Open Journal of Social Sciences, 2026, 14(9), 550-570
https://www.scirp.org/journal/jss
ISSN Online: 2327-5960
ISSN Print: 2327-5952

Research Trends in the Elaboration Likelihood Model: A Bibliometric and Visual Analysis (2015-2024)

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How to cite this paper: Chen, Y., Ma'rof, A. A., Abdullah, H., & Hamsan, H. H. (2026). Research Trends in the Elaboration Likelihood Model: A Bibliometric and Visual Analysis (2015-2024). *Open Journal of Social Sciences, 14,* 550-570.
https://doi.org/10.4236/jss.2026.149034

Received: July 28, 2026
Accepted: September 18, 2026
Published: September 21, 2026

Abstract

The elaboration likelihood model explains the mechanisms by which individuals process persuasive information and subsequently alter their attitudes or behaviors. This theory has been extensively applied in research across various fields. This study examines the current status and research trends of the elaboration likelihood model over the past decade. This study used 808 research papers regarding the elaboration likelihood model published between 2015 and 2024, sourced from the Core Collection of the Web of Science database. CiteSpace visual analysis software was used to sort and summarise the collected data for the number of publications, country/region, and author collaboration, keyword co-occurrence, and burst analysis, reference co-citation, and timeline view studies were used to explain the hotspots and research trends in the applied research domain of the elaboration likelihood model. The findings indicate an overall upward trend in ELM-related publications through 2023. The United States has the highest number of publications. Australia, Spain, and South Korea maintain strong collaborations with other countries. Research by scholars on elaboration likelihood models has focused on online information persuasion, particularly in website design and user-generated content, such as online reviews and electronic word-of-mouth, with an emphasis on developing models to address practical issues. Future research trends focus on social media, websites, and online persuasion, with an emphasis on examining business behaviour. This study presents a bibliometric review of the literature on elaboration likelihood models from the past decade, offering valuable insights for future research and practice.

Keywords

Elaboration Likelihood Model, Visual Analysis, Bibliometric

1. Introduction

In the 1980s, social psychologists Petty and Cacioppo, based on summarising the relevant theories of attitude, cognitive formation and behavioural change, proposed the elaboration likelihood model (ELM). The ELM is one of the most commonly used models in persuasion theory and the most commonly used model for understanding information processing for attitude change (Bitner & Obermiller, 1985). Over the past decade, ELM has experienced significant dynamic development, leading to the emergence of various research hotspots and trends. However, there is a lack of systematic literature summarising the research status, hotspots, and trends of ELM. Analysing the recent decade of research on ELM allows for an understanding of current hotspots and facilitates the anticipation of future research directions in this domain. Mapping knowledge domains analysis has become a prevalent bibliometric research method in recent years, which identifies the interconnections of these domains based on institutions, publications, journals, citations, and authors, determines the orientation of the research, and reveals the output of the research in each domain, the rate of research growth and diversification, and other dynamic changes (Gan et al., 2022). CiteSpace can visualise the relationships between the literature by mapping knowledge domains, helping users sort out the research trajectories and foresee future research prospects (Chen, 2016). Therefore, based on the CiteSpace visual analysis software, this paper analyses the mapping knowledge domains of ELM bibliographic included in the Web of Science (WOS) Data Core Collection from 2015 to 2024 to understand ELM's current research status and development trend. This paper aims to answer the following questions.

1. What is the publication status and trend of research literature related to ELM from 2015 to 2024?

2. Which countries/regions and authors have impacted ELM research more from 2015 to 2024?

3. What are the hot issues and frontiers in ELM research?

2. Methodology

Data were collected from the Web of Science (WOS) Core Collection (SCIE and SSCI). The time span of the literature search was set between 2015 and 2024, and the search query was TS = ("elaboration likelihood model"). The selected language was "English", and the document type were "article" and "review article", and 808 articles were searched. The file format was "plain text", and the record content was "full-text records and citations". The date of retrieval and download was June 10, 2024. After performing the "delete duplicates" function in CiteSpace, no duplicate records were identified; therefore, all 808 records were retained.

This study employed CiteSpace 6.3.R1 for bibliometric analysis. CiteSpace facilitates various bibliometric studies, encompassing collaborative network analysis, keyword co-occurrence analysis, authorship, category, document co-citation analysis, and term and geographical visualisation analysis (Chen, 2017). In CiteSpace, the time slicing is configured for 2015-2024, with the "Years Per Slice" set to 1 year, and the selected "Node Types" include country, author, keyword, and reference. The selection criteria included the g-index (k = 25) and thresholding parameters (c, cc, ccv) of 2, 2, 20; 4, 3, 20; and 3, 3, 20. The project properties were set to LRF = 3.0, L/N = 10, LBY = 5, and e = 1.0. Term sources included Title, Abstract, Author Keywords, and Keywords Plus. Pathfinder and Pruning the merged network were applied to optimise the network structure, emphasise the features of the maps, and display the final maps in two visual formats: "Show Merged Network" and "Cluster View-static".

3. Results

Annual publication number analysis

The quantity of literature indicates the research level and development speed of the associated fields to some degree. Figure 1 illustrates the distribution of publications on ELM within the WOS Core Collection database from 2015 to 2024. Publication output showed an overall upward trend through 2023. After 2020, the upward trend of annual publications increased rapidly, doubling from 72 in 2020 to 145 in 2023, which suggests that ELM research has entered a hot period since 2020. As of June 10, 2024, 79 publications had been recorded, representing a partial-year count.

