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ARTICLE

EVALUATING THE IMPACT OF LANGUAGE ANALYTICS ON COMPETITIVE INTELLIGENCE EFFECTIVENESS

AVALIAÇÃO DO IMPACTO DA ANÁLISE LINGUÍSTICA NA EFETIVIDADE DA INTELIGÊNCIA COMPETITIVA

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ABSTRACT

Purpose: This study examines the effect of language analytics capabilities on competitive intelligence effectiveness, while also evaluating the mediating role of decision-making effectiveness and the moderating role of technological readiness.

Methodology/approach: The study employed an explanatory cross-sectional survey design based on responses from 312 professionals working in competitive intelligence, analytics, data science, and strategy-related functions. The hypotheses were tested using partial least squares structural equation modeling (PLS-SEM) with bootstrapping.

Originality/Relevance: The study conceptualizes language analytics as an organizational capability rather than merely a technical tool. By integrating the Resource-Based View and Dynamic Capability Theory, it explains how text-oriented analytics can generate strategic value in competitive intelligence processes.

Key findings: The results show that language analytics capabilities positively affect competitive intelligence effectiveness ($β = 0.413$, $p < 0.001$) and decision-making effectiveness ($β = 0.524$, $p < 0.001$). Decision-making effectiveness also positively affects competitive intelligence effectiveness ($β = 0.318$, $p < 0.001$) and partially mediates the focal relationship (indirect $β = 0.167$; VAF = 28.8%). In addition, technological readiness strengthens the relationship between language analytics capabilities and competitive intelligence effectiveness ($β = 0.219$, $p < 0.001$). The structural model explained 48.7% of the variance in competitive intelligence effectiveness.

Theoretical/methodological contributions: This study contributes to the competitive intelligence literature by linking language analytics capabilities with intelligence effectiveness through both direct and indirect pathways. It also identifies technological readiness as an important boundary condition, thereby extending capability-based explanations of how organizations create value from text-oriented analytics in intelligence and decision-support environments.

Keywords: Language analytics capabilities. Competitive intelligence effectiveness. Decision-making effectiveness. Technological readiness. PLS-SEM. Resource-Based View. Dynamic Capability Theory.

RESUMO

Propósito: Este estudo examina o efeito das capacidades de análise linguística na efetividade da inteligência competitiva, avaliando também o papel mediador da efetividade da tomada de decisão e o papel moderador da prontidão tecnológica.

Metodologia/abordagem: O estudo utilizou um desenho de pesquisa explicativo de corte transversal, baseado em respostas de 312 profissionais que atuam em inteligência competitiva, analytics, ciência de dados e funções relacionadas à estratégia. As hipóteses foram testadas por meio de modelagem de equações estruturais com mínimos quadrados parciais (PLS-SEM), utilizando bootstrapping.

Originalidade/Relevância: O estudo conceitualiza a análise linguística como uma capacidade organizacional, e não apenas como uma ferramenta técnica. Ao integrar a Visão Baseada em Recursos (Resource-Based View) e a Teoria das Capacidades Dinâmicas (Dynamic Capability Theory), explica como análises orientadas a texto podem gerar valor estratégico nos processos de inteligência competitiva.

Principais resultados: Os resultados mostram que as capacidades de análise linguística afetam positivamente a efetividade da inteligência competitiva ($\beta = 0.413$, $p < 0.001$) e a efetividade da tomada de decisão ($\beta = 0.524$, $p < 0.001$). A efetividade da tomada de decisão também afeta positivamente a efetividade da inteligência competitiva ($\beta = 0.318$, $p < 0.001$) e medeia parcialmente a relação principal (β indireto = 0.167; VAF = 28,8%). Além disso, a prontidão tecnológica fortalece a relação entre capacidades de análise linguística e efetividade da inteligência competitiva ($\beta = 0.219$, $p < 0.001$). O modelo estrutural explicou 48,7% da variância na efetividade da inteligência competitiva.

Contribuições teóricas/metodológicas: Este estudo contribui para a literatura de inteligência competitiva ao conectar as capacidades de análise linguística com a efetividade da inteligência por meio de caminhos diretos e indiretos. Também identifica a prontidão tecnológica como uma importante condição de contorno, ampliando as explicações baseadas em capacidades sobre como as organizações criam valor a partir de análises orientadas a texto em ambientes de inteligência e suporte à decisão.

Palavras-chave: Capacidades de análise linguística. Efetividade da inteligência competitiva. Efetividade da tomada de decisão. Prontidão tecnológica. PLS-SEM. Visão Baseada em Recursos. Teoria das Capacidades Dinâmicas.

1. INTRODUCTION

Rapid market digitalization has transformed competitive intelligence from a largely manual monitoring activity into a technology-enabled organizational capability. Companies now work in a world of volatile demand, shortened innovation cycle, platform competition, and unending information creation on websites, customer review, analyst reports, social media, news feeds, and regulatory disclosures. In this type of environment, competitive intelligence performance relies not just on the ability to gather more information, but on the ability to transform the heterogeneous textual clues into information which is timely and which will be helpful in making decisions. According to recent research, organizations are increasingly more dependent on data-based intelligence systems, business intelligence infrastructures, and AI-guided analytics in order to remain strategically responsive in the era of information overload and environmental turbulence (Madureira et al., 2023; Tsiu et al., 2025).

