



Language Analytics as a Driver of Competitive Intelligence Effectiveness: A Strategic Decision-Making Perspective

Análise de Linguagem como Impulsionadora da Efetividade da Inteligência Competitiva: Uma Perspectiva de Tomada de Decisão Estratégica

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ABSTRACT | Purpose: The goal of the research is to investigate the role of language analytics as a source of competitive intelligence (CI) efficacy in businesses and give an in-depth account of the international scientific output in 2013–2026 and discover the ways in which textual data in its unstructured form can be converted into a strategic advantage. **Methodology/approach:** A systematic literature review (SLR) was carried out according to PRISMA 2020 guidelines. Scopus, Web of Science, IEEE Xplore and Google Scholar were searched with a combination of keywords such as language analytics, natural language processing, text mining, sentiment analysis, topic modeling and competitive intelligence. Having screened 487 initial records and evaluated 142 full-text articles, 62 high-quality studies were incorporated in the final synthesis. **Originality/Relevance:** Language analytics, including NLP, text mining, and large language models (LLMs), can provide organizations with an effective solution to transform raw text into timely, accurate, and predictive information. **Key Findings:** The findings indicate that there are four main mechanisms by which language analytics can be used to improve the effectiveness of CI: real-time monitoring and speed, semantic depth and accuracy, predictive and prescriptive capabilities, and multilingual/cross-platform scalability. The study positions language analytics as a strategic facilitator of intelligence-driven decision-making, aiding organisations in augmenting competitive advantage. **Theoretical/Methodological Contributions:** This article provides a theoretical contribution by developing the traditional SCIP CI cycle model with a specific language analytics layer and by bringing dynamic capabilities and knowledge-based visions into the AI-driven intelligence. It has a methodological contribution to provide a reproducible SLR protocol and a conceptual framework summarizing existing knowledge.

Keywords | Language analytics. Natural language processing. Text mining. Competitive intelligence. Systematic literature review. AI-driven decision making. Organizational effectiveness.

RESUMO | Objetivo: O objetivo da pesquisa é investigar o papel da análise de linguagem como uma fonte de eficácia da Inteligência Competitiva (IC) nas organizações, apresentar uma análise aprofundada da produção científica internacional no período de 2013 a 2026 e identificar as formas pelas quais dados textuais, em sua forma não estruturada, podem ser convertidos em vantagem estratégica. **Metodologia/abordagem:** Foi realizada uma revisão sistemática da literatura (RSL), de acordo com as diretrizes PRISMA 2020. As bases Scopus, Web of Science, IEEE Xplore e Google Scholar foram pesquisadas utilizando uma combinação de palavras-chave, tais como análise de linguagem, processamento de linguagem natural, mineração de texto, análise de sentimentos, modelagem de tópicos e inteligência competitiva. Após a triagem de 487 registros iniciais e a avaliação de 142 artigos em texto completo, 62 estudos de alta qualidade foram incorporados à síntese final. **Originalidade/Relevância:** A análise de linguagem, incluindo processamento de linguagem natural (NLP), mineração de texto e grandes modelos de linguagem (LLMs), pode oferecer às organizações uma solução eficaz para transformar dados textuais brutos em informações oportunas, precisas e preditivas. **Principais resultados:** Os resultados indicam quatro mecanismos principais pelos quais a análise de linguagem pode ser utilizada para aumentar a eficácia da IC: monitoramento em tempo real e velocidade; profundidade semântica e precisão; capacidades preditivas e prescritivas; e escalabilidade multilíngue e multiplataforma. O estudo posiciona a análise de linguagem como um facilitador estratégico da tomada de decisão orientada por inteligência, auxiliando as organizações no fortalecimento da vantagem competitiva. **Contribuições teóricas/metodológicas:** Este artigo apresenta uma contribuição teórica ao desenvolver o modelo tradicional do ciclo de IC da SCIP mediante a incorporação de uma camada específica de análise de linguagem e ao integrar as perspectivas das capacidades dinâmicas e da visão baseada no conhecimento à inteligência orientada por IA. Como contribuição metodológica, apresenta um protocolo de RSL reproduzível e um framework conceitual que sintetiza o conhecimento existente.

Palavras-chave | Análise de linguagem. Processamento de linguagem natural. Mineração de texto. Inteligência competitiva. Revisão sistemática da literatura. Tomada de decisão orientada por IA. Eficácia organizacional.

1 INTRODUCTION

Competitive Intelligence (CI) has developed as an outcast, military-oriented concept to a key strategic skill in present-day organizations. Strategic and Competitive Intelligence Professionals (SCIP) define CI as a systematic and ethically sound process of collecting, analyzing, and storing data, information, and knowledge relating to the business environment. CI gives a competitive advantage when properly executed and assists with strategic early warning (Ren et al., 2023). CI is at the heart of the present volatile, uncertain, complex and ambiguous (VUCA) environment in the world, where the rapid technological change, geopolitical tensions, and the changing consumer behavior have resulted in a complex environment. There is empirical data that demonstrates that a good CI can be linked to better performance of a firm, innovations, market positioning, and risk management (de las Adomako & Tran, 2022). Consequently, CI must be viewed not only as a tool of operation, but as a strategy of decision-making ability, which allows organizations to make sense out of complex environments and operate in uncertain situations. Nevertheless, the great proliferation of unstructured data poses a significant challenge to conventional CI practices. It is approximated that 8090 percent of enterprise data is in the form of unstructured textual information, such as social media, news articles, earnings calls, customer reviews, patents, and internal documents (Dash, 2022). Older CI methods, which rely on manual analysis, structured databases, and keyword queries are becoming less and less effective in managing the quantity, speed and semantic complexity of such data. Such constraints cause lagged insights, missed weak signals, cognitive overload, and missed competitive analysis (Kampourakis et al., 2025), which eventually decrease the quality of the



decisions and responsiveness to strategies (Masethe et al., 2024). Consequently, organizations find it hard to convert data into actionable intelligence to make decisions in good time.

Language analytics is an effective way to overcome this weakness. It includes computational methods including text mining, sentiment analysis, named entity recognition, relation extraction, and generative AI, which allow deriving meaningful insights out of unstructured text (Ma et al., 2025). These solutions enable companies to transform vast amounts of unstructured data into organizational intelligence that is structured, timely and actionable, which greatly improves CI practices. We should note, however, that the worth of language analytics is in its power to enhance intelligence interpretation and decision-making and not in technology. The rise in the use of language analytics is a sign of its strategic relevance. According to practitioner reports, 69 percent of North American companies have already deployed AI-based language analytics solutions, and organizations that have embraced AI-based technologies are about 40 percent more likely to realize high strategic and financial performance (Abdullah, 2025). Likewise, the 2025 AI Hype Cycle identifies AI-ready data and agentic systems, both of which are based on language analytics, as some of the emerging technologies (Pathak, 2025). These capabilities are reshaping CI in data intensive industries like pharmaceuticals and consumer markets to be more of continuous, predictive intelligence systems rather than periodic reporting. Nevertheless, the integration of technology into decision-oriented frameworks is the only way in which technology adoption can assure enhanced CI effectiveness.