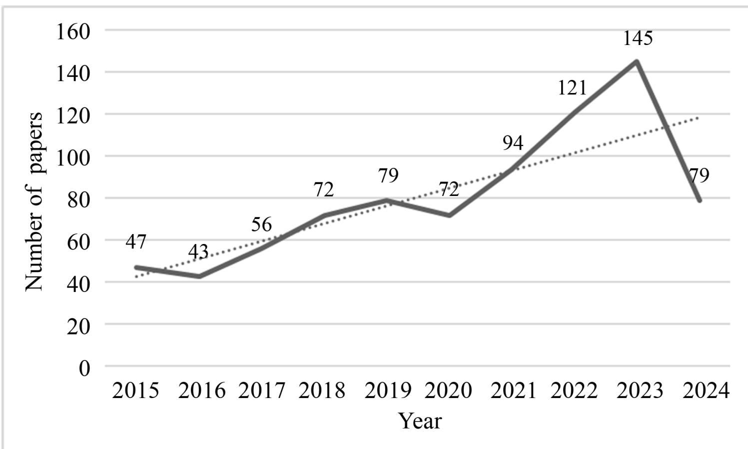

Figure 1. Annual distribution trend of literature from 2015 to 2024 (Source: Authors' work).

Cooperation relations

Country/Region Cooperation Analysis

Analysing the collaborative network between countries/regions allows us to derive the countries/regions with a high volume of publications and influence in ELM research and the collaborative relationships between the countries. The visual map of collaborative countries for the ELM research is shown in Figure 2. The network of collaborative countries consists of 66 nodes and 77 links with a density of 0.0359 for 2015-2024. The circles in the map represent the frequency, and the size of the circle is proportional to the frequency counts; the thickness of the links represents the intensity of cooperation between nodes, and the betweenness centrality indicates the importance of a country/region on the map degree (Zhang et al., 2020).

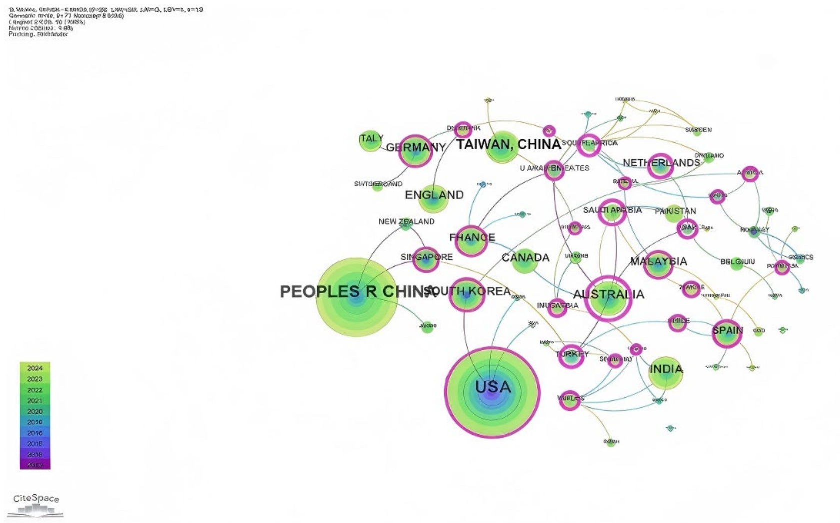

Figure 2. Collaboration network map of countries/regions (Source: Authors' work).

ELM research comes from 66 countries or regions worldwide, and **Table 1** lists the top 10 countries/regions in terms of publications. The country with the largest number of research publications is the United States, with 281 papers indicating that the United States, as the birthplace of research and application of ELM, has the greatest lead and influence in ELM research. The second is Chinese Mainland, with 227 papers published, indicating that Chinese Mainland plays a crucial role in ELM research. The purple-bordered nodes indicate countries with high centrality, which are the hubs of the research network (Cheng et al., 2021).

Table 1. The top 10 countries/regions between 2015 and 2024.

Rank	Regions	Counts	Centrality	Year
1	USA	281	0.12	2015
2	Chinese Mainland	227	0.06	2015
3	Australia	53	1.13	2015
4	Taiwan Region, China	48	0.06	2015
5	England	40	0	2015
6	South Korea	40	0.17	2015
7	Germany	35	0.12	2015
8	France	30	0.12	2015
9	Malaysia	30	0.12	2015
10	Spain	24	0.34	2015

Source: Authors' work.

As shown in Figure 2, the three nodes with the highest betweenness centrality are Australia (Centrality = 1.13), Spain (Centrality = 0.34) and South Korea (Centrality = 0.17). It shows that these three countries cooperate closely with other countries in applied research in ELM. Although Chinese Mainland has more than four times as many publications as Australia, Chinese Mainland's centrality (Centrality = 0.06) is lower than Australia's, indicating that Australia occupies a stronger bridging position in the international collaboration network.

Author Collaboration Analysis

Analysis of author collaboration identifies key authors within a discipline and assesses the degree of collaboration among them. A greater number of publications corresponds to larger nodes. The stronger the cooperation between authors, the thicker the connecting lines between nodes. The visual map of collaborating authors for the ELM study is shown in Figure 3. The network includes 263 nodes and 112 links with a density of 0.0033, indicating that 263 authors contributed to ELM research.