Within this broader transformation, language analytics has emerged as an important organizational capability. In this study, the term refers to a broad set of text-oriented analytical routines, including natural language processing, automated content classification, sentiment analysis, topic modeling, summarization, and information extraction. These methods enable firms to process large volumes of unstructured data, monitor competitor activity, detect market signals, assess customer sentiment across channels, and shorten the distance between information scanning and managerial action (Punukollu, 2023; Taherdoost and Madanchian, 2023; Zhang, Qin, and Xu, 2024). As a result, language-centered AI tools are increasingly being embedded in business intelligence systems and decision-support architectures rather than being treated as isolated technical experiments (Arslan et al., 2023; Kalyampudi, 2025). Language analytics is increasingly relevant to management research and practice, but the organizational evidence base remains fragmented. Much of the recent literature focuses on models, architectures, or domain-specific applications, while giving less attention to whether language analytics capabilities translate into measurable improvements in competitive intelligence effectiveness. Existing studies often stop at technical feasibility, predictive accuracy, or workflow automation, with less emphasis on the organizational processes through which text-oriented analytics creates intelligence value. Important challenges also remain, including data heterogeneity, multilingual content, integration with existing analytical systems, variable data quality, and uneven levels of technological readiness across firms (Olujimi and Ade-Ibijola, 2023; Tyagi and Bhushan, 2023; Wang et al., 2022).

This study is grounded in two complementary theoretical perspectives. The Resource-Based View (RBV) explains why language analytics capabilities can be treated as strategic resources when they are valuable, difficult to imitate, and embedded in organizational routines (Helfat et al., 2023; Chen, Esperança, & Wang, 2022). Dynamic Capability Theory further explains that the value of such resources depends on the organization's ability to reconfigure knowledge, interpret signals, and respond in a timely manner under conditions of uncertainty (Huy & Phuc, 2025; Wang & Liu, 2023). Together, these perspectives support the mediated-moderation model proposed in this study, in which language analytics capabilities influence competitive intelligence effectiveness directly, indirectly through decision-making effectiveness, and conditionally through technological readiness.

Based on this, this study seeks to respond to the following research questions: (1) to test the effect of language analytics capabilities and competitive intelligence effectiveness; (2) to test the effect of language analytics capabilities and decision-making effectiveness; (3) to test the effect of decision-making effectiveness and competitive intelligence effectiveness; (4) to test the mediating role of decision-making effectiveness; and (5) to test whether technological readiness is a strengthening factor between language analytics capabilities and competitive intelligence effectiveness.

Research on competitive intelligence has increasingly converged with AI, analytics, and capability-based perspectives. However, a coherent theoretical explanation is still needed to clarify how language-oriented technologies become strategically meaningful at the organizational level. This section develops the conceptual logic of the proposed model and presents the hypotheses.

2. THEORETICAL FRAMEWORK

According to the Resource-Based View, firms are more likely to achieve superior performance when they possess resources and capabilities that are valuable, rare, difficult to imitate, and effectively embedded in organizational routines. Recent RBV research increasingly recognizes digital, data-related, and AI-enabled capabilities as strategic resources whose value depends on how well they are integrated into firm processes and used to support coordination and adaptation (Helfat et al., 2023). In this study, language analytics capabilities are conceptualized as an organizational capability to acquire, process, interpret, and operationalize knowledge derived from unstructured text related to competitors, customers, technologies, and market trends.

Language analytics is particularly relevant to competitive intelligence because much of the information available in the external environment exists in textual form. Intelligence teams must continuously process product announcements, web pages, regulatory updates, investor communications, review platforms, and social media discourse. Language analytics reduces the time and effort required to convert such raw text into structured signals, thereby enhancing scanning capacity, improving competitor-pattern recognition, and accelerating response formation. Prior research suggests that AI-based resources improve information-processing efficiency and quality, while competitive intelligence studies indicate that digital tools strengthen both intelligence acquisition and practical usability (Chen et al., 2022; Elkaabi, Mamouny, and Elmaallam, 2025; Madureira et al., 2023). In this sense, companies that have better language analytics ought to be in a better position to retrieve market signals and transform them into actionable intelligence products. Therefore, the initial hypothesis is the following: H1: Language analytics capabilities have a positive effect on competitive intelligence effectiveness. Figure 1 gives the conceptual framework of the proposed model.

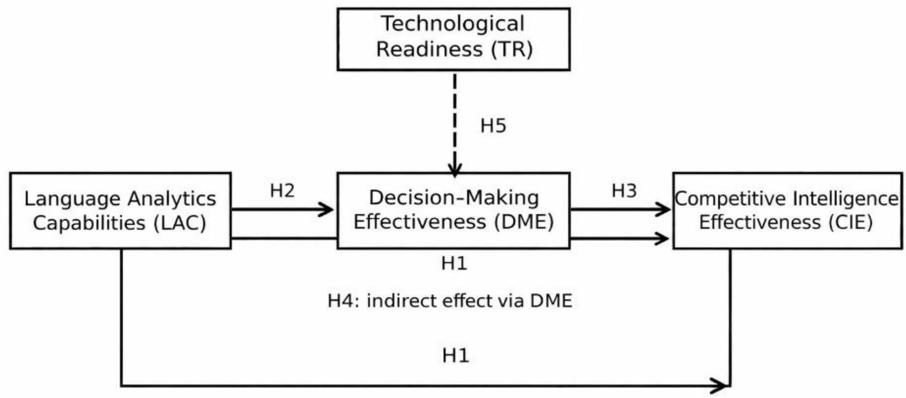

Figure 1. Conceptual framework of the proposed model
Source: Prepared by the author.

