Sufficiency and necessity of influencers for digital collective memory: a study through combined IPMA

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Abstract

Purpose – This study aims to demonstrate the causal effect that content disseminated by influencers has on the formation of collective memories that underlie digital environments.

Design/methodology/approach – This work integrated a recent methodological sequence called combined importance-performance map analysis (cIPMA) that suggests articulating the results of PLS-SEM, necessary conditions analysis and IPMA through a graph that consolidates the causal effects of necessity and sufficiency of the variables contemplated in the study.

Findings – The results suggest that influencers represent the most important input for the adoption of information and the formation of collective memories. In addition, it was also found that people develop a positive attitude towards digital narratives regardless of whether this content lacks quality.

Originality/value – To the best of the authors' knowledge, this paper represents the first formal work that uses an exclusively quantitative methodological sequence to comprehensively demonstrate the causal effect of influencer content on digital collective memory.

Keywords: Social networks, Cognitive analysis, Econometrics, Statistics, Marketing

Paper type: Research paper

1. Introduction

Society has undergone radical changes in the way information is accessed and interacted with; social media is now indispensable for communication (Pérez-Escoda et al., 2021a). These media facilitate real-time data exchange and link individual perception to collective interaction on personal and cultural events and experiences derived from the use of a product or service (Ahmed et al., 2020; Ross et al., 2019). Furthermore, social networks have an unrivalled capacity for immediate dissemination of content, forcing them to continually adapt and positioning themselves as spaces conducive to users expressing their opinions, creating trends and consolidating a “shared memory” (Geana et al., 2019; Hirst and Coman, 2018; Roediger and Abel, 2015).

Some social media platforms such as TikTok, Instagram and YouTube are not only channels of entertainment; they also serve as repositories for the formation of shared memories, beliefs and values. Research shows that these platforms play a central role in the creation of consumption strategies and cultural agendas (Peres et al., 2024; Sutrantiyas et al., 2025). Thus, recent research indicates that the role of public figures on these platforms is not limited to the dissemination of information, because they also influence the adoption of social practices by acting as legitimisers of trust and credibility (Wahab et al., 2025). Consequently, the saturation of sponsored messages leads to a loss of authenticity in content and causes internet users to condition their processes of selecting, validating and accepting information for the subsequent formation of memories (Wahab et al., 2025).

Now, the concept of “collective memory” is defined as those memories that are shared and held by social groups (Halbwachs, 1950). Similarly, Assmann (2011) and West et al. (2021) refer to “collective memory” as a dimension formed by “Communicative” and “Cultural memory”. From the position of the latter authors, a mathematical model St = ut + vt is proposed, where St represents collective memory, ut represents “communicative memory” and vt represents “cultural memory”. Likewise, Rampazzo Gambarato and Heuman (2023) propose that vt is a long-term formative process where cultural aspects and local emotions converge, while Simons et al. (2021) propose that ut is created with everyday communication, showing aspects indexed in the short term.

Based on the above approach, it is necessary to point out that influencers appear to play a decisive role in the formation of shared memories because they have the ability to reach mass audiences, becoming indispensable agents for the creation of narratives in digital environments (Martins and Martins, 2021; Mim et al., 2022). Furthermore, although there are theoretical models that explain the adoption of information, few have focused on digital scenarios. In this regard, works such as those by Sussman and Siegal (2003), Erkan and Evans (2016) and Roldan-Gallego et al. (2023) link dimensions such as credibility, quality, usefulness, necessity and adoption in the analysis of purchase intention; however, they omit an integrated framework that explains how these variables contribute to the collective memory created on social media. This shows that there is an underlying gap in the understanding of the process through which these influential figures generate immediate responses and shared memories, justifying the need to extend the theoretical understanding of digital collective memory but also showing a useful cognitive path for the management of integrated marketing communications in a context of "information saturation".

Therefore, this study contributes to systematising, to some extent, the relationships between psychosocial and communicative variables in the process of consolidating shared memories. It also provides brands and communication managers with tools to identify dimensions that are decisive in the viralisation of messages and in the construction of collective memory on social media. Consequently, the central objective of this work is to offer an analytical, explanatory and empirically validated framework that allows us to understand how psychosocial aspects interact and explain the formation of memory based on relevant digital actors, integrating constructs such as quality, credibility, attitude towards information and perceived usefulness. To this end, a robust methodological combination is adopted that articulates three complementary approaches: structural equations partial least squares – structural equation modeling (PLS-SEM), necessary conditions analysis (NCA) and importance-performance map analysis (IPMA), reinforced by the novel combined importance-performance map analysis (cIPMA) approach (Hauff et al., 2024).

This study represents an innovative contribution to disciplines such as digital marketing, communication and social psychology by proposing a replicable model for analysing the formation of shared digital memories. It also facilitates the distinction between those dimensions that may be influential and/or decisive in the formation of digital memories, which has direct implications for the optimisation of brand communication strategies on social media (Hair et al., 2021; Sarstedt et al., 2022).

2. Literature review

2.1 Social networks and collective memory

According to Pérez-Escoda et al. (2021a, 2021b), social media represents an ideal environment for recording, amplifying and reframing content that ultimately forms shared narratives over time. This implies a shift from the concept of "unidirectional dissemination" towards dynamics focused on interaction, repetition and social approval, representing a necessary process for sustaining the formation of digital collective memory (Hirst and Coman, 2018; Pico-valencia and Holgado-terriza, 2021; West et al., 2021). Thus, the visibility and persistence of memories in these ecosystems are highly dependent on the reach and degree of viralisation of the content but also on continuous exposure. Some studies point out how the dissemination structure – node efficiency – conditions the visualisation of information that becomes embedded in the collective imagination (Martins and Martins, 2021). In turn, the algorithmic recommendation and prioritisation system continuously displays information with which there is greater interaction, generating echo chambers and information bubbles that favour the consolidation of specific narratives (Casais and Gomes, 2022; Dedeoglu, 2019).

On the other hand, phenomena such as homophily and social identity represent determining dynamics in the process of strengthening shared memories, because they increase the spread and adoption of messages (electronic word of mouth [eWOM]) in the digital communities present in these environments (Oquiñena et al., 2025). Furthermore, aspects such as credibility and parasocial relationships enjoyed by influential figures on the internet allow them to shape content evaluation processes (eWOM), affecting the likelihood that such content will remain relevant and be remembered (Wahab et al., 2025). Therefore, understanding the patterns related to propagation, exposure and processing promotes understanding of the phenomenon of collective memory in social networks (Barnea et al., 2023).

2.2 Influencers and dissemination of information

Influencers emerged as important figures in the dissemination of content on social media because of their ability to generate engagement and shape the perception of online communities (Mim et al., 2022). However, depending on their credibility, authenticity and ability to connect with different audiences on an emotional level, they have been positioned as validators and facilitators of the information that is continuously disseminated on the internet (Martins and Martins, 2021; Wahab et al., 2025). Thus, the impact exerted by these public figures is not uniform; that is, it depends on factors such as the frequency of their posts and the degree of interaction they achieve with their respective audiences. Recent research indicates that these dynamics can determine the persistence of messages on the network and increase the likelihood that their content will be socially adopted (Oquiñena et al., 2025; Roche et al., 2022).

Furthermore, in contexts such as “disinformation”, influencers play a dual role. Firstly, they can amplify and reinforce the dissemination of unverified content. On the other hand, they can also act as mediators or validators of narratives when they enjoy credibility and social legitimacy. This role is relevant in ecosystems where the volume and speed of information dissemination make immediate verification difficult (Barnea et al., 2023). Therefore, these social actors condition the process of acceptance, circulation, and social remembrance of content, positioning themselves as key players in digital collective memory.

2.3 Information adoption models

Information adoption models that have been developed over the years have sought to link and contrast aspects of the message that, to some degree, affect perception prior to a decision-making process. Among the first works in this field is that of Sussman and Siegal (2003), who studied in a corporate environment the process of adoption of information sent through e-mails. Here, these authors put forward a conceptual scheme called “information adoption model (IAM)” in which aspects such as the quality, credibility and usefulness of information were assessed prior to acceptance (Figure 1).

