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The Challenges of Enterprise Information Systems in the Era of Social Media

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ABSTRACT

For organizations in the digital age, social media has emerged as a key wellspring of information. These platforms are invaluable for gauging public opinion and discerning market trends or customer behavior, yet they come with their own set of problems: data overload, questions of quality and the prevalence of misinformation.

The present project is an examination of the issues that Enterprise Information Systems (EIS) must contend with in this social media landscape. We look at how information functions in an organization and the architecture behind EIS as it has evolved, while also weighing the risks and opportunities of bringing social media data into the business sphere.

We pay special heed to Artificial Intelligence and Large Language Models (LLMs) and what they can do to improve information quality and aid in decision-making by weeding out the unreliable. Our study does not shy away from the limitations of such tools; it underscores the need for ethical compliance and human oversight alongside the advantages they offer.

Ultimately, our findings show that although incorporating social media can be a great asset to an EIS, it is imperative for an organization to have strong governance and intelligent verification in place to use that information in a strategic and trustworthy manner.

Keywords: Enterprise Information Systems, Social Media, Information Quality, Artificial Intelligence, Large Language Models, Decision Support, Information Governance.

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Dedicace

This achievement doesn’t just belong to the four of us. It is the directly shared result of every single prayer, quiet sacrifice, and late-night word of encouragement that kept us going. With all our love, we dedicate this work:

To our incredible mothers and fathers, whose prayers protected us when things got tough and whose unconditional faith in us was our biggest driving force. Everything we did was to make you proud, and we hope this brings a smile to your faces today.

To our families, for always giving us a safe space to rest, the peace of mind to focus, and the strength to carry on through the most exhausting stretches of our university years.

To our friends and classmates, for your loyalty, your constant push, and for that unforgettable team spirit that reminded us never to settle for just "good enough."

And finally, to our team, In celebrate of our sleepless nights, our shared grit, and the fact that we stuck together and made it to the finish line.

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General Introduction

The way organisations handle information has never been simple, but it has rarely been as complicated as it is today. For decades, Enterprise Information Systems were built around a relatively stable assumption: that the information an enterprise needed to function could be collected, verified, and stored internally, within systems the organisation controlled. Payroll data, inventory records, sales figures, customer contracts these are structured, traceable, and governed. An EIS was designed precisely to manage this kind of information, and for a long time, it did so well. Social media broke that assumption.

Platforms like Facebook, X, LinkedIn, TikTok, and Instagram now produce more information in a single hour than most enterprises could generate in a year. Some of that information is directly relevant to business decisions a wave of negative customer reviews, a competitor's product announcement, a reputational crisis building in real time. Organisations that ignore these signals do so at a cost. But the same platforms that carry genuine intelligence also carry disinformation, manipulation, bot-generated content, and viral falsehoods that spread faster than any verification process can follow. Integrating social media into an EIS is therefore not a straightforward technical upgrade. It is a fundamental governance challenge, because the information environment that enterprises must now navigate is one they do not control and cannot fully trust.

This is the problem this thesis sets out to examine. The central question driving the work is the following: to what extent do social media platforms challenge information quality within Enterprise Information Systems, and how can Artificial Intelligence particularly Large Language Models contribute to addressing these challenges?

The objective of this thesis is threefold. First, to establish a precise theoretical framework for understanding what information quality means in an enterprise context and how social media systematically threatens it. Second, to analyse the architectural capacity of current Enterprise Information Systems to absorb and process social media data without compromising the reliability of managerial decision-making. Third, to evaluate Large Language Models as a technological response to this challenge not in the abstract, but against the specific quality gaps that the analysis reveals and to identify the governance conditions under which their deployment can be considered adequate rather than merely promising.

This question matters because the answer is not obvious. AI is frequently presented as the solution to information quality problems at scale, and there is real substance to that claim: Large Language Models can process volumes of unstructured text that no human team could handle, detect linguistic patterns associated with misleading content, and crossreference claims against verified knowledge bases in near real time. But they also hallucinate, inherit biases from their training data, and can be manipulated by adversarial actors who understand how they work. Whether AI solves the problem or simply shifts it is a question worth asking carefully.

The thesis approaches this question through a systematic review of academic and professional literature published between 1948 and 2026. The approach is qualitative and exploratory: rather than testing a specific hypothesis against empirical data, the work builds a

theoretical framework capable of explaining the relationship between social media integration, information quality, EIS architecture, and AI governance and uses that framework to evaluate the adequacy of current technological responses to a problem that is still evolving.

The work is organised into four chapters, each of which addresses a distinct layer of the problem.

Chapter 1 lays the conceptual groundwork. Before examining how social media challenges information quality within EIS, it is necessary to be precise about what information quality actually means and why it matters for organisational decision-making. The chapter examines the role of information in the enterprise through Simon's (1960) decision-making framework, the six dimensions of information quality accuracy, completeness, reliability, relevance, timeliness, and intelligibility and the communication models of Shannon and Weaver (1949) and Lasswell (1948) that explain how information fails to reach its intended audience with its intended meaning intact. It then turns to the specific quality threats introduced by social media: the mechanics of disinformation, the institutional retreat from professional fact-checking, and the AI-based interventions that have emerged in response, along with their documented limitations.

Chapter 2 shifts focus from information theory to information infrastructure. It traces the historical evolution of Enterprise Information Systems from the Material Requirements Planning tools of the 1960s through to the cloud-based, AI-augmented Digital ERP platforms of the present decade, examining at each stage what new capabilities were introduced and what new vulnerabilities followed. The chapter analyses the principal architectural components of modern EIS ERP, CRM, SCM, and BI and their interdependencies, before examining how cloud computing and AI integration have transformed both the possibilities and the risks of enterprise information management.

Chapter 3 brings the first two chapters into direct contact. It examines the relationship between social media and EIS not as a simple technical integration problem a matter of connecting APIs and processing data streams but as a dynamic that is simultaneously commercially valuable and informationally hazardous. The strategic benefits of social media integration are real: real-time customer sentiment monitoring, early market trend detection, reputational risk management. But so are the risks: information overload, systematic misinformation, and the semantic complexity of user-generated content that NLP systems consistently underestimate. The chapter develops governance recommendations on the basis of this analysis.

Chapter 4 examines Large Language Models as enterprise technologies. It moves beyond the general discussion of AI in Chapters 1 and 3 to evaluate LLMs specifically their transformer-based architecture, their principal applications in CRM, knowledge management, and decision support, their genuine advantages in processing unstructured text at scale, and their significant limitations: hallucination, training data bias, opacity, adversarial vulnerability, and the organisational risk of over-reliance on outputs that appear authoritative but are probabilistic.

A word on what this thesis does not claim to do. It does not present primary empirical data from case studies of specific organisations. It does not benchmark AI systems against one

another under controlled conditions. What it does is build a conceptual framework precise enough to be useful one that specifies where the information quality risks of social media integration are most acute, where current AI architectures are most and least capable of addressing them, and what governance conditions must be in place for AI-assisted EIS integration to be considered reliable rather than merely convenient.

Chapter 1: Information in the Enterprise

Introduction

In modern organizations, information has evolved into a vital strategic resource, forcing Enterprise Information Systems (EIS) to expand beyond internal structured data to manage vast volumes of dynamic, unstructured external data from social media. While information quality is crucial for operational efficiency and reliable decision-making, integrating social media introduces major challenges such as misinformation, data overload, and communication barriers. To address these issues, this chapter establishes the theoretical foundations of enterprise information examining its strategic role, classifications, and quality principles while highlighting the growing importance of artificial intelligence in verifying data and fact-checking modern organizational information flows.

1.1 Role of Information in the Enterprise

Information constitutes the foundation of organisational coordination, control, planning, and decision-making. Modern enterprises depend on continuous information flows to manage operational activities, monitor performance indicators, anticipate market shifts, and support strategic choices at every level of the hierarchy.

Simon's (1960) theory of managerial decision-making identifies three major phases intelligence, design, and choice in each of which reliable and relevant information plays an indispensable role. During the intelligence phase, managers must identify problems and opportunities; during the design phase, they must generate and evaluate alternatives; and during the choice phase, they must select among those alternatives. At every stage, the quality of the decision is constrained by the quality of the information available.

Within this framework, information fulfils four principal organisational functions:

- **Coordination:** Information synchronises activities across departments and ensures that separate units act in a coherent, mutually supportive manner.

- **Control:** Information enables the monitoring of performance against organisational objectives, facilitating timely corrective action.

- **Planning:** Information supports both short-term operational scheduling and longterm strategic forecasting, reducing uncertainty in the allocation of resources.

- **Decision Support:** Accurate, timely information reduces managerial uncertainty and improves the reliability of decisions across all hierarchical levels.

