

Factors Influencing the Adoption of Social Media Analytics for Enhanced Organizational Intellectual Capital: A Systematic Literature Review

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Abstract

The study aimed to identify the factors influencing the adoption of social media analytics (SMA) for enhanced organizational intellectual capital. It also intended to reveal the challenges linked to the effective incorporation of SMA in organizations for the attainment of enhanced intellectual capital. A systematic literature review (SLR) methodology was applied to address the study's objectives. The required studies were retrieved from twelve major academic databases (Web of Science, Scopus, ScienceDirect, SpringerLink, Emerald, Wiley Online Library, Taylor & Francis, Sage, INFORMS, SSRN, Dimensions, and Business Source Complete) along with Google Scholar to ensure comprehensive coverage. A total of 40 peer-reviewed journal articles published between 1 January 2012 and 31 December 2025 were selected based on predefined inclusion and exclusion criteria. The findings manifested that factors of human capital, technological infrastructure, social networks, knowledge management, and big data analytics positively influence the adoption of social media analytics (SMA) in organizations for enhanced intellectual capital. It was also identified that data complexity, skills constraints, integration barriers, and ethical concerns negatively affected the incorporation of SMA in organizations. On the basis of the study's findings, a framework has been developed to efficiently adopt SMA in organizations for enhanced intellectual capital. The framework is universally applicable across all disciplines providing a robust foundation for future empirical validation. The study has provided pertinent theoretical, practical, methodological, and social implications.

Keywords: social media analytics; SMA; intellectual capital; factors; organizations; operational efficiency; SLR



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1. Introduction

Social media analytics (SMA) has emerged as an innovative technological approach that enables organizations to collect, process, and analyze data generated through social media platforms to understand opinions, behaviors, trends, and stakeholder interactions for informed decision-making. The growing utilization of SMA has transformed organizational processes across multiple sectors by supporting data-driven strategies and enhancing organizational capabilities [1]. SMA contributes significantly to the development of organizational intellectual capital by facilitating the effective management and utilization of knowledge resources. Intellectual capital (IC) refers to “intellectual material, knowledge,

experience, intellectual property, information [...] that can be put to use to create [value]" [2]. Enhanced intellectual capital assists organizations in improving their institutional image, strengthening internal capabilities, and promoting effective utilization of organizational resources and services [3]. Previous studies have identified a positive relationship between big data generated through social media platforms and the enhancement of organizational intellectual capital [4]. SMA serves as a significant channel for extracting meaningful insights from diverse communication sources to support knowledge creation, innovation, and organizational competitiveness [5].

The adoption of SMA in organizations is influenced by several technological, organizational, and strategic factors. Informed decision-making is considered a major driver encouraging organizations to integrate SMA into their operational and strategic activities [6]. Similarly, knowledge management capabilities, real-time processing of large-scale data, and the growing need for innovation and competitiveness promote the incorporation of SMA for improving organizational performance and intellectual capital development [1,7,8]. Furthermore, the implementation of SMA supports knowledge sharing, enhances human capital capabilities, and contributes to the development of value-added services and competitive advantage in organizations [9–14]. Despite its growing importance, the effective adoption of SMA faces multiple challenges. The absence of formal implementation guidelines, lack of trust, data authenticity issues, insufficient digital literacy, privacy and security concerns, inadequate IT infrastructure, and shortage of skilled personnel negatively influence SMA adoption in organizations [15–20]. In addition, rapidly evolving technological environments create integration and compatibility challenges for organizations attempting to implement advanced SMA systems [5,21].

Although prior studies have explored SMA, intellectual capital, organizational performance, knowledge management, and related digital transformation perspectives, limited attention has been given to systematically synthesizing the factors influencing the adoption of SMA for enhanced organizational intellectual capital. Existing studies have primarily focused on isolated organizational contexts, specific technological dimensions, and empirical relationships among selected variables. However, no comprehensive systematic literature review (SLR) has specifically examined the influencing factors and associated adoption challenges of SMA in the context of organizational intellectual capital enhancement. The present study employed a systematic literature review methodology to identify the major factors influencing SMA adoption, associated implementation challenges, and an effective framework for enhancing organizational intellectual capital.

The current study provides several theoretical, managerial, methodological, and social contributions. Theoretically, it enriches the existing body of knowledge by synthesizing the worldwide literature related to SMA adoption and organizational intellectual capital. From a managerial perspective, the study offers practical insights to support organizations in implementing SMA effectively for enhanced intellectual capital outcomes. Methodologically, the study applies a systematic literature review approach to comprehensively analyze existing research and identify major adoption factors and barriers. Socially, the study highlights the potential of SMA-driven systems and services to strengthen organizational capabilities and contribute positively to broader societal development.

The objectives of the study are as follows:

- To identify the factors influencing the adoption of social media analytics for enhanced organizational intellectual capital;
- To reveal challenges hindering the incorporation of social media analytics in organizations for enhanced intellectual capital.

The research questions of the study are as follows:

- Which factors influence the adoption of social media analytics for enhanced organizational intellectual capital?
- What are the challenges associated with the implementation of social media analytics in organizations for enhanced intellectual capital?
- What framework can support the effective incorporation of social media analytics for enhanced organizational intellectual capital?

Each research question is addressed in specific sections of the manuscript. RQ1 and RQ2 are systematically answered in Sections 3.4 and 3.5, where the factors influencing SMA adoption and the associated implementation challenges are identified and synthesized through thematic analysis of the selected studies. RQ3 is addressed in Section 4, where the findings from Sections 3.4 and 3.5 are integrated to develop a comprehensive conceptual framework for effective SMA adoption to enhance organizational intellectual capital. This structured mapping ensures clear traceability of research questions to the analytical sections of the study.

Related Research

Previous studies have investigated social media analytics, intellectual capital, knowledge management, organizational performance, and digital transformation from different theoretical and methodological perspectives. Shela et al. [22] investigated human capital and organizational resilience in the manufacturing sector, whereas Al-Omoush and Alghusin [1] examined the relationship between intellectual capital and social media analytics. Ndou et al. [3] explored intellectual capital disclosure in online media big data environments through an exploratory case study approach. Similarly, De Santis and Presti [4] analyzed the relationship between intellectual capital and big data, while Schiuma et al. [5] investigated intellectual capital information shared through Twitter and its effect on firm value. Additional studies examined network-based intellectual capital [6], operational performance from big data analytical capability perspectives [8], social media disclosure of intellectual capital [15], and supply chain resilience through digital technologies and human capital [23].

To provide a clearer synthesis of prior work and identify the existing research gaps, Table 1 presents a comparative summary of key studies, their focus, methodologies, and major findings.

Table 1. Comparative summary of prior studies on SMA, intellectual capital, and digital analytics.

Study	Focus	Methodology	Key Findings	Limitation/Gap
Al-Omoush and Alghusin (2024) [1]	IC and SMA	Empirical	SMA enhances intellectual capital and competitiveness	Limited generalization
Ndou et al. (2018) [3]	IC disclosure in digital media	Case study	Digital platforms enhance IC visibility	Lack of scalability and general framework
De Santis and Presti (2018) [4]	Big data and IC	Review	Big data supports IC development	Fragmented conceptual integration
Vătămănescu et al. (2016) [6]	Network IC	Empirical	Networks enhance knowledge sharing	Limited digital analytics integration
Bharati et al. (2015) [7]	Social media & KM	Survey	Social capital improves knowledge sharing	Weak IC linkage

Table 1. Cont.

Study	Focus	Methodology	Key Findings	Limitation/Gap
Chen and Chen (2022) [8]	Big data capability	Empirical	Analytics improves performance via IC	Limited SMA perspective
Iqbal et al. (2019) [11]	KM and performance	SEM	IC mediates KM-performance link	No SMA integration
Kianto et al. (2017) [12]	HRM and IC	Survey	HR practices enhance IC and innovation	No digital analytics focus
Kwahk and Park (2016) [13]	Enterprise social media	Survey	Social media improves knowledge sharing	Limited IC framework
Gupta and George (2016) [14]	BDA capability	Conceptual	Analytics capability drives value	No SMA-specific IC linkage
Razmerita et al. (2016) [16]	Knowledge sharing	Survey	Social media supports KM behavior	Limited analytics dimension
Erevelles et al. (2016) [17]	Big data analytics	Conceptual	Analytics transforms marketing decisions	No IC integration
Leonardi (2014) [24]	Communication visibility	Field study	Visibility enhances knowledge recombination	No IC framework
Nambisan et al. (2017) [25]	Digital innovation	Conceptual	Digitalization reshapes innovation logic	No SMA-IC synthesis
Cenamor et al. (2019) [26]	Digital platforms	Empirical	Platform capability improves innovation	Weak IC linkage
Trainor et al. (2014) [27]	Social CRM	Empirical	CRM improves customer performance	Limited IC focus
Wamba et al. (2017) [28]	Big data analytics	Empirical	BDA improves firm performance	No SMA + IC integration
Akter et al. (2016) [29]	BDA capability	Empirical	Alignment improves performance	No SMA focus
Maroufkhani et al. (2019) [30]	BDA & performance	SLR	BDA improves firm outcomes	Lack of IC synthesis
Schiuma et al. (2024) [5]	Twitter-based IC disclosure	Empirical	Social media IC disclosure affects firm value	Platform-specific focus

Despite the valuable contributions of past research, a clear pattern emerges: most studies have examined social media analytics, intellectual capital, and big data analytics in isolation and within limited conceptual boundaries. Very few studies provide an integrated synthesis that simultaneously captures (i) the enabling factors of SMA adoption, (ii) the associated organizational challenges, and (iii) their combined impact on intellectual capital development. The present study addresses this critical gap by systematically integrating fragmented evidence on SMA adoption and organizational intellectual capital through a comprehensive systematic literature review (SLR). Unlike prior studies that are largely empirical, sector-specific, and conceptually isolated, this study provides a holistic synthesis of 40 peer-reviewed articles published in the world's reputed digital databases to identify both enabling factors and adoption barriers in a unified framework. This allows for a more comprehensive understanding of how SMA contributes to intellectual capital development in organizations while simultaneously highlighting the operational, technological, and ethical constraints that hinder its adoption.

2. Materials and Methods

The study applied a systematic literature review (SLR) methodology to address the research objectives. An SLR is conducted using structured, reproducible, and transparent methods according to predefined protocols. These protocols provide standardized guidelines for identifying, screening, and synthesizing the relevant literature to ensure rigor and consistency throughout the review process. Such protocols are widely used to maintain validity and credibility in systematic reviews [22,23,31,32]. This systematic literature review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. The review process, including study identification, screening, eligibility assessment, and final inclusion, followed the PRISMA framework to ensure methodological transparency, consistency, and reproducibility. The review protocol was registered with the Open Science Framework (OSF) and is accessible at <https://osf.io/vx28s/> (accessed on 28 May 2026). The PRISMA 2020 checklist is provided in Appendix A (serving as an annexure to the manuscript) to ensure full reporting compliance and transparency in reporting the systematic literature review process.

A total of 2029 records were initially retrieved from 12 academic databases and Google Scholar. After removing duplicates and applying screening procedures based on titles, abstracts, and full-text eligibility assessment, 40 peer-reviewed journal articles were included in the final synthesis. It is important to clarify that 2029 represents the total number of records identified during the search phase, whereas 40 represents the final eligible studies that met all inclusion criteria under the PRISMA framework. Figure 1 illustrates the entire study selection process, from the initial retrieval of records to the final inclusion of eligible studies ($n = 40$) for the systematic literature review. The inclusion of 40 studies is justified by the highly interdisciplinary and emerging nature of research on social media analytics and organizational intellectual capital, which spans management science, information systems, and digital innovation domains. Due to strict eligibility criteria, only methodologically relevant and conceptually aligned studies were retained for synthesis, consistent with prior systematic reviews in similar domains [33–36].