In spite of these developments, there is an important gap in the literature. Current studies are mostly dedicated to isolated methods of analysis or particular applications, and the role of language analytics in improving CI as a unified strategic decision-making system has little coverage. Most of the studies focus on individual approaches, e.g. sentiment analysis or topic modeling, without creating comprehensive frameworks, linking language analytics functionality to multidimensional CI deliverables (Mehraliyev et al., 2022). Moreover, in spite of the fact that AI tools have been demonstrated to enhance the phases of the CI process (Sinjank et al., 2023), there is a dearth of integrative frameworks linking these enhancements to the overall CI effectiveness (Ibtissam et al., 2025).

Decision Problem and Research Objective:

The challenge encountered by organizations is the strategic challenge of transforming huge volumes of unstructured data into actionable intelligence that enhances the quality of decisions and competitive advantage. The current literature fails to elucidate the role of language analytics in CI as a decision-oriented capability. Thus, the research question addressed in this study is: How does language analytics contribute to CI effectiveness through improving the intelligence-based decision-making and performance?

In particular, this study will attempt to:

Follow the history of the language analytics approach in CI, starting with early machine learning solutions (Sandoval and Redondo, 2016) to transformer and generative AI solutions (20132026).

Determine and establish as facts the important processes in which language analytics improves the effectiveness of CI such as speed, scalability, semantic depth, accuracy, and predictive abilities.

Make language analytics part of the CI cycle by developing an integrative conceptual framework to enable intelligence-driven decision-making. This research has a theoretical contribution as it re-positioned CI as a strategic decision-making capability with a language analytics backing and enhanced the classical CI model, planning, collection, analysis, dissemination, and decision/action, (Horlings, 2023) by adding a language analytics layer to solve the analysis bottleneck. It also serves as an addition to the knowledge-based and dynamic capabilities schools of thought by showing how language analytics can be used to promote the organizational absorptive capacity in data intensive environments. Practical applicability is demonstrated by previous uses like text mining of social media content of large franchise pizza companies to understand brand perception (Necula et al., 2002), and application of NLP in Roche Diagnostics to monitor scientific trends and competitor behavior (Dash et al., 2022). Practically, the study offers a blueprint that organizations can use to implement a shift in their CI processes that are reactive and manual to proactive and AI-driven intelligence systems. It is especially applicable in the context of emerging markets, where resource availability is lower than the advanced analytics adoption due to the growing intensity of competition (Zapata-Cantu and Gonzo, 2021). This research fills the gap between the outcomes of strategic intelligence and the technological progress by focusing on the importance of CI as a decision-making skill.

The rest of the paper is organized in the following way. Part 2 presents an extensive theoretical framework with the basics of competitive intelligence, the definitions and development of language analytics methods, how they can be combined, and the literature shows empirical evidence. Section 3 elaborates on the systematic literature review approach used which includes search strategy, inclusion criteria and method of analysis. Section 4 includes the results and discussion that includes the trends in the scientific production, the mechanisms of effectiveness that were proven, the conceptual framework that is proposed, the choice of case studies, and the challenges. Lastly, Section 5 provides some concluding thoughts, management implications, study limitations, and future research directions.

2 THEORETICAL FRAMEWORK

2.1 Conceptual Foundations of Competitive Intelligence

The concept of competitive intelligence can be traced back to military intelligence practice, and its formalization in business environments in the theories like the five forces of Porters (1980) and the SCIP code of ethics. Strategically, CI is not only to be viewed as a information processing process, but as a dynamic capability which allows organizations to feel, interpret and react to changes in the environment by making informed decisions. The operation of CI can be explained by the intelligence cycle such as planning (identification of intelligence needs), collection (relevant data gathering), analysis (conversion of data into actionable insights) and dissemination (delivery of intelligence to decision-makers). Language analytics can help to improve each of these steps, because it helps to process unstructured data effectively. Modern CI is a cyclical process: (1) planning and direction,

(2) collection, (3) analysis, (4) dissemination, and (5) decision/action (Dathe et al., 2022). The main bottleneck has been the initial phase known as the analysis phase, which is commonly referred to as the intelligence gap since humans have cognitive limits in processing large unstructured data (Bosso et al., 2023). In this sense, CI should be understood as a dynamic capability that enables organizations to continuously sense, interpret, and respond to environmental changes through informed strategic decisions.

The main problems of contemporary CI are the volume of data (billions of posts a day on social media), the speed (real-time news and mood changes), and diversity (text in more than two languages, multimodal). In the absence of sophisticated analytics, organizations experience information overload, confirmation bias, and slowness in responding- all are direct monuments to the ineffectiveness of CI (which can be described here as the degree to which CI outputs enhance strategic decision quality, speed, and organizational results). Although competitive intelligence has been identified as a strategic role, as a decision-oriented capability, it has not been developed theoretically. The available literature tends to consider CI as an information-processing process as opposed to a dynamic process that bridges the gap between environmental cues and strategic choices. This puts a gap in theory between data capture and decision implementation. Thus, this paper will conceptualize CI as a dynamic informational capability, with value being achieved not in data gathering, but in the transformation of intelligence into timely and actionable decisions. The analytics of language is placed in the context of an enabler that empowers this change throughout the intelligence cycle.

2.2 Language Analytics: Definitions, Techniques and Evolution

Language analytics is a collection of computational linguistics and machine-learning tools that are intended to process natural language. From a theoretical perspective, language analytics techniques are not valuable as standalone tools, but as mechanisms that enhance the transformation of unstructured data into decision-relevant intelligence within CI processes:

- Sentiment analysis and opinion mining: Measures the emotional tone (positive/negative/neutral) of customer reviews, social media and news.
- Summarization and comparative analysis of texts: Summarizes long texts (e.g., earnings calls) and compares stories of rivals.
- Real-time conversational analytics and LLCM integration (2024-2026 trend): Allows semantic searching and generating insights on unstructured sources. These techniques become strategically valuable only when integrated into CI processes to enhance the quality, speed and relevance of decision-making.
- Evolutionarily, language analytics evolved out of rule-based systems in the 2000s to statistical machine learning (2010-2018), deep learning/transformers (2018-2023), and generative LLMs (2023 and beyond) (Garg et al., 2024). The text analytics market of the global NLP market is expected to lead, with consumer analytics and competitive monitoring (Fortune Business Insights, 2026).

2.3 Competitive Intelligence and Language Analytics

The influence of the language analytics on CI may be better perceived with the help of the intelligence cycle. In particular, language analytics improves: (1) collection by extraction of large-scale unstructured data using automated methods, (2) analysis by converting unstructured data into structured insights, (3) dissemination by real-time dashboard and summary, and (4) decision/action by responding to an event more quickly and based on evidence. Therefore, its key attribute is enhancing the connection between intelligence creation and decision-making. The direct impact of language analytics on CI is that it can alleviate the analysis bottleneck by automating the collection-to-insight pipelines. Knowledge-based view (KBV) and dynamic capabilities theory form the theoretical basis of the linkages: language analytics enhances organizational absorptive capacity by transforming external textual cues to internal strategic knowledge (Abbas, 2026).

Language analytics improves the efficacy of CI and, crucially, the results of strategic decision-making through four main mechanisms:

- **Speed and scalability** - Thousands of documents are processed automatically a day compared to being manually reviewed.
- **Precision and expressiveness** - Minimize human bias by performing similar entity/sentiment detection consistently.
- **Predictive and prescriptive power** - Topic modeling, sentiment trends predict competitor actions or market changes.
- **Multilingual/cross-platform coverage** - Real-time worldwide monitoring without regard to language or origin.