It bears emphasising that information's value is conditional, not absolute. As Davenport (1998) observes, even technically sophisticated information systems cannot compensate for poor-quality input data: the traditional principle of 'garbage in, garbage out' remains as applicable in the era of AI-powered analytics as it was in the early days of computing. Poor-quality information may produce incorrect decisions, operational failures, or strategic misjudgements whose consequences are

amplified, rather than mitigated, by the speed at which modern systems process and distribute information.

1.2 Forms of Information Information

within the enterprise takes multiple forms, classified by its nature, origin and intended use, These axes are not mutually exclusive: a single piece of information may be simultaneously strategic in nature, critical in impact, and confidential in terms of sensitivity, which directly determines the governance mechanisms that must govern its collection and dissemination.

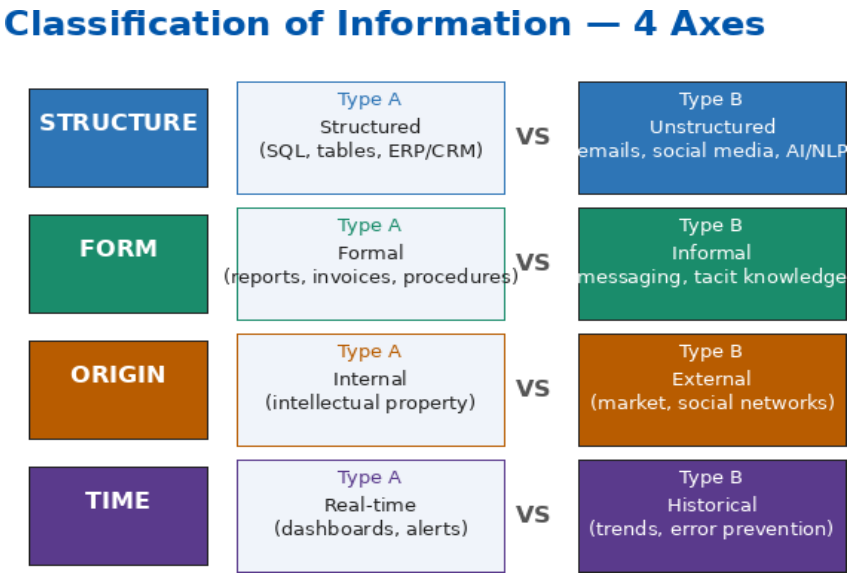


Fig. 1.1 — The 4 classification axes of information in the enterprise

Figure 1.1 illustrates the multidimensional nature of enterprise information. This diversity increases the complexity of Enterprise Information Systems, particularly when integrating unstructured and externally generated social media data.

1.3 Representation of Information

Information representation concerns the encoding, structuring, and organisation of data to facilitate processing, storage, and transmission. Several levels of representation are relevant to enterprise systems:

- **Data encoding:** At the lowest level, information is represented as binary data (bits and bytes), numbers, text, or multimedia (audio and video).

- **Data models:** At a higher level of abstraction, data is organised according to structural models relational, hierarchical, object-oriented, or semi-structured (XML and JSON) each of which reflects different assumptions about how data elements relate to one another.

• **Metadata:** 'Data about data' provides contextual, descriptive, and management information that is essential for locating, interpreting, and governing data assets.

The choice of representation model is not neutral: it shapes what information can be stored, how it can be queried, and how easily it can be integrated with other systems. The shift from relational models, which dominated EIS design throughout the 1990s, toward semi-structured formats such as JSON now prevalent in social media APIs illustrates how representational choices are driven by the nature of the information being managed (W3C, 2004).

1.4 Information Quality

Information quality refers to the degree to which information is suitable for its intended use. High-quality information is essential for effective decision-making, whereas poor-quality information can generate operational inefficiencies and strategic risks.

The principal dimensions of information quality include:

• **Accuracy:** Information correctly reflects reality.

• **Completeness:** Required data is available without significant omissions.

• **Reliability:** Information is dependable and reproducible.

• **Relevance:** Information is useful for a specific decision or activity.

• **Timeliness:** Information is available at the appropriate moment.

• **Intelligibility:** Information is understandable and clearly presented.

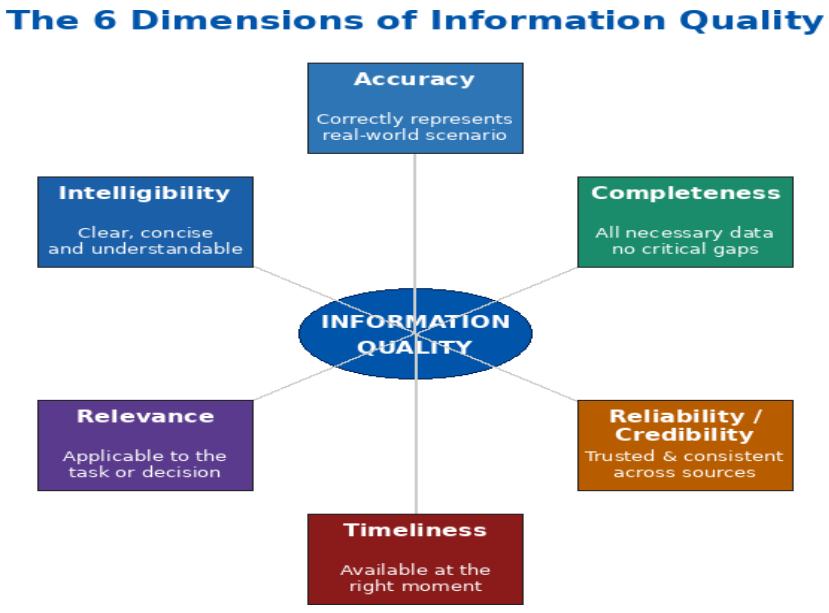


Fig. 1.2 — The 6 dimensions of information quality (hexagonal model)

Figure 1.2 highlights the multidimensional nature of information quality. In social media environments, maintaining these dimensions becomes increasingly difficult due to information overload, misinformation, and the rapid circulation of unverified content.

These dimensions are not independent: improving timeliness, for instance by integrating real-time social media feeds, often creates a trade-off with accuracy, since the speed of publication typically outpaces verification. Managing information quality therefore requires balancing competing demands rather than optimising each dimension in isolation.

The traditional principle of "garbage in, garbage out" illustrates that even advanced systems cannot produce reliable outputs when the input information is inaccurate or misleading.

1.4.1 Reliability, Credibility and Consistency — Key Distinctions

Three closely related but conceptually distinct properties deserve particular attention in the context of digital information environments:

- **Reliability** refers to the stability and reproducibility of information: a source is reliable if it consistently produces accurate results under similar conditions.

- **Credibility** concerns the trustworthiness and perceived legitimacy of the source from which information originates.

- **Consistency** refers to agreement between multiple independent sources: information is consistent if it is corroborated by sources that have no common origin .

A critical insight for EIS design follows from distinguishing these three properties: on social media platforms, information may appear highly reliable in the sense that it is repeatedly reproduced across many accounts while entirely lacking credibility or cross-source consistency. The algorithmic mechanisms that drive viral circulation are indifferent to factual accuracy; they reward engagement rather than truth. Enterprise information systems that integrate social media data without accounting for this structural feature risk systematically importing high-volume, low-credibility information into their knowledge bases.

1.5 DIKW Model (Data → Information → Knowledge → Wisdom)

The Data–Information–Knowledge–Wisdom (DIKW) hierarchy, introduced by Ackoff (1989) and elaborated by Rowley (2007), describes the progressive transformation of raw data into strategic organisational value through successive stages of contextualisation, interpretation, and judgement.

- **Data:** Raw, unprocessed facts that carry no inherent meaning in isolation.

- **Information:** Data organised within a meaningful context that enables it to answer questions such as who, what, when, and where.

• **Knowledge:** Information interpreted through analysis, experience, and reasoning to produce an understanding of how and why.

• **Wisdom:** The capacity to apply knowledge to make sound strategic decisions that serve long-term organisational goals.

