_169

McQuail, D. (2010). *McQuail's mass communication theory* (6th ed.). SAGE Publications.

Milner, R. M. (2013). FCJ-156 Hacking the social: Internet memes, identity antagonism, and the logic of lulz. *The Fibreculture Journal, 22*(22), 62-92.

Pariser, E. (2011). *The filter bubble: What the Internet is hiding from you*. Penguin UK.

Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In *Advances in experimental social psychology* (pp. 123-205). https://doi.org/10.1016/s0065-2601(08)60214-2

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Slater, M. D. (2007). Reinforcing spirals: The mutual influence of media selectivity and media effects and their impact on individual behavior and social identity. *Communication Theory, 17*(3), 281-303. https://doi.org/10.1111/j.1468-2885.2007.00296.x

Sunstein, C. R. (2017). *#Republic: Divided democracy in the age of social media*. Princeton University Press.

Tufekci, Z. (2017). *Twitter and tear gas: The power and fragility of networked protest*. Yale University Press.

Woolley, S. C., & Howard, P. N. (2018). *Computational propaganda: Political parties, politicians, and political manipulation on social media*. Oxford University Press. https://doi.org/10.1093/oso/9780190931407.001.0001