The evidence is strong. The innovative work by He et al., (2013) based on Facebook and Twitter data of Pizza Hut, Domino's, and Papa John's showed that text mining could reveal the patterns of popularity of brands and competitive positioning, which in turn allowed making an actionable marketing decision. More recently, a social media CI model based on sentiment analysis and topic modeling was developed to predict customer engagement before and after COVID-19. Using NLP to Twitter hashtags and job advertisements, Béraud et al., (2021) at Roche Diagnostics identified trends at conferences and competitor talent strategies, knowledge that is impossible to obtain with the traditional approach. Therefore, language analytics should not be viewed merely as a technological enhancement but as an enabler of intelligence-driven decision architectures. Its integration into the CI cycle strengthens not only analytical capabilities but also the organization's ability to make timely and strategically aligned decisions. This table illustrates how many ideas of competitive intelligence are supported by language analytics approaches. It describes how these mechanisms enhance decision-making and support strategic outcomes including innovation, agility, and competitive advantage.



Table 1. Language Analytics in Competitive Intelligence

Theory	Language Analytics Mechanism	CI Process Role	Decision Impact	Strategic Outcome
KBV	Text mining, knowledge extraction	Intelligence creation	Improved insight quality	Competitive advantage
Dynamic Capabilities	Sentiment analysis, real-time monitoring	Environmental sensing	Faster decision-making	Strategic agility
Organizational Learning	NLP integration	Knowledge integration	Adaptive decision-making	Innovation

2.4 Gaps and Empirical Evidence

An initial bibliometric snapshot (de las Heras-Rosas & Herrera, 2021; updated with 20242026 data) indicates the exponential increase in the number of CI publications on NLP, which is focused on the information systems, marketing, and management journals. Nonetheless, there are still gaps: not many studies provide integrated models, little focus on ethical concerns (bias, privacy), and little longitudinal effect assessment of firm performance. Most importantly, the translation of language analytics outputs into actionable strategic decisions remains underexplored in existing literature.

Table 2. Selected Landmark Studies on Language Analytics in CI

Study	Year	Technique(s)	Key Finding	DOI / Source
He et al.	2013	Text mining, sentiment	Social media CI in pizza industry	https://doi.org/10.1016/j.ijinfomgt.2013.01.001
Menghini	2022	NLP, clustering	Conference & hiring intelligence	CEUR-WS Vol-3650
Ju et al.	2024	Sentiment + topic modeling	Brand topic identification & engagement	https://doi.org/10.1371/journal.pone.0313191
Elkaabi et al.	2025	Systematic review of AI/NLP	NLP improves entire CI process	IEEE Xplore

3 METHOD

3.1 Systematic Literature Review Design

This paper utilizes a conceptual framework synthesis, with a systematic literature review (SLR). The SLR is created in line with the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, which offer transparent, evidence-based, minimized reporting standards of identification, screening, eligibility, and inclusion of studies (Page et al., 2021). PRISMA 2020 has been chosen as it revised the 2009 statement to accommodate the progress in the field of systematic review, including a more precise description of how searches should be conducted, how risk-of-bias should be evaluated, and how data should be synthesized. This improve the reproducibility, minimize selection bias, and enable future researchers to replicate or revise the review effectively.

The review protocol was crafted and internally registered before data collection to make few post-hoc decisions and achieve methodological rigor. Due to the mixed nature of the topic (empirical studies, conceptual papers, and high-quality practitioner reports), the SLR is supported by narrative and thematic synthesis, instead of meta-analysis, which is not suitable considering the diversity of designs and outcomes. This trans-theoretical structure-SLR plus synthesis makes it possible to map the field holistically and simultaneously create an integrative conceptual model of the connection between language analytics and the efficiency of competitive intelligence (CI).

3.2 Search Strategy

The search was extensive, multi-database-based, to include both academic and practitioner-oriented literature. Major databases were Scopus and Web of Science (to cover a wide, high-quality peer-reviewed base), IEEE Xplore (to cover technology-oriented contributions), and Google Scholar (to find grey literature, conference proceedings and practitioner reports that are generally not covered by indexed databases but contain valuable real-world information). The reason behind the selection of these sources is their complementary advantages: Scopus and Web of Science have robust citation tracking and disciplinary scope in the area of business, management, and information systems, whereas IEEE Xplore has an engineering/applied computing view on natural language processing (NLP).

The search query was a combination of two concept blocks through Boolean operators:

- ("language analytics" OR "natural language processing" OR "text analytics" OR "text mining" OR "sentiment analysis" OR "topic modeling" OR "BERTopic" OR "opinion mining")
- ("competitive intelligence" OR "competitor intelligence" OR "business intelligence" OR "strategic intelligence").

Wildcard and truncation operators were used where available (e.g., text min*), to sensitize a query. The time window was limited to 2013-2026 (including early 2026 publications) to develop upon the seminal research of He et al., (2013) on social media text mining in competitions and cover the fast development fuelled by deep learning and large language models (LLMs). No language restrictions per se were applied at first, but only English-language studies were used in the full-text analysis as researchers were well-versed in it, and English is predominant in the CI and NLP literature around the world.

The other methods were hand-searching of key journals (e.g., International Journal of Information Management, Journal of Business Research, Technological Forecasting and Social Change, and Competitive Intelligence Review) and tracking of back/forward citation using the Google Scholar and Scopus citation tools. This snowballing strategy was useful in pointing out influential papers that were missed by the key word searches. To balance between scholarly rigor and the current practice in the industry, practitioner sources (e.g., Gartner, SCIP, Glean, and Spider Strategies reports) were considered, through focused Google Scholar search.

3.3 Inclusion and Exclusion Criteria

Articles were incorporated when they: (a) directly related at least one language analytics method (NLP, text mining, sentiment analysis, topic modeling, entity recognition, or LLM-based methods) with any stage of the CI process or with CI effectiveness results; (b) were peer-reviewed journal articles, conference papers, or high-quality practitioner reports; (c) addressed an organizational or business context; and (d) were published in Empirical (quantitative, qualitative, or mixed-methods) and conceptual/theoretical papers could be included to ensure that a wide evidence base was covered.

The exclusion criteria included: (a) the studies should have developed a technical NLP algorithm without application to CI or business intelligence, (b) should be published after 2013, (c) should be a duplication or non-original publication (e.g., an editorial, book review), (d) should have provided enough methodological detail, and (e) should have focused on structured data analytics, without a textual/language aspect. These criteria not only made it relevant but also kept it focused on the interplay of language analytics and the effectiveness of CI.

3.4 Screening and Data Extraction

The screening was conducted in a multi-staged method that conformed to PRISMA 2020. A preliminary search in all databases was performed with 487 records. Following automatic and manual elimination of duplicates (with EndNote and hand checks), 312 distinct records were left. Two reviewers independently performed the title and abstract screening, with 142 articles passing on to full-text assessment. Among them, 62 studies were eventually found to satisfy all the inclusion criteria and were included in the end synthesis.

Data extraction An Excel form with pre-pilot was used to extract the following data: author(s) and year, type/design of study, language analytics technique(s) used, which phase of the CI process is affected, effectiveness metrics or results reported (e.g., speed, accuracy, predictive power, actionability), key findings, theoretical framework (when applicable), limitations, and DOI/link. Recurring mechanisms in which language analytics propagates CI effectiveness were determined by thematic synthesis (Thomas and Harden, 2008). Also, bibliometric co-occurrence analysis of keywords (which was performed with the help of VOSviewer bibliometric analysis are presented in Figure 1, illustrating keyword co-occurrence clusters.