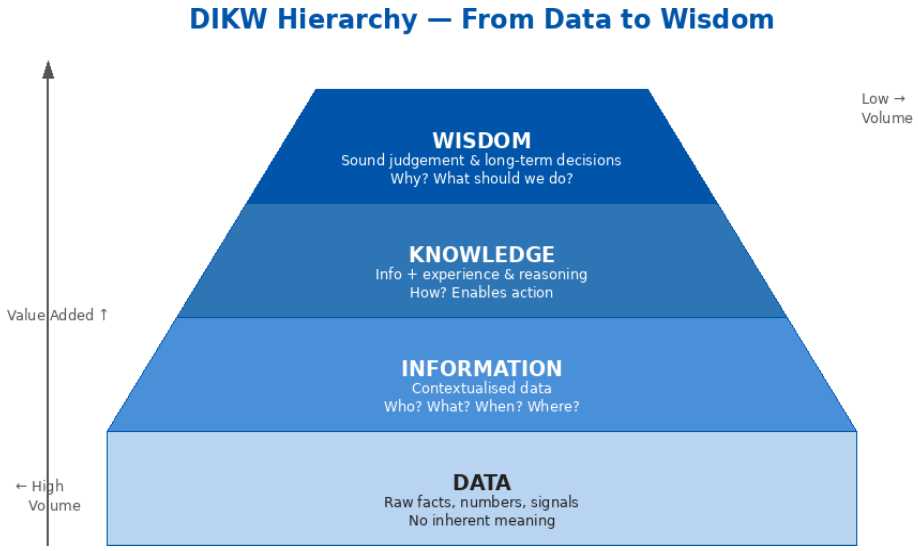


Fig. 1.3 — The DIKW Pyramid (Ackoff, 1989; Rowley, 2007)

Figure 1.3 illustrates the progressive transformation of raw data into strategic knowledge.

The DIKW framework remains particularly relevant in the context of Enterprise Information Systems because organisations increasingly depend on transforming large volumes of digital information into actionable knowledge.

However, the rise of social media and AI-generated content complicates this transformation process. Large quantities of inaccurate or misleading information may contaminate higher levels of the hierarchy, thereby affecting managerial judgement.

1.6 Communication Problems

Communication is defined as the process of transmitting meaning from a sender to a receiver via a given channel. Three levels of communication problems remain analytically relevant in an organisational context:

• **Technical Problem:** How accurately can the symbols or signals composing the message be transmitted through the channel? Ex: email not received due to a server issue. Solution: channel redundancy, reliable protocols (TCP/IP), encryption.

• **Semantic Problem:** How accurately does the transmitted message convey the intended meaning? Word ambiguity, language or cultural differences can cause misunderstandings. Ex: "Pass me the mouse" (computer or animal?). Solution is to clear, precise messages adapted to context.

• **Effectiveness Problem:** How successfully does the received meaning influence the recipient's behaviour in the desired direction? The message may be received and understood but ignored or misapplied. Solution is to appropriate channels, confirmation feedback, recipient engagement.

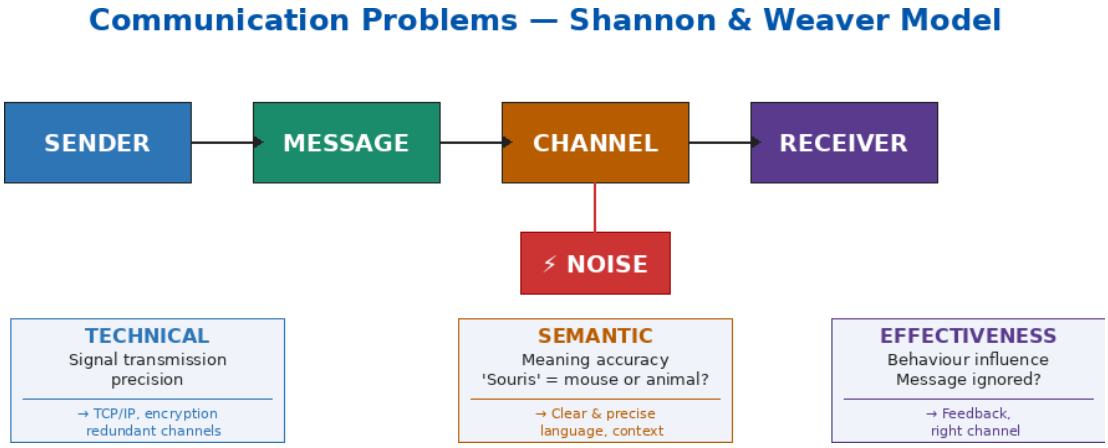


Fig. 1.4— Three communication problems (Weaver, 1949)

1.7 Information Quality in the Era of Social Media:

Social media has fundamentally transformed the conditions under which enterprise information is produced, circulated, and consumed. Platforms such as Facebook, X (formerly Twitter), LinkedIn, Instagram, and TikTok continuously generate massive quantities of usercreated content that enterprises cannot afford to ignore: they carry real signals about customer sentiment, brand perception, emerging market trends, and reputational risks. At the same time, these platforms are structurally inhospitable to the information quality dimensions identified in Section 1.4.

For enterprises, social media presents a dual character: it is simultaneously a valuable intelligence resource and a potential vector for misinformation, manipulation, and data overload. Realising the former benefit while managing the latter risk is the central information governance challenge of the current era.

1.7.1 The Challenge of Disinformation

The traditional dimensions of information quality accuracy, reliability, and timeliness are profoundly threatened in social media environments. Disinformation spreads through automated bots, AI-generated deepfakes, and viral sharing mechanisms, producing what researchers have described as an 'infodemic': a surplus of information, much of it false or misleading, that overwhelms the capacity of individuals and organisations to identify reliable signals (Glauser, 2026).

The institutional responses to this problem have themselves become a source of concern. In 2025, major platforms including Meta discontinued their partnerships with professional, third-party fact-checking organisations, replacing them with participatory 'community notes' systems. While this model offers scalability, it sacrifices the consistency and expertise that professional fact-checking provides, and its effectiveness under adversarial conditions where coordinated actors seek to manipulate community assessments remains undemonstrated.

1.7.2 Technological Interventions: LLMs at the EIS Periphery

Several technological interventions have been developed or proposed to address the disinformation problem at the interface between social media and enterprise systems:

- **Algorithmic warning labels:** Algorithms that flag potentially false content before it reaches users. Large-scale experimental studies indicate that such labels significantly reduce both belief in disinformation and its redistribution.

- **LLM-based fact-checking:** Large Language Models can cross-reference social media claims against verified knowledge bases in near real time, offering scalable verification at a speed that human fact-checkers cannot match (Renault et al., 2025).

- **Algorithmic de-referencing:** AI systems that reduce the algorithmic reach of inaccurate posts by deprioritising them in recommendation feeds, limiting their propagation without removing them entirely.

- **Accuracy nudges:** Low-cost behavioural interventions that prompt users to reflect on the accuracy of content before sharing it have been shown to be consistently effective across multiple experimental settings (Lin, MIT/Cornell).

Of these interventions, LLM-based fact-checking is the most directly applicable to EIS integration because it can be embedded as an architectural layer rather than depending on end-user behaviour. Accuracy nudges and warning labels, by contrast, operate at the platform level and cannot be controlled by the enterprise. This distinction matters for EIS design: enterprises must build their quality-assurance mechanisms around technologies they can govern, not those they depend on third-party platforms to maintain.

1.7.3 Limitations and Open Research Questions

Despite these technological advances, important limitations constrain the reliability of AI-driven information verification:

- **Coverage gap:** AI-driven content moderation, even at its current state of development, misses between 21% and 28% of misleading content when benchmarked against expert human oversight a non-trivial margin in high-stakes decision contexts (Glauser, 2026).

- **Transparency and auditability:** Automated fact-checking systems require continuous independent auditing to remain trustworthy. Current evidence suggests that corporate commitment to such transparency is insufficient.

- **Unintended consequences**: Some verification interventions produce unexpected behavioural effects, including reductions in overall platform engagement that may inadvertently suppress legitimate as well as misleading content.

- **Adversarial adaptation:** As AI detection systems improve, disinformation actors adapt their tactics a dynamic arms race that precludes any permanent technological solution.

1.7.4 Implications for the DIKW Hierarchy and EIS Design

From an information systems design perspective, integrating AI-based fact-checking at the periphery of the EIS between the raw social media data layer and the validated information layer that feeds managerial decision-making constitutes a critical quality gate in the DIKW pipeline. Raw social media data that has been subjected to AI verification filters can be treated as contextualised, validated information suitable for informing managerial knowledge and, ultimately, organisational wisdom. Data that fails these filters must either be discarded or flagged for human review before being used in consequential decisions..