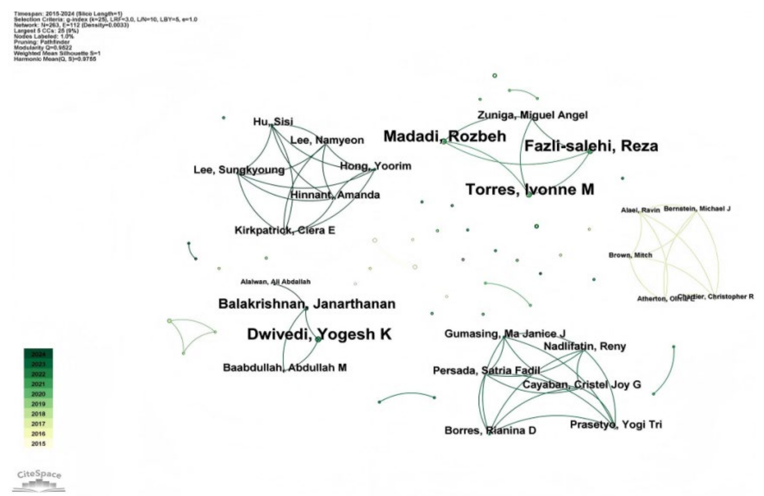

Figure 3. Collaboration-network map of authors (Source: Authors' work).

Table 2 summarises the ten most collaborating authors in the ELM application study. Overall, the impact of collaboration between authors was low, as all collaborating authors had a betweenness centrality of 0. Specifically, Madadi, Rozbeh. Fazli-Salehi, Reza. Torres, Ivonne M. Dwivedi, Yogesh K. ranked in the top 4 with the highest co-authorship publications and indicated relatively close collaboration between these four authors and their peers.

In addition, Figure 3 shows several collaborating teams from the last three years with different research interests. (1) A collaborative group consisting of Madadi, Rozbeh, Fazli-Salehi, Reza, and Torres, Ivonne M. focused on the relationship between ethnic identity and brand attachment and brand love. The group collaborated to construct an assessment of ethnic identity and consumer brand love, providing managers with practical tools to improve the effectiveness of ethnic-targeted advertising (Madadi et al., 2021, 2022). In another paper, the group demonstrated the effect of consumers' personality traits on self-brand associations and community brand associations for anthropomorphic and materialised brands (Fazli-Salehi et al., 2022). (2) A research team led by Dwivedi Yogesh K studied chatbots and customer buying behaviour from an ELM perspective, extending ELM by introducing new dimensions for human-computer interaction at the heart of digital transformation (Dwivedi et al., 2023). In addition, the team developed a conceptual model for use in smart tourism technology and heritage tourism development by formulating key reasoning for ELM and flow theory (Balakrishnan et al., 2023). The above collaborative analysis shows the diversity of themes in the application area of ELM elaboration.

Table 2. The top 10 authors between 2015 and 2024.

Rank	Author	Count	Centrality	Year
1	Madadi, Rozbeh	4	0	2021
2	Fazli-Salehi, Reza	4	0	2021
3	Torres, Ivonne M	4	0	2021
4	Dwivedi, Yogesh K	4	0	2023
5	Khong, Kok Wei	3	0	2015
6	Brinol, Pablo	3	0	2015
7	Teng, Shasha	3	0	2015
8	Benlian, Alexander	3	0	2015
9	Aghakhani, Navid	3	0	2018
10	Balakrishnan, Janarthanan	3	0	2023

Source: Authors' work.

Co-occurrence analysis

Keyword co-occurrence analysis

In academic papers, keywords summarise the article's central idea and provide a brief overview of the content. Keyword analysis is often used to reveal the core attributes of a subject area and can reasonably predict new trends in research and future directions. **Figure 4** presents the keyword co-occurrence visualisation map for the ELM literature, comprising 394 nodes and 710 links, with a density of 0.0092. **Table 3** lists the top 15 most frequently cited or mentioned keywords from 2015-2024. Among the selected keywords, "elaboration likelihood model" is the most frequently used keyword, with 510 citations. Overall, "impact" (200 times), "information" (177 times), "word of mouth" (133 times), "moderating role" (129 times), and "social media" (117 times) are the five most common co-occurring keywords. These highly co-occurring keywords are closely related to the application areas of the ELM, suggesting that scholars' applied research on the ELM focuses on the field of information persuasion, specifically on social media and websites, and in particular on the application of social media and electronic word-of-mouth (eWOM). In their research, scholars focus on constructing models to solve practical problems and exploring how model variables influence each other. For example, studying how online information influences investors' decisions, developing models of persuasive influence in crowdfunding, and exploring how online customer reviews influence consumers' purchase decisions (Allison et al., 2017; Bi et al., 2017; Cheng & Ho, 2015).

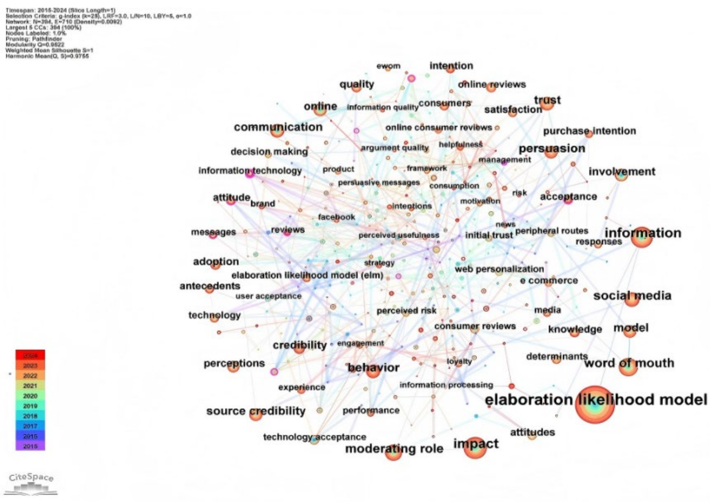

Figure 4. Keyword co-occurrence visualisation map of ELM from 2015 to 2024 (Source: Authors' work).