These authors took a holistic approach that involved combining “technology acceptance models” or TAMs, stating directly that adoption is determined by perceived usefulness and ease of use (Davis, 1989), but they also linked a “likelihood of elaboration” or ELM model that posits that people process messages that are persuasive through a central route linked to the quality of the argument or a peripheral route linked to the credibility of the sender (Massaro et al., 1988). However, Erkan and Evans (2016) made a proposal that directly articulates the adoption of information coming from “Social Networks”, in which it was recognised that in digital media there is a dominant phenomenon called eWOM that has significant effects on decision-making processes related to purchase; however, it was concluded that not all messages influence in the same proportion, so they integrated elements related to the information and behaviour of the receiver, proposing the IACM model or “information acceptance model” (Figure 2).

In the previous work, the authors also proposed a comprehensive approach by combining the “Information adoption model (IAM)” of Sussman and Siegal (2003) and elements linked to the “theory of reasoned action (TRA)” proposed by Fishbein and Ajzen (1975), justifying the inclusion of new variables shown in Figure 2 (Table 1):

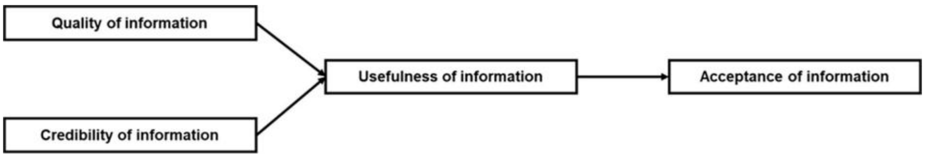

Figure 1. Information adoption model (IAM)

Source: Sussman and Siegal (2003)

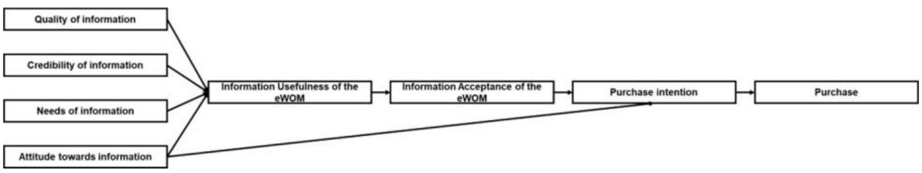

Figure 2. Information acceptance model (IACM)

Source: Erkan and Evans (2016)

Table 1. Variables and theories for the IACM model

Teoría	Descriptor	Authors	Variables
IAM	Information adoption model	Sussman and Siegal (2003)	Quality, credibility, utility and adoption
TRA	Theory of reasoned action	Fishbein and Ajzen (1975)	Attitude, intention
eWOM	Electronic word of mouth	Sundaram *et al.* (1998)	Need

Source(s): Authors' own elaboration

Subsequently, the study conducted by Roldan-Gallego et al. (2023) allowed us to analyse how "Influencers" affected the adoption of information coming from "social networks". In this case, the authors took up the structure proposed in the IACM model, and argued for the inclusion of other variables related to "purchase intention" based on the "theory of planned behaviour" proposed by Ajzen (1991). As in the work of Erkan and Evans (2016), this research assumed that the adoption processes of information coming from social networks were affected by aspects related to the characteristics of the messages and the attitude of internet users; however, it integrated a new element called "Influencers" as a phenomenon that affects the quality of the information that circulates on social networks and that is considered for decision-making in the purchasing processes (Figure 3).

2.4 Proposed information acceptance model

This research proposes that the adoption of information on social media arises from the interaction of three components: information source, message elements and consumer determinants. Consequently, the adoption of online information depends on factors that specify which content is valid for sharing and, therefore, contributes to the repositories that make up the digital collective memory (Pérez-Escoda et al., 2021b; Roche et al., 2022). Thus, the structure and order of constructs is justified based on the stimulus–organism–response (S-O-R) theory and previously proposed models such as IACM by Erkan and Evans (2016) and Roldan-Gallego et al. (2023).

The S-O-R model proposed by Mehrabian and Russell (1974) establishes that stimuli (S)

have significant effects on the organism (O), generating a response in them (R). Here, influencers represent the fundamental stimulus because they are perceived by audiences as reliable sources of information (Pozharliev et al., 2022), generating emotional engagement (Mim et al., 2022) to focus public attention on specific causes (Casais and Gomes, 2022), which involves the activation of cognitive and social processes that trigger collective interaction and the formation of shared memories (Momennejad, 2022). Furthermore, these figures have the ability to quickly connect with internet users, allowing them to shape perceptions and make content go viral, which directly influences the process of evaluating the credibility, quality, usefulness and necessity of narratives (Rodner et al., 2022; Wahab et al., 2025). Therefore, this research aims to evaluate whether:

H1. Influencer content has a significant effect on the credibility of the content.

H2. Influencer content has a significant effect on content quality.

H3. Influencer content has a significant effect on the usefulness of the content.

H4. Influencer content has a significant effect on the need for the content.

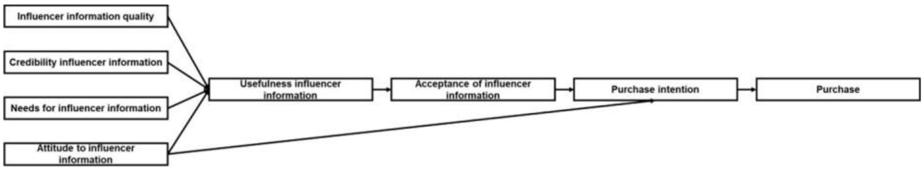

Figure 3. Information acceptance and purchase model (IACPM)

Source: Roldan-Gallego et al. (2023)

In addition to the above, the elements that make up a message are decisive in determining the attitude that an internet user takes towards the information they find on social media. Thus, the literature links three key dimensions; the first corresponds to credibility, understood as the reliability and verifiable support that narratives have (Wahab et al., 2025). The second factor corresponds to perceived quality, associated with the clarity, structure, and adequacy of the content circulating on the network (Martins and Martins, 2021). Finally, usefulness represents the last variable in this group, defined as the practical relevance that information may have in aspects related to everyday life (Casais and Gomes, 2022). These constructs explain the cognitive path that people follow when evaluating and deciding to replicate content on the Web, leading this research to identify whether:

H5. The credibility of content has a significant effect on attitudes towards information.

H6. The quality of content has a significant effect on attitudes towards information.

H7. Usefulness of content has a significant effect on attitude towards information.

Now, the organism (O) refers to the internal processes that mediate between the stimulus and the response. In this case, they represent consumer determinants such as attitude and need for information. The first factor reflects people's cognitive and emotional inclination towards messages; that is, it is triggered by previous experiences related to the source of the message (Roche et al., 2022). On the other hand, necessity is associated with the willingness of social network users to search for, process and internalise information that they consider relevant (Alrwashdeh et al., 2022; Barnea et al., 2023; Oquiñena et al., 2025). Therefore, this study evaluates whether:

H8. The need for content has a significant effect on the adoption of information.

H9. Attitude towards content has a significant effect on information adoption.

Finally, the response (R) involves actions that derive from internal processes within the organisation. In this context, it manifests itself through the adoption of information and its subsequent incorporation into the collective digital memory. The adoption process occurs when messages are perceived as credible, useful and relevant, increasing the likelihood that they will be replicated and remembered by a wider virtual community (Geana et al., 2019; West et al., 2021). Thus, the proposed model (see Figure 4) seeks to articulate the role of influencers as stimuli, providing a comprehensive and up-to-date framework that shows how the adoption of information on social media is linked to the formation of collective memory. Therefore, the following hypotheses are proposed:

H10. The adoption of information from social networks has a significant effect on the formation of digital collective memory.

H11. Influencers have a significant effect on the formation of digital collective memory.