1.8 Information Classification

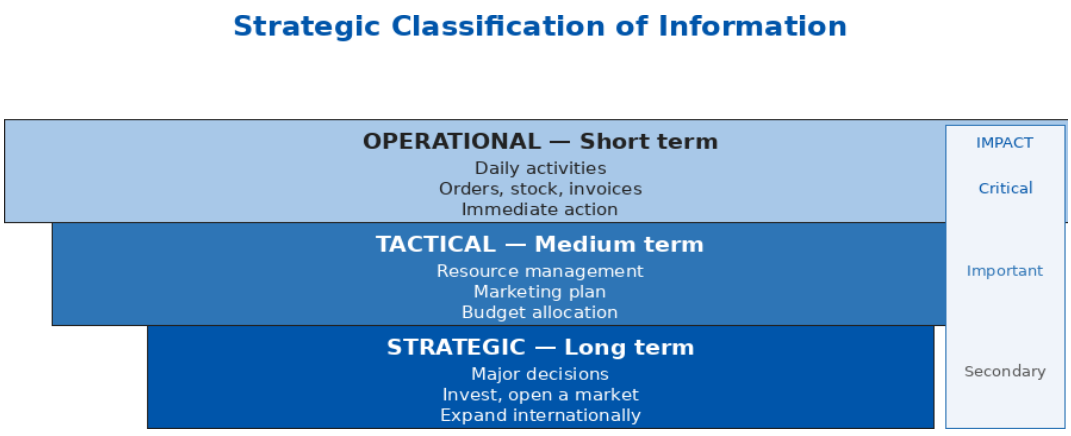


Fig. 1.6 — Strategic classification of information (3 levels)

The classification of information is essential for defining access-control policies, cybersecurity strategies, and governance mechanisms within Enterprise Information Systems.

1.8.1 By Organisational Role

Category	Horizon	Examples
Strategic	Long-term	Major decisions: invest, enter a market, international expansion
Tactical	Medium-term	Resource management: marketing plan, budget allocation
Operational	Short-term	Daily activities: orders, stock, invoicing

Table 1.1 — Classification of enterprise information by organisational role.

1.8.2 By Impact

Critical information carries a major organisational impact if it is false or absent financial data, security-related records, and regulatory filings fall into this category. A forecasting error based on incorrect financial data, for instance, can produce cascading operational failures across multiple departments.

1.8.3 By Sensitivity (security)

Level	Accessibility
Public	Accessible to all
Internal	Reserved for the enterprise
Confidential	Limited access
Secret	Highly protected — restricted access

Table 1.2 — Classification of enterprise information by sensitivity level

1.8.4 By Source

• **Primary sources**: Information collected directly and originally (surveys, sensor readings, field observations).

• **Secondary sources:** Information derived from pre-existing data (reports, academic articles, summarised datasets).

1.9 Harold Lasswell's Communication Model

Harold Lasswell's (1948) model analyses communication through five sequential questions: Who says what, through which channel, to whom, with what effect? Applied to enterprise information flows, each element carries distinct analytical significance:

Component	Question	Description	Importance
WHO	Sender	Individual (journalist, professor), Organisation, System (AI, social network)	Credibility & intention (to inform or manipulate?)
SAYS WHAT	Message	Text, image, video, data (numbers, statistics)	Clarity, precision, absence of ambiguity
WHICH CHANNEL	Medium	Oral, written (email, PDF), digital (social media), audiovisual (TV)	Speed and possible distortion of the message
TO WHOM	Receiver	Individual, group, target audience	Interpretation according to culture, knowledge, context → semantic problem
WHAT EFFECT	Impact	Understanding, action (buy, decide), change of opinion	Measures effectiveness → effectiveness problem

Table 1.3 — Lasswell's communication model applied to enterprise information flows

While Lasswell's model offers a useful analytical lens for examining the influence of intentional communication acts, its explanatory power is limited in decentralised digital ecosystems where any individual can simultaneously occupy the roles of sender, receiver, and amplifier. This limitation is particularly salient in the context of social media, where no single agent controls the communicative process and where the 'effect' of any given message is mediated by algorithmic systems whose logic is opaque to both senders and receivers.

1.10 Information Intent and Influence

Information is rarely produced or circulated neutrally. Messages are typically generated with a specific objective whether to inform, persuade, manipulate, or generate commercial engagement and the distinction between these objectives is not always transparent to the recipient. Informational influence can operate at three levels: cognitive (shaping what the recipient knows or believes), affective (shaping emotional responses), and behavioural (shaping decisions and actions).

Several factors are known to amplify informational influence: source credibility, emotional intensity, repetition, and social context. The last of these is particularly significant in social media environments, where algorithmic recommendation systems create echo chambers that reinforce pre-existing beliefs and accelerate the circulation of emotionally

resonant content. Repeated exposure to false information, even when it is initially recognised as potentially unreliable, progressively increases its perceived credibility a cognitive bias known as the 'illusory truth effect' (Hasher, Goldstein, and Toppino, 1977), which is systematically amplified by viral circulation mechanisms.

1.11 Information Governance Challenges

The foregoing analysis reveals that the increasing integration of social media information into EIS creates governance challenges that cannot be resolved by technological means alone. Enterprises must simultaneously maintain openness to strategically valuable external information while protecting against misinformation; act rapidly in response to realtime signals while ensuring the reliability of the information that informs those actions; and leverage the analytical power of AI systems while maintaining human oversight over consequential decisions.

AI technologies substantially improve the capacity of enterprises to process unstructured information at scale, but they also introduce new risks: algorithmic bias, opacity in decision processes, over-reliance on automated outputs, and dependency on external platform providers whose governance arrangements are beyond the enterprise's direct control (European Parliament and Council, 2024). Modern organisations therefore require governance frameworks that integrate data quality management, cybersecurity, algorithmic transparency, and ethical compliance into a coherent whole.

1.12 Conclusion

This chapter has established the theoretical foundations necessary for understanding the challenges that social media integration poses to Enterprise Information Systems. It has examined the strategic role of information in organisational decision-making (Simon, 1960), the multidimensional character of information quality, the mechanisms by which communication can fail at technical, semantic, and effectiveness levels (Shannon and Weaver, 1949), and the structural threats to information quality inherent in social media environments. The DIKW framework (Ackoff, 1989; Rowley, 2007) provides a conceptual architecture that reveals precisely where social media integration introduces risk at the foundational data layer and why AI-based verification mechanisms are a necessary, if imperfect, response to that risk.

Chapter 2: Enterprise Information Systems (EIS)

Introduction

The theoretical framework established in Chapter 1 particularly the DIKW hierarchy, the dimensions of information quality, and the challenges posed by social media acquires concrete institutional significance when applied to the architecture and operation of Enterprise Information Systems. EIS are the organisational infrastructure through which enterprises collect, process, and distribute information; they are, in effect, the institutional embodiment of the information management principles examined in the preceding chapter.

This chapter examines the evolution, architecture, and principal components of EIS, before analysing the transformative impact of cloud computing, artificial intelligence, and social media integration on contemporary enterprise systems.

2.1 Definition and Core Characteristics of Enterprise Information Systems

An Enterprise Information System is broadly defined as an integrated, organisationwide platform designed to coordinate, consolidate, and manage information flows across all functional domains of the enterprise (Al-Mashari, 2002). Its critical distinguishing feature is cross-functional integration: unlike the isolated, department-specific systems that preceded it, an EIS creates a coherent informational backbone that spans the entire organisational value chain from procurement and production through sales, customer service, and financial reporting. The core characteristics of a modern EIS can be summarised as follows:

Integration and real-time processing are mutually reinforcing: integration ensures that all modules share a single data source, while real-time processing ensures that this source reflects current reality rather than a static snapshot. Modularity and configurability complement this foundation modularity allows the system to grow by adding functional components incrementally, while configurability ensures each component can be adapted to the specific business rules of the enterprise without modifying its core code. Scalability, finally, guarantees that all these properties are preserved as the organisation expands in size, geography, or transaction volume a critical requirement given that EIS are expected to serve the enterprise for decades.

2.2 Historical Evolution of Enterprise Information Systems

The evolution of EIS reflects the progressive digital transformation of organisational management over six decades. Understanding this trajectory is important not merely as historical background, but because each successive generation of systems introduced capabilities and vulnerabilities that continue to shape the challenges enterprises face today.

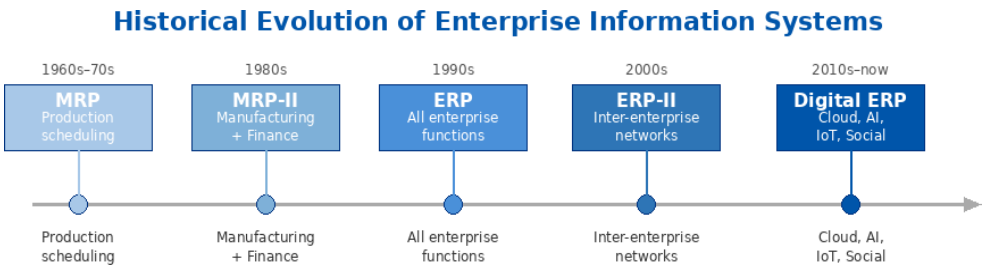


Fig. 2.1 — EIS evolution from MRP (1960s) to Digital ERP (2010s–present)

Generation	Era	Scope	Key Innovation
MRP	1960s–70s	Production scheduling	Bill of Materials processing; time-phased procurement
MRP-II	1980s	Manufacturing + Finance	Closed-loop planning; financial simulation
ERP	1990s	All enterprise functions	Unified database; single process logic (SAP R/3, 1992)
ERP-II	2000s	Inter-enterprise networks	Web-enabled; CRM/SCM/BI; supply chain visibility
Digital ERP	2010s–present	Digital ecosystem	Cloud, AI, IoT, social media; real-time analytics

Table 2.1 — Historical evolution of Enterprise Information Systems (Jacobs and Weston, 2007

Several features of this evolutionary trajectory are noteworthy. First, the scope of EIS has expanded continuously from isolated production tools to organisation-wide platforms to digital ecosystems spanning multiple organisations and data sources. Second, each expansion has introduced new integration challenges which is the transition to Digital ERP, in particular, requires EIS to process not only structured internal data but also the unstructured, highvolume, low-reliability data characteristic of social media platforms.