The SLR methodology is widely applied across disciplines including management sciences, information management, social sciences, and digital transformation studies. It provides theoretical, methodological, and practical insights, supporting evidence-based decision-making and policy development. SLR findings are considered reliable and valuable for identifying research gaps and informing organizational and strategic improvements [37–39].

2.1. Planning of Systematic Literature Review (SLR)

First of all, planning was carried out for conducting a study on the factors influencing the adoption of social media analytics for enhanced organizational intellectual capital. The following focused study's objectives were constructed:

- To identify the factors influencing the adoption of social media analytics for enhanced organizational intellectual capital;
- To reveal challenges hindering the incorporation of social media analytics in organizations for enhanced intellectual capital.

These objectives assisted in providing focused directions to carry out the SLR-based study systematically.

To ensure methodological rigor, transparency, and reproducibility, the inclusion and exclusion criteria were established based on systematic review procedures commonly employed in evidence synthesis studies. The previous methodological literature emphasizes that predefined eligibility criteria help in reducing selection bias and ensuring consistency

during study identification, screening, and eligibility assessment by defining boundaries related to language, publication type, temporal coverage, relevance, and source quality [40,41]. Similar criteria have also been employed in previous systematic and scoping reviews conducted in related technological and information science domains, including fake news detection, digital media research, artificial intelligence, social media algorithms, and linked data adoption studies [31–33,42]. These studies applied comparable eligibility procedures concerning language restrictions, peer-reviewed literature selection, relevance screening, temporal boundaries, and source quality to ensure methodological consistency and reliability.

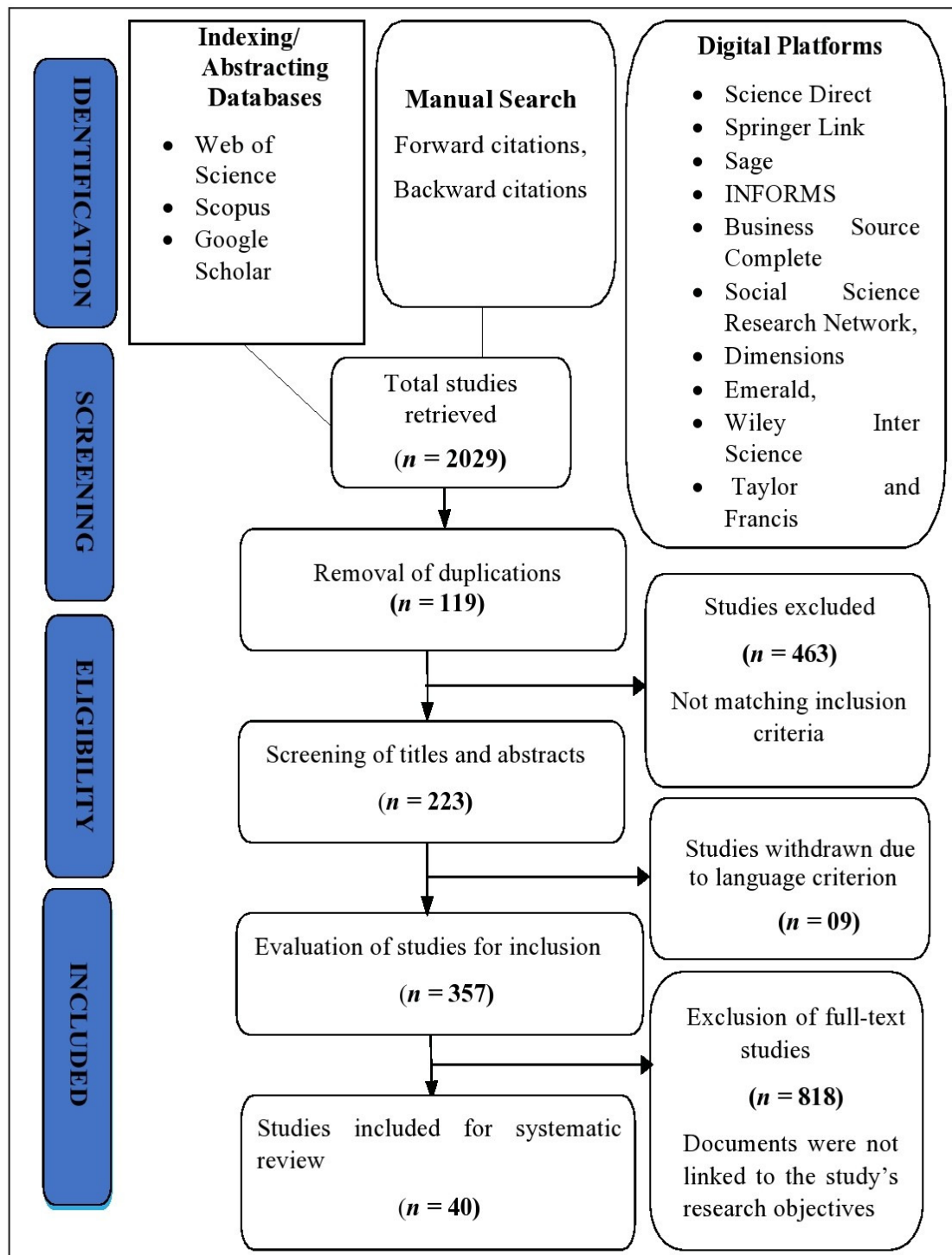


Figure 1. Four-phase PRISMA flow chart.

Language restrictions were applied to include studies published in English because English remains the dominant language of scientific communication and facilitates consistent synthesis and interpretation of findings. Furthermore, only peer-reviewed journal articles were considered to ensure the quality, scientific rigor, and credibility of the evidence base while gray literature and non-peer-reviewed sources were excluded. The temporal coverage from 1 January 2012 to 31 December 2025 was selected because social media analytics emerged as an important organizational and analytical research domain during the early 2010s owing to increased adoption of social media platforms, big data technologies, and analytics-driven decision-making practices. The review period (2012–2025) was purposefully chosen to provide a comprehensive perspective on the emergence, evolution, and maturation of social media analytics (SMA) within organizational settings. Although SMA is a rapidly evolving field, earlier studies published during the initial phase of its development provide important theoretical foundations regarding analytics capabilities, knowledge management, intellectual capital, and digital transformation. Including studies across this period enabled a comprehensive examination of how adoption-related factors have evolved over time rather than restricting the analysis to recent developments only. Furthermore, the objective of the review was not merely to assess contemporary technological trends but to synthesize the broader body of knowledge connecting SMA adoption with organizational intellectual capital across different stages of scholarly development. Table 2 presents the inclusion and exclusion criteria adopted in the study.

Table 2. Inclusion and exclusion criteria.

Sr. No.	Parameter	Inclusion Criteria	Exclusion Criteria
1	Language	Studies published in English	Non-English studies
2	Coverage	Documents addressing the study's objectives	Documents unrelated to the objectives
3	Time Span	Articles from 1 January 2012 to 31 December 2025	Articles prior to 2012
4	Variables	Studies on social media analytics for organizational intellectual capital and adoption challenges	Studies without relevant variables
5	Content Type	Peer-reviewed journal articles (empirical, conceptual, review, and theory-building studies)	Conference papers, proceedings, book reviews, books, theses, reports, gray literature, magazines, newspapers
6	Sources	Research indexed in key academic databases	Blogs, repositories, social media, search engines
7	Relevancy	Addressing at least one objective	Irrelevant to all objectives

Twelve key digital databases and Google Scholar were applied to retrieve required studies from the worldwide published literature on the topic under investigation: Web of Science, Scopus, Sage, Science Direct, Springer Link, INFORMS, Business Source Complete, Social Science Research Network, Dimensions, Emerald, Wiley Inter Science, and Taylor & Francis.

Although the review primarily focused on peer-reviewed journal research papers, the final dataset comprised a predominantly empirical evidence base with clearly defined methodological diversity. Specifically, the included studies consisted of quantitative survey-based research ($n = 10$), panel data analysis ($n = 1$), meta-analytic studies ($n = 1$), exploratory case studies ($n = 1$), content analysis studies ($n = 1$), and mixed-methods approaches ($n = 2$), alongside a small number of conceptual papers ($n = 2$), literature review studies ($n = 1$),

and qualitative conceptual analyses ($n = 1$). These non-empirical studies were retained only when they provided substantial theoretical or integrative contributions directly relevant to the research objectives. Importantly, these studies were not included to increase the volume of evidence but rather to capture conceptual developments and theoretical insights regarding social media analytics adoption and organizational intellectual capital. During the synthesis process, careful attention was given to minimize potential overlap between review-based and primary empirical studies to ensure balanced interpretation and avoid disproportionate influence on the thematic findings.

Although the review period spans from 2012 to 2025 to ensure comprehensive coverage of the emergence and evolution of social media analytics research, the distribution of included studies shows a strong concentration in recent years. Specifically, the final dataset includes 1 study (2012–2014), 12 studies (2015–2017), 17 studies (2018–2020), and 10 studies (2021–2024). This distribution indicates that the majority of the evidence base is derived from the most recent research phases, reflecting the rapid growth and increasing maturity of social media analytics and its application in organizational contexts. The inclusion of earlier studies (2012–2014) was intended to capture foundational theoretical developments, while the dominance of studies from 2015 onwards ensures adequate representation of contemporary research trends. Therefore, the selected temporal scope supports both historical development analysis and identification of current and emerging research directions in alignment with the objectives of this systematic literature review.

2.2. Search Strategy

Several strategies were used to ensure a comprehensive searching of the required documents. These strategies are displayed through Table 3.

Table 3. Search strategies to retrieve studies.

S. No.	Approach	Objective
1	Derive themes from the formulated research questions	Determine the primary concepts and key terms
2	Use article titles as core search phrases	Maintain strong alignment with the topic
3	Incorporate alternative spellings	Account for linguistic and regional differences
4	Choose keywords consistent with research objectives	Preserve clarity and direction of the study
5	Formulate a comprehensive research question	Provide a structured basis for systematic searching
6	Utilize keyword combinations from related studies	Maintain methodological consistency
7	List equivalent terms and related expressions	Increase the scope of literature retrieval
8	Apply the Boolean operator “AND”	Restrict results to overlapping concepts
9	Apply the Boolean operator “OR”	Expand results to include alternative terms
10	Apply the Boolean operator “NOT”	Eliminate irrelevant or unwanted records

Table 4 illustrates the queries and filters that were used in different digital databases to retrieve studies.

2.3. Study Selection Process

The PRISMA 2020 framework was followed across four stages: identification, screening, eligibility, and inclusion. After removing duplicates and screening studies based on predefined criteria, 40 studies were finally included to conduct the SLR on the topic.

To ensure reliability in study selection, a dual-reviewer process was applied. Two independent reviewers evaluated studies at both title/abstract and full-text stages. Any disagreements were resolved through discussion and consensus. Inter-rater reliability was assessed using Cohen’s Kappa coefficient ($\kappa = 0.81$), indicating substantial agreement and ensuring consistency in the selection process.

Table 4. Search results from databases and tools.