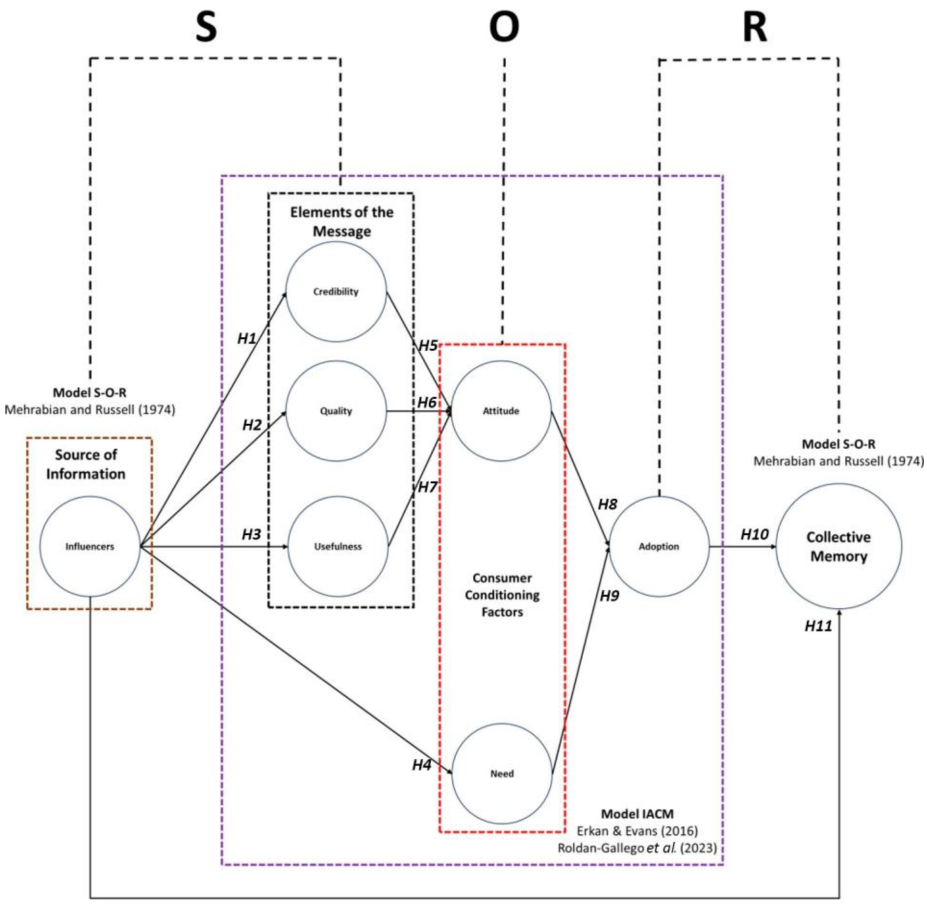

Figure 4. Proposed model

Source: Authors' own elaboration

3. Methodology

3.1 Study design

This work adopted a quantitative and explanatory approach using cross-sectional data. The extended methodology proposed by Hauff et al. (2024) in their manuscript on the requirements for implementing combined IPMA (cIPMA) was used.

3.2 Population and sample

This research used non-probabilistic chain sampling, assuming the advantages of this type of sampling in the rapid collection of data (Casadiego-Alzate et al., 2025). In addition, the ethics committee of the University of Medellín-Colombia, under approval No. 18 of 12 July 2024, approved the fieldwork. An online form was used and was available from June to December 2024, defining the criteria for participation as being of legal age, having an active account on a social network and following at least one influencer.

Different strategies were implemented to distribute the questionnaire, such as posting the link on Facebook groups and Instagram and WhatsApp stories, facilitating access to different socio-demographic profiles and reducing selection bias. In addition, during the data collection process, a total of 855 responses were obtained, 800 of which were valid, resulting in a set of observations that significantly exceeds the minimum recommended for studies implementing PLS-SEM (Hair et al., 2021). Thus, 55.38% were women and 44.63% were men, all Colombian residents. Furthermore, the average age was 27.28 years with a standard deviation of 10.30. In addition, more than 64% of participants stated that they were single, with 55.63% being professionals or technicians with an employability rate of 58.50%.

3.3 Instrument

The questionnaire had three sections. The first included items related to the title, research objectives, informed consent statement and guidelines on how the information provided would be treated. The second section included filter questions to determine the suitability of participants along with some socio-demographic aspects. Finally, there was the section on each of the items that operationalised the constructs considered in the model. These items were adapted from previous research and were displayed with a five-point Likert scale where 1 was “Strongly disagree” and 5 was “Strongly agree” (Table 2). With respect to the “collective memory” construct, five items were given for “communicative memory” (MC1–MC7) and 7 for “cultural memory” (MC8–MC12).

3.4 Data processing and analysis

The statistical processing and analysis were carried out in several stages. The first phase consisted of estimating the PLS-SEM to assess the quality of the measurement model by verifying aspects such as internal consistency, convergent validity and discriminant validity. The second phase consisted of the IPMA analysis to assess the relative importance and performance of each construct included in the model. In the third phase, the NCA was applied to establish the necessary conditions for the consolidation of the digital “collective memory”. In the fourth phase, aspects such as collinearity, statistical significance of the path coefficients and the explanatory and predictive capacity of the structural model were reviewed, differentiating and prioritising the constructs that are most relevant for the formation of collective memories. Finally, the cIPMA graph integrating the results of the previous phases was constructed. The data analysis was carried out with RStudio software version 4.3.3.

4. Results

4.1 Reliability and validity of the measurement model

Table 3 shows the general behaviour of the items used. All items presented values close to the midpoint of the scale with standard deviations greater than 1. This indicates a uniform distribution and optimal capture of information (Carretero-dios et al., 2005). On the other hand, the skewness and kurtosis values ranged between −0.99 and 0.11; these figures being close to zero and resembling the normal distribution (Carretero-dios et al., 2005). Finally, the homogeneity index for each indicator exceeded the minimum threshold of 0.3, indicating that participants’ responses did not vary significantly from the mean.

Table 4 shows the results on the statistical quality of the measurement model (Richter et al., 2020). Thus, it can be seen how the items contribute significantly to the formation of each construct, as their weights, loadings and communality demonstrate their relative importance. Furthermore, each dimension has adequate convergent validity (average variance extracted ≥ 0.5) and internal consistency ($0.7 \geq$ Rho C, Rho A, $\alpha \leq 0.95$). Finally, discriminant validity was tested with the heterotrait–monotrait criterion (HTMT), obtaining values between 0.7 and 0.9 for the constructs among themselves.

Table 2. Authors of the items per construct

Constructs	Code	Items	Authors
Quality	Qa1	The information shared by an influencer on social media is understandable	Sussman and Siegal (2003), Erkan and Evans (2016), Roldan-Gallego et al., 2023)
	Qa2	The information shared by an influencer on social media is clear	
	Qa3	The information shared by an influencer on social media is of quality	
Credibility	Cr1	The information shared by an influencer on social media is convincing	
	Cr2	The information shared by an influencer on social media is credible	
	Cr3	The information shared by an influencer on social media is accurate	
Need	Ne1	The information shared by an influencer on social media is necessary when I want to know new things	
	Ne2	Information shared by an influencer on social media is relevant when I need clarity on an issue	
	Ne3	Information shared by an influencer on social media is important when I am considering new opinions	
Attitude	Ac1	I always read and consider the information shared by an influencer on social media	
	Ac2	I find that information shared by an influencer on social media helps me make better decisions	
	Ac3	I find that information shared by an influencer on social media gives me confidence	
Usefulness	Ut1	Information shared by an influencer on social media is generally useful	
	Ut2	La información compartida por un influenciador en las redes sociales es valiosa	
	Ut3	I can use the information shared by an influencer on social media to my advantage	
Adoption	Acep1	With the information shared by an influencer on social media, it is easier to make decisions	
	Acep2	I find that my decisions are more effective whenever I consider the information shared by an influencer on social media	
	Acep3	Information shared by an influencer on social media allows me to make more informed decisions about purchasing products and services	
Influencer	In1	I feel comfortable with the posts of my favourite influencers	Al Sulaiti et al. (2024)
	In2	I am fascinated by the content of my favourite influencers.	
	In3	I find that my favourite influencers share information related to my interests (fashion and otherwise)	

(*continued*)

Constructs	Code	Items	Authors
Collective memory	MC1	I remember the topic that generated a lot of conversation on social media in recent months around the name of an influencer, athlete, politician or some other public figure	Own elaboration
	MC2	I remember my point of view on the conversations that were generated on social media about events that happened in the past few months	
	MC3	I remember more easily the contents that went viral in recent months through social networks, because I gave my opinion and defended my position against that of other users	
	MC4	I remember the point of view and positions of other users in conversations that were generated on social networks about events that occurred in recent months	
	MC5	I remember changing my point of view in conversations that were generated in social networks, because of the arguments used by other users	
	MC6	I remember writing a comment about an advertising message I saw recently on social media	
	MC7	I remember being part of a conversation around a controversial (contentious) issue that has occurred in the last year and that was widely reported or covered on social media	
	MC8	I can mention a cultural symbol or icon of my nation that was widely shown on social media	
	MC9	I remember some song, typical or iconic dance that went viral through social media in recent years	
	MC10	I could name a sporting event that was important to my nation's culture and that was widely shown on social media in recent years	
	MC11	I can recall a historical event relevant to my nation because it was widely shown on social media in recent years	
	MC12	I could name some artistic, sporting or literary work of my nation that became popular, thanks to social media in recent years	