2.3 Core Components of Enterprise Information Systems

Modern Enterprise Information Systems consist of interconnected modules responsible for managing organisational activities.

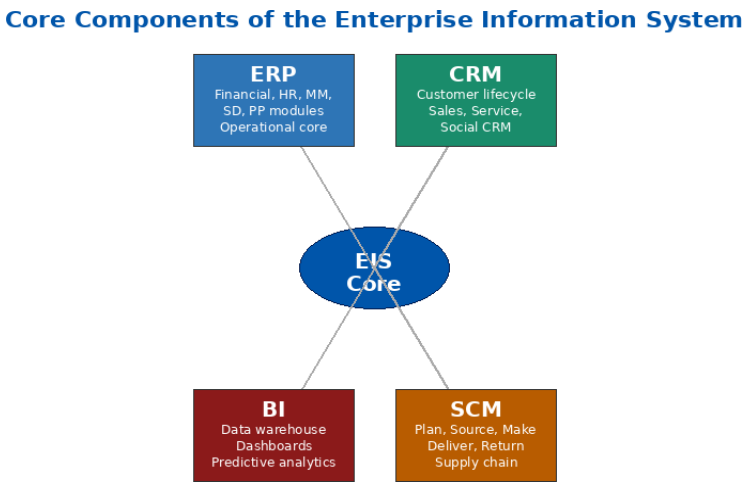


Fig. 2.2 — Four core components of the EIS (ERP, CRM, SCM, BI)

Figure 2.2 highlights the integrated nature of Enterprise Information Systems. Modern organisations increasingly depend on interconnected modules capable of centralising operational, managerial, and external digital information flows.

The ERP system generally functions as the central component of the architecture, while additional modules support specialised activities such as customer management, supply chain coordination, human resource administration, and business analytics.

Component	Primary Function	Key Output
ERP	Transactional backbone: FI, HCM, MM, SD, PP modules	Financial statements; operational reports
CRM	Customer lifecycle management; Operational, Analytical, Collaborative CRM	Pipeline forecasts; satisfaction scores
SCM	Supply chain coordination: Plan, Source, Make, Deliver, Return	Inventory levels; on-time delivery rate
BI	Data analytics: Data Warehouse, ETL, OLAP, Dashboards, Predictive models	Dashboards; predictive analytics

The interdependence of these components is significant: the BI layer can only generate accurate analytics if the ERP, CRM, and SCM modules feed it consistent, up-to-date data. A company whose CRM records customer interactions in isolation from its ERP sales data will produce BI dashboards that misrepresent actual customer profitability. This integration challenge becomes more complex when social media data which carries no inherent structure compatible with ERP schemas must also be incorporated into the BI layer.

2.4 Information Flows and Decision-Making

EIS centralise information originating from both internal organisational activities and external digital environments customers, suppliers, market data sources, and increasingly, social media platforms. The integration of these diverse information flows is what enables organisations to move up the DIKW hierarchy: from raw operational data through contextualised information to actionable managerial knowledge.

Simon's (1960) model of managerial decision-making comprising intelligence, design, and choice phases maps directly onto the EIS architecture. The intelligence phase corresponds to the data collection and monitoring functions of BI and CRM modules; the design phase corresponds to the analytical and modelling capabilities of BI tools; and the choice phase corresponds to the executive dashboards and decision-support outputs that present recommendations to managers.

The growing integration of social media data into this flow significantly increases informational complexity. Information overload an excess of data that exceeds the analytical capacity of both human and automated systems threatens the reliability of the intelligence phase; the prevalence of misinformation threatens the validity of the design phase; and both, in combination, degrade the quality of the choice phase. This is why Davenport's (1998) observation that enterprise systems cannot compensate for poor-quality input data remains as relevant as ever.

2.5 Architectural Frameworks and Cloud Computing

Modern EIS rely on interoperable architectures that facilitate communication between applications, databases, APIs, and cloud services. Standardised data exchange formats particularly XML and JSON enable heterogeneous systems to communicate across organisational and platform boundaries (W3C, 2004), and are the primary mechanism through which social media platforms expose their data to enterprise systems.

Cloud computing has substantially transformed EIS by improving scalability, accessibility, and operational flexibility (Mell and Grance, 2011; Gartner, 2022). Cloud-based deployment reduces the capital expenditure associated with on-premise infrastructure andfacilitates real-time data sharing across geographically distributed organisations. However, it simultaneously introduces important challenges:

- **Cybersecurity:** Distributed cloud environments expand the attack surface available to malicious actors and require more sophisticated security architectures than on-premise systems.

- **Data sovereignty:** Regulatory frameworks such as the GDPR impose requirements about where personal data may be stored and processed that can conflict with cloud providers' infrastructure architectures.

- **Vendor dependency:** Organisations that deploy critical systems on third-party cloud platforms assume strategic risks associated with provider availability, pricing, and policy

changes.

- **Regulatory compliance:** The legal landscape governing cloud-hosted data continues to evolve rapidly, creating compliance uncertainty for enterprises operating across multiple jurisdictions.

Enterprises must therefore manage cloud adoption as a strategic risk–benefit calculation, rather than treating it as an unambiguous technological improvement.

2.6 Artificial Intelligence and Information Verification

As social media becomes an increasingly significant source of enterprise intelligence, ensuring information quality at the point of integration has become one of the central design challenges for modern EIS. Artificial intelligence now supports this function through information filtering, pattern-based anomaly detection, sentiment analysis, and automated decision support. AI technologies are particularly suited to processing the large volumes of unstructured text that characterise social media data, which would be intractable through manual methods alone.

AI-based systems can identify suspicious information patterns, cross-reference claims against verified knowledge bases, and flag potentially misleading content before it is integrated into the EIS knowledge base (Renault et al., 2025). However, it is important not to overstate the reliability of these systems. As discussed in Section 1.7.3, even state-of-the-art AI moderation misses a significant proportion of misleading content, and AI systems themselves may produce biased or inaccurate outputs as a result of training data limitations or adversarial manipulation (European Parliament and Council, 2024). Human supervisory capacity therefore remains an essential complement to automated verification systems, particularly in high-stakes decision contexts.

2.7 External Environment and Enterprise Challenges

Enterprise Information Systems are influenced not only by internal organisational requirements but also by broader political, economic, social, technological, ecological, and legal environments.

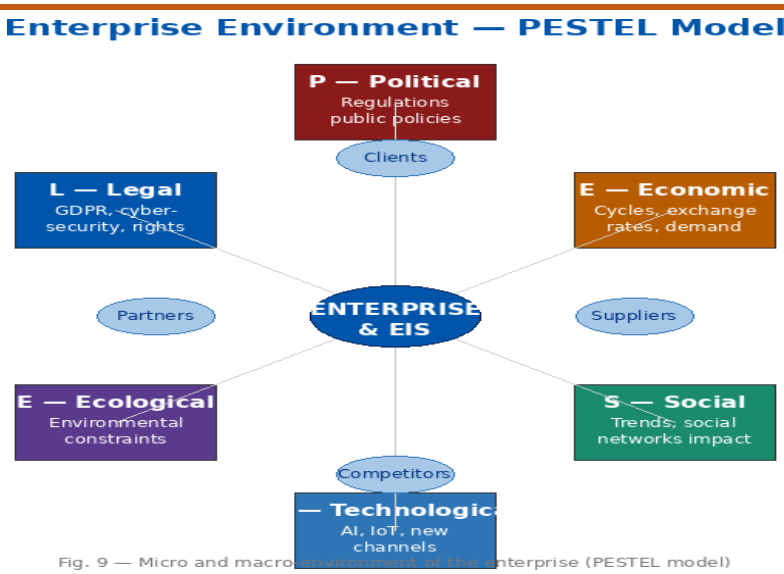


Fig. 9 — Micro and macro-environment of the enterprise (PESTEL model)

Fig. 2.3 — Micro and macro-environment of the enterprise (PESTEL)

Figure 2.3 demonstrates that Enterprise Information Systems operate within complex external environments that continuously influence organisational strategies and technological adaptation.