2.1 Language Analytics and Decision-Making Effectiveness

Dynamic Capability Theory extends the Resource-Based View by explaining how firms renew and reconfigure resources in changing environments. Competitive intelligence is inherently dynamic because the strategic value of market signals declines when organizational responses are delayed. Language analytics supports this dynamic dimension by reducing processing time, structuring complex signals, identifying emerging themes, and enabling continuous sense making across multiple streams of text. In this way, it does not merely increase the volume of processed information; it also improves the speed and quality of managerial cognition.

Recent findings associate AI prowess with quality of decision making, responsiveness of the process, and organizational performance. Decision speed, comprehensiveness, and depth of evidence can be enhanced with the help of language-oriented AI tools that can translate unstructured information into similar categories and summaries and predictive indicators (Sawant and Sonawane, 2024; Hossain et al., 2024; Neiroukh, Emeagwali, and Aljuhmani, 2025). These tools in combination with the larger business-process can be used to increase dynamism in decision-making where there is an abundance of digital conditions (Huy and Phuc, 2025). Thus, companies, which have better language analytics, are expected to have higher decision-making performance. H2: Language analytics capabilities have a positive effect on decision-making effectiveness.

2.2 Effectiveness of Decision-Making as a Mediation Process

In this study, decision-making effectiveness is treated not only as an outcome variable but also as a mechanism through which analytical capability is translated into organizational value. Even high-quality intelligence outputs will have limited strategic impact if managers are unable to evaluate alternatives, assess trade-offs, and act in a timely manner. Prior studies suggest that AI and business intelligence often influence performance indirectly through stronger decision-making, knowledge integration, and managerial responsiveness (Alzghoul et al., 2024; Khaddam et al., 2023; Neiroukh et al., 2025).

In the competitive intelligence area, the effectiveness of decision-making is particularly crucial since the accumulation of information does not justify the intelligence activities but their value to the strategic decisions. The companies that apply intelligence to aid in pricing, competitor reaction, innovation focus, alliances choice or risk forecasting must convert analytic deliverables into quality decisions. In this way, H3: Decision-making effectiveness has a positive effect on competitive intelligence effectiveness. H4: Decision-making effectiveness mediates the relationship between language analytics capabilities and competitive intelligence effectiveness.

2.3 Moderating Position of Technological Preparedness

Technological readiness refers to an organization's capacity to implement and use advanced digital resources, including infrastructure quality, data-integration capability, technical support, governance arrangements, and user preparedness. The AI literature consistently shows that readiness conditions whether firms actually realize performance gains from advanced analytical investments. Organizations with low readiness often face fragmented workflows, weak system integration, limited user adoption, and lower returns even when powerful analytical tools are available (Jamil et al., 2025; Gao et al., 2022).

In the present context, the value of language analytics is likely to increase when the organization possesses the technical environment needed to embed text-based pipelines into dashboards, workflows, reporting routines, and decision forums. Accordingly, the performance payoff of language analytics should be stronger in organizations with higher technological readiness. H5: Technological readiness positively moderates the relationship between language analytics capabilities and competitive intelligence effectiveness. The outcome construct of competitive intelligence effectiveness also requires clarification. Competitive intelligence should not be evaluated solely in terms of the volume of data collected or the sophistication of the analytical platform. Instead, effectiveness refers to the extent to which the intelligence capability improves environmental sensing, anticipates competitor actions, supports opportunity recognition, reduces strategic surprise, and provides timely input for decision-making. Recent competitive intelligence research increasingly emphasizes usefulness, practical relevance, and routine integration rather than the mere accumulation of information (Madureira et al., 2023; Ibrahim, Ahmad, and Abu Bakar, 2025). Rival intelligence cannot be evaluated only based on the amount of data gathered and the level of the analytic platform. Instead, effectiveness focuses on the issue of whether the intelligence capability enhances environmental intelligence, predicts the actions of the competitor, aids in the recognition of opportunities, minimizes the concept of strategic surprise and provides timely information. Modern CI studies are moving towards issues of usefulness, practical relevance, and routine integration and not mere accumulation of information (Madureira et al., 2023; Ibrahim, Ahmad, and Abu Bakar, 2025).

3. METHOD

This study adopts a quantitative empirical design that is aligned with the objective of testing theoretically specified relationships among organizational capabilities, process variables, and performance outcomes. The methodological choices were made to ensure coherence among the problem statement, theoretical framework, and analytical strategy.