Source(s): Authors' own elaboration

Table 3. Description of data

Ítem	Mean	SD	Skewness	Kurtosis	Homogeneity index
Qa1	3.08	1.11	−0.25	−0.56	0.60
Qa2	3.07	1.04	−0.26	−0.54	0.65
Qa3	2.93	1.09	−0.05	−0.57	0.59
Cr1	303	1.08	−0.11	−0.62	0.62
Cr2	2.84	1.06	0.02	−0.54	0.60
Cr3	2.90	1.07	0.01	−0.56	0.61
Ne1	3.12	1.15	−0.18	−0.80	0.58
Ne2	2.92	1.11	−0.04	−0.73	0.58
Ne3	3.00	1.14	−0.07	−0.78	0.57
Ac1	2.90	1.18	0.01	−0.89	0.52
Ac2	2.76	1.16	0.11	−0.81	0.51
Ac3	2.82	1.13	0.03	−0.73	0.55
Ut1	2.94	1.09	−0.11	−0.59	0.60
Ut2	2.90	1.06	−0.06	−0.53	0.61
Ut3	3.08	1.14	−0.19	−0.69	0.58
Acep1	2.90	1.13	−0.07	−0.72	0.56
Acep2	2.76	1.14	0.10	−0.74	0.53
Acep3	3.03	1.16	−0.12	−0.82	0.56
In1	3.19	1.13	−0.32	−0.59	0.60
In2	3.13	1.15	−0.22	−0.71	0.58
In3	3.23	1.17	−0.34	−0.67	0.58
MC1	3.05	1.19	−0.24	−0.84	0.54
MC2	3.04	1.18	−0.16	−0.83	0.54
MC3	2.97	1.18	−0.14	−0.88	0.53
MC4	2.96	1.15	−0.12	−0.80	0.55
MC5	2.91	1.15	−0.10	−0.86	0.55
MC6	2.77	1.20	0.06	−0.95	0.48
MC7	2.87	1.22	−0.03	−0.99	0.48
MC8	3.06	1.17	−0.18	−0.81	0.55
MC9	3.21	1.19	−0.32	−0.76	0.56
MC10	3.11	1.19	−0.25	−0.78	0.54
MC11	3.13	1.19	−0.30	−0.80	0.55
MC12	3.13	1.21	−0.20	−0.86	0.53

Source(s): Authors' own ela oration

Source(s): Authors' own elaboration

4.2 Importance-performance map analysis

The IPMA analysis involves the identification of the importance and performance of the variables in the model. Thus, Table 5 shows the performance values for each construct, calculated from the simple average of the factor loadings. It can be seen that all factors perform similarly, with "quality" having the highest value. Analysed together, an average performance of 82.30% is shown, a considerably high value on a scale of 0–100 points and establishing a guide to the desired level of performance in the construct of interest (90%).

In addition to the above, Table 6 describes the total effects (significance) of the PLS-SEM analysis. Here, it can be seen that "influencers" have the greatest impact on "collective memory", followed by "acceptance", "attitude" and "usefulness". However, variables such as "need" and "credibility" also show significant effects, albeit with lower values. Quality represents the only non-significant factor in the consolidation of shared memories. Together, it can be established that the mean significance is 0.29, suggesting that the constructs have a moderate effect on "collective memory". Finally, it is important to mention that, with these results, it can be suggested that "influencer", "acceptance" and "usefulness" are the most important variables for the creation of digital "collective memory".

Table 4. Summary of the results of the reflective measurement model

Constructs	Indicators	Weights	Loadings	Indicator communality (squared loadings)	AVE	Composite reliability	Cronbach's α	Rho A	Does it me the HTMT criterion?
Quality	Qa1	0.370	0.846	0.716	0.670	0.858	0.860	0.861	Yes
	Qa2	0.372	0.850	0.723					
	Qa3	0.369	0.843	0.710					
Credibility	Cr1	0.359	0.777	0.603	0.636	0.840	0.840	0.840	Yes
	Cr2	0.371	0.802	0.644					
	Cr3	0.403	0.873	0.762					
Need	Ne1	0.382	0.795	0.632	0.662	0.855	0.855	0.855	Yes
	Ne2	0.379	0.788	0.622					
	Ne3	0.388	0.808	0.654					
Attitude	Ac1	0.385	0.859	0.737	0.691	0.870	0.869	0.871	Yes
	Ac2	0.381	0.851	0.724					
	Ac3	0.354	0.791	0.626					
Usefulness	Ut1	0.374	0.804	0.646	0.696	0.873	0.872	0.874	Yes
	Ut2	0.383	0.823	0.678					
	Ut3	0.379	0.814	0.662					
Adoption	Acep1	0.359	0.798	0.636	0.676	0.862	0.861	0.863	Yes
	Acep2	0.379	0.842	0.710					
	Acep3	0.384	0.852	0.726					
Influencer	In1	0.390	0.851	0.724	0.716	0.883	0.883	0.883	Yes
	In2	0.368	0.803	0.645					
	In3	0.372	0.811	0.658					
Collective memory	MC1	0.313	0.816	0.665	0.585	0.844	0.844	0.845	Yes
	MC2	0.314	0.821	0.674					
	MC3	0.311	0.800	0.639					
	MC4	0.310	0.795	0.633					
	MC5	0.315	0.830	0.689					
	MC6	0.397	0.712	0.507					
	MC7	0.397	0.712	0.506					
	MC8	0.301	0.728	0.530					
	MC9	0.304	0.748	0.559					
	MC10	0.303	0.744	0.553					
	MC11	0.304	0.750	0.563					
	MC12	0.301	0.729	0.532					

Source(s): Authors' own elaboration

Table 5. Performance of rescaled latent variables

Source(s):

Constructs	Performance value, average
Quality	84.62
Credibility	81.73
Need	79.73
Attitude	83.35
Usefulness	81.36
Adoption	83.07
Influencer	82.16

Source(s): Authors' own elaboration

Authors' own elaboration

Table 6. Total effects of PLS-SEM analysis

	Memoria colectiva		
Constructs	Total effects	95% bootstrap confidence intervals	Statistically significant ($p < 0.05$)?
Quality	−0.04	[−0.14; 0.04]	No
Credibility	0.14	[0.02; 0.31]	Yes
Need	0.11	[0.03; 0.19]	Yes
Attitude	0.33	[0.23; 0.45]	Yes
Usefulness	0.21	[0.11; 0.32]	Yes
Adoption	0.45	[0.32; 0.58]	Yes
Influencer	0.79	[0.73; 0.85]	Yes

Source(s): Author ’ own elaboration

Source(s): Authors’ own elaboration

4.3 Necessary conditions analysis identification

To apply the NCA, rescaling and reduction of variables was carried out using plots, calculating the simple average with the scores of the items in each construct. Thus, the roof lines were estimated for each variable in the model with respect to “collective memory” (Figure 5), showing gaps in the upper left area and suggesting that these factors might be necessary conditions.

Additionally, Table 7 shows the effect size (d) and statistical significance for each

dimension. From these results, it is possible to state that “influencers” represent the main condition necessary for the formation of digital “collective memory”. As for the other factors, they have a moderate relative effect size on the formation of shared memories. Also, it is important to mention that all constructs are statistically significant, reinforcing their role in the consolidation of memories.

In addition to the above, Table 8 shows the bottlenecks that specify the level required for each variable to achieve a given result (Hauff et al., 2021). Thus, at low levels of “collective memory” (<60%) there are no restrictions. However, when this reaches 70%, variables such as “influencer”, “quality” and “usefulness” act as bottlenecks; that is, if the minimum level of these factors is not reached, it is possible that the consolidation of digital memories will be affected. Furthermore, it is worth mentioning that to reach a 100% level of “collective memory”, exposure to 66.7% of “Influencer” and 58% of “Need” is necessary. This reinforces the premise that these last two variables represent the major constraints of the system.