Modern EIS face several major challenges related to:

- Misinformation.
- Cybersecurity.
- information overload.
- Interoperability.
- governance complexity.
- dependence on external digital platforms.

Traditional Enterprise Information Systems were initially designed for structured and internally generated information. However, contemporary organisations increasingly operate within environments dominated by unstructured and rapidly evolving digital information flows.

This transformation requires enterprises to adopt more flexible, intelligent, and adaptive information infrastructures.

2.8 Conclusion

This chapter has examined the definition, evolution, architecture, and external context of Enterprise Information Systems. It has demonstrated that EIS have evolved from narrowly focused production-planning tools (MRP) into integrated digital ecosystems capable of processing complex, multi-source information flows. The integration of cloud computing, AI, and social media data into this architecture offers genuine strategic advantages — improved analytical capabilities, enhanced responsiveness, richer customer intelligence — but also introduces challenges related to cybersecurity, misinformation, governance, and vendor dependency.

The following chapter examines the synergies and tensions between social media platforms and EIS in greater analytical depth, focusing specifically on the governance mechanisms and technological architectures through which enterprises can realise the former while managing the latter.

Chapter 3: Synergy Between Social Media and Enterprise Information Systems (EIS)

Introduction

The preceding chapters have established two parallel lines of analysis: Chapter 1 examined the theoretical properties of information and the quality challenges introduced by social media; Chapter 2 examined the architecture and evolution of EIS and the structural pressures that social media integration places upon them. The present chapter synthesises these lines of analysis by examining the relationship between social media and EIS as a dynamic and sometimes contradictory interaction rather than a simple technical integration problem.

The central argument of this chapter is that social media integration transforms EIS in ways that are simultaneously valuable and hazardous: it enriches the informational environment available to managers but also introduces systemic risks to information quality that require deliberate governance responses.

3.1 The Integration of Social Media into Enterprise Information Systems

In conventional EIS environments, information flows were predominantly internal, structured, and subject to organisational control. Social media fundamentally disrupts this pattern by introducing massive quantities of external, unstructured, and largely uncontrolled information into enterprise ecosystems. This disruption is not merely quantitative a matter of processing larger data volumes but qualitative: social media data differs from traditional EIS data in its structure, its provenance, its reliability, and its interpretive requirements.

Despite these challenges, social media integration offers enterprises capabilities that were not available through traditional EIS data sources:

- **Real-time customer sentiment monitoring:** Continuous analysis of social media content enables enterprises to track customer opinions and emotional responses to products, services, and brand events at a granularity and timeliness that surveys and focus groups cannot match.

- **Market trend detection:** Emerging consumer preferences and market shifts often manifest in social media content before they appear in formal market research data, providing enterprises with an early-warning capability.

- **Reputational risk management:** Social media monitoring enables enterprises to detect reputational threats negative viral content, crisis events, competitor activity in real time, reducing response latency.

- **Competitive intelligence:** Public social media activity by competitors, suppliers, and

partners provides a continuous stream of strategic intelligence at minimal cost.

Social media data is increasingly integrated into CRM modules which benefit directly from enriched customer profiles and into BI systems, which are the primary mechanism for transforming raw social media signals into managerial intelligence. According to the DIKW framework developed in Chapter 1, this integration represents an attempt to incorporate social media data into the foundational data layer of the hierarchy and to transform it, through AI-assisted processing, into information and ultimately knowledge that can guide strategic decisions. Two dimensions of this quality challenge warrant detailed examination: the quantitative paradox of information overload, and the qualitative problem of semantic misinterpretation — both of which have direct implications for the architecture of AImediated EIS integration.

3.2 Information Quality Challenges

The strategic benefits of social media integration are substantially offset by the information quality challenges it introduces. Social media environments are characterised by a structural tension between informational speed and informational reliability: the mechanisms that maximise the velocity and reach of content algorithmic amplification, frictionless sharing, network effects are largely indifferent to its accuracy.

Two dimensions of this quality challenge warrant detailed examination are the quantitative paradox of information overload, and the qualitative problem of semantic misinterpretation both of which have direct implications for the architecture of AI-mediated EIS integration.

3.2.1 The Quality Paradox

The volume of social media information available to enterprises has grown to a point where it frequently exceeds human analytical capacity, generating what researchers have termed 'infobesity' an excess of information that, paradoxically, impairs rather than improves decision quality. The problem is not merely quantitative. False, manipulated, or strategically deceptive information may enter enterprise information systems and, if not detected, corrupt the organisational knowledge base upon which strategic decisions depend. This risk is directly analogous to the 'garbage in, garbage out' problem identified in Chapter1, but magnified by the scale and velocity of social media data flows

3.2.2 Communication Challenges

The communication problems identified by Shannon and Weaver (1949) and discussed in Chapter 1 manifest in specific forms when social media is the communication medium. Technical problems arise from the instability of social media APIs, platform policy changes that restrict data access, and the frequency with which platforms modify their data structures without notice. Semantic problems are particularly acute: social media language routinely employs irony, sarcasm, slang, culturally specific references, and contextual abbreviations that literal natural language processing cannot reliably interpret. Sentiment analysis algorithms trained on formal text may systematically misclassify sarcastic posts as positive, leading to

erroneous customer satisfaction assessments. Addressing these semantic challenges requires contextually sophisticated NLP capabilities that go well beyond keyword matching.

3.3 Artificial Intelligence as an Integration Interface

Given the information quality challenges described above, artificial intelligence has emerged as the primary technological mechanism through which enterprises mediate the integration of social media data into their information systems. Rather than connecting social media platforms directly to core EIS components a design that would expose the organisational knowledge base to unfiltered social media data modern architectures insert an AI-based filtering and verification layer between the external data source and the validated information layer used for decision-making.

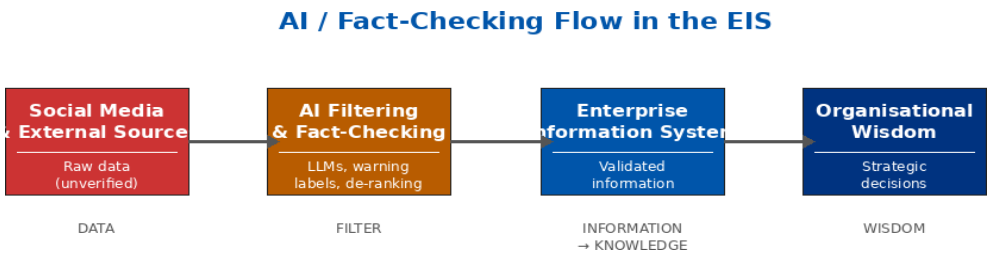


Fig.3.1— Role of AI as quality filter between social media and EIS

Within this architecture, AI systems serve several functions: filtering irrelevant or low-quality content; detecting potential misinformation through cross-referencing with verified knowledge bases; performing sentiment and topic analysis to extract structured intelligence from unstructured text; and flagging anomalous patterns that may indicate coordinated manipulation or disinformation campaigns. Large Language Models, examined in detail in Chapter 4, play an increasingly important role in each of these functions by virtue of their capacity to process natural language at scale and with contextual sensitivity (Renault et al., 2025).

Modern architectures also increasingly rely on microservices and API gateway patterns (Fowler and Lewis, 2014) to isolate social media data flows from the central ERP infrastructure. This isolation serves two purposes: it prevents unverified social media data from contaminating the core transactional database, and it allows the social media integration layer to be updated or replaced independently of the ERP core an important consideration given the pace of change in social media platforms and AI technologies.

It must be acknowledged, however, that AI-based filtering is not a complete solution. The coverage gaps, transparency limitations, and adversarial adaptation dynamics identified in Section 1.7.3 mean that automated verification must be complemented by human oversight, particularly for information that will inform high-stakes strategic decisions.

3.3.1 Proposed AI-Based Verification Prototype

To illustrate the role of AI as an intermediary verification layer between social media platforms and Enterprise Information Systems, a prototype web application was developed as part of this project. The objective of the system is to analyse information originating from social media environments and evaluate its reliability before it is integrated into enterprise decision-support processes.

The prototype functions as a verification interface between external information sources and the enterprise information environment. Users can submit textual content through the web interface, after which the system processes the information using a Large Language Model combined with external reference sources and verification prompts. The system then generates an evaluation indicating whether the information appears reliable, misleading, uncertain, or requires further human verification.

This architecture reflects the theoretical model discussed in the previous sections, where AI systems act as filtering and validation mechanisms positioned between unstructured social media flows and structured enterprise knowledge systems. The prototype therefore serves as a practical demonstration of how AI-assisted verification can support information quality management in modern EIS environments.