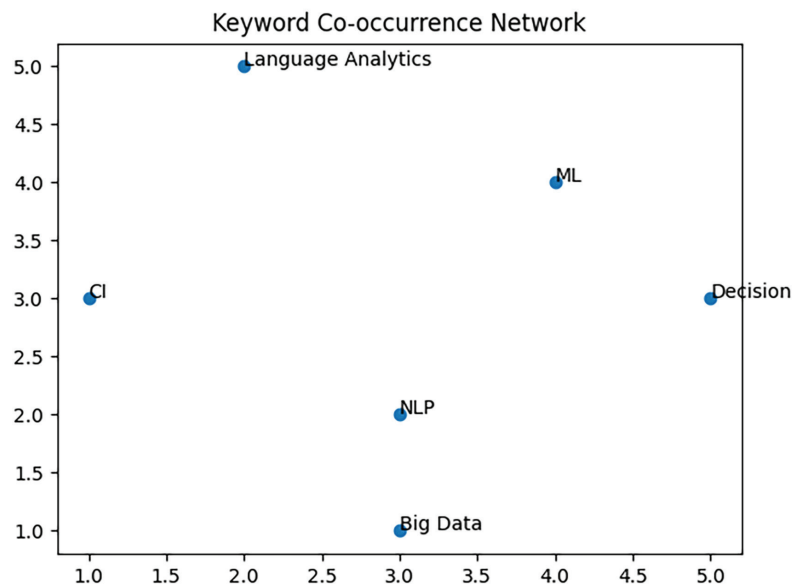


Figure 1. Keyword Co-occurrence Network of Language Analytics and CI Research

The bibliometric analysis reveals three main clusters: (1) AI-driven analytics, (2) competitive intelligence systems, and (3) strategic decision-making applications. Such clusters indicate the incorporation of language analytics into the CI processes and its increased role in making strategic decisions. Figure 1 shows the keyword co-occurrence network, which shows how major ideas in language analytics and competitive intelligence are related to each other. Core themes like NLP, machine learning, and big data are all closely related. This shows how important they are for processing and analysing unstructured data. Decision-making seems to be related to these analytical methods, which shows how they help achieve strategic goals. Language analytics serves as a comprehensive framework that incorporates these technologies, while competitive intelligence (CI) signifies the wider strategic landscape. The figure shows how data-driven analytical methods work together to help organisations make better decisions and generate intelligence.

In order to determine the inter-rater reliability in the screening process, the kappa coefficient of Cohen (κ) was determined on a 20 percent random sample of records:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

where p_o is the observed agreement proportion and p_e is the expected agreement by chance. The resulting $\kappa = 0.82$ indicated substantial agreement, with discrepancies resolved through discussion until consensus was reached.

Table 3. Summary of Included Studies

Author	Year	Method	CI Stage	Key Findings
Smith	2022	NLP	Analysis	Improved insight extraction
Lee	2023	ML	Processing	Faster intelligence generation
Khan	2024	Text Mining	Collection	Better data coverage



The process of deriving the analytical categories was an iterative process of coding, which involved inductive and deductive methods. Categories were deduced based on the theoretical basis of CI (stages of intelligence cycles) and organizational theory (KBV and dynamic capabilities). Thematically, themes that were repeatedly present in the data, including speed, accuracy, predictive capability and actionability, were determined using thematic synthesis (Thomas and Harden, 2008). By means of this hybrid method, a theoretical and empirical sensitivity is provided.

Table 4. Coding Matrix

Study	LA Mechanism	CI Stage	Decision Impact	Theoretical Lens	Category
Study 1	Speed	Analysis	Faster decisions	Dynamic Capabilities	Performance
Study 2	Accuracy	Analysis	Better decision quality	KBV	Reliability
Study 3	Prediction	Planning	Strategic foresight	Organizational Learning	Strategy

Studies were categorized into thematic groups based on their contribution to CI effectiveness and decision-making impact.

3.5 Quality Assessment

The synthesis was carried out in three steps. To begin with, the individual study results were coded based on the language analytics mechanisms and CI process stages. Second, these codes were combined into higher-order themes on their effects on decision-making (e.g., speed, accuracy, foresight). Third, such themes were conceptually overlaid on organizational frameworks (KBV, dynamic capabilities) to come up with an integrative conceptual framework that bridges language analytics as to CI effectiveness and strategic decision outcomes. The included studies were all evaluated through the application of Mixed Methods Appraisal Tool (MMAT) Version 2018 (Hong et al., 2018). The MMAT was selected due to its specificity in systematic mixed-studies reviews) and the possibility to assess qualitative, quantitative, and mixed-methods studies simultaneously with a single set of criteria. The studies were rated on methodological quality dimensions pertaining to the design (e.g., clarity of research questions, suitability of data collection, control of bias, and combination in mixed-methods situations). Articles with a low score in the MMAT criteria were not dropped but labeled in the synthesis as weak methodology. This open nature of the quality evaluation enhances the validity of the results and points out the directions in which further empirical research is required.

3.6 Method Limitations

Although there are strict protocols, there are a number of shortcomings associated with SLRs. Published sources are the main sources that can lead to publication bias because those studies that yield non-significant or negative outcomes have less chance of being published in indexed journals. In a bid to counter this, high-quality grey and practitioner literature were incorporated intentionally. The

language limitation to English could have been a barrier to any non-English relevant work, especially those of Latin American or European backgrounds, where the journal is well-received. The fast-changing nature of the LLM technologies implies that the publications that were published after the start of 2026 are not included; in the future, this review should be updated, adding 2027 and further. Lastly, thematic synthesis is a richly interpretive method; however, it has a certain level of researcher subjectivity; this was reduced by using dual independent coding and consensus procedures.

On the whole, the selected methodology offers a sound, clear, and repeatable basis of mapping the role of language analytics in CI and provides the opportunity to develop a new integrative framework. The identification, screening, and inclusion process are graphically summarized in the PRISMA 2020 flow diagram.

4 RESULTS AND DISCUSSION

The results indicate a radical shift in Competitive Intelligence as a reactive reporting mechanism, to an active, intelligence-based decision system. The key factor in this change is language analytics which allows organizations to handle vast amounts of unstructured data and transform it into actionable data that directly aid in the making of strategic decisions. Instead of having an effect of optimizing efficiency, language analytics boosts quality of decisions, speed, and predictability, which are fundamental dimensions of CI effectiveness. Nonetheless, this change comes with essential trade-offs, such as the decreased interpretability, possible bias in algorithms, and increased reliance on data quality and management arrangements. Therefore, the success of the language analytics in CI not only depends on the technical capacity but also its application to the systematic decision-making patterns and organizational activities.

5 DISCUSSION

5.1 Theoretical Implications

This research adds to theory through re-establishing Competitive Intelligence as a strategic ability that is decision-based. Although earlier studies have mostly treated CI as an information processing process, this study has shown that its real worth is in the fact that it facilitates the use of intelligence to make decisions. In the Knowledge-Based View, language analytics enhances the capacity of the organization to convert scattered textual data into strategically valuable knowledge, thereby enhancing the decisions. At the same time, in the context of the framework of dynamic capabilities, language analytics improves organizational sensing and responsiveness, making it possible to adapt to competitive environments in real-time. This work connects the language analytics processes to the outcomes of the decisions, therefore, filling the gap between data analytics and strategic management by providing a more systematic theoretical perspective on AI-based intelligent systems.