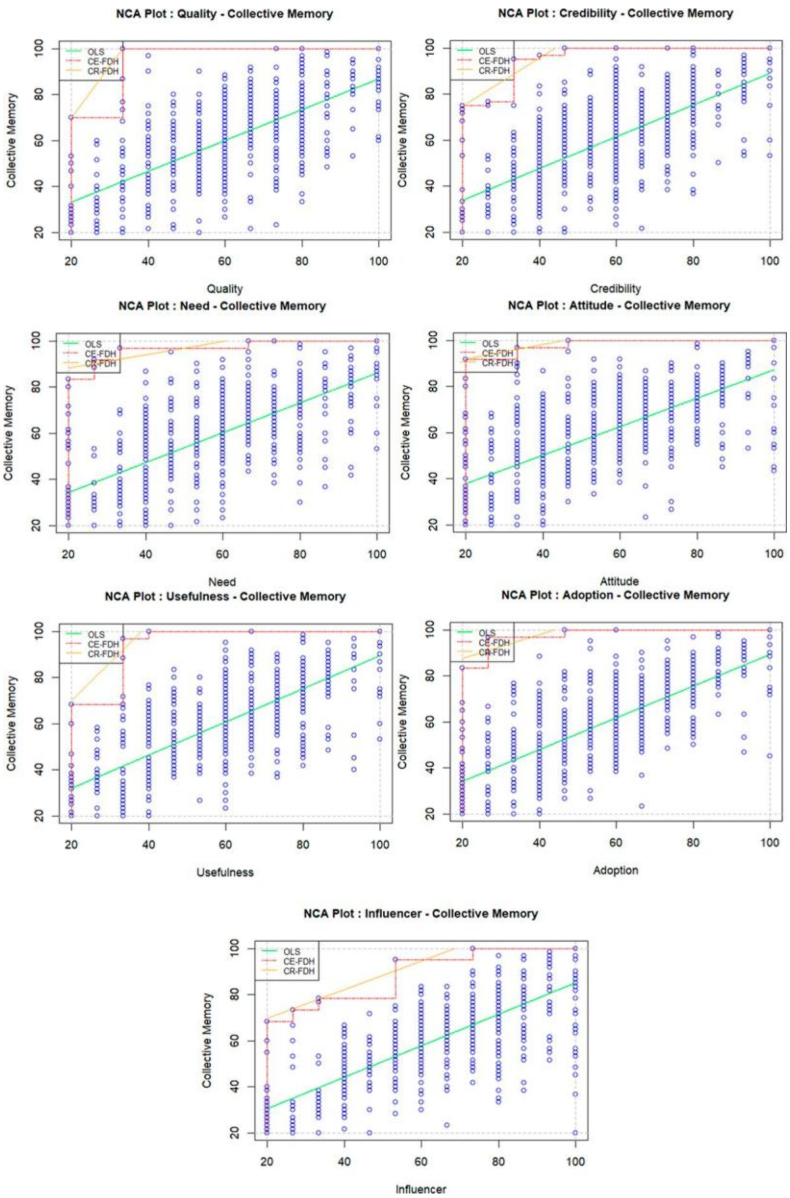

Figure 5. Collective memory and other necessary conditions

Source: Authors’ own elaboration

Table 7. Necessity effect sizes (CE-FDH ceiling line)

	Collective memory	
Construct	Effect size, *d*	*p*-Value
Quality	0.163	0.001
Credibility	0.159	0.001
Need	0.143	0.002
Attitude	0.124	0.013
Usefulness	0.169	0.001
Adoption	0.128	0.013
Influencer	0.244	0.001

Source(s): Authors’ own elab(ration

Source(s): Authors’ own elaboration

Table 8. Bottleneck table collective memory, actual values (based on the rescaled PLS-SEM latent variable scores from 0 to 100)

Collective memory	Quality	Credibility	Need	Attitude	Usefulness	Adoption	Influencer
0	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
10	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
20	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
30	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
40	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
50	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
60	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*	*NN*
70	16.70	8.30	*NN*	*NN*	16.70	*NN*	16.70
80	16.70	16.70	8.30	*NN*	16.70	8.30	41.70
90	16.70	16.70	16.70	16.70	16.70	8.30	41.70
100	16.70	33.30	58.30	33.30	25.00	33.30	66.70

Source(s): Authors' own elaboration

Table 9 shows the percentage of individuals not achieving the required level on the constructs. For example, 7.2% of the individuals did not reach the necessary position of "quality" to allow a score of 90% on "collective memory". At the same level, the corresponding percentages for the other conditions are 7.5% for "credibility"; 8.1% for "need"; 11.6% for "attitude"; 8.6% for "usefulness"; 7.1% for "adoption" and 23.4% for "influencer". These values will be used to expand on the results of the IPMA.

Table 9. Collective memory at bottlenecks: actual values of collective memory and percentiles of antecedent constructs

	Quality		Credibility		Need		Attitude		Usefulness		Adoption		Influencer	
Collective memory	%	# cases	%	# cases	%	# cases	%	# cases	%	# cases	%	# cases	%	# cas
0	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
10	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
20	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
30	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
40	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
50	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
60	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
70	7.2	58	4.8	38	*0*	*0*	*0*	*0*	8.6	69	*0*	*0*	8.4	67
80	7.2	58	7.5	60	5.8	46	*0*	*0*	8.6	69	7.1	57	23.4	187
90	7.2	58	7.5	60	8.1	65	11.6	93	8.6	69	7.1	57	23.4	187
100	7.2	58	23.9	191	56.9	45	11.6	246	13.00	104	26.8	214	58.9	471

Source(s): Authors' own elaboration

4.4 Evaluation of the structural model in PLS-SEM

To evaluate the fit of the structural model, first, the statistical significance of the effects between the constructs is described. Thus, Table 10 allows us to see that all the hypotheses initially put forward are valid, with the exception of the path coefficient between "quality" and "attitude".

Table 10. Structural coefficients and statistical significance

Path	Effect	Statistician *t*
Direct effects		
Influencer ! credibility	0.78	30.39
Influencer ! quality	0.79	32.41
Influencer ! usefulness	0.83	32.68
Influencer ! need	0.79	29.35
Credibility ! attitude	0.41	2.02
Quality ! attitude	−0.11	−0.83
Usefulness ! attitude	0.62	5.14
Attitude ! adoption	0.73	9.84
Need! adoption	0.24	3.04
Adoption ! collective memory	0.45	6.71
Influencer! collective memory	0.46	6.75
Efectos indirectos		
Influencer ! attitude	0.74	25.20
Influencer ! adoption	0.74	23.82
Quality ! adoption	−0.08	−0.82
Credibility ! adoption	0.30	1.96
Usefulness ! adoption	0.45	4.64
Influencer ! collective memory	0.33	6.52
Quality ! collective memory	−0.03	−0.81
Credibility ! collective memory	0.14	1.88
Usefulness ! collective memory	0.20	3.85
Need ! collective memory	0.11	2.66
Attitude ! collective memory	0.33	5.78

Source(s): Authors' own elaboration

On the other hand, indirect effects can also be appreciated, allowing the identification of stimulation routes in collective memory from the existing mediation between the variables. Significance was determined using a bootstrap of 10,000 subsamples, verifying that the t-statistic value exceeds the figure of 1.96.

Table 11 facilitates the identification of the explanatory power of the model (R2) and possible collinearity problems. Regarding the R2, all estimates show satisfactory fit figures; moreover, the model manages to explain 75.73% of the variance in the "collective memory". However, all [AQ]VIF values are less than 5, allowing us to conclude that there are no collinearity problems in the structural model (Hair et al., 2021).