Database	Search Query	Applied Limiters	Results Retrieved
Google Scholar	("Social Media Analytics" OR "Social Media Data Analytics" OR "Enterprise Social Media") AND ("Intellectual Capital" OR "Human Capital" OR "Structural Capital" OR "Relational Capital") AND ("Adoption" OR "Implementation" OR "Big Data Capability" OR "Analytics Capability") AND ("Challenges" OR "Barriers" OR "Integration issues" OR "Organizational constraints")	Language: English Years: 2012–2025 Document type: Peer-reviewed articles	1240
Web of Science	("Social Media Analytics" OR "Big Data Analytics") AND ("Intellectual Capital disclosure" OR "Organizational intellectual capital") AND ("Adoption factors" OR "Determinants") AND ("Barriers" OR "Challenges")	Language: English Years: 2012–2025 Document type: Articles	312
Scopus	("Social media analytics" OR "Enterprise social media") AND ("Intellectual capital" OR "Knowledge management" OR "Social capital") AND ("Adoption" OR "Integration") AND ("Challenges" OR "Resistance")	Language: English Years: 2012–2025 Source type: Journals	428
SAGE	("Social media" AND "Intellectual capital") AND ("Organizational performance" OR "Competitive intelligence") AND ("Adoption factors" OR "Barriers")	Language: English Years: 2012–2025 Publication type: Peer-reviewed	96
ScienceDirect	("Social Media Analytics" OR "Big Data capability") AND ("Intellectual capital" OR "Human capital" OR "Structural capital") AND ("Adoption" OR "Organizational integration") AND ("Challenges")	Language: English Years: 2012–2025 Research articles	515
SpringerLink	("Digital technologies" OR "Social media analytics") AND ("Intellectual capital management") AND ("Adoption determinants" OR "Implementation barriers")	Language: English Years: 2012–2025 Article type: Journal articles	267
INFORMS	("Analytics capability" OR "Big data analytics") AND ("Organizational performance" OR "Intellectual capital") AND ("Adoption factors" OR "Barriers")	Language: English Years: 2012–2025 Journals	143
Business Source Complete	("Social media analytics" OR "Enterprise social media") AND ("Intellectual capital disclosure" OR "Knowledge management practices") AND ("Adoption" OR "Implementation") AND ("Challenges" OR "Organizational resistance")	Language: English Years: 2012–2025 Peer-reviewed articles	384
Social Science Research Network (SSRN)	("Social media analytics" OR "Big data analytics") AND ("Intellectual capital" OR "Firm value") AND ("Adoption" OR "Digital transformation")	Language: English Years: 2012–2025 Scholarly papers	158
Dimensions	("Social media disclosure" OR "Online media big data") AND ("Intellectual capital") AND ("Adoption drivers" OR "Barriers")	Language: English Years: 2012–2025 Articles	296
Emerald	("Social media analytics" OR "Knowledge management") AND ("Intellectual capital" OR "Human capital") AND ("Adoption factors" OR "Organizational challenges")	Language: English Years: 2012–2025 Peer-reviewed journals	221
Wiley InterScience	("Big data analytics capability" OR "Social media data") AND ("Intellectual capital" OR "Innovation performance") AND ("Adoption determinants" OR "Integration challenges")	Language: English Years: 2012–2025 Research articles	189
Taylor & Francis	("Enterprise social media" OR "Digital analytics") AND ("Intellectual capital disclosure" OR "Organizational knowledge") AND ("Adoption" OR "Barriers")	Language: English Years: 2012–2025 Peer-reviewed articles	174

2.4. Quality Assessment and Risk of Bias

Assessing the quality of selected studies is a critical stage in systematic literature reviews. It enables evaluation of methodological rigor, potential risk of bias, reliability of findings, and external validity. A structured appraisal process ensures that the included studies adequately address the research objectives and contribute meaningfully to evidence synthesis [31]. In social sciences, the selection of appraisal tools depends on the methodological nature of the included studies. Therefore, adopting a standardized framework enhances transparency, consistency, and objectivity.

For the present review, the Critical Appraisal Skills Programme (CASP) checklist was used to assess the methodological quality of the included studies ($n = 40$). The checklist consisted of ten structured criteria evaluating research objectives, methodology, sampling strategy, data collection rigor, bias consideration, analytical robustness, credibility of findings, and overall coherence. Each study was evaluated using a five-point weighted scale of Yes (2), Satisfactorily (1.5), Partially (1), Barely (0.5), and No (0), resulting in a maximum score of 20 per study. A minimum threshold of 12/20 (60%) was applied to ensure inclusion of methodologically sound studies. Studies below this threshold were excluded from final synthesis. To ensure reliability, two independent reviewers applied the CASP checklist. The CASP framework has been widely applied in systematic reviews in information science and digital transformation research, supporting its suitability for this study. Table 5 displays the CASP checklist for quality appraisal.

Table 5. CASP checklist for quality appraisal.

QA ID	Checklist Questions
QA 1	Are the study's objectives clear?
QA 2	Has an appropriate research methodology been applied?
QA 3	How have sampling methods been recruited?
QA 4	Has required data been collected through rigorous techniques?
QA 5	Have confounding and bias factors been considered?
QA 6	Has the gathered data been analyzed efficiently?
QA 7	Are the results clear and credible?
QA 8	Is the study clear overall?
QA 9	Is the study rigorous throughout?
QA 10	Are all the study's sections relevant to one another?

Note: Yes = 2, Partially = 1, No = 0, Barely = 0.5, Satisfactorily = 1.5. Source: Shahzad and Tariq (2025) [43].

Table 6 shows the CASP quality assessment scores of the included studies.

Table 6. CASP quality assessment scores of included studies.

Study (Author, Year)	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	QA9	QA10	Total (/20)
Al-Omoush & Alghusin (2024) [1]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Ndou et al. (2018) [3]	2	1.5	1.5	1.5	1	1.5	2	1.5	1.5	1.5	15
De Santis & Presti (2018) [4]	2	2	1.5	1.5	1	1.5	2	1.5	1.5	2	16.5
Vătămănescu et al. (2016) [6]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Bharati et al. (2015) [7]	2	1.5	1	1.5	1	1.5	1.5	1.5	1	1.5	14
Chen & Chen (2022) [8]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Schiurma et al. (2024) [5]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Al-Sartawi (2020) [15]	2	1.5	1.5	1.5	1	1.5	2	1.5	1.5	1.5	15
Ozgun et al. (2022) [9]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Sagić et al. (2019) [10]	2	1.5	1	1.5	1	1.5	1.5	1.5	1	1.5	14
Iqbal et al. (2019) [11]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Kianto et al. (2017) [12]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Kwahk & Park (2016) [13]	2	1.5	1.5	1.5	1	1.5	2	1.5	1	1.5	15

Table 6. Cont.

Study (Author, Year)	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	QA9	QA10	Total (/20)
Gupta & George (2016) [14]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Razmerita et al. (2016) [16]	2	1.5	1.5	1.5	1	1.5	2	1.5	1	1.5	15
Erevelles et al. (2016) [17]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Fang et al. (2015) [18]	2	1.5	1	1.5	1	1.5	1.5	1.5	1	1.5	14
Rippa & Secundo (2019) [19]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Ferraris et al. (2019) [20]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Bag et al. (2020) [21]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Côrte-Real et al. (2017) [44]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Mikalef et al. (2018) [45]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Wamba et al. (2017) [28]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Akter et al. (2016) [29]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Mikalef et al. (2019) [46]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Leonardi (2014) [24]	2	1.5	1	1.5	1	1.5	2	1.5	1	1.5	14
Cao et al. (2016) [47]	2	1.5	1.5	1.5	1	1.5	2	1.5	1.5	1.5	15
Trainor et al. (2014) [27]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Tajvidi & Karami (2021) [48]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Parveen et al. (2015) [49]	2	1.5	1.5	1.5	1	1.5	2	1.5	1	1.5	15
Mention (2012) [50]	2	1.5	1	1.5	1	1.5	1.5	1.5	1	1.5	14
Inkinen (2015) [51]	2	1.5	1.5	1.5	1	1.5	1.5	1.5	1	1.5	14.5
Del Giudice & Della Peruta (2016) [52]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Nambisan et al. (2017) [25]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Cenamora et al. (2019) [26]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Ainin et al. (2015) [53]	2	1.5	1.5	1.5	1	1.5	2	1.5	1	1.5	15
Ahani et al. (2017) [54]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Chatterjee et al. (2021) [55]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Maroufkhani et al. (2019) [30]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5
Santoro et al. (2018) [56]	2	2	1.5	2	1.5	2	2	2	1.5	2	18.5

2.5. Data Extraction

A structured data extraction form was used to collect relevant information from each study, including the following:

- Author(s) and publication year;
- Journal/source;
- Factors influencing adoption of social media analytics;
- Challenges in implementation.

2.6. Data Synthesis

The extracted data were analyzed using thematic synthesis to identify recurring patterns and themes across studies. The analysis focused on the following:

- Adoption factors of social media analytics for intellectual capital enhancement;
- Organizational and technological challenges;
- Geographic and disciplinary distribution;
- Methodological approaches used in literature.

The synthesis was narrative and interpretive in nature. Reporting bias was not statistically assessed due to the qualitative nature of the dataset. However, methodological rigor was ensured through PRISMA compliance, CASP quality appraisal, inter-rater reliability testing, and structured bias assessment. To further ensure transparency in the synthesis process, the methodological composition of the included studies was analyzed. The final dataset comprised a predominantly empirical evidence base, with quantitative survey-based studies representing the majority of the literature. Specifically, 10 studies

employed survey-based quantitative methods, while additional studies utilized panel data ($n = 1$), meta-analytic techniques ($n = 1$), content analysis ($n = 1$), mixed-methods approaches ($n = 2$), exploratory case study design ($n = 1$), and qualitative conceptual analysis ($n = 1$). In addition, a limited number of conceptual ($n = 2$) and literature review-based studies ($n = 1$) were included due to their significant theoretical contributions to the development of social media analytics and intellectual capital discourse. This distribution indicates that the synthesis is primarily grounded in empirical evidence, while conceptual and review-based studies were incorporated selectively to enhance theoretical depth and contextual understanding.

3. Results

Table 7 presents a structured synthesis of extracted data. It shows information about the studies' authors and publishing years. It provides information about geographical territories and journals of the published articles. It also shows factors influencing the adoption of SMA for enhanced organizational intellectual capital and adoption challenges in organizations.

Table 7. Thematic data extraction and synthesis of included studies ($n = 40$).