3.1 Research Design

An explanatory cross-sectional survey design was employed. The unit of analysis was the organization, represented by knowledgeable professionals working in competitive intelligence, business analytics, data science, digital strategy, and related decision-support functions. The model includes language analytics capabilities as the focal predictor, decision-making effectiveness as the mediator, technological readiness as the moderator, and competitive intelligence effectiveness as the dependent variable. PLS-SEM was selected because it is well suited to prediction-oriented models, latent constructs measured through multiple indicators, and the simultaneous testing of mediation and moderation effects. PLS-SEM is also methodologically appropriate for the structure of the proposed model. The study includes multiple latent constructs, directional hypotheses, a mediating mechanism, and a moderated relationship that can be estimated simultaneously within a variance-based structural framework. This approach has been widely used in organizational technology research, particularly when the emphasis is on prediction, theory extension, and the estimation of relatively complex path structures. It is therefore well suited to research that links emerging technological capabilities with behavioral and strategic outcomes, as in the present study.

Data were collected using a snowball sampling approach, whereby initial respondents referred additional eligible participants from their professional networks.

3.2 Sampling and Data Collection

Data were collected through snowball sampling from 312 professionals working in technology, manufacturing, finance, and healthcare organizations. The respondents held roles closely related to market sensing and evidence-based decision support, including competitive intelligence analysts, data scientists, business intelligence managers, and strategic planners. The questionnaire was distributed online through professional networks, industry communities, and organizational contacts. Before full administration, the instrument was pre-tested with academic experts and industry professionals to improve item clarity, wording, and contextual relevance.

The final sample provided adequate analytical power for the proposed PLS-SEM model. The respondent profile reflects a relevant cross-section of sectors and functions associated with language-based intelligence work. This strengthens the practical relevance of the findings while maintaining an empirical focus on organizations already operating in digital information environments.

A survey-based design was appropriate because the focal constructs are organizational and partly perceptual in nature. Competitive intelligence effectiveness and decision-making effectiveness are not always directly observable through archival indicators, particularly when firms differ in market context and information infrastructure. Accordingly, responses from qualified professionals offered a practical and theoretically consistent way to capture the maturity and perceived value of language analytics routines within organizations.

Although snowball sampling was appropriate for reaching professionals engaged in competitive intelligence and analytics-related work, it imposes limitations on representativeness and generalizability. Because participants were recruited through professional networks and referrals, the sample may overrepresent respondents who are already digitally engaged, analytically oriented, or professionally connected to intelligence-related communities. Therefore, the findings should be interpreted as evidence of theoretically consistent relationships among the focal constructs rather than as population estimates generalizable to all firms or sectors.

3.3 Measurement Model

All constructs were also measured with multi-item perceptual scales based on recent AI, business intelligence, and competitive intelligence literature. The responses were documented on a five-point Likert scale, which is 1 = strongly disagree to 5 = strongly agree. Language analytics capabilities are the capacity of the organization to implement and apply text-analytic methods in order to derive meaning out of unstructured data. Decision-making effectiveness is a measure of the perceived speed, clarity and accuracy of strategic decision processes. Competitive intelligence effectiveness reflects the extent to which intelligence activities improve the firm's ability to identify competitor moves, recognize opportunities, and support timely strategic responses. Technological readiness is the state of infrastructural sufficiency and integration capacity and company readiness to deploy advanced analytics.

The measurement items were adapted from prior studies to fit the competitive-intelligence context of this research. The adaptation process involved three steps. First, items were selected from established scales that were conceptually aligned with language analytics capabilities, decision-making effectiveness, competitive intelligence effectiveness, and technological readiness. Second, item wording was adjusted to reflect organizational use of text-oriented analytics in intelligence and decision-support settings while preserving the original construct meaning. Third, the adapted instrument was pre-tested with academic experts and industry professionals to assess clarity, contextual relevance, and wording consistency before full data collection. This procedure helped strengthen content validity and contextual fit.

The measurement logic was designed to preserve conceptual distinctiveness while maintaining substantive relevance. The language analytics capability items focus specifically on the organization's ability to interpret and apply textual data rather than on General IT capability. The decision-making effectiveness items capture the speed, clarity, and usefulness of analytics-supported decisions rather than overall organizational performance. The competitive intelligence effectiveness items reflect sensing and response outcomes associated with intelligence activities, whereas the technological readiness items emphasize infrastructure, integration, and organizational preparedness. This distinction is important because it keeps the measurement model aligned with the theoretical structure of the manuscript. The capability items of language analytics revolve around the organizations capacity to interfere and put into practice the textual data, rather than generic IT capability. The effectiveness of decision making items are concerned with rapidity, lucidity, and utility of decisions that are backed by analytics, as opposed to overall organizational performance. The items of competitive intelligence effectiveness include sensing and response results related to intelligence operations. The items of technological readiness highlight the infrastructure, integration, and preparedness. This difference is significant as it makes the measurement model consistent with the theoretical structure of the manuscript.

To improve response quality, several procedural steps were taken. The questionnaire included brief construct definitions, context-specific wording, and a neutral response format to reduce ambiguity. The survey introduction clarified that responses should reflect organizational practices rather than personal preferences. In addition, items were grouped according to construct logic, and the instrument was pre-tested to identify possible wording overlap and content redundancy. These steps helped strengthen content validity and reduce the likelihood that the observed relationships were driven by instrument-design problems rather than substantive organizational differences.