Table 3. Top15 keywords in frequency and centrality between 2015 and 2024.

Rank	Keywords	Frequency Count	Centrality	Year
1	elaboration likelihood model	510	0	2015
2	impact	200	0	2015
3	information	177	0.02	2015
4	word of mouth	133	0.05	2015
5	moderating role	129	0.03	2015
6	social media	117	0	2015
7	persuasion	106	0.01	2015
8	behaviour	103	0.01	2016
9	source credibility	88	0.06	2015
10	trust	83	0.04	2015
11	model	81	0.06	2015
12	communication	78	0.03	2015
13	credibility	65	0	2015
14	online	64	0.02	2015
15	involvement	61	0.02	2015

Source: Authors' work.

Keyword clustering analysis helps to generalise the relationships between high-frequency keywords further. In this paper, the keyword network is clustered using local linear regression (LLR), and the nouns of the feature words with the highest LLR algorithm values are used as cluster names. The results show that the keyword clustering network contains 18 clusters, the number of nodes is 394, and there are 710 connecting lines between the nodes, and the value of the clustering module is Q = 0.6826 > 0.3, which is a significant clustering structure; and the value of the average profile of the clusters is S = 0.8366 > 0.5, which indicates that the clustering is reasonable. The information on 18 keyword co-occurrence clusters is shown in Table 4.

Table 4. Information on the 18 co-occurrence clusters of keywords.

Cluster	Size	Silhouette	Mean (Year)	Label (LLR)
0	40	0.857	2017	social influence
1	38	0.747	2018	corporate social responsibility
2	31	0.746	2019	online health community
3	28	0.86	2019	persuasive technology
4	27	0.786	2019	information security
5	25	0.878	2019	consumer attitude
6	25	0.871	2018	water conservation campaigns
7	20	0.876	2017	elaboration likelihood model
8	20	0.828	2017	responses
9	19	0.834	2019	issue involvement
10	19	0.956	2019	argumentation from example
11	18	0.867	2018	electronic word-of-mouth
12	18	0.855	2017	emotional contagion
13	17	0.871	2020	customer engagement
14	15	0.891	2019	narrative
15	14	0.87	2015	individual differences
16	8	0.942	2022	content analysis
17	8	0.984	2021	signalling theory

Source: Authors' work.

The 18 main clusters are shown in Figure 5, where we can find that these co-occurring keywords cover several topics. Some clusters focus on user-generated content, mainly electronic word of mouth or online reviews, such as #0 social influence, #7 elaboration likelihood model, #11 electronic word of mouth, and #13 customer engagement. Many online customer reviews significantly impact consumers' purchase decisions, both positive and negative, and consumers perceive online customer reviews as providing useful information. Consequently, researchers have focused on the relationship between the social influence of electronic word-of-mouth and consumer information adoption or consumer purchasing behaviour (Chang et al., 2015; Cheng & Ho, 2015; Hussain et al., 2017). Yusuf and Busalim (2018) proposed a new model of IWOM engagement that considers information characteristics, consumer behaviour, technology, and social factors. In addition, Filieri et al. (2018) analysed consumers' information diagnosis of online reviews in terms of central cues (redundancy, relevance, current and factual) and peripheral cues (source credibility, composite ranking scores).

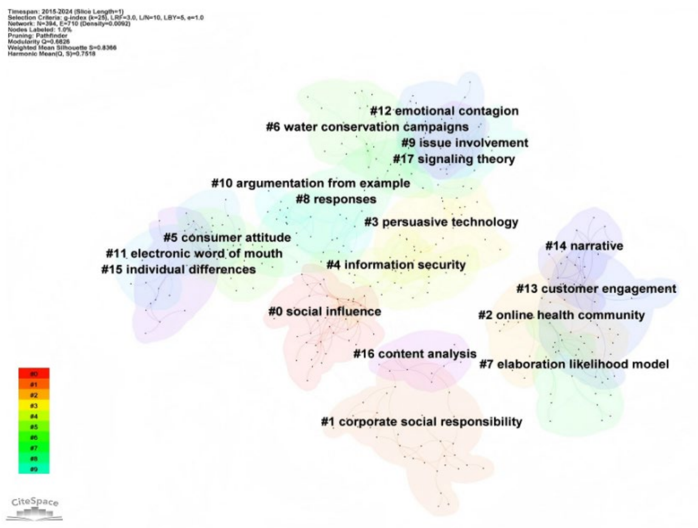

Figure 5. Cluster map of keywords (Source: Authors' work).