Table 11. VIF and R2 values for the endogenous constructs

		Endogenous constructs		
		Attitude	Adoption	Collective memory
Constructs	R^2	VIF	VIF	VIF
Quality	0.62	4.65	—	—
Credibility	0.60	4.31	—	—
Usefulness	0.68	4.84	—	—
Need	0.62	—	4.01	—
Attitude	0.82	—	4.01	—
Adoption	0.90	—	—	2.93
Influencer	—	—	—	2.93
Collective memory	0.75	—	—	—

Source(s): Authors' own elaboration

Finally, Table 12 reflects the metrics that facilitate the interpretation of the predictive power of the model. In this case, it was decided to analyse the root mean square error because it minimises large deviations in the predictions. In addition, Q2 was used to test the model in forecasting new data. In the first indicator, the current model predicts better compared to the reference model (averages). In the second, most of the items present a Q2 between 0.30 and 0.45, indicating that the current model has a moderate predictive capacity. From the results presented, it is possible to affirm that the proposed measurement and structural model meet all the statistical requirements that theoretically support its approach.

Table 12. Predictive metrics for the items

Item	RMSE target	RMSE benchmark	Q^2
Qa1	17.87	18.94	0.35
Qa2	16.72	18.07	0.36
Qa3	17.24	18.05	0.37
Cr1	16.97	18.03	0.38
Cr2	17.35	18.38	0.33
Cr3	17.85	19.04	0.30
Ne1	16.42	16.93	0.43
Ne2	16.49	17.24	0.39
Ne3	17.30	18.03	0.42
Ac1	17.80	18.53	0.40
Ac2	18.31	19.11	0.32
Ac3	18.27	19.07	0.35
Ut1	19.89	20.71	0.29
Ut2	19.74	20.21	0.28
Ut3	18.19	18.82	0.35
Acep1	17.52	18.12	0.40
Acep2	18.64	19.14	0.33
Acep3	17.28	17.66	0.45
MC1	18.07	18.55	0.43
MC2	17.96	18.46	0.42
MC3	18.70	19.31	0.37
MC4	18.29	19.04	0.37
MC5	18.73	19.40	0.34
MC6	21.28	22.13	0.22
MC7	21.00	21.79	0.27

MC8	18.72	19.52	0.36
MC9	18.46	19.11	0.40
MC10	19.10	19.86	0.36
MC11	18.93	19.76	0.37
MC12	19.64	20.52	0.34

Source(s): Authors' own elaboration

4.5. Combined importance-performance map analysis

The combined IPMA represents a novel tool that integrates the results of PLS-SEM, NCA and IPMA. Thus, the coordinates for each construct were taken from Tables 5 and 6. With respect to the size of the bubbles, setting a reference level of 90% for "collective memory", the values of the percentage of the number of cases that did not reach the required level in each factor are taken (Table 9). Figure 6 shows that the variables "influencer", "adoption" and "attitude" are the most important constraints in the process of formation of shared memories. Regarding the other variables, it can be mentioned that, although they are perceived by Internet users, they are not the main drivers of digital "collective memory". Finally, it is important to note that "credibility" and "need" present an interesting closeness, suggesting that they play a similar role in the formation of shared memories.

5. Discussion, conclusions and limitations of the study

5.1 Discussion

This paper analysed the effect of variables related to the adoption of information and the creation of "collective memory", using a methodological sequence that integrated PLS-SEM, NCA and IPMA. In the first instance, it is important to mention that the measurement model proposed to operationalise the variables satisfactorily complies with psychometric aspects such as low bias and random error; reliability; consistency; convergent; and discriminant capacity. This indicates that the items used reflect well the theoretical dimensions and suggests that this model can be replicated in future studies. In terms of structural effects, H1 supports the premise that people are more likely to trust information shared by authority figures. Likewise, H2–H4 prove that influencers increase the perceived relevance and applicability of content shared on social networks. Similarly, H5 and H7 confirm that when users perceive information as "trustworthy", they view it positively.

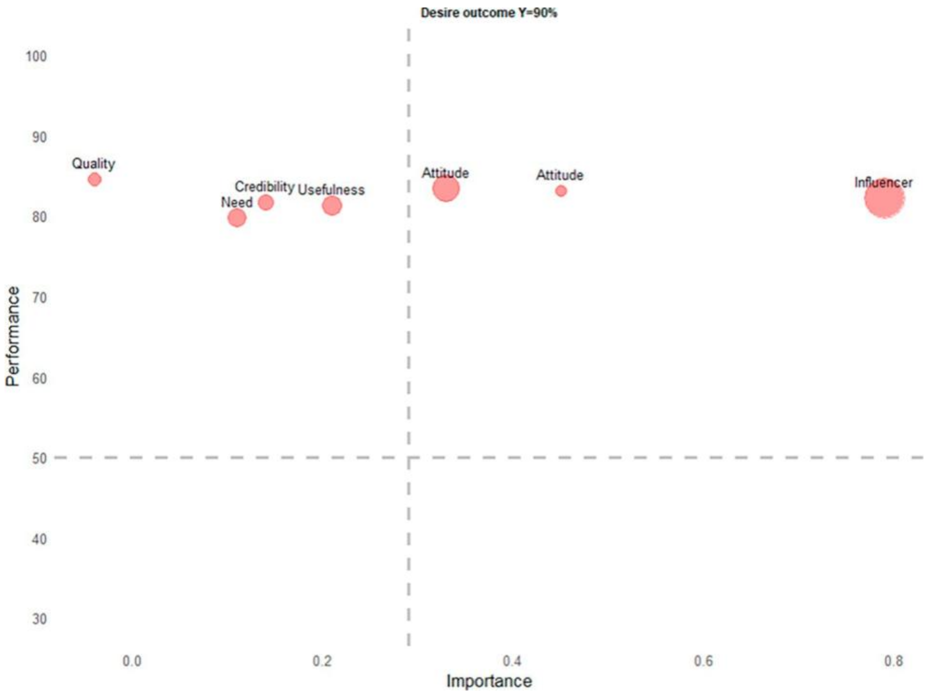

Figure 6. Importance-performance map for digital collective memory

Source: Authors' own elaboration

However, H6 showed that internet users do not always base their readiness for digital narratives on structure and depth of content, which are often aspects related to the "quality" of information. H8 and H9 suggest that because people continuously search for interesting stories, they develop a positive attitude towards this and facilitate their ultimate "adoption". Furthermore, H10 empirically confirms that following the mental process of accepting information, there is a greater propensity to retain and share it collectively. Finally, H11 concludes that influencers have the greatest impact on the consolidation of joint memories, coinciding with previous studies that highlight the role that these characters play in the viralisation of information and the consolidation of digital narratives (Martins and Martins, 2021; Zhang et al., 2020). Moreover, this effect reflects the ability of influencers to disseminate information and shape people's perception of aspects such as "credibility", "acceptance" and "attitude" towards a brand (Aslam et al., 2021; Osei-frimpong and Mclean, 2017).

In addition, the PLS-SEM results reveal a set of indirect pathways that broaden the picture of the information adoption process. The presence of significant indirect effects supports the existence of mediations in the "collective memory" creation process, suggesting that the impact of the issuing source on information adoption may operate not only through a "rational" but also an "affective" channel. This is supported by the findings of Sussman and Siegal (2003), who through their IAM model showed how people evaluated the quality of the content – rational – and the legitimacy of the sender – affective. Furthermore, Erkan and Evans (2016) empirically showed that credibility and usefulness represent transcendental dimensions in digital adoption processes; thus, the mediating effects of these variables support the idea that social media influencers act as mnesic vectors that amplify and stabilise content in collective memories (Ferron and Massa, 2014; West et al., 2021). Thus, these new routes reflect socio-cognitive mechanisms, where the symbolic validation of influencers activates processes of memorisation but also behavioural adherence.

With the results of the performance of the variables in the model, dimensions such as "usefulness" and "attitude" showed high values, confirming their role as catalysts in the adoption of content from influencers. These findings are enhanced when looking at total effects, where they also exhibit the highest loadings in terms of intention to act, articulating the principles of IAM (Sussman and Siegal, 2003). On the other hand, the NCA findings identify that the construct "credibility" has a high necessary condition figure, suggesting that, if there is no minimum level of trust in the source issuing the messages, the other mechanisms of persuasion will not be activated. This same situation is shown in the bottlenecks, revealing that, as higher thresholds of "collective memory" are desired, "credibility" should increase proportionally, reaffirming its role as a non-compensable cognitive feature (Dul, 2016). Furthermore, this study shows a relevant proportion of individuals studied who do not meet the necessary conditions, suggesting that the effectiveness of a message might depend on structural preconditions such as emotional load (Ferron and Massa, 2014; Roediger and Abel, 2015).