Table 1 – Measurement scales and sources

Construct	Items	Sample indicator	Source(s)
Language analytics capabilities	5	Our organization effectively uses text-analytic tools to extract insight from unstructured text.	Chen et al. (2022); Chatterjee et al. (2022)
Decision-making effectiveness	4	Language-analytics outputs improve the speed and accuracy of our strategic decisions.	Alzghoul et al. (2024); Katebi et al. (2022)
Competitive intelligence effectiveness	5	Our language-analytics systems help us identify competitor moves more quickly than before.	Madureira et al. (2023); Elkaabi et al. (2025)
Technological readiness	4	Our organization has the infrastructure and integration capability required for advanced analytics.	Jamil et al. (2025); Gao et al. (2022)

Source: Prepared by the author.

3.4 Data Analysis Procedure

The data were analyzed in two stages using SmartPLS 4. First, the measurement model was assessed for internal consistency reliability, convergent validity, and discriminant validity. Cronbach's alpha and composite reliability were used to evaluate internal consistency, with values above 0.70 considered acceptable. Convergent validity was examined through the Average Variance Extracted (AVE), with 0.50 used as the minimum threshold. Discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT), with values below 0.85 indicating acceptable discriminant validity.

Second, the structural model was evaluated using bootstrapping with 5,000 resamples to test the direct, indirect, and interaction effects. Path significance was assessed through standardized coefficients, standard errors, t-values, and p-values. In addition, SRMR, R^2, Q^2, and VIF values were examined to assess model fit, predictive relevance, and multicollinearity. Table 2 summarizes the analytical procedures and decision criteria used in the study.

Table 2 – Summary of data analysis procedures and criteria

Stage	Assessment	Criterion	Technique
Measurement model	Internal consistency	Cronbach's $\alpha > 0.70$; CR > 0.70	Reliability analysis
Measurement model	Convergent validity	AVE > 0.50	Factor loadings; AVE
Measurement model	Discriminant validity	HTMT < 0.85	HTMT analysis
Structural model	Direct effects (H1–H3)	β significant at $p < 0.05$	PLS algorithm + bootstrapping
Structural model	Mediation (H4)	Indirect β significant	Bootstrapped indirect effects
Structural model	Moderation (H5)	Interaction β significant	Interaction term in PLS-SEM

Source: Prepared by the author.

Because the study relies on perceptual, self-reported, and cross-sectional survey data, common method bias was explicitly considered. Procedurally, the questionnaire used clear construct definitions, neutral wording, and psychologically separated construct blocks to reduce evaluation apprehension and item-pattern responding. Statistically, collinearity diagnostics were reviewed and the variance inflation factor values remained below critical thresholds, indicating that common method bias was unlikely to distort the structural relationships substantially. Nevertheless, this possibility cannot be fully ruled out and should be considered when interpreting the results.

4. RESULTS AND DISCUSSION

This section reports the empirical results and interprets them in relation to the proposed hypotheses. Tables and figures are presented in the order in which they are discussed, and each visual is explicitly linked to the substantive argument of the paper.

4.1 Descriptive Statistics and Sample Profile

The sample comprised 312 professionals drawn from technology, manufacturing, finance, and healthcare settings, with respondents occupying roles associated with competitive intelligence, analytics, business intelligence, data science, and strategic planning. This profile is suitable for the study because the respondents were positioned close to organizational routines involving market sensing, text-based analysis, and decision support. Figure 2 summarizes the respondent industry profile.

Table 3 presents the descriptive statistics for the main constructs. The mean values indicate moderately positive assessments of language analytics capabilities (M = 3.74), decision-making effectiveness (M = 3.82), competitive intelligence effectiveness (M = 3.69), and technological readiness (M = 3.61). The standard deviation, skewness, and kurtosis values suggest acceptable distributional behavior, with no indication of severe asymmetry or abnormal dispersion. Overall, the descriptive results are consistent with a sample operating in digitally enabled organizational environments while still showing meaningful variance across the focal constructs.

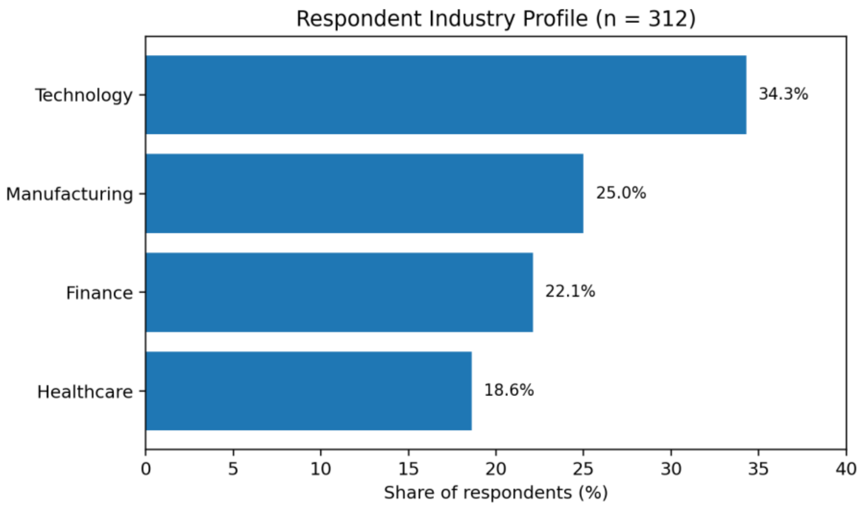

Figure 2. Respondent industry profile
Source: Prepared by the author.