Some clusters focus on the impact studies of online information, e.g., the representative paper of #1 corporate social responsibility found that relational advertising messages may be more effective for less engaged consumers than for more engaged consumers in increasing positive attitudes towards CSR activities (Choi, 2022). In cluster #2 online health community, Zhao et al. (2021) proposed a health misinformation detection model that combines central layer features (including topic features) and peripheral layer features (including linguistic features, emotional features and user behavioural features). In #3 persuasive technology, the representative paper investigated the factors affecting the perceived trustworthiness of websites providing dietary and nutritional information and found that the accuracy of the information improves the perceived trustworthiness of the website, regardless of the level of expertise of the information source (Jung et al., 2016). In cluster #4, information security, a paper discusses how to design persuasive information security messages to increase employee engagement in protection-motivated behaviours, and the findings have important implications for organisational information security management in designing effective information security messages (Xu & Warkentin, 2020). During the app download phase, Pappas et al. (2016) investigated Android users' information processing and privacy concern formation and proposed and tested emerging privacy protection mechanisms. In addition, in #5, consumer attitude, a paper examines the persuasive effects of virtual reality (VR) and augmented reality (AR) video advertising (Jayawardena et al., 2023).

Some clusters focus on persuasive research. For example, #6 water conservation campaigns, #9 issue involvement, #10 argumentation from example, and #14 narrative. Nera et al. (2018) investigated the effect of conspiracy narratives on real-world conspiracy beliefs in a study that observed a significant relationship between conspiracy mindset and enjoyment. This relationship was fully mediated by two dimensions of perceived realism: credibility and narrative coherence. McDermott and Lachlan (2020) examined audiences' ELM processing routes to evaluate image repair messages. They showed that the relationship between inclination and peripheral processing was curvilinear, with an increase in the use of peripheral processing at the extremes of inclination. Self-involvement fully mediated this relationship for most messages. Mikkilineni et al. (2024) examined the effects of student-athletes' health promotions on college students' attitudes and behavioural intentions towards binge drinking. Schellens et al. (2017) explored whether argumentation schemes could play a role in the critical processing of arguments by laypeople, and the findings supported the discursive traditional validity of the dialectical argumentation scheme rule and provided a more specific view of central processing in ELM.

Keyword burst analysis

Bursting keywords have a strong co-occurrence, which, to some extent, reflects the mutation turning point of the related research direction. Research frontiers have a temporal advancement routine; early bursting keywords can reflect early research frontiers, while current bursting keywords can forecast future research hotspots (Wu et al., 2021). Keyword burst analysis to obtain the top 21 burst keywords in the research field of ELM is used to clearly show the evolution of the research frontiers between 2015-2024. Based on **Figure 6**, we have the following findings: (1) Specifically, the top five keywords with the strongest bursts were "user acceptance" (Strength = 4.99), "initial trust" (Strength = 4.52), "experience" (Strength = 4.46), "reviews" (Strength = 3.89), "determinants" (Strength = 3.26). (2) In recent years, research has focused on "experience", "reviews", "online consumer reviews" and "identification". Among them, "experience" and "reviews" are the overlapping words of the burst and recent research keywords, reflecting that scholars are very concerned about the application of ELM to information processing in online social media, such as user-generated content, especially the study of online reviews and electronic word-of-mouth (Chen et al., 2022; Hur et al., 2017; Wang et al., 2022). It shows that scholars may continue focusing on these keywords in the future, leading to more research results.

Co-citation analysis

Reference co-citation analysis

Reference co-citation is a phenomenon where the same literature cites two references. Co-citation reference analysis can reveal the knowledge structure of a research field, reflecting research frontiers and key literature (Chen & Liu, 2020).

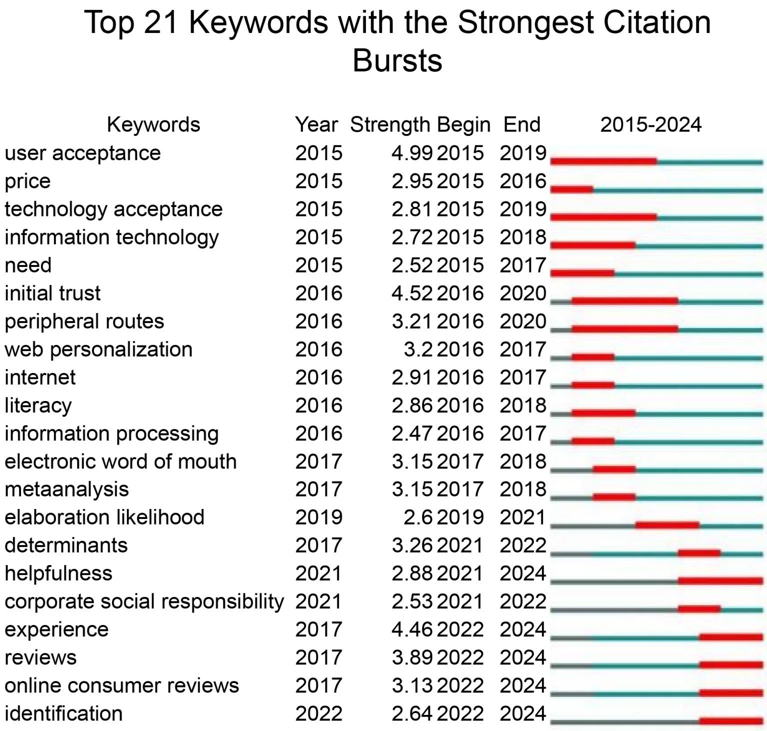

Figure 6. Top 21 Keywords with the strongest citation burst (Source: Authors' work).