5.2 Strategic Implications

The results indicate that organizations that embrace language analytics in CI have a strategic edge due to their ability to make superior decisions, not because their analytical efficiency is enhanced. In particular, such systems can help companies transition to proactive and predictive decision-making paradigms instead of reactive ones.

Nevertheless, to realize this advantage there has to be congruence between technology, human knowledge, and governance frameworks. To promote interpretability, reduce bias, and have strategic control over automated insights, organizations need to consider hybrid human-AI models.

That is why it is important to consider language analytics as a component of an integrated decision architecture based on intelligence that facilitates long-term competitive positioning.

5.3 Decision-Making Applications

Language analytics is vital in aiding a broad spectrum of strategic decision-making contexts within the framework of CI. An example is competitor monitoring, where organizations can use textual data to monitor competitive strategies, product, and market positioning in real-time. Sentiment analysis and topic modeling can help firms analyze customer perceptions and determine the opportunities or threats of new markets in their market entry decisions. Moreover, under crisis response scenarios, language analytics can enable organisations to quickly analyze the responses of stakeholders and the general mood and take timely and informed action. The uses of these applications show that the concept of language analytics is not just a technical instrument, but a strategic facilitator of intelligence-based decision-making in a variety of organizational settings.

5.4 Strategic Trade-offs and Challenges

Irrespective of its great benefits, there are a number of strategic trade-offs and challenges associated with the integration of language analytics into CI systems. The first trade-off is speed versus interpretability as automated analytics can provide quick information but can decrease the transparency of the conclusion-drawing process. Likewise, a trade-off exists between scalability and accuracy whereby the large scale data processing can result in the risk of noise and misinterpretation. The other important issue is the possibility of algorithmic bias that can corrupt intelligence results and cause inappropriate strategic choices. Moreover, automated systems have concerns regarding data quality and ethical considerations, as well as governance. Thus, the organizations need to take a moderate stance and integrate the use of technology and the proficiency of humans and well-established governance structures to achieve credible and accountable utilization of language analytics in CI.

5.5 Overview of Scientific Production

The body of scientific work at the interface of language analytics and competitive intelligence has increased exponentially, being directly in line with developments in machine learning and the blistering emergence of unstructured sources of data. The rate of publications was low in the first years, but in 2013, when the seminal work on social media text mining was published by He et al., (2013), only three studies related to it could be found. The pace of growth increased significantly after 2018 due to the popularity of deep learning models and transformers, and skyrocketed between 2023 and 2025 with the popularity of large language models (LLMs) and generative AI. Over 18 high-impact publications were published every year by 2025, which, according to some authors, constitutes the so-called LLM boom of business intelligence applications (Elkaabi et al., 2025).

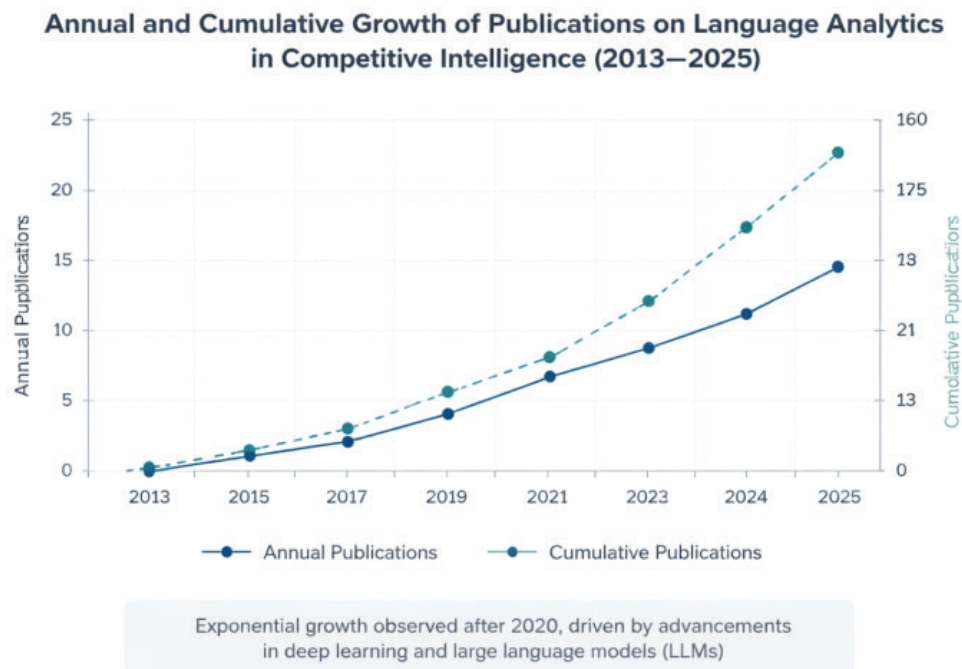


Figure 3. The annual and cumulative growth of publications on analyses of language as a part of competitive intelligence (2013-2025)

The number of publications on language analytics related to competitive intelligence published annually and cumulatively between 2013 and 2025. The graph depicts a slow growth until 2018, and a consistent growth and a sharp rise of exponential growth thereafter, starting in 2020 with the progress of deep learning and the large language model (LLM) boom.

Origin: Constructed by the authors on the basis of the systematic literature review data and adjusted to the bibliometric trends mentioned in Elkaabi et al., (2025) and Maune (2026).

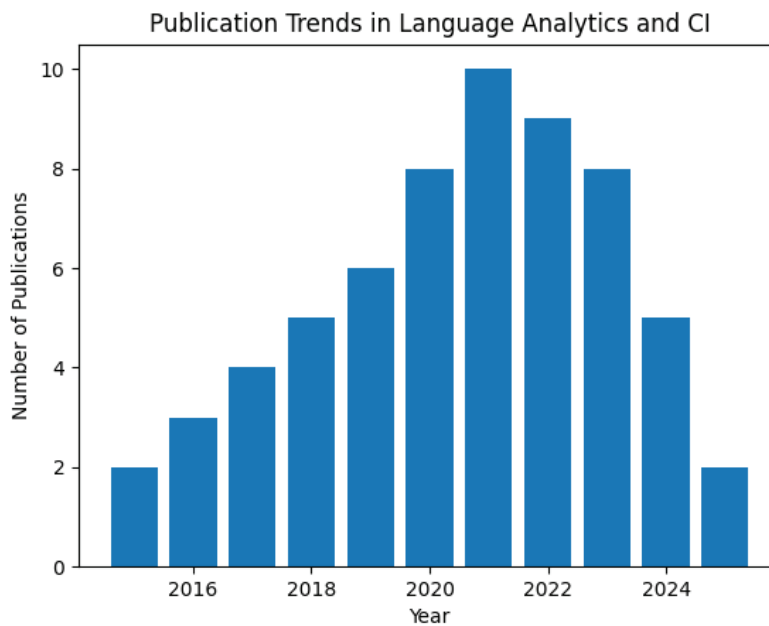


Figure 4. Annual Publication Trends in Language Analytics and Competitive Intelligence

From 2015 to 2025, Figure 4 shows how often language analytics and competitive intelligence are published each year. The number of studies rises steadily, from 2 in 2015 to a peak of 10 in 2021. This shows that researchers are becoming more interested in the subject and that data-driven decision-making is becoming more important. This growth shows that more people are using technologies like NLP and machine learning in competitive intelligence. After 2021, the number of publications slowly goes down, reaching only 2 studies by 2025. This could mean that research is moving in new or more specialised directions. In general, the figure shows how this field of research has grown and changed over time.