3.4 Recommendations and Best Practices

On the basis of the analysis developed in this and preceding chapters, three strategic recommendations who are not of equal priority that can be advanced for enterprises seeking to integrate social media into their information systems effectively and responsibly.

3.4.1 Establish Formal Social Information Governance

Enterprises should establish formal governance frameworks that define verification protocols, quality thresholds, and accountability structures for social media information before it is integrated into the EIS. Such frameworks should include source validation mechanisms (assessing the credibility and provenance of data sources), automated misinformation detection (using the AI tools discussed above), and identity protection mechanisms that comply with applicable data protection regulations. Governance frameworks should be treated as living documents, reviewed regularly to account for changes in the social media landscape, evolving regulatory requirements, and improvements in AI capabilities.

3.4.2 Adopt Predictive Social Analytics

Enterprises should move beyond reactive social media monitoring which identifies events after they have occurred toward predictive analytical approaches capable of anticipating customer behaviour shifts, market changes, and reputational crises before they fully materialise. Predictive sentiment analysis, anomaly detection, and trend forecasting models, applied to social media data streams that have been filtered and verified through the

AI layer described above, can provide enterprises with a genuine strategic early-warning capability.

3.4.3 Embed Ethical and Legal Compliance

The use of social media data must respect the ethical and legal frameworks that govern personal data processing. This includes compliance with data protection regulations (notably the GDPR), transparency in the use of automated decision systems (as required by the EU AI Act), and active avoidance of discriminatory or manipulative applications of social media intelligence. Enterprises must also guard against excessive dependence on automated systems: AI-assisted analysis should inform, but not replace, human judgement in strategic decision-making contexts.

3.5 Conclusion

This chapter has examined the growing integration of social media into Enterprise Information Systems as a dynamic characterised by genuine strategic value and significant informational risk. Social media enriches the data layer available to EIS and enables capabilities real-time sentiment monitoring, early trend detection, reputational risk management that traditional internal data sources cannot provide. At the same time, the structural features of social media environments the prevalence of misinformation, the impossibility of source control, the acute semantic challenges of user-generated content impose governance requirements that demand deliberate architectural and organisational responses.

Chapter 4: Large Language Models and Enterprise Information Systems

Introduction

The preceding chapters have established that AI-based filtering and verification systems are a necessary architectural component of any enterprise seeking to integrate social media data into its information systems reliably. Among the AI technologies currently available for this purpose, Large Language Models (LLMs) represent a qualitative advance over earlier natural language processing systems. Their capacity to process, contextualise, and generate natural language at scale makes them particularly well suited to the challenges of social media data which is, above all, a linguistic phenomenon.

This chapter examines LLMs as enterprise technologies: their architecture and capabilities, their principal applications within EIS, the genuine advantages they offer, and the limitations and risks that must be managed if they are to be deployed responsibly in organisational decision-making contexts

4.1 Definition of Large Language Models

Large Language Models are artificial intelligence systems trained on massive quantities of textual data typically hundreds of billions of tokens using deep learning architectures, most notably the transformer architecture introduced by Vaswani et al. (2017). The transformer's self-attention mechanism enables the model to identify complex long-range dependencies within text, supporting a degree of contextual sensitivity that earlier sequential architectures (RNNs, LSTMs) could not achieve at scale.

Contemporary LLMs including GPT-4 (OpenAI), Llama 2 (Touvron et al., 2023), and Mistral 7B (Mistral AI, 2023) demonstrate capabilities that encompass text generation, summarisation, question answering, language translation, sentiment classification, and the analysis of unstructured textual content. Many enterprise deployments of LLMs now employ Retrieval-Augmented Generation (RAG) architectures (Lewis et al., 2020; Gao et al., 2023), which ground LLM outputs in verified external knowledge bases rather than relying solely on the parametric knowledge encoded during pre-training — a design choice with direct relevance to the information verification challenges examined in Chapter 3.

4.2 Role of LLMs in Enterprise Information Systems

EIS increasingly manage large volumes of unstructured information: emails, customer feedback, internal reports, social media content, regulatory filings, and supplier communications. Traditional EIS architectures were designed for structured, tabular data; they have no native capacity to interpret, classify, or extract intelligence from free-form text. LLMs address this limitation directly, functioning as intelligent interfaces between unstructured information sources and the structured data environments of core EIS components.



Fig.4.1— Integration of LLMs within Enterprise Information Systems

Specifically, LLMs can support EIS through: automated processing and routing of customer communications; extraction of structured data fields (dates, product mentions, sentiment scores) from unstructured text; summarisation of large document corpora for executive consumption; natural language interfaces that allow non-technical users to query EIS databases without SQL expertise; and critically for the present thesis, cross-referencing of social media claims against verified knowledge bases as part of the AI verification layer described in Chapter 3. Of these capabilities, the last cross-referencing social media claims against verified knowledge bases is the most directly relevant to the thesis's central argument. The preceding four functions improve operational efficiency; this fifth function addresses a qualitative information integrity problem that no prior EIS technology could solve at the scale required by modern social media data volumes. The prototype eveloped within this project applies these principles in practice by using a Large Language Model as a verification interface for social media information. The implemented system demonstrates how LLMs can assist in analysing unstructured textual content and generating contextual evaluations that support information quality assessment. Although the prototype remains experimental, it illustrates the practical feasibility of integrating LLM-based verification mechanisms into enterprise-oriented information systems.

4.3 Applications of Large Language Models in Enterprises

4.3.1 Customer Relationship Management

CRM is currently the enterprise domain most extensively transformed by LLM deployment. Intelligent chatbots and virtual assistants powered by LLMs can handle a substantial proportion of routine customer enquiries at a fraction of the cost of human agents, while simultaneously generating structured interaction records that feed into the analytical CRM layer. More sophisticated deployments use LLMs to analyse open-ended customer feedback from surveys, social media, and support transcripts extracting finegrained sentiment, topic, and intent signals that structured rating scales cannot capture. This capability is directly relevant to the social media integration challenge: it enables enterprises to transform the unstructured social media data discussed in Chapter 3 into the structured customer intelligence that CRM systems require.

4.3.2 Information Analysis and Knowledge Management

Beyond CRM, LLMs offer significant capabilities in the broader domain of enterprise information analysis. Their ability to generate accurate summaries of large document collections legal contracts, research reports, regulatory filings, news corpora reduces the time

and cognitive burden associated with information processing tasks that previously required specialised human expertise. In the context of social media monitoring, LLMs can synthesise hundreds of thousands of social media posts into concise, structured intelligence briefs, enabling managers to extract signal from noise at a scale that would otherwise be unachievable.

4.3.3 Decision Support

LLMs are increasingly used as components of decision support systems, where they can identify patterns, generate scenario analyses, and produce structured recommendations from heterogeneous information sources. However, the appropriate scope of LLM involvement in decision support must be carefully delineated. LLMs are particularly well suited to information processing and pattern identification tasks, they are substantially less reliable as sources of normative judgement or strategic wisdom precisely the dimensions that occupy the upper levels of the DIKW hierarchy. Organisational governance frameworks should reflect this distinction, ensuring that LLM outputs inform but do not substitute for human managerial judgement in consequential decisions.

4.4 Advantages of Large Language Models

The integration of Large Language Models (LLMs) into Enterprise Information Systems (EIS) provides several important advantages for organisations. One major benefit is the ability to process large amounts of unstructured data such as customer reviews, emails, and social media posts. Tasks that would be difficult and time-consuming for human teams can be performed automatically and continuously by LLM-based systems. This also allows companies to monitor information from different platforms and in multiple languages more efficiently.

Another important advantage is the contextual understanding offered by LLMs. Traditional keyword-based systems often fail to interpret the real meaning of a sentence, especially when irony, negation, or informal language is used. For example, a sentence such as “this product is not bad” may be incorrectly classified as negative by simple NLP systems, while an LLM can better identify its positive meaning. This improves the quality of sentiment analysis and decision-making processes.

LLMs are also adaptable to specific enterprise environments. Through techniques such as fine-tuning and Retrieval-Augmented Generation (RAG), organisations can connect language models to their own databases and knowledge sources. As a result, the generated responses become more relevant and aligned with the company’s domain and activities.

In addition, LLMs simplify interaction with enterprise systems. Employees who do not have technical knowledge can access information using natural language instead of complex queries or commands. For instance, a manager can ask questions such as “Which suppliers had delivery delays during the last month?” and receive a direct answer from the system. This makes enterprise data more accessible to non-technical users and encourages wider use of analytical tools within organisations.

4.5 Limitations and Risks of Large Language Models

Despite their advantages, Large Language Models (LLMs) also present several limitations and risks that must be considered before their integration into enterprise decision-making systems. One of the main issues is hallucination, where an LLM generates false or inaccurate information while presenting it confidently as if it were correct. In an enterprise environment, this can become problematic if generated information is used in reports or decision-making processes without verification. For example, an LLM used to verify information from social media could accidentally spread misinformation instead of filtering it.