Table 3 – Descriptive statistics

Construct	Mean	Std. Dev.	Skewness	Kurtosis
Language analytics capabilities (LAC)	3.74	0.681	-0.312	0.147
Decision-making effectiveness (DME)	3.82	0.649	-0.278	0.203
Competitive intelligence effectiveness (CIE)	3.69	0.712	-0.341	0.189
Technological readiness (TR)	3.61	0.728	-0.295	0.221

Source: Prepared by the author.

4.2 Measurement Model Assessment

Before testing the structural relationships, the measurement model was evaluated for reliability and validity. The reliability and convergent-validity results indicate satisfactory measurement quality across all four constructs. Cronbach's alpha values ranged from 0.841 to 0.882, composite reliability values ranged from 0.893 to 0.912, and all AVE values exceeded the recommended threshold of 0.50. These results demonstrate satisfactory internal consistency and convergent validity. Figure 3 presents the reliability and convergent-validity indicators across constructs.

Discriminant validity was then assessed using HTMT ratios. As shown in Table 4, all values remained below the recommended threshold of 0.85, indicating that language analytics capabilities, decision-making effectiveness, competitive intelligence effectiveness, and technological readiness are empirically distinct constructs. This distinction is important because the theoretical model treats capability, process, context, and performance as related but non-redundant dimensions.

Figure 3 shows the reliability and convergent validity indicators.

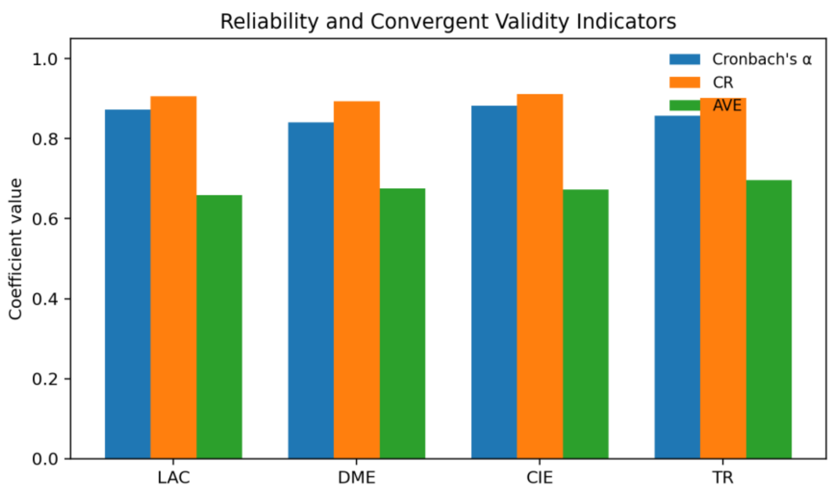

Figure 3. Reliability and convergent validity indicators
Source: Prepared by the author.

Table 4 – Discriminant validity (HTMT ratios)

	LAC	DME	CIE	TR
LAC	0.82			
DME	0.724	0.79		
CIE	0.761	0.698	0.84	
TR	0.643	0.581	0.617	0.80

Source: Prepared by the author.

4.3 Structural Model and Hypothesis Testing

After the adequacy of the measurement model had been established, the structural model was estimated using PLS-SEM with 5,000 bootstrap resamples. The direct effects are reported in Table 5. H1 is supported, as language analytics capabilities have a significant positive effect on competitive intelligence effectiveness ($\beta = 0.413$, $t = 6.771$, $p < 0.001$). H2 is also supported and represents the strongest direct path in the model, showing that language analytics capabilities significantly improve decision-making effectiveness ($\beta =$

0.524, t = 9.703, p < 0.001). H3 is likewise supported, as decision-making effectiveness has a significant positive effect on competitive intelligence effectiveness (β = 0.318, t = 4.746, p < 0.001).

Model-level indicators also support the adequacy of the structural specification. As shown in Table 6, the SRMR value of 0.061 is below the recommended threshold of 0.08. The model explains 48.7% of the variance in competitive intelligence effectiveness and 27.4% of the variance in decision-making effectiveness. Positive Q^2 values indicate predictive relevance, and the maximum VIF value of 2.31 suggests that multicollinearity is not a concern. Figure 4 provides a visual summary of the structural model, including path coefficients and explanatory power for the endogenous constructs.

Table 5 and Table 6 present the structural path coefficients and model fit indices, respectively.

Table 5 – Structural path coefficients — direct effects

Hypothesis	Path	β	Std. error	t-value	p-value	Decision
H1	LAC → CIE	0.413	0.061	6.771	<0.001	Supported
H2	LAC → DME	0.524	0.054	9.703	<0.001	Supported
H3	DME → CIE	0.318	0.067	4.746	<0.001	Supported

Source: Prepared by the author.