Thus, this approach provided a detailed understanding of the relationship between "influencer", "credibility", "usefulness", "quality" and "adoption" of content available on social networks. The application of cIPMA helped to identify the influential variables in the "collective memory", but also to establish those that are actually necessary in its formation. The identification of "credibility" as a high-impact construct suggests that organisations should develop strategies to ensure that their information is of quality whenever they use a public figure to represent their campaigns (Casais and Gomes, 2022). These findings extend the current knowledge on "collective memory", as they validate the hypothesis that the interaction that happens in social networks facilitates the dissemination of information and shapes the way people retain content and reinterpret social aspects (Geana et al., 2019).

Additionally, this strengthens the conclusions put forward in previous research where it is claimed that "collective memory" is created from the interaction mediated by technology where people select and reiterate their points of view, contributing to certain narratives remaining in the collective imaginary (Pico-valencia and Holgado-terriza, 2021).

However, the "need" for information turned out to have significant effects; however, as these are not determinants in the "collective memory", it indicates that people continuously search for information on social networks for particular queries, but the selection of content that manages to be collectively retained also depends on aspects such as "usefulness" and "acceptance" (Erkan and Evans, 2016; Geana et al., 2019). This helps to highlight the importance of designing narratives that are of quality and relevant to internet users' purchase decision-making processes.

Another important aspect to mention is the role of algorithms that prioritise the visualisation of content, as this system amplifies the reach based on the interactions that are had with any type of information. This represents a risk because it can generate "echo chambers" that polarise people's opinions based on particular interests that take advantage of these recommendation systems. The findings of this work suggest that the reiterative exposure to messages – driven by algorithms – facilitates the consolidation of contents of interest that affect collective perception. Moreover, this also articulates with what Casais and Gomes (2022) described, who argue that the structure of repetition of information in social networks permeates and conditions access to information, facilitating access to some content and marginalising others.

Finally, the methodological design assumed in this research offers an innovative approach to the study of social networks by articulating three statistical analyses that allow us to quantify the causal effects and identify the necessary conditions for the formation of "digital collective memory". Consequently, this work represents a methodological basis for future research that aims to study similar phenomena. Therefore, it not only contributes to the understanding of the role of influencers in the consolidation of joint memories but also represents a methodological guide for future work that aims to articulate technological, communication and behavioural aspects.

5.2 Conclusions and future lines of research

This study demonstrated that influencers play a determining role in the formation of digital "collective memory", being catalysts in the dissemination and consolidation of information. The use of cIPMA evaluated the effect of different constructs and identified those really necessary for the creation of shared memories in social networks. The theoretical impact of this work is based on the possibility of measuring a concept such as "collective memory" and quantifying the effects of variables related to its formation in digital media. In the organisational context, this research contributes with a theoretically replicable model that facilitates linking new dimensions and quantifying their impact on the formation of memories, which translates into brand positioning.

The findings of this research lead to the conclusion that the processes of information adoption and intention to act (remember, share and buy) are dependent on a set of mediated relationships that articulate cognitive evaluation (utility) and affective predisposition (attitude). The identified mediations demonstrate that persuasion through digital channels is not direct, as it depends on a set of internal filters in users. Additionally, the proposed model confirms that influencers transcend the boundaries of interaction, as they contribute to the stabilisation or decay of shared memories in contemporary digital environments (West et al., 2021).

In future work, it would be important to explore the effect of recommendation algorithms on the formation of digital "collective memory", but it would also be necessary to analyse the role of misinforming content and the stability of narratives over time. Finally, the impact of media literacy actions on the "credibility" and "quality" of content could be analysed.

Ethics statement

This study was approved by the University of Medellín Research Ethics Committee (approval no. 18) on July 12, 2024.

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References

Ahmed, W., Seguí, F.L., Vidal-Alaball, J. and Downing, J. (2020), "COVID-19 and the 5G conspiracy theory: Social network analysis of twitter data", Journal of Medical Internet Research, Vol. 22 No. 5, doi: 10.2196/22374.

Ajzen, I. (1991), "The theory of planned behavior", Organizational Behavior and Human Decision Processes, Vol. 50 No. 2, pp. 179-211, doi: 10.1016/0749-5978(91)90020-t.

Alrwashdeh, M., Ali, H., Helalat, A., Ahmad, D. and Alkhodary, A. (2022), "The mediating role of brand credibility between social media influencers and patronage intentions", International Journal of Data and Network Science, Vol. 6 No. 2, pp. 305-314, doi: 10.5267/j.ijdns.2022.1.007.

Al Sulaiti, S., Ben Mimoun, M.S. and Elgohary, H. (2024), "Instagram influencers attributes and parasocial relationship: a dataset from Qatar", Data in Brief, Vol. 53, p. 110128, doi: 10.1016/j.dib.2024.110128.

Aslam, W., Mehfooz Khan, S., Arif, I. and Zaman, S.U. (2021), "Vlogger's reputation: Connecting trust and perceived usefulness of vloggers' recommendation with intention to shop online", Journal of Creative Communications, Vol. 17 No. 1, pp. 49-66, doi: 10.1177/09732586211048034.

Assmann, J. (2011), Cultural Memory and Early Civilization: Writing, Remembrance, and Political Imagination, Cultural Memory and Early Civilization: Writing, Remembrance, and Political Imagination Cambridge University Press, doi: 10.1017/CBO9780511996306.

Barnea, U., Meyer, R.J., Nave, G. and Behavioral, W. (2023), "The effects of content ephemerality on information processing", Journal of Marketing Research, Vol. 60 No. 4, pp. 750-766, doi: 10. 1177/00222437221131047.

Carretero-Dios, H., Pérez, C. and De Granada, U. (2005), “Normas Para el desarrollo y revisión de estudios instrumentales”, International Journal of Clinical and Health Psychology, Vol. 5, pp. 521-551.

Casadiego-Alzate, R., Marín-Cuartas, I., Toro-Herrera, C.S., Silva-Cortés, A. and Luzardo-Briceño, A. (2025), “Predictors of purchase intention in gastronomic establishments in the city of medellin”, Int. J. Applied Decision Sciences, Vol. 18 No. 1, pp. 113-135, doi: 10.1504/IJADS.2025.143090.

Casais, B. and Gomes, L.R. (2022), “Fashion bloggers’ discourse on brands under corporate crisis: a netnographic research in Portugal”, Journal of Fashion Marketing and Management, Vol. 26 No. 3,

pp. 420-435, doi: 10.1108/JFMM-09-2020-0206/FULL/PDF, Emerald Group Holdings Ltd

Davis, F.D. (1989), “Perceived usefulness, perceived ease of use, and user acceptance of information technology”, MIS Quarterly, Vol. 13 No. 3, pp. 319-339, doi: 10.2307/249008.

Dedeoglu, B.B. (2019), “Are information quality and source credibility really important for shared content on social media?: the moderating role of gender”, International Journal of Contemporary Hospitality Management, Vol. 31 No. 1, pp. 513-534, doi: 10.1108/IJCHM-10-2017-0691.

Dul, J. (2016), “Necessary condition analysis (NCA): logic and methodology of ‘necessary but not sufficient’ causality”, Organizational Research Methods, Vol. 19 No. 1, pp. 10-52, doi: 10.1177/ 1094428115584005.

Erkan, I. and Evans, C. (2016), “The influence of eWOM in social media on consumers’ purchase intentions: an extended approach to information adoption”, Computers in Human Behavior, Vol. 61,

pp. 47-55, doi: 10.1016/j.chb.2016.03.003.

Ferron, M. and Massa, P. (2014), “Beyond the encyclopedia: Collective memories in wikipedia”,

Memory Studies, Vol. 7 No. 1, pp. 22-45, doi: 10.1177/1750698013490590.

Fishbein, M., and Ajzen, I. (1975), Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research, Addison-Wesley, Reading, MA.

Geana, A., Duker, A. and Coman, A. (2019), “An experimental study of the formation of collective memories

in social networks”, Journal of Experimental Social Psychology, Vol. 84 No. May, p. 103813, doi: 10. 1016/j.jesp.2019.05.001.

Hair, J.F., Hult, T., Ringle, C., Sarstedt, M., Danks, N., and Ray, S. (2021), Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R, Springer.