We analysed the literature co-citation network related to the ELM. **Table 5** lists the top 10 most frequently cited references from 2015-2024. The specific findings are as follows. (1) Most references in the top 10 co-cited rankings are studies of online persuasion of websites, pointing primarily to consumer behaviour. Specifically, Cyr et al. (2018) used the ELM to determine the influence of argument quality as a central route to affecting attitude change versus the influence of design and social factors as peripheral routes to attitude change, identifying the role of website design and how an individual's engagement with a question can be a prerequisite for changing a user's attitude. Chang et al. (2020) study concluded that it is recommended that sellers on Facebook's second-hand marketplace provide as accurate and complete information about their goods as possible to enhance the positive impression of their posts. Ho and Bodoff (2014) investigated how Web personalisation can be managed to increase advertising revenue or sales revenue. Shahab et al. (2021) conducted a study on the role of fine processing likelihood models in consumer behaviour research and reviewed its extension to new technologies. (2) The 4th ranked co-cited reference is a study on persuasion, which used the ELM to develop and test a model of persuasive influence in crowdfunding (Allison et al., 2017). (3) The 6th ranked co-cited reference responded to the fact that the model frequently used in applied research for ELM modelling is Partial Least Squares Structural Equation Modelling (PLS) and that the Structural Equation Models (SEM) are analysed using SmartPLS software (Hair et al., 2019). (4) The 10th-ranked co-cited reference is a study on information dissemination behaviour. The paper systematically investigates the determinants of individual communication behaviour on SNS based on the ELM (Shahab et al., 2021).

Table 5. Top 10 most-cited references from 2015 to 2024.

Rank	References	Frequency Count	Centrality	Year
1	Cyr D, 2018, INFORM MANAGE-AMSTER, V55, P807	63	0.04	2018
2	Chang HH, 2020, INFORM MANAGE-AMSTER, V57, P0	42	0.04	2020
3	Ho SY, 2014, MIS QUART, V38, P497	35	0.01	2014
4	Allison TH, 2017, J BUS VENTURING, V32, P707	30	0.05	2017
5	Shahab MH, 2021, INT J CONSUM STUD, V45, P664	25	0.03	2021
6	Hair JF, 2019, EUR BUS REV, V31, P2	25	0.01	2019
7	Zhou T, 2016, INFORM SYST FRONT, V18, P265	22	0	2016
8	Kang JW, 2019, INT J HOSP MANAG, V78, P189	21	0.34	2019
9	Bi S, 2017, J BUS RES, V71, P10	21	0.26	2017
10	Shi J, 2018, INTERNET RES, V28, P393	21	0.04	2018

Source: Authors' work.

The cited reference is the knowledge base, and in the co-citation analysis of literature, the network of co-cited references was clustered using local linear regression (LLR). The analysis yielded 17 clusters consisting of 291 nodes and 595 links, with a modularity value of Q = 0.7742, reflecting a clear delineation of the clusters, and a weighted mean of S = 0.8992, indicating that the clusters are reasonable (Figure 7). The cluster numbers are labelled in increasing order from 0. The smaller the number, the more literature is included in the corresponding cluster, reflecting that it is more important in the applied research of ELM, and the co-cited references cover a wide range of topics. The analysis focused on the first four largest clusters.

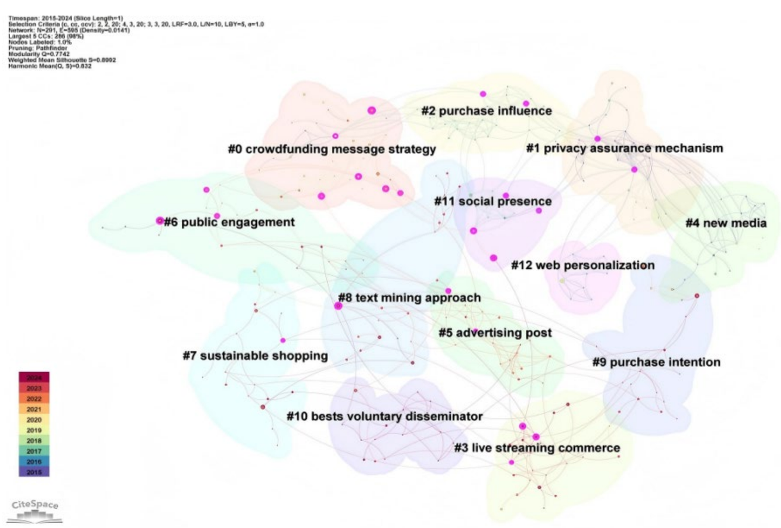

Figure 7. Co-citation-cluster map of cited references (Source: Authors' work).

(1) The largest cluster was named the #0 crowdfunding message strategy. These references discuss backers' willingness to fund in crowdfunding. The literature uses the ELM as an overarching theory to explore what messages affect backers' willingness to fund and whether personal characteristics influence backers' funding decisions (Wang & Yang, 2019). The representative paper of this clustering also explores how the focus of claims in crowdfunding messages affects the support decisions of two types of backers (consumers and investors) (Xiang et al., 2019). (2) Cluster #1 privacy assurance mechanism has also received much attention in response to the research on privacy protection mechanisms. The perspective of ELM is used to investigate how individuals perceive and deal with privacy assurance mechanisms (Bansal et al., 2015). Zhou (2017) used ELM to examine the privacy issues of location-based service (LBS) users. (3) Cluster #2 purchase influence focuses on purchase influence research. Goh et al. (2017) present a model linking argument quality, website quality, and reviewer quality to purchase influence and behavioural intention and show how these factors influence the use and adoption of electronic word of mouth. Zhou et al. (2017) examined the impact of the value of corporate microblogging information on consumer purchase intentions and explored how perceived usefulness affects the relationship between the value of microblogging information and consumer purchase intentions. (4) Cluster #3, live streaming commerce, focuses on the impact study of live streaming commerce. It explores how technical quality, quality of experience, herd behaviour, pop-ups and anchors in live-streaming commerce affect customers' purchase intention (Gao et al., 2023; Yang & Lee, 2024; Zeng et al., 2023).