Table 6 – Model fit indices

Indicator	Value	Threshold	Assessment
SRMR	0.061	< 0.08	Acceptable
R^2 (CIE)	0.487	> 0.25	Moderate–strong
R^2 (DME)	0.274	> 0.25	Acceptable
Q^2 (CIE)	0.318	> 0	Predictive relevance confirmed
Q^2 (DME)	0.179	> 0	Predictive relevance confirmed
VIF (max)	2.31	< 5.0	No multicollinearity

Source: Prepared by the author.

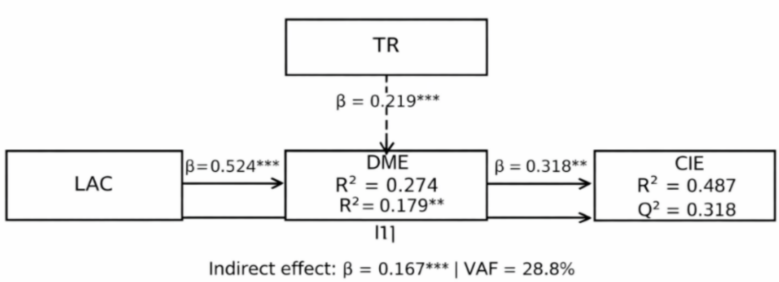

Figure 4. Full structural model with path coefficients, R^2, and Q^2 values
Source: Prepared by the author.

4.4 Mediation Analysis

Table 7 presents the mediation results. Language analytics capabilities exert a significant indirect effect on competitive intelligence effectiveness through decision-making effectiveness (indirect $\beta = 0.167$, 95% CI [0.101, 0.238]). Because both the direct effect and the indirect effect remain significant, the mediation pattern is best interpreted as partial mediation rather than full mediation. The variance-accounted-for value of 28.8% indicates that nearly one-third of the total effect of language analytics capabilities on competitive intelligence effectiveness is transmitted through decision-making effectiveness.

Table 7 shows the mediating analysis results.

Table 7 — Mediation analysis - indirect effects

Path	Direct effect (β)	Indirect effect (β)	Total effect (β)	95% CI	Mediation type
LAC → DME → CIE	0.413***	0.167***	0.580	[0.101, 0.238]	Partial mediation

Source: Prepared by the author.

4.5 Moderation Analysis

Table 8 presents the moderation results. The interaction between language analytics capabilities and technological readiness has a significant positive effect on competitive intelligence effectiveness ($\beta = 0.219$, $t = 3.776$, $p < 0.001$), with a small-to-moderate effect size ($f^2 = 0.087$). This finding supports H5 and indicates that the performance value of language analytics is stronger when it is implemented in a technologically supportive organizational environment.

The mediation and moderation findings should be interpreted jointly. The mediation result shows that language analytics creates value by improving decision processes, whereas the moderation result shows that this value becomes stronger when the technological context is supportive. Together, these findings suggest that firms need both analytical capability and enabling organizational conditions. A technically capable firm with weak integration may struggle to realize intelligence value, while a technologically prepared firm with weak analytical capability may still fail to generate high-quality intelligence outputs.

Table 8 — Moderation analysis - technological readiness

Interaction term	β	Std. error	t-value	p-value	f²	Decision
LAC × TR → CIE	0.219	0.058	3.776	<0.001	0.087	Supported

Source: Prepared by the author.

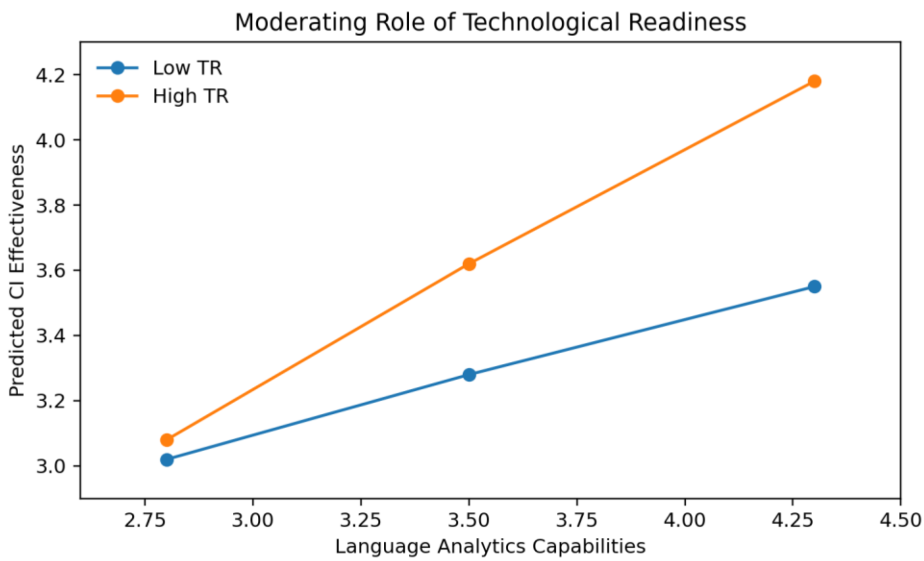

Figure 5. Moderating role of technological readiness
Source: Prepared by the author.

4.6 Discussion

The findings show that language analytics should be understood as a strategic intelligence capability rather than merely a software tool. The positive and significant H1 coefficient indicates that organizations with stronger text-oriented analytical routines are better able to identify competitor actions, detect market changes, and support more responsive intelligence processes. This finding is consistent with recent competitive intelligence research emphasizing the growing importance of AI-mediated information acquisition and intelligence generation, while also extending that literature through a direct empirical test at the organizational level (Elkaabi et al., 2025; Madureira et al., 2023).