Halbwachs, M. (1950), “Space and the collective memory”, The Collective Memory, 1st ed., New York, NY.

Hauff, S., Guerci, M., Dul, J. and van Rhee, H. (2021), “Exploring necessary conditions in HRM research: Fundamental issues and methodological implications”, Human Resource Management Journal, Vol. 31 No. 1, pp. 18-36, doi: 10.1111/1748-8583.12231.

Hauff, S., Richter, N.F., Sarstedt, M. and Ringle, C.M. (2024), “Importance and performance in PLS-SEM and NCA: Introducing the combined importance-performance map analysis (cIPMA)”, Journal of Retailing and Consumer Services, Vol. 78, doi: 10.1016/j.jretconser.2024.103723.

Hirst, W. and Coman, A. (2018), “Building a collective memory: the case for collective forgetting”,

Current Opinion in Psychology, Vol. 23, pp. 88-92, doi: 10.1016/j.copsyc.2018.02.002.

Martins, P. and Martins, F.A. (2021), “Launcher nodes for detecting efficient influencers in social networks”, Online Social Networks and Media, Vol. 25 No. February, p. 100157, doi: 10.1016/j. osnem.2021.100157.

Massaro, D.W., Petty, R.E. and Cacioppo, J.T. (1988), “Communication and persuasion: Central and peripheral routes to attitude change”, The American Journal of Psychology, Vol. 101 No. 1, doi: 10.2307/1422805.

Mehrabian, A., and Russell, J.A. (1974), An Approach to Environmental Psychology, The MIT Press,.

Mim, K.B., Jai, T.C. and Lee, S.H. (2022), “The influence of sustainable positioning on eWOM and brand loyalty : analysis of credible sources and transparency practices based on the S-O-R model”, Sustainability (Switzerland), Vol. 14 No. 19.

Momennejad, I. (2022), “Collective minds: Social network topology shapes collective cognition”, Philosophical Transactions of the Royal Society B: Biological Sciences, Vol. 377 No. 1843, doi: 10.1098/rstb.2020.0315.

Oquiñena, I., Sánchez, J. and Monfort, A. (2025), “The influence of homophily and social identity on eWOM in streaming consumption behaviour”, Spanish Journal of Marketing - ESIC, Vol. 29 No. 2,

pp. 207-228, doi: 10.1108/SJME-05-2023-0131.

Osei-Frimpong, K. and Mclean, G. (2017), “Examining online social brand engagement : a social presence theory perspective”, Technological Forecasting and Social Change, No. October, doi: 10.1016/j.techfore.2017.10.010.

Peres, R., Schreier, M., Schweidel, D.A. and Sorescu, A. (2024), “The creator economy: an introduction and a call for scholarly research”, International Journal of Research in Marketing, Vol. 41 No. 3, 1 September, doi: 10.1016/j.ijresmar.2024.07.005.

Pérez-Escoda, A., Barón-Dulce, G. and Rubio-Romero, J. (2021a), “Mapping media consumption among youngest: Social networks, fake news and trustworthy in pandemic times”, Index. Comunicacion, Vol. 11 No. 2, pp. 187-208, doi: 10.33732/ixc/11/02Mapeod.

Pérez-Escoda, A., Pedrero-Esteban, L.M., Rubio-Romero, J. and Jiménez-Narros, C. (2021b), “Fake news reaching young people on social networks: Distrust challenging media literacy”, Publications, Vol. 9 No. 2, doi: 10.3390/publications9020024.

Pico-Valencia, P.A. and Holgado-Terriza, J.A. (2021), “Detección de noticias falsas en redes sociales basada en aprendizaje automático y profundo : una breve revisión sistemática detección de noticias falsas en redes sociales basada en aprendizaje automático y profundo : una breve revisión sistemática”, Iberian Journal of Information Systems and Technologies, No. February,

Pozharliev, R., Rossi, D. and De Angelis, M. (2022), “Consumers’ self-reported and brain responses to advertising post on instagram: the effect of number of followers and argument quality”, European Journal of Marketing, Vol. 56 No. 3, pp. 922-948, doi: 10.1108/EJM-09-2020-0719/ FULL/XML.

Rampazzo Gambarato, R. and Heuman, J. (2023), “Beyond fact and fiction: Cultural memory and transmedia ethics in netflix’s the crown”, European Journal of Cultural Studies, Vol. 26 No. 6,

pp. 803-821, doi: 10.1177/13675494221128332.

Richter, N.F., Schubring, S., Hauff, S., Ringle, C.M. and Sarstedt, M. (2020), “When predictors of outcomes are necessary: guidelines for the combined use of PLS-SEM and NCA”, Industrial Management and Data Systems, Vol. 120 No. 12, pp. 2243-2267, doi: 10.1108/IMDS-11-2019-0638.

Roche, A., Pimenta De Almeida, M.A. and Ogécia-Drigo, M. (2022), “Valores y educación Para los medios en el « canal do negão » (YouTube)”, Redes Sociales y Ciudadania, Vol. 2no, pp. 135-141. 1

Rodner, V., Goode, A. and Burns, Z. (2022), “Is it all just lip service?’: on instagram and the normalisation of the cosmetic servicescape”, Journal of Services Marketing, Vol. 36 No. 1, pp. 44-58, doi: 10.

1108/JSM-12-2020-0506/FULL/PDF.

Roediger, H.L. and Abel, M. (2015), “Collective memory: a new arena of cognitive study”, Trends in Cognitive Sciences, Vol. 19 No. 7, pp. 359-361, doi: 10.1016/j.tics.2015.04.003.

Roldan-Gallego, J.S., Sánchez-Torres, J.A., Argila-Irurita, A. and Arroyo-Cañada, F.J. (2023), “Are social media influencers effective? An analysis of information adoption by followers”, International Journal of Technology Marketing, Vol. 17 No. 2, pp. 188-211, doi: 10.1504/ IJTMKT.2023.130026.

Ross, B., Pilz, L., Cabrera, B., Brachten, F., Neubaum, G. and Stieglitz, S. (2019), “Are social bots a real threat? An agent-based model of the spiral of silence to analyse the impact of manipulative actors in social networks”, European Journal of Information Systems, Vol. 28 No. 4, pp. 394-412, doi: 10.1080/0960085X.2018.1560920.

Sarstedt, M., Hair, J.F., Pick, M., Liengaard, B.D., Radomir, L. and Ringle, C.M. (2022), “Progress in partial least squares structural equation modeling use in marketing research in the last decade”, Psychology and Marketing, Vol. 39 No. 5, pp. 1035-1064, doi: 10.1002/mar.21640.

Simons, G., Muhin, M., Oleshko, V. and Sumskaya, A. (2021), “The concept of interdisciplinary research on intergenerational transmission of communicative and cultural memory”, Journal of Russian Media and Journalism Studies, Vol. 1, pp. 64-91.

Sundaram, D.S., Mitra, K. and Webster, C. (1998), “Word-of-mouth communications: a motivational analysis”, Advances in Consumer Research, Vol. 25, pp. 527-532.

Sussman, S.W. and Siegal, W.S. (2003), “Informational influence in organizations: an integrated approach to knowledge adoption”, Information Systems Research, Vol. 14 No. 1, pp. 47-65, doi: 10.1287/isre.14.1.47.14767.

Sutrantiyas, R.R., Arif, N.F. and Sugandini, D. (2025), “The effect of influencer credibility on purchase intention of beauty products among TikTok users in the special region of Yogyakarta through trust as a mediator”, American Journal of Economic and Management Business, Vol. 4.

Wahab, H.K.A., Alam, F. and Lahuerta-Otero, E. (2025), “Social media stars: how influencers shape consumer’s behavior on instagram”, Spanish Journal of Marketing - ESIC, Vol. 29 No. 2, pp. 188-206, doi: 10.1108/SJME-09-2023-0257.

West, R., Leskovec, J. and Potts, C. (2021), “Postmortem memory of public figures in news and social media”, Proceedings of the National Academy of Sciences, Vol. 118 No. 38, doi: 10.1073/pnas. 2106152118.

Zhang, X., Nekmat, E. and Chen, A. (2020), “Crisis collective memory making on social media: a case study of three Chinese crises on Weibo”, Public Relations Review, Vol. 46 No. 4, p. 101960, doi: 10.1016/j.pubrev.2020.101960.

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