In conclusion, valuable references can continuously contribute to the research field of ELM application, and researchers can use these core references to stimulate the research process.

Reference co-citation timeline view analysis

Figure 8 depicts how the network is divided into co-cited clusters over time. In the network, the average literature time in each cluster was calculated to reflect the temporal characteristics of the literature cited in the corresponding cluster. The colours of the cluster labels represent the time when the literature was established; the further back in time, the colours tend to be cooler, and conversely, the closer the time is to the present, the warmer the colours tend to be. The change in colour throughout reflects the evolution of the research. Below are some of the detailed findings.

(1) The earliest co-occurring cluster of co-cited references is #4 new media. The most cited article discusses the effectiveness of social media in persuasive communication for students wishing to study abroad (Teng et al., 2015). Chang et al. (2015) explored how persuasive messages (i.e., quality of arguments, popularity of posts, and attractiveness of posts) can lead Internet users to like and share information in social media marketing campaigns. This literature provides valuable suggestions for social media marketing campaigns. (2) The most recent emerging cluster is the #10 best voluntary disseminator. The main article in this cluster dis-

cusses users' voluntary retweeting behaviours, which examines three types of factors that modulate the effects of preference matching on individuals' retweeting behaviours, including personal characteristics, tweet characteristics, and sender-recipient relationships (Shi, 2024). (3) The newest and dynamically active cluster in the analysis is the #8 text mining approach. The main articles in this cluster used the text mining approach and discussed ELM-based models to study the impact of online reviews on hotel ratings and online review information consistency on consumer behaviour in the e-commerce industry (Guo & Yan, 2023; Li et al., 2024).

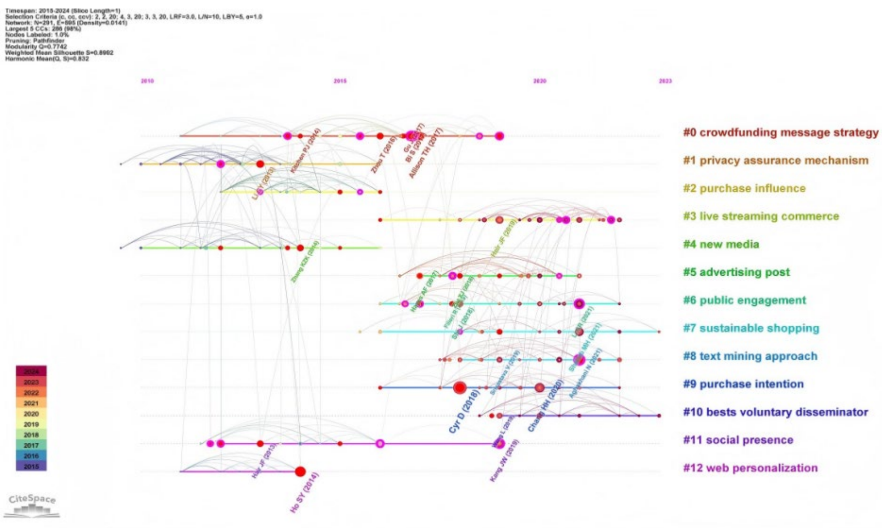

Figure 8. Co-citation-timeline map of cited reference (Source: Authors' work).

4. Discussion

This study provides bibliometric analysis of ELM research over the past decade (2015-2024), covering the field's growth, collaborative structures, thematic composition, and intellectual evolution. The findings raise several points that are worth discussing in relation to the broader literature on persuasion theory and digital communication.

The accelerating growth of ELM research

The sharp rise in output after 2020 likely reflects more than the general growth of academic publishing. During this period, digital communication continued to expand, providing new contexts for persuasive communication in areas such as public health messaging and e-commerce. Researchers needed theoretical frameworks to make sense of how people process information in these digital contexts, and the ELM's dual-process structure made it a ready-made tool for the job. During the same period, a wave of studies applied the model to online reviews, social media marketing, and health communication, coinciding with the post-2020 increase in publications.

The pattern fits a broader trend: dual-process models often see renewed use when technological shifts change how people encounter information. Earlier examples include the rise of web advertising in the early 2000s and the spread of social media in the 2010s, both of which prompted researchers to revisit how central versus peripheral processing operates in new settings (Shahab et al., 2021). Whether the current growth continues will depend on whether digital platforms keep evolving in ways that raise new questions about persuasion—but for now, the ELM remains a go-to framework.

Collaboration patterns and geographical disparities

The collaboration network reveals a mismatch between output and influence. The US and China publish the most, but Australia, Spain, and South Korea have higher betweenness centrality—meaning they connect otherwise separate parts of the network. This pattern suggests that sheer volume does not guarantee a bridging role in international collaboration.

The low overall network density in author collaboration (0.0033) is worth noting. The fragmented nature of scholarly cooperation in ELM research may limit theoretical integration and methodological innovation. Similar patterns have been observed in other bibliometric studies of social science fields, where disciplinary silos and institutional barriers often impede the formation of cohesive research networks (Gan et al., 2022). More structured collaborative initiatives could help address this limitation.