Author(s) and Publishing Years	Affiliations	Journals	Factors Influencing the Adoption of SMA for Enhanced Organizational Intellectual Capital	Adoption Challenges of SMA in Organizations
Ahani et al. (2017) [54]	Malaysia	<i>Computers in Human Behavior</i>	• Social CRM adoption readiness • Technological capability • Customer relationship management integration • Organizational support for analytics • Data-driven customer engagement	• Complexity in social CRM implementation • Lack of analytical expertise • High implementation and maintenance costs
Ainin et al. (2015) [53]	Malaysia	<i>Industrial Management & Data Systems</i>	• Social media adoption capability • Customer engagement through social media • Organizational learning capability • Relational capital enhancement • Knowledge sharing and collaboration	• Lack of strategic planning for social media use • Limited managerial support • Difficulty measuring business value
Akter et al. (2016) [29]	Australia	<i>International Journal of Production Economics</i>	• Big data analytics capability • Business strategy alignment • Data-driven organizational culture • Human capital with analytical expertise • Organizational capability enhancement	• Strategic misalignment between analytics and business goals • Data integration complexity • Shortage of analytical professionals
Al-Omoush and Alghusain (2024) [1]	Jordan	<i>Human Behavior and Emerging Technologies</i>	• Human capital • Structural capital • Relational capital • Competitive intelligence • Intellectual capital	• Data privacy and security concerns • Lack of analytical skills • Integration complexity with existing systems
Al-Sartawi (2020) [15]	Kingdom of Bahrain	<i>International Journal of Learning and Intellectual Capital</i>	• Human capital disclosure • Structural capital disclosure • Relational capital disclosure • Social media communication strategy • Stakeholder engagement through social platforms	Measuring the impact of IC disclosure on firm value Data credibility and accuracy on social media Limited guidance on standardized IC reporting via social media
Bag et al. (2020) [21]	France	<i>Resources, Conservation and Recycling</i>	• Big data analytics capability • Human capital with analytical expertise • Structural capital supporting data-driven operations • Integration of analytics into operational processes • Knowledge sharing across supply chain networks	• Data complexity and volume management • Lack of skilled personnel for analytics • Integration challenges with existing operational systems

Table 7. Cont.

Author(s) and Publishing Years	Affiliations	Journals	Factors Influencing the Adoption of SMA for Enhanced Organizational Intellectual Capital	Adoption Challenges of SMA in Organizations
Bharati et al. (2015) [7]	USA	<i>Journal of Knowledge Management</i>	• Social capital • Knowledge management capability • Knowledge sharing behavior • Collaborative work environment • Organizational learning capability	Resistance to knowledge sharing Information overload Knowledge quality and credibility issues
Cao et al. (2016) [47]	China	<i>Internet Research</i>	• Employee engagement through social media • Knowledge sharing behavior • Communication visibility • Social collaboration capability • Human capital enhancement	• Employee distraction and reduced productivity • Privacy concerns in workplace social media use • Managing communication overload
Cenamor et al. (2019) [26]	Sweden	<i>Journal of Business Research</i>	• Digital platform capability • Network capability • Organizational ambidexterity • Knowledge sharing networks • Innovation capability	• Difficulty managing digital ecosystems • Dependence on external platform providers • Coordination complexity among networks
Chatterjee et al. (2021) [55]	India	<i>Industrial Marketing Management</i>	• AI-based CRM capability • Customer knowledge management • Competitive advantage through analytics • Human capital development • Organizational intelligence enhancement	• High costs of AI integration • Resistance to AI adoption • Ethical and privacy concerns in AI-driven analytics
Chen and Chen (2022) [8]	Taiwan	<i>Chinese Management Studies</i>	• Human capital • Structural capital • Relational capital • Big data analytical capability • System integration capability	Lack of effective coordination among key stakeholders
Côrte-Real et al. (2017) [44]	Portugal	<i>Journal of Business Research</i>	• Big data analytics capability • Organizational decision-making capability • Technological infrastructure • Data-driven innovation culture • Business value creation through analytics	• Challenges in extracting business value from analytics • Data governance and privacy issues • Lack of analytical competencies
Del Giudice and Della Peruta (2016) [52]	Italy	<i>Journal of Knowledge Management</i>	• IT-based knowledge management systems • Knowledge creation capability • Innovation support through digital systems • Structural capital enhancement • Organizational learning processes	• Integration difficulties of IT systems • Knowledge management complexity • Resistance to technological change
De Santis and Presti (2018) [4]	Italy	<i>Meditari Accountancy Research</i>	• Knowledge management capability • Data-driven decision-making culture • Technological infrastructure for big data • Organizational learning capability • Innovation capability	• Data overload and complexity • Lack of skilled human resources • Integration issues between big data and intellectual capital systems
Erevelles et al. (2016) [17]	USA	<i>Journal of Business Research</i>	• Big data consumer analytics capability • Technological infrastructure for data processing • Human capital with analytical expertise • Data-driven decision-making culture • Integration of analytics into marketing and organizational processes	• Data privacy and security concerns • Managing large volumes of complex data • Lack of skilled personnel for analytics interpretation
Fang et al. (2015) [18]	Singapore	<i>Organization Science</i>	• Social network position of employees • Relational capital within organizational networks • Human capital traits (personality, skills) • Knowledge sharing through social ties • Collaborative interactions in networks	Cyber security threats
Ferraris et al. (2019) [20]	Italy	<i>Management Decision</i>	• Big data analytics capability • Knowledge management practices • Human capital with analytical skills • Structural capital supporting knowledge processes • Technology infrastructure for data processing	• Lack of skilled personnel for analytics • Integration complexity with existing knowledge systems • Data quality and consistency issues

Table 7. Cont.

Author(s) and Publishing Years	Affiliations	Journals	Factors Influencing the Adoption of SMA for Enhanced Organizational Intellectual Capital	Adoption Challenges of SMA in Organizations
Gupta and George (2016) [14]	USA	<i>Information & Management</i>	• Big data analytics capability • Technological infrastructure • Data-driven decision-making culture • Human capital with analytical skills • Integration of analytics into organizational processes	• Lack of skilled personnel for analytics • Data management complexity • Difficulty integrating analytics with existing systems
Inkinen (2015) [51]	Finland	<i>Journal of Intellectual Capital</i>	• Human capital development • Structural capital enhancement • Relational capital strengthening • Knowledge management capability • Innovation and performance orientation	• Difficulty measuring intellectual capital performance • Limited empirical consistency • Challenges in IC management integration
Iqbal et al. (2019) [11]	Pakistan	<i>Journal of Enterprise Information Management</i>	• Human capital development • Structural capital enhancement • Relational capital strengthening • Knowledge management practices • Innovation activities as a mediator	Lack of personal interest
Kianto et al. (2017) [12]	Finland	<i>Journal of Business Research</i>	• Knowledge-based human resource management practices • Human capital development • Structural capital enhancement • Relational capital strengthening • Innovation capability	Unauthentic datasets
Kwahk and Park (2016) [13]	South Korea	<i>Computers in Human Behavior</i>	• Network sharing among employees • Knowledge sharing activities • Human capital development • Relational capital enhancement • Collaboration through enterprise social media	• Resistance to knowledge sharing • Low participation in networked platforms • Managing the quality and relevance of shared knowledge
Leonardi (2014) [24]	USA	<i>Information Systems Research</i>	• Communication visibility through social media • Knowledge sharing transparency • Relational capital enhancement • Collaborative communication networks • Organizational learning capability	• Information overload in digital communication • Privacy concerns among employees • Managing communication transparency
Maroufkhani et al. (2019) [30]	Malaysia	<i>Information</i>	• Big data analytics capability • Organizational performance enhancement • Technological readiness • Human analytical capability • Knowledge-driven decision-making	• Data management complexity • Lack of analytical expertise • High infrastructure investment requirements
Mention (2012) [50]	Luxembourg	<i>Business and Economic Research</i>	• Intellectual capital management • Innovation capability • Human capital development • Relational capital enhancement • Knowledge-based organizational performance	• Difficulty operationalizing intellectual capital constructs • Measurement inconsistency across organizations • Limited integration between IC and innovation systems
Mikalef et al. (2018) [45]	Norway	<i>Information Systems and e-Business Management</i>	• Big data analytics capabilities • Organizational data management capability • Human analytical competencies • Technological capability • Strategic alignment of analytics initiatives	• Shortage of skilled analytics professionals • Data quality and governance issues • Complexity in analytics implementation
Mikalef et al. (2019) [46]	Norway	<i>British Journal of Management</i>	• Big data analytics capability • Dynamic capabilities • Innovation capability • Environmental adaptability • Organizational learning capability	• Environmental uncertainty • Difficulty transforming analytics into innovation outcomes • Resource limitations for analytics deployment
Nambisan et al. (2017) [25]	USA	<i>MIS Quarterly</i>	• Digital innovation management • Knowledge integration capability • Digital collaboration networks • Innovation ecosystem participation • Technology-enabled organizational learning	• Rapid technological changes • Managing digital innovation complexity • Coordination challenges across digital ecosystems

Table 7. Cont.

Author(s) and Publishing Years	Affiliations	Journals	Factors Influencing the Adoption of SMA for Enhanced Organizational Intellectual Capital	Adoption Challenges of SMA in Organizations
Ndou et al. (2018) [3]	Italy	<i>Meditari Accountancy Research</i>	- Online media data availability - Stakeholder engagement through social media - Organizational transparency and visibility - Knowledge creation and sharing through digital platforms - Institutional reputation management	- Difficulty in measuring intellectual capital through online data - Lack of clear guidelines for intellectual capital disclosure in social media - Data reliability and credibility issues
Ozgun et al. (2022) [9]	Turkey	<i>Healthcare Analytics</i>	- Social capital - Human capital development - Structural capital enhancement - Relational capital improvement - Innovation activities as a mediator	Integration issues
Parveen et al. (2015) [49]	Malaysia	<i>Telematics and Informatics</i>	- Social media usage capability - Organizational communication enhancement - Customer relationship development - Knowledge sharing practices - Relational capital improvement	- Lack of clear social media policies - Measuring social media effectiveness - Security and privacy concerns
Razmerita et al. (2016) [16]	Denmark	<i>Journal of knowledge Management</i>	- Trust among employees - Social capital - Perceived benefits of knowledge sharing - Collaborative culture - Communication through social media platform	- Lack of motivation to share knowledge - Concerns about knowledge misuse
Rippa and Secundo (2019) [19]	Italy	<i>Technological Forecasting and Social Change</i>	- Digital technology adoption - Human capital development - Structural capital enhancement - Knowledge sharing and collaboration - Innovation and entrepreneurial orientation	Lack of skilled workforce
Sagic et al. (2019) [10]	Serbia	<i>Ekonomika preduzeca</i>	- Human capital development - Structural capital improvement - Relational capital strengthening - Adoption of leading information technology trends - Knowledge management capability	Leadership shortage
Santoro et al. (2018) [56]	Cyprus	<i>Technological Forecasting and Social Change</i>	- Internet of Things integration - Knowledge management capability - Open innovation practices - Knowledge sharing systems - Technological capability enhancement	- IoT security and privacy risks - Complexity of integrating IoT with existing systems - Data management and interoperability issues
Schiuma et al. (2024) [5]	Italy	<i>Journal of Intellectual Capital</i>	- Social media engagement - Human capital disclosure - Relational capital visibility - Structural capital reporting - Real-time knowledge sharing	- Data reliability and authenticity on social media - Difficulty in linking IC disclosure to firm value - Managing large volumes of social media information
Trainor et al. (2014) [27]	USA	<i>Journal of Business Research</i>	- Social CRM capability - Customer relationship performance - Social media technology usage - Knowledge integration capability - Relational capital enhancement	- Integration challenges between CRM and social media systems - Data management complexity - Lack of employee expertise in social CRM
Tajvidi and Karami (2021) [48]	United Kingdom	<i>Computers in Human Behavior</i>	- Social media capability - Customer engagement enhancement - Knowledge sharing practices - Digital communication effectiveness - Organizational performance improvement	- Difficulty managing social media content - Data privacy and ethical concerns - Limited analytical capabilities for social media data

Table 7. Cont.