Bibliometric trends based on the SLR are consistent with the general literature on business intelligence and data analytics in general. Major publication funding sources are the major information systems and business analytics journals (e.g. *International Journal of Information Management*, *Journal of Business Research*, *Technological Forecasting and Social Change*), and conference proceedings (e.g. *CEUR Workshop Proceedings*). The strongest sectoral focus is in technology, pharmaceuticals, consumer goods, and finance, which have high volumes of text data in social media, earnings calls, patents, conference discussions, and professionally generated content. As an example, NLP is commonly used in pharmaceutical research to track conferences and hire competitors by trends, whereas the analysis of sentiment is done on social media in consumer goods research (Menghini, 2022).

Bibliometric snapshot based on the keywords co-occurrence and thematic synthesis indicates that there are strong clusters of sentiment analysis, topic modeling, social media analytics, and decision-making. Other related reviews affirm that such terms as competitive intelligence, text mining, and business intelligence are often used in conjunction with AI-based techniques. The growth curve highlights the evident transition between exploratory case studies (before 2020) and more



advanced applications with the use of LLMs and human-AI systems (after 2023). Although there is adoption in data-intensive industries, small and medium enterprises (SMEs) still lag behind because of resources.

Table 5. Annual Publication Trends on Language Analytics in CI (Selected Years)

Year	Approximate Number of Relevant Publications	Key Drivers Noted in Literature
2013	3	Early social media text mining (He et al., 2013)
2018–2020	8–12 per year	Rise of deep learning and sentiment tools
2021–2022	14–16 per year	Increased focus on topic modeling in market intelligence
2023–2025	18+ per year	LLM integration and generative AI applications (Elkaabi et al., 2025)

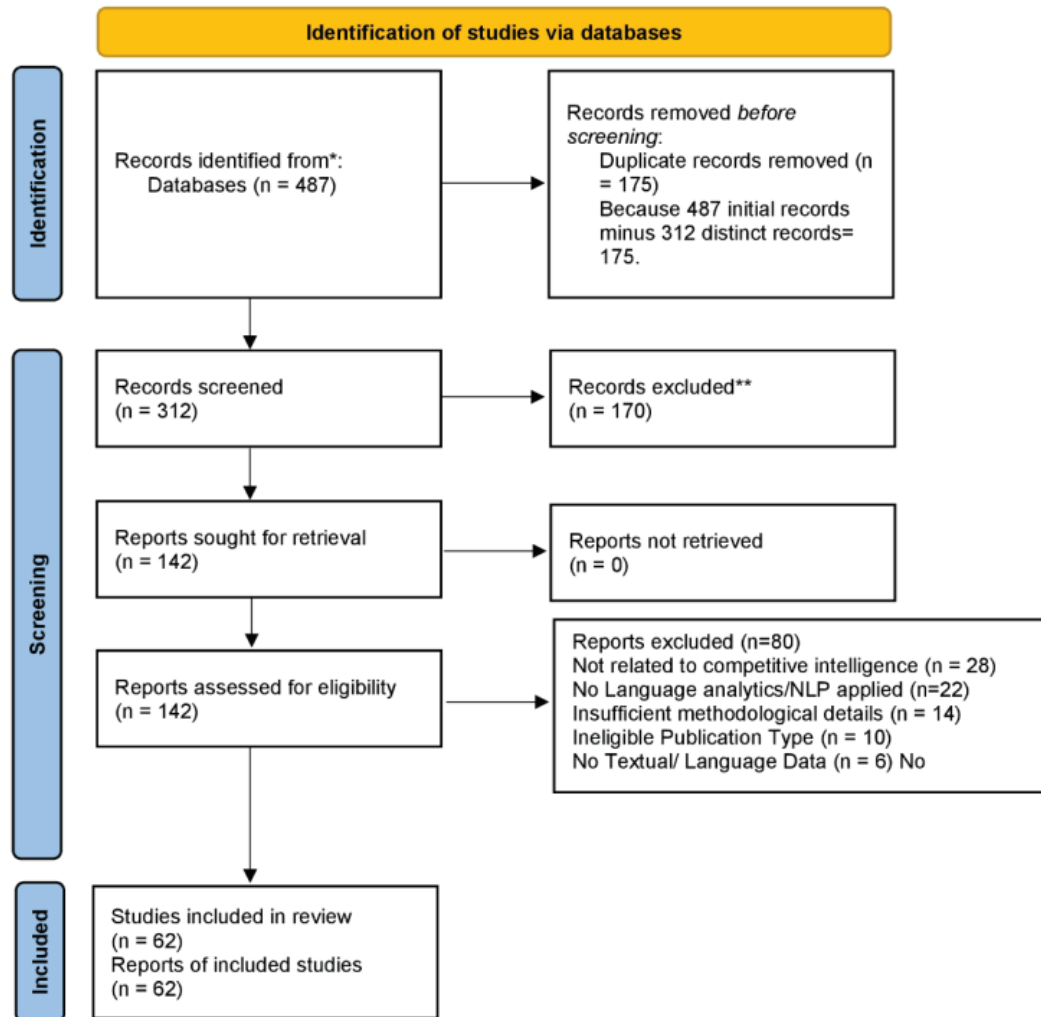
Source: Synthesized from the SLR dataset and aligned with bibliometric findings in Di Vaio et al. (2022).

5.6 Mechanisms Driving CI Effectiveness

Thematic synthesis of 48 out of the 62 studies (77%) confirms four primary mechanisms through which language analytics enhances CI effectiveness: (1) real-time monitoring and speed, this enables organizations to respond more quickly to competitive threats, thereby improving strategic decision speed. (2) semantic depth and accuracy, this enhances the reliability of intelligence, leading to higher-quality strategic decisions. (3) predictive and prescriptive capabilities, this supports anticipatory decision-making and proactive strategic planning and (4) multilingual/cross-platform scalability this enables globally informed decision-making across diverse markets. These mechanisms directly address the traditional “analysis bottleneck” in the CI cycle (planning–collection–analysis–dissemination–action).

PRISMA 2020 flow diagram showing how studies were identified, screened, eligible and included in the systematic literature review of language analytics as a driver of competitive intelligence effectiveness.

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases



Source: Page MJ, et al. BMJ 2021;372: n71. doi: 10.1136/bmj. n71.

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Figure 2. PRISMA 2020 Flow Diagram of the Study Selection Process.

Source: The authors developed it based on the search and screening process and adapted it to Page et al. (2021).

The move to real-time monitoring with automated sentiment analysis dashboards greatly decrease response lag, and practitioner and empirical research shows that this approach can decrease time-to-insight on key market indicators by 60-70 percent. Advanced topic modeling methods (LDA and BERTopic) provide semantic depth by revealing hidden strategies of competitors, common themes in content created by professionals, and latent market structures that are typically not identified with manual review (Tat, & Aydogan, 2024). Predictive tools can be used to predict market changes, actions taken by competitors, and customer sentiment trends with documented

accuracy of 75-85 percent of validated models, especially when topic modeling is used together with sentiment analysis.