Thematic evolution and new frontiers

The keyword and co-citation analyses collectively show a clear thematic evolution in ELM research over the past decade. The field has moved from studies on website design and technology acceptance in the mid-2010s to a more diversified research landscape that includes social media persuasion, e-commerce, health communication, and information security.

Three directions deserve attention. First, the rise of live streaming commerce as a research cluster extends the ELM to real-time, interactive persuasive settings. Unlike traditional e-commerce, live streaming commerce involves simultaneous visual, auditory, and social cues that may activate both central and peripheral processing routes at the same time (Gao et al., 2023; Yang & Lee, 2024).

Second, the emergence of text mining and computational approaches marks a methodological shift in ELM research. Natural language processing, machine learning, and big data analytics now allow researchers to analyse persuasive message characteristics at scale (Guo & Yan, 2023; Li et al., 2024).

Third, growing attention to health communication represents an important expansion of the ELM's application domain. The spread of health misinformation on social media platforms has created an urgent need for frameworks that can explain how individuals evaluate the credibility and persuasiveness of health-related messages (Zhao et al., 2021).

Future research agenda

The bibliometric results point to several directions worth pursuing. One possible direction is AI-generated persuasion. As chatbots and recommendation algorithms produce more of the persuasive content people encounter, it becomes important to ask whether the ELM's central-peripheral distinction still applies when the "source" is not a person.

A second gap is cross-cultural variation. The ELM was developed in a US context, and our data show that the US still dominates the field. Yet cultural dimensions such as individualism-collectivism may shift how people weigh argument quality against peripheral cues. Few studies have tested this systematically, which limits the model's claim to generality.

The field relies heavily on survey-based structural equation modelling. Complementary methods—experiments that manipulate processing conditions, longitudinal designs that track attitude change over time, or neuroimaging that can distinguish central from peripheral processing at a neural level—would strengthen causal claims and deepen theoretical understanding.

Finally, emerging platforms raise new questions for the ELM. In live-streaming commerce, augmented reality shopping, and voice-based AI assistants, the boundary between central and peripheral cues may blur in ways the original model did not anticipate. These settings offer natural experiments for testing whether the dual-process framework needs updating.

5. Conclusions

This study conducted a bibliometric analysis of 808 ELM-related articles published between 2015 and 2024, using CiteSpace visualisation software to map the knowledge domain across multiple analytical dimensions. The principal findings are as follows.

ELM research has experienced sustained growth over the past decade, with a pronounced acceleration after 2020 that coincides with the expansion of digital commerce and online communication. The United States remains the leading contributor, followed by Chinese Mainland.

The collaboration network analysis shows that while Australia, Spain, and South Korea are important intermediary nodes with high betweenness centrality, the overall intensity of author collaboration remains low, pointing to untapped potential for cross-institutional partnerships.

Keyword co-occurrence and clustering analyses identify online information persuasion—particularly electronic word-of-mouth, online reviews, and social media—as the dominant research focus. Burst detection analysis further shows a temporal shift from technology acceptance and trust formation toward experiential and evaluative dimensions of online information processing.

Reference co-citation analysis uncovers the intellectual foundations of ELM research, with the four largest clusters covering crowdfunding message strategy, privacy assurance mechanisms, purchase influence, and live streaming commerce.

Implication for Theory and Practice

This study enriches the discourse on applying the theory by demonstrating the evolving application of the ELM over a decade of research. Theoretically, this study used the Citespace visualisation bibliometric tool to describe how the ELM has been applied to various new media contexts, particularly in digital marketing, online persuasion and social media interactions. It demonstrates that the ELM remains valuable for understanding how people process persuasive messages in an increasingly digital world. Key areas where ELM can be extended to accommodate new forms of media and technology are identified, emphasising the robustness and flexibility of the ELM.

In practical terms, this study provides important insights for researchers and practitioners. Firstly, this study describes the current status and research focus of the ELM and predicts future research directions, helping researchers grasp cutting-edge research directions, pay attention to research hotspots in this field, and gain inspiration from research. Second, it helps researchers and practitioners gain a comprehensive understanding of the current new directions and topics in applying this theory, especially in terms of online persuasion strategies such as website design and user-generated content. Finally, this study provides a valuable reference for business researchers to help them apply the ELM to social media and business platforms to develop more effective marketing strategies, optimise user services, enhance the user experience, and maintain a competitive advantage.

Limitations and Recommendations

The articles analysed in this study came only from the core collection of the Web of Science database, and only journal articles were searched, excluding other relevant publication types in this field, which limited the research sample. Therefore, future studies can use multiple databases to make literature searches more comprehensive and make the conclusions more reliable and valuable. Secondly, the text study only selected English literature and ignored non-English literature, which may have ignored some important literature in this field. This deficiency can be supplemented in future studies by selecting more papers in other languages. Finally, this study's literature search time span was set between 2015 and 2024, and the article search download date was June 10, 2024. Therefore, some important literature that was not within the time frame may have been overlooked. Future studies can extend the literature search time frame to include more literature to improve this deficiency.

Author Contributions

Y.C. designed the study, conducted the CiteSpace analysis, and wrote the manuscript. A.A.M., H.A. and H.H.H. supervised the study and critically revised the manuscript.

Acknowledgements

Not applicable.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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