Author(s) and Publishing Years	Affiliations	Journals	Factors Influencing the Adoption of SMA for Enhanced Organizational Intellectual Capital	Adoption Challenges of SMA in Organizations
Vatamanescu et al. (2016) [6]	Romania	<i>Journal of knowledge management</i>	• Social capital • Knowledge sharing capability • Organizational knowledge management processes • Trust among employees • Collaborative culture	• Knowledge quality control issues • Resistance to knowledge sharing • Information overload
Wamba et al. (2017) [28]	France	<i>Journal of Business Research</i>	• Big data analytics capability • Dynamic capabilities • Organizational agility • Data-driven strategic decision-making • Innovation and performance capability	• Challenges in managing massive datasets • Shortage of skilled analytics workforce • Difficulty aligning analytics initiatives with organizational strategy

The dataset synthesized in this study comprises 40 peer-reviewed journal articles published across 24 countries, reflecting a broad geographical distribution and interdisciplinary research interest in social media analytics (SMA) and organizational intellectual capital. The selected studies span multiple reputable journals in the fields of information systems, knowledge management, business research, and organizational studies, indicating strong academic engagement with the topic. Methodologically, the dataset is predominantly quantitative in nature, with survey-based approaches representing the most frequently used design, alongside a smaller number of qualitative and mixed-method studies. The extracted data reveal two main analytical dimensions: (i) factors influencing the adoption of SMA for enhancing organizational intellectual capital, and (ii) associated adoption challenges. Across the literature, five dominant factor categories emerge that include human capital, technological infrastructure, social networks, knowledge management, and big data analytics. Challenges are primarily grouped into data complexity, skills constraints, integration barriers, and ethical concerns.

To ensure the robustness and credibility of the extracted dataset, a validation process was applied to examine the comprehensiveness and representativeness of the included studies. The final dataset ($n = 40$) was derived through a structured PRISMA-guided selection process, supported by clearly defined inclusion and exclusion criteria, multi-database searching, and a dual-reviewer screening procedure with substantial inter-rater agreement ($\kappa = 0.81$). In addition, quality appraisal using the CASP checklist further ensured that only methodologically sound and relevant studies were retained for synthesis.

Beyond procedural rigor, a conceptual validation of the dataset was conducted by comparing the thematic coverage of the included studies with the established literature streams in social media analytics, big data analytics, knowledge management, and intellectual capital research. This comparison confirms that the dataset adequately covers the widely cited contributions in the field, including seminal and highly influential works on analytics capability, knowledge sharing, and digital transformation (e.g., [24,25,28,29,45]). These works are widely recognized as foundational in shaping analytical capability and digital innovation perspectives relevant to SMA adoption.

To further assess potential omissions, backward and forward citation tracking was conceptually reviewed during the final stage of synthesis. This process indicated that additional studies identified in related systematic reviews largely converge with the included dataset in terms of theoretical constructs and do not introduce substantially new categories beyond those already synthesized. While some studies focusing exclusively on adjacent domains (e.g., general social media marketing without intellectual capital linkage) were identified, they were excluded due to misalignment with the review's inclusion criteria.

Therefore, although no systematic review can claim absolute exhaustiveness, the convergence of database coverage, PRISMA-based screening, quality appraisal, and thematic saturation suggests that the final dataset provides a sufficiently comprehensive and representative evidence base. The inclusion of 40 studies is thus considered adequate to achieve theoretical saturation for identifying adoption factors and challenges of social media analytics in relation to organizational intellectual capital.

3.1. Summary of the Extracted Dataset

The final dataset synthesized in this systematic literature review consists of 40 peer-reviewed journal articles published between 2012 and 2025, reflecting a broad interdisciplinary and geographical coverage of research on social media analytics (SMA) and organizational intellectual capital. The included studies span 24 countries, indicating strong global research interest in this domain, with notable contributions from the USA, Italy, Malaysia, and several European and Asian countries.

From a methodological perspective, the dataset is predominantly quantitative, with survey-based approaches representing the most frequently applied research design. A smaller proportion of studies employed qualitative and mixed-method approaches, reflecting the exploratory and evolving nature of SMA research in organizational contexts.

Thematic analysis of the extracted studies reveals two dominant dimensions. First, five key categories of factors influencing SMA adoption for enhancing organizational intellectual capital were identified. These included human capital, technological infrastructure, social networks, knowledge management, and big data analytics. Second, four major categories of challenges affecting SMA implementation were observed, including data complexity, skills constraints, integration barriers, and ethical concerns.

The dataset shows strong conceptual convergence across studies, with recurring emphasis on the role of digital capabilities, human expertise, and data-driven decision-making in enabling effective SMA adoption. At the same time, the synthesis highlights persistent structural, technical, and organizational barriers that hinder full-scale implementation. This structured dataset therefore provides a robust empirical foundation for deriving thematic insights and developing the integrative framework presented in this study.

3.2. Geographical Distribution of the Selected Studies

The results displayed that most of the selected studies were contributed from the USA and Italy ($n = 6$ each) while Malaysia produced four studies. The selected studies ($n = 40$) were contributed from 24 different countries of the world. Figure 2 displays the geographical distribution of the selected studies.

3.3. Research Methods Used in the Selected Studies

The findings showed that quantitative (survey questionnaire method) was the most frequently applied in the studies ($n = 22$). Figure 3 shows that 13 different research methodologies were employed in the included studies ($n = 40$).

3.4. Factors Influencing the Adoption of SMA for Enhanced Organizational Intellectual Capital

The study identified five major categories of factors that influenced the adoption of SMA for enhanced organizational intellectual capital. These factors included human capital, technological infrastructure, social networks, knowledge management, and big data analytics. These factors are interpreted as follows systematically:

3.4.1. Human Capital (HC)

Human capital is a key factor that influences the adoption of social media analytics (SMA) for enhanced organizational intellectual capital [1,8]. Skilled manpower proves

fruitful in converting raw social media insights into practical inputs for strengthening intellectual capital [17,21]. HC supports organizations to make impactful dealings with all stakeholders [5,15]. HC with analytic expertise ensures the integration of strategic and operational decision-making [14,20]. Personality traits of the employees enable organizations to enhance efficiency to deliver maximum performance for addressing set objectives and meeting expected goals [12,18]. Continuing professional development of HC through participation in need-based training activities supports innovation and leads towards enhanced organizational intellectual capital [11,13]. Human capital acts as a mediator between technological resources and organizational learning to ensure that SMA effectively contributes to intellectual capital enhancement [9,21,57].

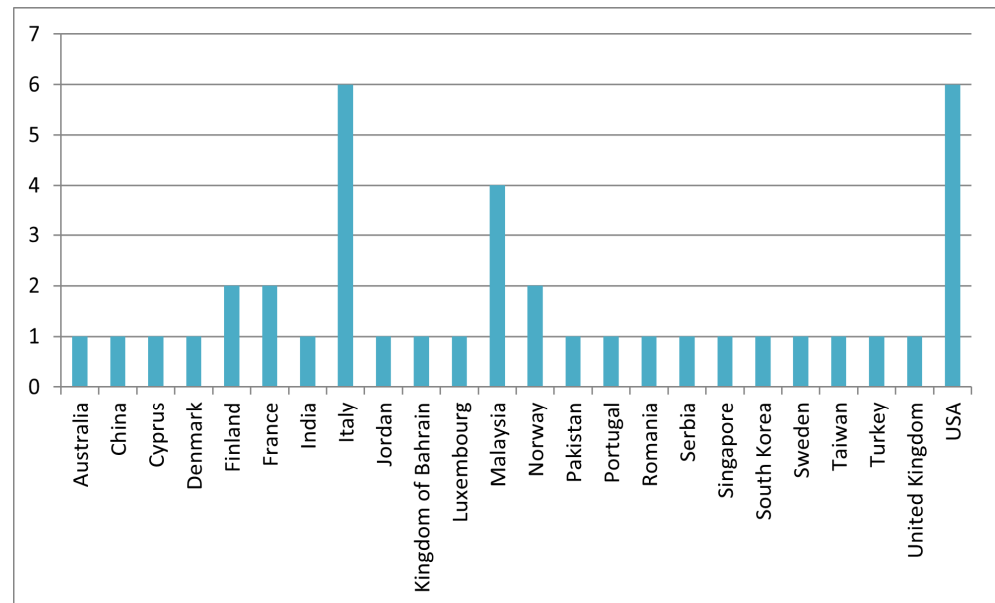


Figure 2. Geographical distribution of the selected studies.

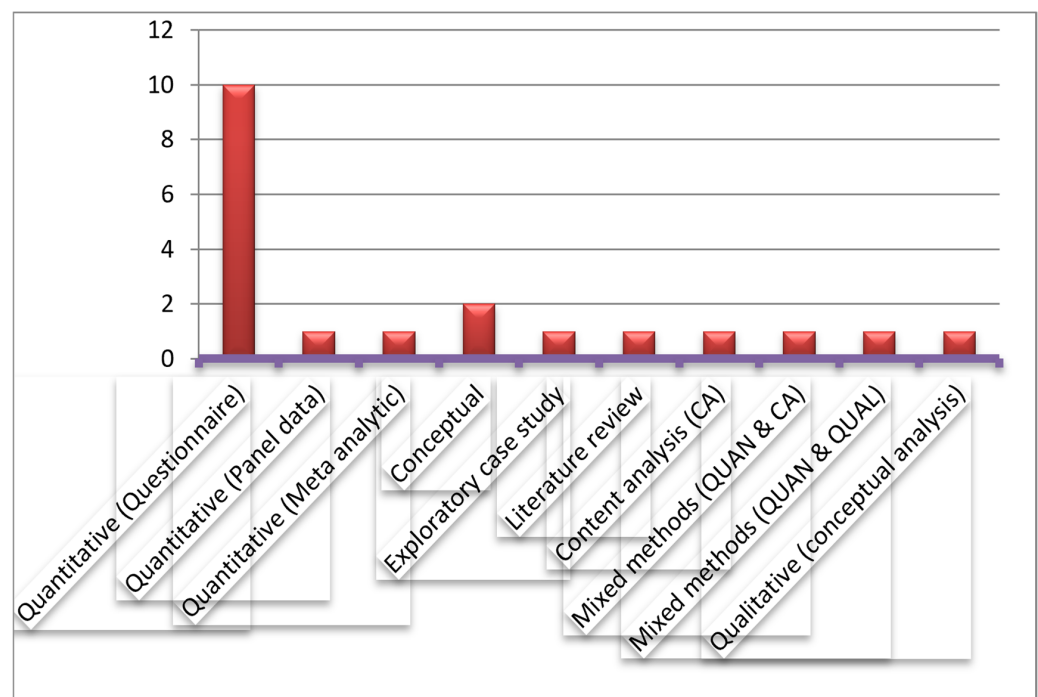


Figure 3. Research methodologies used in the selected studies.

Furthermore, human analytical competencies, customer knowledge management abilities, and organizational intelligence enhancement encourage firms to integrate SMA for improving innovation and organizational performance [45,55]. Employee engagement through communication visibility and collaborative interactions further supports the effective utilization of SMA for strengthening organizational learning and intellectual capital development [24,47]. Human capital development also facilitates innovation orientation and improves organizational capability enhancement through strategic use of analytics and knowledge resources [29,50].

3.4.2. Technological Infrastructure

The availability of technological infrastructure proves fruitful for the adoption of social media analytics (SMA) for enhanced organizational intellectual capital [1,8]. Robust organizational structure supports in adopting SMA effectively and efficiently for the attainment of innovative outcomes in the workplace [20,21]. Structural capital increases transparency that promotes engagement and trust among key stakeholders to incorporate SMA for fostering intellectual capital in the best interests of the organizations [5,15]. The provision of technological infrastructure supports SMA implementation for effective organizational learning [4,17,58]. The integration of SMA tools with existing systems and services assists in accessing real-time data for improving operational efficiency and responsiveness [8,14]. The presence of emerging IT tools enables the adoption of SMA for supporting innovative knowledge practices [10,21]. The availability of technological resources ensures the adoption of SMA in contributing sustainable intellectual capital development [11,20].