Another important limitation concerns bias in training data. Since LLMs are trained on large datasets collected from the internet and other sources, they may reproduce existing social, cultural, or demographic biases. In practice, this can affect tasks such as sentiment analysis, customer relationship management, or recruitment systems. Some expressions or communication styles may also be misunderstood depending on cultural context. In addition, the internal functioning of large neural networks is often difficult to interpret, which makes identifying and correcting these biases more complicated. This lack of transparency can also create regulatory and ethical concerns, especially with recent frameworks such as the European Union AI Act.

Security and over-reliance are also major concerns in the context of social media integration. Malicious users may attempt to manipulate LLMs through adversarial prompts hidden in online content, causing the system to produce misleading outputs or reveal sensitive information. Another risk is that users may trust LLM-generated responses too much because of the fluency and confidence of the generated text. As a result, organisations should not rely entirely on automated outputs. Human supervision, verification procedures, and governance policies remain necessary to ensure that LLM-based systems are used responsibly and effectively.

During the implementation of the prototype system, several practical limitations of LLM-based verification were also observed. Some responses lacked consistency when analysing ambiguous or highly contextual information, while certain outputs required manual interpretation to avoid inaccurate conclusions. The reliability of the generated results also depended heavily on prompt formulation and the availability of sufficiently clear contextual information. These observations confirm that, despite their strong analytical capabilities, LLMs should be used as assistive tools rather than fully autonomous verification systems in enterprise environments.

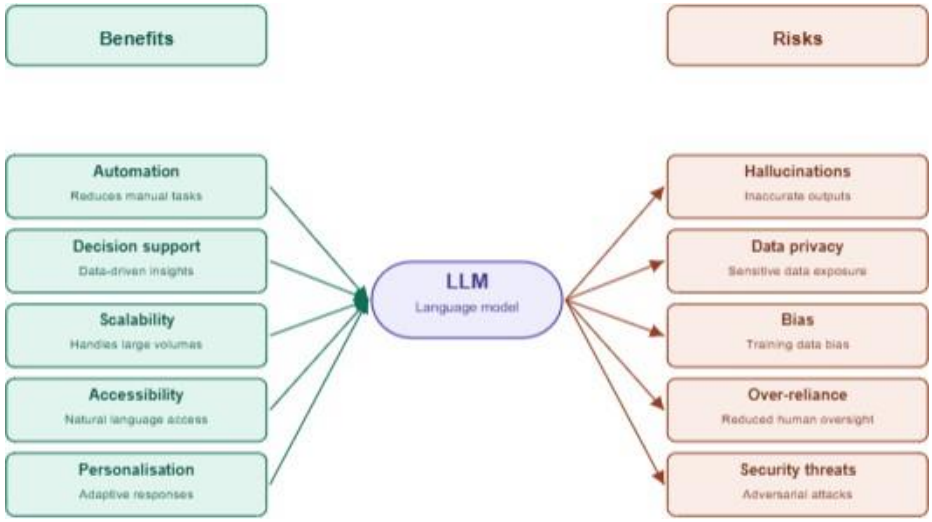


Fig.4.2— Advantages and Risks of Large Language Models

4.6 Future Perspectives of LLMs in Enterprise Information Systems

The future development of Large Language Models (LLMs) is expected to bring several improvements that are directly relevant to enterprise social media management and analysis. One important development is the progress of Retrieval-Augmented Generation (RAG) systems. Unlike traditional LLMs that rely mainly on pre-trained information, RAG models can access updated external databases and verified sources while generating responses. This helps reduce hallucinations and improves the reliability of generated information. In enterprise environments, such systems could help verify social media content more accurately by comparing online claims with trusted and regularly updated information sources.

Another major evolution is the emergence of multimodal models. These models are capable of processing not only text, but also images, audio, and video content. This is especially important because misinformation on social media increasingly appears in visual forms such as edited images, manipulated videos, and AI-generated deepfakes. Current LLMbased verification systems are mainly focused on textual information, while multimodal architectures extend verification capabilities to different types of media content.

At the same time, governments and regulatory institutions are developing frameworks to control the use of artificial intelligence technologies. The European Union AI Act introduces a risk-based approach where AI systems used in sensitive domains such as healthcare, recruitment, finance, or credit evaluation must satisfy stricter requirements related to transparency, accountability, and human supervision. For enterprises, this means that governance and compliance will become essential aspects of AI deployment. Companies that establish clear governance frameworks early may reduce operational risks and adapt more easily to future regulations. Therefore, the challenge for organisations is not only whether to adopt LLM technologies, but also how to integrate them responsibly while limiting ethical, legal, and security risks.

4.7 Conclusion

This chapter has examined the role of Large Language Models as enterprise technologies capable of addressing the information quality challenges that social media integration imposes on EIS. LLMs offer genuine capabilities processing capacity, contextual sensitivity, natural language interaction, adaptability that make them well suited to the filtering, verification, and analysis functions required at the social media–EIS interface. These capabilities must, however, be assessed realistically against documented limitations: hallucination, bias, opacity, adversarial vulnerability, and the risk of organisational overreliance.

The integration of LLMs into EIS is not, in itself, a solution to the information governance challenges identified throughout this thesis; it is, rather, a powerful instrument that, when embedded within appropriate governance frameworks and complemented by human supervisory capacity, can substantially improve an enterprise's ability to extract reliable intelligence from the social media environment. The development of such frameworks — combining technological capability with ethical commitment, regulatory compliance, and organisational discipline is the defining information management challenge facing modern enterprises.

General Conclusion

This thesis set out to examine a problem that is, at its core, a problem of trust. Enterprises have always depended on the quality of the information available to them, and they have always had to manage the risk that this information might be incomplete, unreliable, or misleading. What social media has changed is not the nature of that risk but its scale, its speed, and the degree to which it originates from sources that are entirely outside the organisation's control.

The analysis developed across four chapters leads to three conclusions that, taken together, define the current state of the problem and the limits of available solutions.

The first conclusion is that social media integration into EIS is strategically unavoidable but architecturally unresolved. Organisations cannot afford to ignore the intelligence value that social media provides the real-time signals about customer sentiment, market shifts, and reputational threats that no internal data source can replicate at comparable speed. At the same time, the architectural frameworks examined in Chapter 2 were not designed for data of this character: unstructured, high-volume, partially unverifiable, and produced by actors whose intentions range from genuine expression to deliberate manipulation. The gap between what social media demands of an EIS and what current EIS architectures can reliably deliver remains significant, and no purely technical intervention has closed it.

The second conclusion is that Artificial Intelligence, and Large Language Models in particular, represents a necessary but insufficient response. The capabilities documented in Chapter 4 are real: LLMs can process unstructured text at a scale no human team could match, interpret contextual cues that earlier NLP systems missed, and cross-reference claims against verified knowledge bases in near real time. These capabilities make them the most promising available technology for managing social media information quality at the EIS periphery. But the limitations are equally real. A miss rate of 21 to 28 percent on misleading content, the persistent problem of hallucination, the opacity of model reasoning, and the risk of adversarial manipulation mean that LLMs cannot be treated as a reliable quality guarantee. They reduce the problem; they do not resolve it.

The third conclusion is that governance is not a complement to the technological response it is its precondition. The analysis in Chapter 3 showed that the information quality risks introduced by social media integration cannot be managed by filtering algorithms alone, because those algorithms operate on data whose credibility is precisely what is in question. Governance frameworks that define verification protocols, accountability structures, human oversight requirements, and ethical boundaries are what transform a technically capable AI system into a trustworthy organisational instrument. Without them, deploying LLMs at the EIS periphery may create an illusion of quality control while leaving the underlying vulnerability intact.

These conclusions carry limitations that should be stated plainly. This thesis is a literaturebased study. It has not collected primary data from organisations navigating these challenges in practice, and it has not empirically tested the governance frameworks it proposes. The claims made here are theoretical, grounded in existing research rather than in

field observation. Future research should address these limitations through comparative case studies of enterprises at different stages of social media integration, empirical benchmarking of LLM-based verification against expert human review in real enterprise settings, and the development of governance models adapted to the specific constraints of small and medium-sized enterprises, which face the same information quality challenges as large corporations but with substantially fewer resources to address them.

The broader stakes of this problem extend beyond any individual organisation. Enterprises are not passive consumers of the information environment; they are also participants in it. The governance choices they make whether to verify before integrating, whether to maintain human oversight over automated decisions, whether to treat ethical compliance as a genuine constraint or a procedural formality collectively shape the information ecosystem that everyone, inside and outside the enterprise, depends on. That is a responsibility the technology alone cannot carry.

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