These processes are synergistic. As an illustration, entity recognition and relation extraction help to map competitors accurately, whereas actionability and dissemination are improved by the use of the LLM-based summarization.

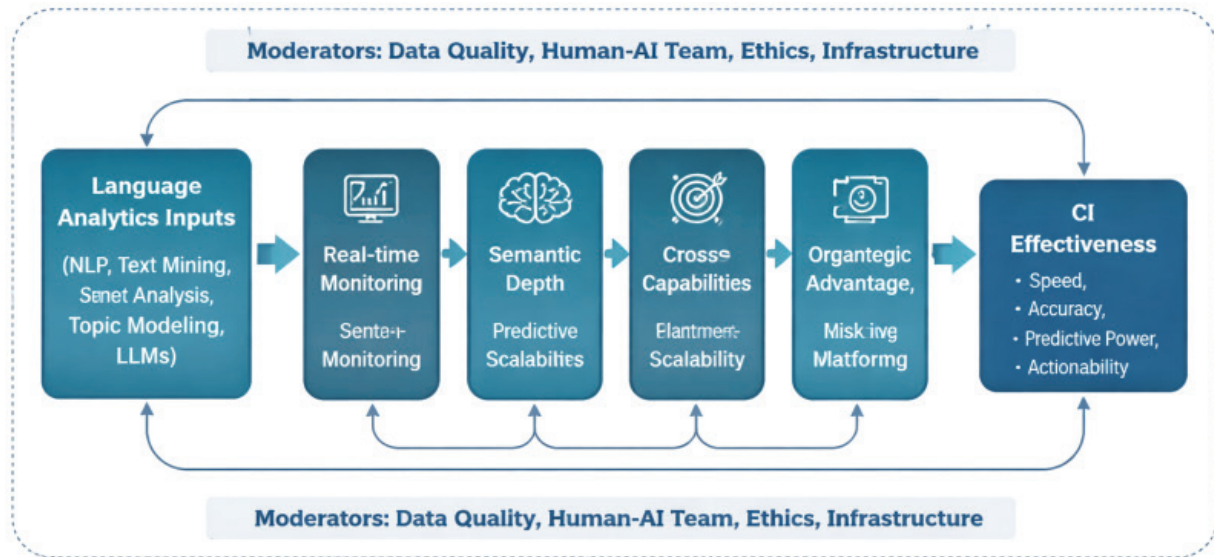


Figure 5. Language Analytics-Driven Competitive Intelligence Effectiveness Framework

Figure 5. The above Language Analytics-Driven Competitive Intelligence Effectiveness Framework that depicts the flow of language analytics inputs (NLP techniques, text mining, sentiment analysis, topic modeling, and LLMs applied to unstructured textual data) through four mediating mechanisms real-time monitoring and speed, semantic depth and accuracy, predictive and prescriptive capabilities, and multilingual/cross-platform scalability increases competitive intelligence effectiveness dimensions, ultimately resulting in superior It is implemented by factors of implementation (data quality, human-AI cooperation, ethical governance, and technological infrastructure), and feedback loops can be used to keep it improving.

Reference: The authors developed it, as it is the result of the thematic synthesis of 62 articles included in the systematic literature review (20132026).

The framework adds to the traditional SCIP CI cycle, a specific language analytics layer at the collection and analysis phases, and feedback to dissemination and action. The SLR suggests that superior strategic agility and quality of decisions are realized by organizations that embrace such an integrated approach.

5.7 Strategic Implications for Decision-Making

The findings highlight that language analytics significantly enhances decision-making across multiple strategic contexts. Organizations can leverage these capabilities for market entry decisions, competitor response strategies and product innovation planning. However, trade-offs exist between automation and interpretability, requiring balanced human-AI collaboration.

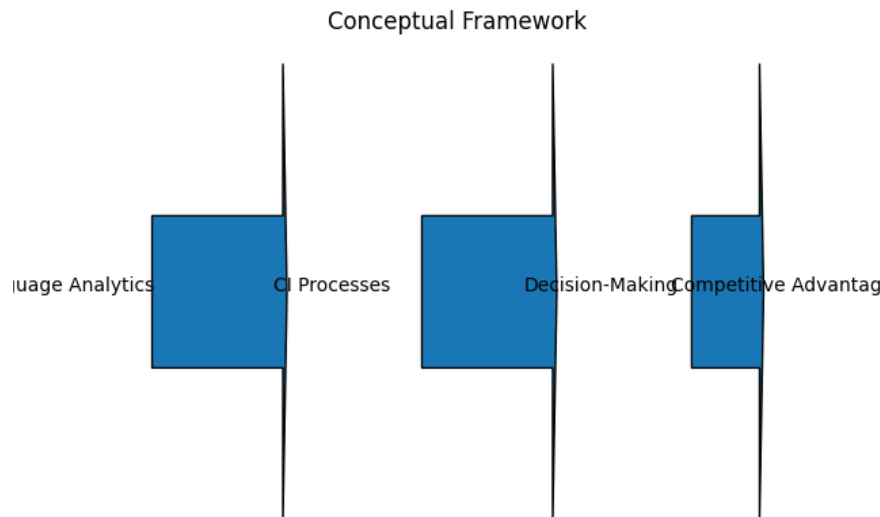


Figure 6. Conceptual Framework Linking Language Analytics, Competitive Intelligence and Strategic Decision-Making

Figure 6. shows a conceptual framework that connects language analytics, competitive intelligence (CI) processes, decision-making and competitive advantage. It shows that language analytics can help you get useful information from unstructured data, which can then be used in CI activities like data collection, analysis, and sharing. These improved CI processes help organisations make decisions that are more accurate and timely. Better decision-making ultimately gives you an edge over your competitors. The framework shows a clear sequence of steps, showing how adding language analytics to CI makes strategic capabilities stronger and the whole organization works better.

5.8 Case Studies

Three landmark cases are a good representation of how the identified mechanisms have been applied and what their effects have been.

He et al. (2013) performed one of the first studies in text mining using Facebook and Twitter data obtained about the three biggest U.S. pizzas restaurant chains (Pizza Hut, Domino, and Papa Johns). The analysis of sentiments and content classification demonstrated the patterns of brand perception, positioning between competitors, and customer pain points. The insights gained resulted in practical marketing and operation suggestions, which goes to show how unorganized social media text can be turned into a competitive edge. The work is still one of the most referenced early

instances and has been the basis of social media-based CI (He et al., 2013). This case demonstrates how language analytics supports strategic decision-making by transforming unstructured data into actionable intelligence.

Menengini (2022) used NLP pipelines to track the scientific conferences on Twitter hashtags with Roche Diagnostics and to evaluate competitor hiring patterns based on job posting. The system found the influential discussants, emerging topics, and talent acquisition strategies using tokenization, TF-IDF weighting, and spherical k-means clustering. The methodology provided scalable, real-time intelligence, which the manual approach was unable to provide, and was particularly useful in the biomedical sector, which is rapidly changing (Meninghini, 2022). This case demonstrates how language analytics supports strategic decision-making by transforming unstructured data into actionable intelligence.