Digital platform capability, IT-based knowledge management systems, and technological readiness significantly contribute to SMA implementation and support evidence-based organizational processes [26,30,52]. Advanced technological infrastructure further assists organizations in enhancing organizational communication, digital collaboration, and technology-enabled learning practices through SMA initiatives [25] (Parveen et al., 2015). The integration of Internet of Things (IoT) technologies and social CRM systems also strengthens organizational capability to utilize SMA for innovation and customer relationship enhancement [27,56].

3.4.3. Social Networks

Effective social networks support in the adoption of social media analytics (SMA) in organizations for enhancing operational efficiency [1,18]. Social media forums strengthen relational capital by supporting real-time engagements and expertise collaboration across networks [5,13]. The perceived benefits of knowledge exchange practices encourage employees to adopt social media analytics initiatives [6,16]. The effectiveness of relational networks enhances organizational innovation for attaining optimal performance and output from manpower [7,9]. The authenticity and credibility of organizational knowledge is enhanced through external networks [3,11,15,18]. The adoption of SMA in organizations assists in transforming digital interactions into actionable knowledge for strategic benefits [5,12].

Communication visibility and knowledge sharing transparency through enterprise social media improve collaborative communication networks and organizational learning capabilities [24]. Customer engagement through social media platforms and social CRM initiatives also supports the development of relational capital and customer relationship performance in organizations [27,53]. Digital collaboration networks and innovation ecosystem participation further encourage organizations to adopt SMA for strengthening network capability and organizational ambidexterity [25,26]. Social media capability additionally

improves digital communication effectiveness and supports organizational performance enhancement through sound stakeholder interaction and collaboration [48].

3.4.4. Knowledge Management (KM)

Knowledge management is a central factor that influences the incorporation of social media analytics (SMA) for enhanced organizational intellectual capital [4,7]. Organizations can adopt SMA for transforming raw datasets into evidence-based knowledge for strengthening intellectual capital [10,11]. Knowledge sharing behaviors encourage the incorporation of SMA for showing organizational efficiency and to address competitive challenges innovatively [6,13,16]. Strategic outcomes are achieved through a sustainable adoption of SMA in organizations [14,20,21]. KM practices support in continuous improvement of organizations to deliver valuable strategies, policies, and insights [3–5,19]. Embedding SMA within knowledge sharing practices strengthens competitive intelligence to foster a sustainable intellectual capital base [7,9].

Knowledge integration capability, knowledge creation capability, and organizational learning processes significantly enhance the adoption of SMA for supporting innovation and evidence-based organizational decision-making [25,52]. Open innovation practices and knowledge sharing systems further encourage organizations to adopt SMA for improving collaborative learning and innovation capability [46,56]. Customer knowledge management and data-driven customer engagement also assist organizations in utilizing SMA outputs to strengthen organizational intelligence and sustainable competitive advantage [54,55]. Effective KM capability additionally promotes innovation orientation and strengthens organizational performance through strategic utilization of intellectual capital resources [50,51].

3.4.5. Big Data Analytics

Big data analytics (BDA) is an important factor that supports the implementation of SMA for enhanced organizational intellectual capital [14,20,21]. BDA proves fruitful in integrating SMA into organizational workflows for providing evidence-based insights to improve decision-making procedures [4,17]. Data-driven insights assist in applying SMA outputs in a systematic manner for improving processes and strategic outcomes [4,14]. Analytic tools support in the interpretation of complex social media patterns and to extract useful data for enhancing intellectual capital [17,21]. The incorporation of SMA in organizations increases the worth of social media insights and enhances intellectual capital for meeting organizational objectives [3,5,17,20]. Big data and analytical tools connect human, relational and structural capital for supporting organizations to convert social media insights into sustainable competitive advantage [19,21].

Strategic alignment of analytics initiatives, organizational data management capability, and dynamic capabilities support organizations in effectively integrating SMA into innovation and performance-oriented activities [45,46]. Big data analytics capability also improves organizational agility, decision-making capability, and business value creation through data-driven innovation culture [28,44]. The integration of analytics with organizational strategy and customer relationship management systems further enhances competitive advantage and organizational capability enhancement through evidence-based intelligence [29,54]. Technological readiness and human analytical capability additionally strengthen the adoption of SMA for achieving sustainable organizational performance and innovation outcomes [30,55].

Figure 4 displays the factors influencing the adoption of SMA for enhanced organizational intellectual capital.

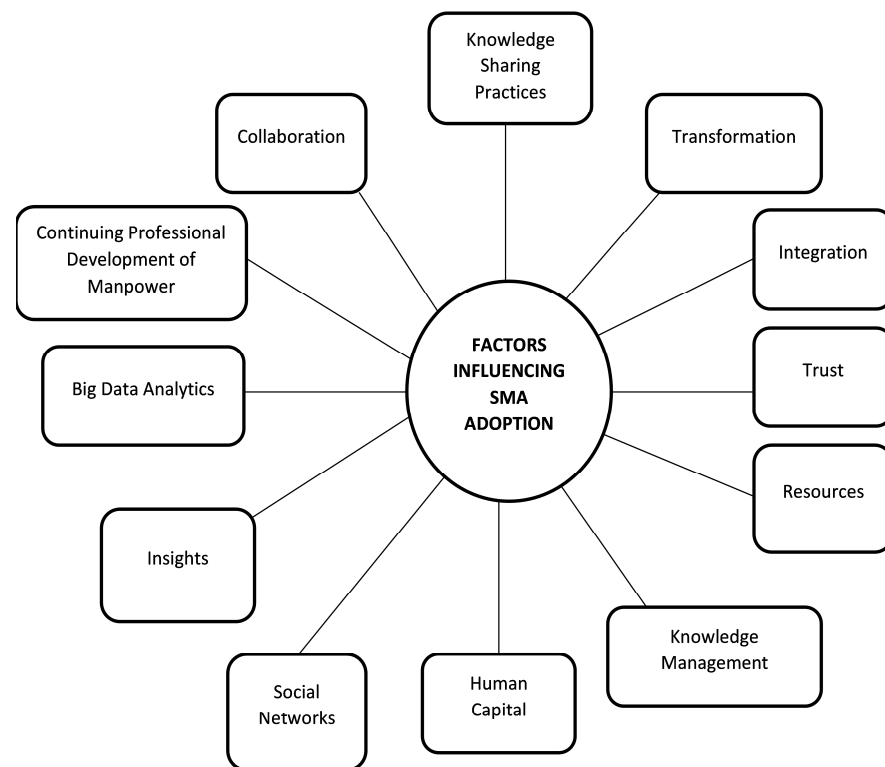


Figure 4. Factors influencing the SMA adoption.

3.5. Challenges to Incorporate SMA in Organizations for Enhanced Intellectual Capital

The study identified that data complexity, skills constraints, integration barriers, and ethical concerns cause challenges for the effective incorporation of SMA in organizations for enhanced intellectual capital. These challenges are interpreted as follows alternately:

3.5.1. Data Complexity

Data complexity is a major barrier causing a challenge for the adoption of social media analytics (SMA) for the attainment of enhanced intellectual capital [4,21]. Organizations may not conveniently manage unstructured and heterogeneous data [5,17]. It is difficult to ensure the authenticity, credibility, reliability, and accuracy of datasets for informed decision-making [3,15]. Inconsistent datasets create challenges for the extraction of meaningful knowledge [5,12]. Information flood on the social media platforms may cause problems for the decision makers to implement data-based policies [6,7]. The unavailability of data management standards in social media contexts causes challenges for its efficient integration in organizations [3,15]. Due to different formats of datasets, a coherent framework may not be adopted for the attainment of enhanced organizational intellectual capital [20,21].

The rapid growth of big data analytics environments and difficulties in managing massive datasets intensify data processing burdens and cause challenges for organizations to derive actionable intelligence from SMA outputs [28,45]. Challenges in extracting business value from analytics and ensuring data governance compliance further complicate effective SMA utilization for intellectual capital development [30,44]. Information overload in digital communication environments reduces decision-making clarity [24,47].

3.5.2. Skills Constraints

Skills limitations cause challenges for the effective adoption of social media analytics (SMA) for enhanced organizational intellectual capital [14,20]. Lack of analytical compe-

tencies creates problems for organizations to transform raw datasets into impactful knowledge for enhancing intellectual capital [17,21]. Organizations face difficulties in engaging workforces with SMA tools due to a lack of knowledge sharing practices [7,13]. Lack of inspiration, low level of personal interest, and unavailability of innovative leadership cause challenges for the efficient and sustainable incorporation of SMA in organizations [10,11,16]. The presence of skilled human capital is necessary for data analysis and to ensure adequate coordination among key stakeholders for strategic actions [8,9,19,21]. Organizations need to provide continuing professional development opportunities to their manpower for the adoption of SMA for enhanced organizational intellectual capital [14,20].

A shortage of skilled analytics professionals and limited analytical expertise significantly hinder the effective use of big data and social media analytics capabilities within organizations [29,45]. Resistance to technological change and low employee readiness further negatively affect the successful adoption of digital and AI-enabled analytics systems [52,55]. Limited managerial support and weak strategic orientation also reduce employees' motivation to effectively engage in SMA-based decision-making processes [49,53].

3.5.3. Integration Barriers

The integration of social media analytics (SMA) with existing organizational systems and services is a significant challenge for the attainment of enhanced organizational intellectual capital [1,14]. Technical gaps happen while adopting new tools in organizations due to integration barriers with already implemented systems [20,21]. Integration barriers negatively affect organizational performance and SMA is not efficiently linked to existing tools [5,8,15,19]. Differences in system architectures, technological tools versions, and standards cause challenges for the sustainable adoption of SMA in organizations [4,21]. Insufficient guidance on the best practices related to SMA adoption creates challenges for manpower related to successful integration [3,10]. A huge technological investment is required to manage integration challenges [1,9].

Strategic misalignment between analytics systems and business objectives further complicates the integration of SMA into organizational workflows [28,29]. Managing digital ecosystems and coordinating across complex innovation networks also creates additional integration difficulties in digitally enabled environments [25,26]. Integration challenges between CRM systems and social media platforms further restrict organizations from achieving seamless knowledge flow and relational capital enhancement [27,54]. Technological complexity in IoT and IT-based knowledge systems also intensifies system integration challenges in SMA adoption [52,56].

3.5.4. Ethical Concerns

Cyber security issues are linked to the adoption of social media analytics (SMA) in organizations for enhanced intellectual capital [1,17]. Organizations face barriers in collecting, storing, and using social media data with ethical and legal considerations for protecting intellectual property [15,18]. Mismanagement of data privacy damages trust, organizational prestige and the sustainability of SMA for the long term [5,21]. Misuse of datasets violates transparency in the dissemination of knowledge that causes critical ethical concerns [15,16]. Unauthorized access to confidential information can demotivate employees to participate in SMA-based activities [16,18]. Organizations face difficulties in protecting proprietary information while sharing insights through social media platforms [3,5]. Robust governance mechanisms, security protocols, and ethical standards need to be adopted to ensure sustainable SMA incorporation in organizations for enhanced intellectual capital [1,17].