The strongest direct relationship in the model is the path from language analytics capabilities to decision-making effectiveness. This result supports the Dynamic Capability perspective, according to which language analytics improves intelligence value not only by increasing information-processing capacity but also by reshaping how organizations interpret signals and respond to environmental change. Prior studies on AI capability and digital transformation similarly suggest that data-driven technologies create value when they improve managerial cognition, decision speed, and evidence quality (Neiroukh et al., 2025; Huy and Phuc, 2025).

The mediation result further clarifies the underlying mechanism. Nearly 29% of the total effect of language analytics capabilities on competitive intelligence effectiveness operates through decision-making effectiveness. This pattern indicates partial mediation and suggests the presence of two complementary pathways. The first is a direct pathway through which language analytics improves scanning, extraction, and signal visibility. The second is an indirect pathway through which the same capability improves how managers frame alternatives, prioritize issues, and integrate intelligence into strategic decisions. This interpretation is consistent with prior work on mediated performance relationships in business intelligence and AI, while extending that logic specifically to the competitive intelligence context (Alzghoul et al., 2024; Khaddam et al., 2023).

The moderation result shows that capability alone is not sufficient. The positive interaction effect indicates that the performance payoff of language analytics is greater when technological readiness is high. From a managerial perspective, this means that firms should avoid tool-centered adoption strategies. Dashboards, data integration, workflow redesign, governance mechanisms, and user support are not peripheral issues; they are part of the broader capability configuration required to generate intelligence effectiveness. This also helps explain why firms using similar AI tools often report very different returns from implementation (Jamil et al., 2025; Gao et al., 2022).

The study also contributes theoretically by integrating the Resource-Based View and Dynamic Capability Theory within a single competitive intelligence model. RBV explains why language analytics can be treated as a valuable organizational resource, whereas Dynamic Capability Theory explains how that resource is translated into value through interpretation, integration, and action. In this respect, the study moves beyond descriptive discussions of digital transformation and offers a more explicit explanation of performance variation based on organizational capabilities.

The findings are also relevant to the broader debate over whether AI-related performance gains are primarily technological or organizational. The results support an organizational interpretation. Although the direct effect of language analytics capabilities is substantial, the mediation and moderation findings show that intelligence gains depend heavily on organizational processing and preparedness. This interpretation is aligned with recent capability-based research showing that AI resources become more valuable when they are embedded in learning processes, knowledge integration routines, and complementary organizational assets (Leoni et al., 2022; Tan et al., 2025).

At the same time, the findings should be interpreted with appropriate caution. Because the study is based on cross-sectional perceptual data, favorable evaluations of language analytics may partly reflect respondent optimism, organizational self-enhancement, or role-related bias rather than purely objective performance differences. In addition, organizations with stronger digital cultures may be more likely to report both higher technological readiness and higher intelligence effectiveness, which may strengthen the observed relationships among the constructs. These limitations do not invalidate the model, but they do indicate that future research should use longitudinal designs, multi-informant data, and objective performance indicators to test the stability and boundary conditions of these effects more rigorously.

5. FINAL CONSIDERATIONS

This study examined the effect of language analytics capabilities on competitive intelligence effectiveness and clarified the organizational mechanisms through which this effect occurs. Based on data collected from 312 professionals, the findings show that language analytics capabilities positively influence competitive intelligence effectiveness both directly and indirectly through decision-making effectiveness. The results also demonstrate that technological readiness strengthens the effect of language analytics on competitive intelligence effectiveness. Taken together, these findings indicate that language analytics contributes most strongly to intelligence performance when it is embedded in decision processes and supported by an enabling technological environment.

The study contributes to the competitive intelligence literature in three ways. First, it conceptualizes language analytics as an organizational capability rather than a narrow technical tool. Second, it explains value creation through a mediated pathway, showing that part of the impact of language analytics emerges through improved decision-making effectiveness. Third, it identifies technological readiness as a meaningful boundary condition, demonstrating that the intelligence payoff of analytics depends on the broader organizational context in which the capability is deployed.

The study also has practical implications. Managers should avoid treating language analytics as a stand-alone adoption project and instead align it with intelligence workflows, decision forums, governance mechanisms, and integration infrastructures. Firms are more likely to realize intelligence value when text-oriented analytics is connected to managerial interpretation, escalation routines, and cross-functional coordination.

Several limitations should be acknowledged. The cross-sectional design restricts causal inference, the use of snowball sampling limits representativeness, and the reliance on perceptual self-reported data raises the possibility of common method bias and respondent optimism. Future research should therefore employ longitudinal designs, multi-source data, and objective indicators of intelligence outcomes. Comparative studies across industries and organizational maturity levels would also help clarify how and when language analytics capabilities produce sustained competitive intelligence advantages.

Author contributions

All authors contributed substantially to the conception and design of the study, methodology development, data collection and analysis, interpretation of results, and manuscript preparation. All authors participated in reviewing and editing the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflict of Interest

The author declares no conflict of interest.

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