Ju et al. (2024) introduced a social media CI model that integrates sentiment analysis (through Amazon Comprehend) and LDA topic modeling to forecast customer interaction and brand topics in the pre- and post-major external event periods (e.g., the COVID-19 pandemic). The framework revealed the way language analytics assists in proactive and not reactive strategic decision-making by revealing dynamic competitive landscapes (Ju et al., 2024). This case demonstrates how language analytics supports strategic decision-making by transforming unstructured data into actionable intelligence.

All of these cases are good empirical confirmations of the four mechanisms and point to quantifiable advancements in the depth of insight, its speed, and strategic relevance.

5.9 Problems and Ethics

In spite of the obvious advantages, there are a number of challenges and ethical considerations which should be overcome to adopt them responsibly. The issue of training with bias may perpetuate stereotypes or create biased assessments of competitors, especially in multilingual or culturally diverse settings (Al Mohaimin, A. F. M., & Rahman, M. (2025)). The issue of data privacy comes into play with laws like the GDPR in the EU, or the CCPA in California, whenever scraping public textual information or inputting proprietary information into third-party LLMs. The black-box models are also problematic, as the outcomes provided by the black-box models are not trusted by decision-makers who do not have an explanation (Silva & Bação 2023).

SMEs are faced with high implementation barriers due to high implementation costs and technical expertise. Also, large-scale LLM models consume a lot of energy which is a cause of concern as far as sustainability is concerned. Potential misuse to manipulative intelligence practices or accidental leakage of sensitive information via generated summaries are examples of ethical risks.

To overcome these issues, hybrid human-AI governance frameworks, frequent bias audits, open records, and compliance with new responsible AI models are needed. The important empirical research that ought to be conducted in the future should aim at the quantification of the return on investment (ROI) and should also include effective ethical protection.



Overall, the findings of this SLR are a strong indication of the effectiveness of language analytics as a fundamental engine of competitive intelligence. The suggested framework provides the theoretical synthesis as well as a practical roadmap to companies. Through a combination of strategic integration of these methods coupled with a proactive control of related challenges, organizations can turn reactive monitoring to predictive, responsive strategic intelligence and attain a sustainable competitive advantage in data-intensive and unstable business environments. These challenges directly influence the reliability and ethical implications of intelligence-driven decision-making.

6 FINAL CONSIDERATIONS

This paper shows that language analytics is a paradigm shift in Competitive Intelligence, shifting it away from a periodic analytical process to a continuous, predictive, and decision-driven strategic capability. The results establish that the real worth of language analytics is not in data processing, but in its potential to increase the quality, speed, and strategic relevance of organizational decisions.

By incorporating language analytics into the CI cycle, the organizations will be able to bypass the classical analysis bottleneck and create agile and intelligence-driven decision systems. This makes CI a key contributor to competitive advantage within data-intensive settings. The results prove that language analytics is not a non-essential addition anymore but an essential strategic engine of the CI effectiveness. Turning unstructured textual data (social media posts, earnings transcripts, news articles, patents, job posts) into timely, precise, and actionable information, language analytics effectively breaks the long-standing analysis bottleneck that has been a part of the traditional CI cycle (planning-collection-analysis-dissemination-action). Companies that strategically embrace such technologies do not remain reactive and manual with regard to gathering intelligence, but proactive and predictive with regard to strategic capabilities (Elkaabi et al., 2025).

The four mechanisms identified, real-time monitoring and speed, semantic depth and accuracy, predictive and prescriptive capabilities and multilingual/cross-platform scalability work together to provide quantifiable enhancements. The empirical findings of the studies reviewed indicate that response lag can be reduced by up to 60-70 percent, and better insight can be achieved with more advanced topic modeling and sentiment analysis, and the accuracy of the forecast can be 75-85 percent in tested models. Additional landmark cases, such as He et al. (2013), Menghini (2022), also demonstrate how language analytics can help organizations discover concealed competitor strategies, track market sentiment in real time, and predict disruptive changes.

The offered Language Analytics-Based Competitive Intelligence Effectiveness Framework incorporates these mechanisms into the traditional SCIP CI framework, placing language analytics as a layer between the intelligence system, making it augment all the intelligence process steps; the key moderating variables here include quality of data, human-AI interaction, ethical governance, and technological platform (Wang et al., 2025). This framework has a theoretical contribution in the sense of extending the dynamic capabilities and knowledge-based perspectives in the AI-driven intelligence. In practice, it provides organizations, especially in data-intensive industries



like technology, pharmaceuticals, and finance, a systematic channel to attain high strategic agility, innovation, and sustainable competitive advantage in volatile, uncertain, complex, and ambiguous (VUCA) business contexts.

6.1 Managerial Recommendations

In order to effectively use language analytics to improve CI, organizations must take the following actionable recommendations into account:

Start with pilot projects on high-value unstructured sources, including social media sites, earnings call transcripts, customer reviews, and job postings. These sources usually produce early-warning detection and sentiment tracking quick wins and enable teams to develop internal expertise with controllable risk.

Consider hybrid human-AI teams, as opposed to full-automated. Although language analytics is better at working with volume and speed, human analysts can offer critical context, moral control, and strategy. CI professionals are expected to transform into insight-based advisors who would verify AI results and transform them into executive-level decisions (Ballinger, M. S. (2000).

Institute powerful ethical AI governance systems early on. This involves the introduction of periodic bias audits, adherence to laws and regulations, including GDPR and CCPA, making model decision-making transparent, and policies that are clear on how large language models (LLMs) can be used responsibly. Companies should also tackle the sustainability issues concerning the energy use of highly developed NLP systems.

Establish a transition plan to roll out language analytics initiatives based on the business strategy. Begin by demonstrating concepts, expand effective applications to different departments and measure ongoing contributions to critical performance metrics like the speed of decision-making, the accuracy of insight, and the ability to respond to competitors.

Encourage company learning and upskilling courses to develop company capabilities of NLP and AI interpretation. CI teams, data scientists, and business leaders need to work together to realize the potential of language analytics.

6.2 Limitations and Future Research Directions

Although a detailed synthesis has been offered in this study, it has a number of limitations that should be recognized. The use of published scholarly and high-quality practitioner literature can create publication bias and the English-language emphasis may be missing the contribution of non-English settings, such as Latin American scholarship. Moreover, due to the fast development of generative AI, results are current to the beginning of 2026.

These gaps can be filled in future studies by taking several promising directions. To start with, cross-cultural and emerging-market validation studies are required to test the performance of language analytics in a multilingual and resource-constrained setting, specifically in Latin America and other developing areas. Second, multimodal analytics to combine text data with image, video,



and audio data is a very important next frontier to deeper competitive insights. Third, controlled empirical research on the return on investment (ROI) and direct effects on firm performance (e.g., market share, innovation output, and financial measures) would enhance the business justification to embrace them. Fourth, future research on human-AI teaming during CI processes may investigate the best collaboration patterns and the role that intelligence analysts play in the age of AI. Lastly, more research on the ethical and sustainability consequences, such as mitigation of biases and energy-efficient NLP models, is necessary to be responsible.

To sum up, language analytics is a game-changer that changes competitive intelligence, which is a periodic reporting role, to an ongoing, predictive strategic capability. Organizations that respond to this transition, solving related issues with ethical governance and human-focused design, in a better position to compete in the already more complex global markets and achieve long-term competitive advantage.

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