Privacy concerns in workplace social media use and ethical risks in AI-driven analytics create significant barriers to SMA implementation in organizations [47,55]. Data governance

challenges and security risks in big data environments complicate ethical compliance and reduce organizational willingness to fully adopt SMA solutions [44,56]. Concerns related to information transparency, communication visibility, and misuse of shared knowledge also cause trust issues among employees and limit participation in SMA-driven initiatives [24,49].

Figure 5 shows the challenges to incorporate SMA in organizations for enhanced intellectual capital.

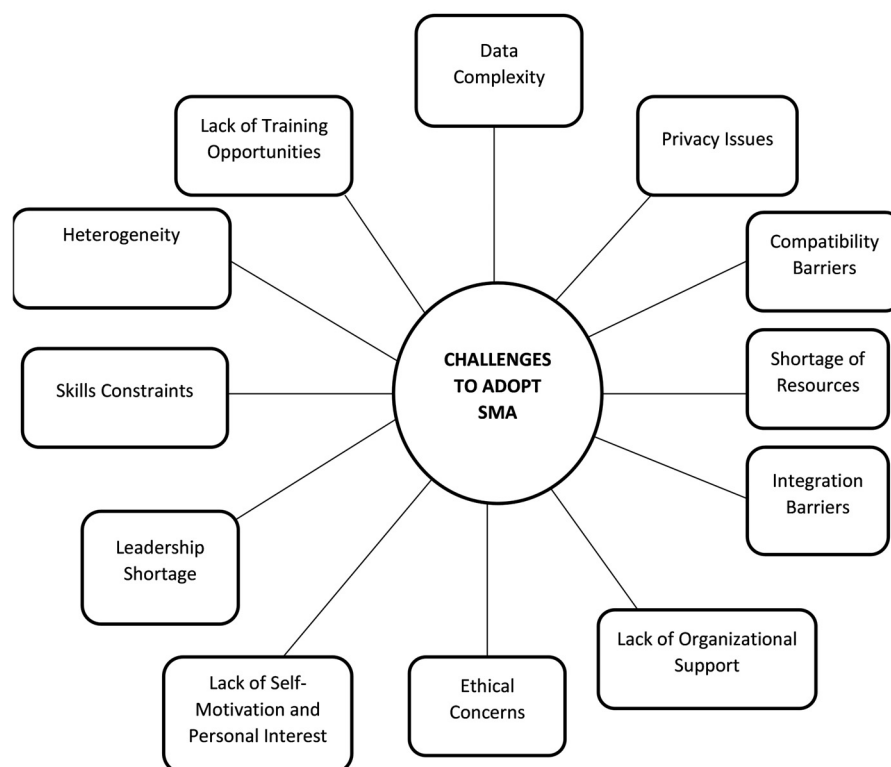


Figure 5. Challenges to adopt SMA in organizations.

4. Discussion

The present study systematically examined the factors influencing the adoption of social media analytics (SMA) for enhancing organizational intellectual capital and the key challenges hindering its implementation. In contrast to past investigations that examined SMA, intellectual capital, and big data analytics in isolation, this review integrates evidence across human, technological, relational, knowledge, and analytical dimensions. It identifies SMA adoption as a socio-technical transformation rather than a purely technological upgrade.

A key finding of this review is that SMA adoption is shaped by the interaction of multiple interdependent capabilities rather than isolated determinants. Across prior studies, human capital has consistently been identified as a key enabler of analytics and digital transformation [14,28,29]. However, while earlier research primarily treats human capital as a supporting resource for analytics utilization, this review aligns with Kianto et al. [12] and Inkinen [51] in extending this view by demonstrating that human capital functions as a bridging mechanism that connects technological systems with knowledge creation and intellectual capital formation. It shows human expertise as an enabler and a conversion layer between data and organizational learning outcomes. Similarly, technological infrastructure has been widely recognized in the literature as a core driver of analytics capability and organizational performance [14,44]. However, comparative analysis across studies reveals inconsistent findings regarding its standalone impact. While some studies emphasize direct performance effects, others [29,45] argue that technological infrastructure generates value only when embedded within strategic and organizational capabilities. The current

review supports the latter position and further consolidates this debate by showing that infrastructure alone is insufficient unless aligned with knowledge processes, organizational strategy, and human competencies. This clarifies a key inconsistency in the prior literature regarding whether SMA value is technology-driven.

Social networks and relational capital are also consistently highlighted in prior research as important drivers of knowledge sharing and organizational performance [16,18]. However, comparative synthesis shows a divergence in emphasis: earlier studies focus primarily on network structure and connectivity, whereas more recent research [6,24] highlights communication visibility and transparency as critical mechanisms. This review integrates both perspectives and demonstrates that network structure alone is insufficient unless accompanied by structured interaction and visibility mechanisms that enable transformation of social interactions into actionable intellectual capital. This extends the findings of Kwahk and Park [13], who emphasize that enterprise social media generates value only when actively managed within organizational systems. Knowledge management emerges as the most consistently supported integrative mechanism across the literature. Prior studies broadly agree that knowledge management enhances innovation and organizational performance [7,11,20]. However, there remains limited consensus on its role within SMA adoption frameworks. This review resolves this ambiguity by positioning knowledge management as the central transformation layer that converts SMA outputs into structured intellectual capital. This synthesis is consistent with Del Giudice and Della Peruta [52] and Santoro et al. [56], and further extends their findings by explicitly linking knowledge management with SMA-enabled intellectual capital development rather than general innovation outcomes. Big data analytics capability is similarly recognized across studies as a key driver of organizational agility and performance [28,46]. Nevertheless, comparative analysis shows variation in how this capability is conceptualized ranging from a technical resource to a dynamic organizational capability. This study aligns with Côte-Real et al. [44] and Chen and Chen [8] in supporting the latter interpretation and further advances the literature by conceptualizing analytics capability as a mechanism that integrates human, relational, and structural capital into a unified decision-making system.

The analysis of challenges also reveals important cross-study consistencies and divergences. Data complexity is widely acknowledged as a barrier in the big data and analytics literature [30,45]. However, comparative synthesis with studies such as Ndou et al. [3] and Schiuma et al. [5] suggests that data volume and heterogeneity, and the inability of organizations to translate fragmented data into coherent intellectual capital, are the critical issues. This shifts the focus from technical limitations to interpretive capability gaps. Skills constraints represent another widely agreed challenge across studies [14,29]. Yet, the earlier literature tends to treat this as a technical training issue, whereas recent studies [9,12] emphasize cultural and organizational learning dimensions. This review integrates both perspectives and shows that skills constraints are embedded in broader organizational capability and knowledge sharing structures, rather than being purely individual-level deficiencies.

Integration barriers are similarly consistent across prior research, particularly in studies on digital ecosystems and platform-based innovation [25,26]. However, comparative analysis reveals a key distinction. While earlier studies emphasize technical interoperability, this review highlights that integration failure often results from misalignment between analytics systems, organizational strategy, and knowledge structures [27,29]. This provides a more holistic interpretation of integration challenges as both technical and organizational in nature. Ethical concerns represent a prominent theme in the recent literature. Prior studies consistently highlight privacy, trust, and governance issues [5,15,47]. However, this review extends these findings by synthesizing evidence showing that ethical risks affect

compliance and directly influence employee participation, trust, and knowledge sharing willingness [6,49]. This indicates ethics as a behavioral and organizational barrier rather than only a regulatory concern.

The current study demonstrates that SMA adoption for intellectual capital enhancement is not explained by isolated technological and organizational factors, but by the interaction of capabilities across multiple dimensions. Compared to prior fragmented studies, this review contributes a more integrated and theoretically coherent understanding of SMA as a socio-technical capability system in which value creation depends on alignment between human, technological, relational, knowledge, and governance structures.

Based on the challenges identified through the findings of the study, a framework has been developed to effectively adopt and sustain social media analytics for enhanced intellectual capital. The framework consists of four constructs that include data governance and quality management, analytical capability development, system integration and technological alignment, and change enablement and ethical compliance. It is detailed as follows systematically:

Data governance and quality management emphasizes the need to effectively manage the complexity of social media data by establishing robust governance mechanisms. It involves defining clear standards for data collection, storage, processing, and validation to ensure accuracy, consistency, and reliability. Considering the unstructured and heterogeneous nature of social media data, organizations must implement advanced tools and frameworks to filter noise and extract meaningful information. Data quality management also includes ensuring authenticity and credibility to support evidence-based decision-making. Proper governance structures help reduce ambiguity and enhance trust in analytical outputs. Furthermore, standardized data practices enable seamless knowledge extraction and sharing across different functional areas.

Analytical capability development focuses on controlling skills-related challenges by building strong analytical competencies among individuals and teams. It highlights the importance of continuous training programs, workshops, and learning initiatives to enhance proficiency in social media analytics tools and techniques. Developing capabilities in data interpretation, visualization, and strategic analysis is essential for converting raw data into actionable insights. It also encourages critical thinking and problem-solving skills, which are necessary for leveraging analytics in complex decision-making contexts. Supportive learning environments and knowledge sharing practices further strengthen these capabilities. Promoting interdisciplinary expertise facilitates effective integration of analytical insights into broader strategic goals. As a result, enhanced analytical capability significantly contributes to intellectual capital formation and utilization.

The construct of system integration and technological alignment addresses the challenges associated with integrating SMA tools into existing technological ecosystems. It involves ensuring compatibility between new analytics platforms and current systems, databases, and workflows. Organizations must align their technological infrastructure to support seamless data exchange and real-time analysis. This includes upgrading legacy systems, adopting interoperable technologies, and following standardized protocols. Effective integration reduces operational disruptions and enhances efficiency in data processing and utilization. It also enables better coordination between different departments by providing unified access to insights. Moreover, technological alignment supports scalability and flexibility in adopting future innovations.

The construct of change enablement and ethical compliance integrates the need to manage resistance to change while addressing ethical concerns associated with social media analytics. It focuses on fostering a mindset that is open to innovation, adaptability, and continuous improvement. Clear communication about the benefits and purpose

of SMA helps in reducing uncertainty and building acceptance among individuals and leadership. Training and engagement initiatives further support smooth transitions toward data-driven practices. At the same time, ethical compliance ensures responsible handling of data, including privacy protection, transparency, and adherence to legal standards. Establishing strong governance policies and security measures enhances trust among stakeholders. Encouraging accountability and ethical awareness minimizes risks related to data misuse. This construct promotes sustainable and ethical adoption of SMA for strengthening intellectual capital.

These constructs collectively lead towards the sustainable adoption of social media analytics (SMA) in organizations for the attainment of enhanced intellectual capital. Organizations should consider the incorporation of data governance and quality management, analytical capability development, system integration and technological alignment, and change enablement and ethical compliance so that SMA can be innovatively implemented in workplaces for the attainment of enhanced intellectual capital to deliver efficient outcomes to uplift the organizations in the current age of competitive landscapes.

Figure 6 displays the framework for the effective adoption of social media analytics in organizations for enhanced intellectual capital.

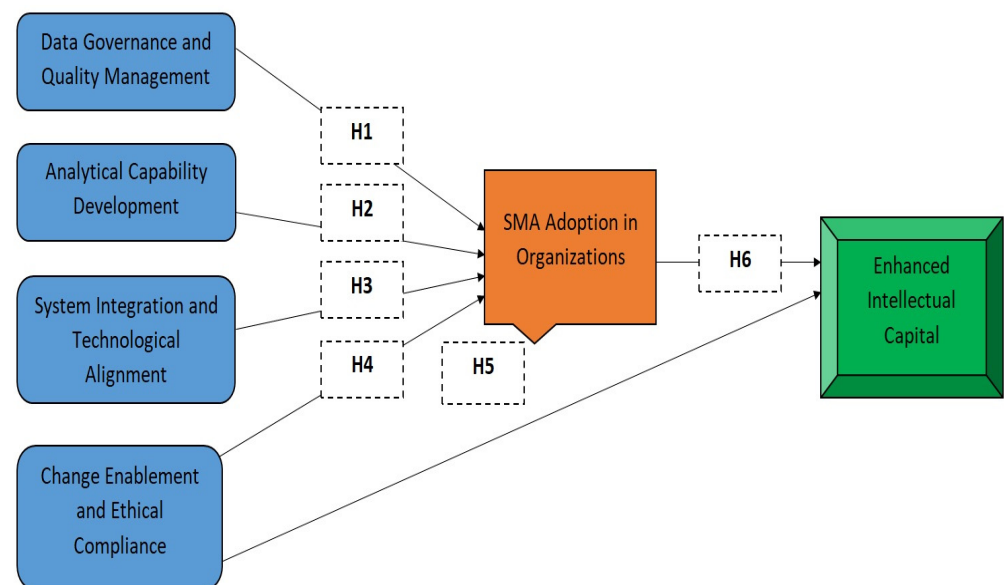


Figure 6. Framework to adopt SMA for enhanced intellectual capital.

The study has offered valuable theoretical, managerial, methodological, and social implications by conducting an in-depth SLR on the factors influencing the adoption of social media analytics (SMA) for enhanced organizational intellectual capital. It has added a significant amount of literature to the existing body of knowledge. It has opened new horizons for future investigators to further explore new regions related to SMA and intellectual capital. It has provided practical implications for management bodies through the provision of practical solutions to efficiently incorporate SMA in organizations for the attainment of enhanced intellectual capital. It has delivered methodological contributions by conducting a comprehensive systematic literature review-based study on the topic. It has also provided social implications as the adoption of SMA in workplaces delivers fruitful outcomes for the uplift of society through enhanced intellectual capital.

5. Conclusions

This study systematically reviewed and synthesized evidence from 40 peer-reviewed articles to examine the factors influencing the adoption of social media analytics (SMA)

for enhancing organizational intellectual capital. The findings directly address the three research questions guiding this study. In relation to RQ1, the study identifies five key determinants of SMA adoption for enhancing organizational intellectual capital. These factors include human capital, technological infrastructure, social networks, knowledge management, and big data analytics capability. These factors collectively demonstrate that SMA adoption is not driven by a single dimension but emerges through the interaction of human, technological, and organizational capabilities. Among these, human capital plays a central role in transforming analytical outputs into meaningful intellectual capital through skills, learning, and decision-making competencies.

Regarding RQ2, the review highlights four major categories of challenges that include data complexity, skills constraints, integration barriers, and ethical concerns. These findings indicate that the value of SMA is constrained not only by technical limitations but by organizational readiness, governance structures, and workforce capabilities. Persistent issues such as unstructured data overload, shortage of analytical expertise, system incompatibility, and privacy and trust concerns significantly hinder the effective translation of SMA into organizational intellectual capital. In response to RQ3, the study proposes a four-dimensional framework comprising data governance and quality management, analytical capability development, system integration and technological alignment, and change enablement and ethical compliance. This framework provides a structured roadmap for organizations to bridge the gap between SMA adoption and value realization by aligning technological systems with human capabilities, governance mechanisms, and organizational change processes.

This study contributes to the intellectual capital and social media analytics literature by integrating fragmented findings into a unified socio-technical perspective of SMA adoption. It advances existing research by conceptualizing SMA not merely as a technological tool but as an integrated capability system where human, structural, relational, and analytical resources jointly determine intellectual capital outcomes. This synthesis also extends prior work by simultaneously examining enabling factors and constraints within a single consolidated analytical framework. From a practical perspective, the findings provide actionable guidance for managers and policymakers. Organizations should prioritize the development of analytical skills, strengthen knowledge sharing cultures, and invest in interoperable technological infrastructures to support SMA integration. In addition, effective data governance, ethical compliance, and change management strategies are essential to ensure sustainable and responsible use of social media data. The proposed framework serves as a practical roadmap for aligning organizational resources to maximize the value of SMA in enhancing intellectual capital.

6. Limitations

Despite its contributions, this study has several limitations that should be acknowledged, particularly in relation to the scope of the extracted dataset and methodological design. First, the study is based on a systematic literature review (SLR) using secondary data. While this approach ensures transparency, rigor, and reproducibility, it does not allow for direct empirical validation of relationships between social media analytics (SMA) and organizational intellectual capital. Consequently, the findings reflect synthesized interpretations of existing studies rather than context-specific empirical evidence. Second, the final dataset consists of 40 peer-reviewed journal articles, which were selected following inclusion criteria and PRISMA guidelines. Although this ensures quality control, the relatively limited sample size may restrict the comprehensiveness of the evidence base, especially given the rapidly expanding nature of SMA research. As a result, some relevant studies may not have been covered due to database indexing limitations or search constraints.

In addition, a small number of included studies were conceptual and review-oriented in nature. While these studies contributed valuable theoretical and integrative perspectives, they may have discussed evidence reported in primary empirical studies included elsewhere in the dataset. To mitigate this issue, review-based and conceptual studies were not included in frequency-based coding or quantitative synthesis and were used only for contextual interpretation. Accordingly, caution is required when interpreting thematic patterns that may partially reflect conceptual rather than purely empirical convergence. Although the synthesis process emphasized conceptual interpretation rather than quantitative aggregation, some degree of overlap in the underlying evidence base cannot be entirely ruled out. Therefore, findings should be interpreted with recognition of the possibility of partial conceptual redundancy across studies. Furthermore, the review covered literature published between 2012 and 2025 to capture the historical development of SMA adoption and its relationship with organizational intellectual capital. While this broader temporal scope facilitated examination of the field's evolution, some earlier studies may reflect technological conditions, organizational practices, and analytical capabilities that differ from contemporary environments. Consequently, the applicability of certain findings to current SMA ecosystems should be interpreted with appropriate contextual consideration. Although the temporal scope enhances historical coverage, it may also reduce the analytical focus on recent advancements in artificial intelligence-driven social media analytics.

Third, the review excluded gray literature sources such as conference proceedings, book chapters, dissertations, and technical reports. While this decision enhanced methodological rigor and ensured focus on high-quality peer-reviewed evidence, it may have introduced publication bias and excluded valuable practical and emerging insights from non-journal sources. Fourth, the literature search was primarily conducted using major academic databases (e.g., Scopus and Web of Science). Although these sources are highly reputable, the exclusion of broader repositories and institutional databases may have limited the diversity of perspectives included in the synthesis. Fifth, the included studies demonstrate significant methodological and contextual heterogeneity, including differences in research design, geographic regions, industrial sectors, and measurement approaches. While this diversity strengthens thematic generalization, it also limits direct comparability across studies. Finally, the study relies on thematic synthesis, which involves interpretive judgment in coding and categorization. Although reliability was strengthened through PRISMA procedures and inter-rater agreement ($\kappa = 0.81$), a degree of subjectivity in theme development cannot be fully eliminated.

7. Future Research Directions

Future research should focus on empirically validating the proposed framework using quantitative, qualitative, and mixed-method research designs. Such studies would strengthen the robustness and generalizability of the findings and provide deeper insights into how SMA contributes to intellectual capital development across diverse organizational settings. In addition, future studies should expand the data scope by including conference proceedings, book chapters, dissertations, and other gray literature sources. This would help reduce publication bias and provide a more comprehensive understanding of SMA adoption dynamics in both academic and practical contexts.

Methodologically, future research may also employ bibliometric analysis, meta-analysis, and scoping review techniques to map research trends, intellectual structures, and thematic evolution in the field. These approaches would provide analytical depth and complement the findings of this systematic literature review. Future systematic reviews may also conduct comparative analyses across different time periods, such as focusing exclusively on the most recent five to seven years. Such an approach would enable researchers to

distinguish foundational determinants of SMA adoption from emerging factors associated with contemporary artificial intelligence, advanced analytics, and digital transformation initiatives. In addition, future evidence syntheses may consider separately analyzing empirical studies and review-based studies to further assess the potential influence of conceptual overlap within the knowledge base. Finally, longitudinal and cross-sectoral studies are recommended to examine how SMA capabilities evolve over time and how contextual factors such as industry type, organizational size, and digital maturity influence intellectual capital outcomes. Empirical validation of the proposed framework across different contexts will be essential to enhance its theoretical rigor and practical applicability.

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Data Availability Statement: The dataset comprises 40 peer-reviewed journal articles selected through predefined inclusion and exclusion criteria and PRISMA-guided screening. Detailed information about these selected studies has been presented in Table 7 of the manuscript. No additional datasets were generated or analyzed during the current study.

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Abbreviations

The following abbreviations are used in this manuscript:

SLR	Systematic Literature Review
SMA	Social Media Analytics
IC	Intellectual Capital
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
INFORMS	Institute for Operations Research and the Management Sciences
CASP	Critical Appraisal Skills Programme
HC	Human Capital
KM	Knowledge Management
BDA	Big Data Analytics

Appendix A

Table A1. PRISMA 2020 checklist.

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
TITLE			
Title	1	Identify the report as a systematic review.	Title page (“systematic literature review”)
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Abstract section (structured according to PRISMA 2020 for Abstracts checklist)
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Section 1: Introduction

Table A1. Cont.

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Section 1; (objectives + research questions)
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Table 2 (inclusion/exclusion criteria)
Information sources	6	Specify all databases, registers, websites, organizations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Section 2.1 (databases listed)
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Table 4 (search queries & filters)
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Section 2.2 (selection + PRISMA explanation)
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Section 2.5 (data extraction process)
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Section 2.4 (“adoption factors” “challenges” “contextual variables”)
	10b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Table 5 (study characteristics)
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Section 2.3 (CASP checklist, Table 5)
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results.	Not applicable (no meta-analysis; qualitative synthesis)
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Section 2.6 (data synthesis)
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Sections 2.3 and 2.4 (extraction + thematic synthesis)
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Table 7, Figures 2–6
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Section 2.4 (thematic analysis)
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g., subgroup analysis, meta-regression).	Not applicable
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Not applicable
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Not applicable
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Not applicable

Table A1. Cont.

Section and Topic	Item #	Checklist Item	Location Where Item is Reported
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Figure 1 (PRISMA flow diagram)
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Section 2.2 (exclusion explanation)
Study characteristics	17	Cite each included study and present its characteristics.	Table 7
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Table 5 (CASP quality assessment results)
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g., confidence/credible interval), ideally using structured tables or plots.	Table 7 (study-level extracted data)
Results of syntheses	20a	For each synthesis, briefly summarize the characteristics and risk of bias among contributing studies.	Sections 3.2–3.5
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Not applicable
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Not applicable
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Not applicable
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Not applicable
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Not applicable
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Section 4: Discussion
	23b	Discuss any limitations of the evidence included in the review.	Section 6 (limitations)
	23c	Discuss any limitations of the review processes used.	Section 6
	23d	Discuss implications of the results for practice, policy, and future research.	Section 4 + Section 5
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Section 2.1 (OSF link)
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Section 2.1 (OSF statement)
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Funding section
Competing interests	26	Declare any competing interests of review authors.	Declared in Conflicts of Interest section
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Data Availability Statement

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