

# AI-Driven Generation of Key Intelligence Topics and Questions: Enhancing the Work of CI Professionals

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**Abstract:** Competitive Intelligence (CI) is a critically important instrument for monitoring an organization's external environment, providing management with unique insights into markets, competitors, trends, and other entities influencing the organization's strategic position. Simultaneously, it serves as an effective tool for mitigating risks by identifying and interpreting early signals from the competitive landscape, while also uncovering opportunities for capturing competitive advantages. Recent developments in artificial intelligence (AI), particularly the emergence of Large Language Models (LLMs), have opened new possibilities for enhancing Competitive Intelligence (CI) processes. This paper explores the potential of LLMs in addressing specific CI tasks through CI-oriented prompt design. The study specifically focuses on the planning phase, demonstrating how LLMs can support the identification and formulation of Key Intelligence Topics (KITs) and Key Intelligence Questions (KIQs). In addition, the paper discusses the application of LLMs in the data collection phase, emphasizing their role in identifying relevant sources aligned with the direction of the KIQs. The implications of integrating LLMs into CI are substantial; however, this implementation must be approached cautiously to ensure accuracy, reliability, and ethical compliance emphasizing the need for thorough validation and human oversight.

**Keywords:** Competitive intelligence, Large language models, Prompt engineering, Prompt design, Intelligence cycle

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## 1. Introduction

The hypercompetitive environment exerts increasingly stronger pressure on contemporary organizations across numerous aspects of their operations. Due to technological advancements, particularly in the context of artificial intelligence, organizations are becoming progressively more vulnerable, especially regarding the rational communication of data and information with respect to verification, relevance, and application in decision-making processes. As (Ansoff 1975) notes, management faces information overload that can generate multiple risk factors for businesses or organizations throughout their lifecycle. Currently, verified information with an emphasis on delivery prioritization is just one of multiple factors for companies to gain competitive advantage. What matters significantly is the ability to respond to rapid market changes, including the unprecedented variability of relevant information directly affecting the company. Competitive Intelligence (CI), a traditional system of processes that assists businesses with market environment orientation, provides companies with a tool capable of fully capturing both positive and negative phenomena, leading to opportunity utilization and, conversely, risk aversion or the application of predetermined measures (Ansoff 2019; Gilad 2003). As (Ansoff 2019) adds, transforming direct dangers that a company faces into opportunities has always been the most prioritized capability in the history of the American business spectrum.

(Murphy 2006) returns to the generally accepted fact that CI cannot be related solely to competitors, stating that *"...scope is not limited to researching and assessing other firms and acting to outperform them. It embraces all factors that could endanger or enhance a company's revenues and profits."*

One of the most frequently cited definitions comes from the Society of Competitive Intelligence Professionals (SCIP), which describes CI as "the legal and ethical collection and analysis of information regarding the capabilities, vulnerabilities, and intentions of business competitors... for use in planning and decision-making" (Dishman & Calof 2008). This definition underscores both the ethical dimension of intelligence activities and the decision-oriented nature of CI. (Du Toit 2007) highlights in the context of CI that while *environmental scanning* takes a broad sweep of external trends, CI is more targeted in shaping immediate or near-term strategies through explicit questions and organizational needs. In this sense, CI harnesses methodologies from market research, scenario planning, and business analytics to formulate *forward-looking insights*.

The process increasingly penetrates diverse, often narrowly focused business areas and is also becoming an important tool for the public sector. For example, (Cantonnet et al. 2015) investigated CI activities in small and medium-sized enterprises (SMEs) in the industrial sector, revealing that a company's features and environment significantly influence the development of CI activities. (Safa et al. 2015) studied the application of CI techniques for construction contractor evaluation, demonstrating that CI has potential to improve the process of assessing and selecting contractors through supporting unbiased and auditable decision-making processes. The banking

sector has increasingly adopted CI practices. (Du Toit 2013) compared CI practices between two retail banks in Brazil and South Africa, noting that both banks monitored competition but needed to enhance their analytical capabilities. (Hanif et al. 2022) explored the CI process and strategic performance of the banking sector in Pakistan, finding that all components of the CI process significantly affect banks' strategic performance. They recommended the implementation of formal CI units and awareness programs to improve participation of employees in the CI process.

The hospitality industry has begun to recognize the value of CI. (Köseoglu et al. 2016) examined CI practices in hotels, finding that hotel managers demonstrated a low level of knowledge and awareness of CI, engaging in CI activities primarily for tactical rather than strategic purposes. (Köseoglu et al. 2019) further developed a holistic CI model incorporating all CI efforts at the management level within a hotel organization, identifying disconnection among management levels in coordination of CI practices. In response to the COVID-19 pandemic, (Tulungen et al. 2021) developed a CI approach for establishing an e-tourism strategy, proposing five basic strategies implemented with an e-tourism model and simple management pattern utilizing information technology. Regarding the public sector, we can also mention the defense industry case study conducted by (Barnea 2014) focused on CI in the Israeli defense industry, noting that CI is used intensively in the highly competitive environment of defense products to support decision-making processes.

Developments concerning CI in both academic and corporate environments also confirm the utilization of a wide spectrum of data and information sources in CI. For example, (He et al. 2015) demonstrated how social media analytics can provide valuable competitive intelligence, examining data from two retail chains. (Kim et al. 2016) used social media analytics for CI, comparing iPhone 6 and Galaxy S5 through Twitter data analysis. (Prantl and Prantl 2018) examined CI tools Alexa and SimilarWeb for website traffic data estimation, finding limitations in their accuracy for determining website rankings. Ranjan and (Foroapon 2021) explored how Big Data analytics can contribute to building organizational CI, finding that companies prefer a rather centralized informal process and face multiple challenges regarding the use of big data analytics in CI.

The utilization of artificial intelligence in CI processes is likewise evident. Artificial intelligence (AI) and related technologies have transformed how companies approach CI, enabling more efficient data collection, deeper analysis, and more accurate predictions. (Paschen et al. 2021) discuss how AI can be used to automate data collection and analysis, allowing companies to gain insights more quickly and efficiently. Recent studies showed advanced development related to collection phase. For example, (Ju 2024) presents a social media competitive intelligence framework that not only detects brand topics but also predicts customer engagement. (Liu et al. 2021) employ patent analysis and patent mapping methods to study the 5G competition situation, using visualization analysis with AI-driven software. (Stallings et al. 2024) present an approach for classification of data using machine learning that facilitates aggregation and analysis of intelligence information. Their concept proof extends a model for automatic mapping of publicly available budget data. (Lalitha and Gokila 2024) propose a query model to enhance the precision and relevance of search results for corporate users by systematically structuring keywords and utilizing advanced search techniques.

From the literature, it is evident that AI and related technologies are being applied by companies to most phases of the CI lifecycle; however, very little attention is focused on the initial part of CI, namely planning including Key Intelligence Topics (KITs) and Key Intelligence Questions (KIQs) identifications. The importance of these entities is evident. When examining the process of identifying relevant KITs and subsequently formulating KIQs that shape corporate decision-making (assuming that a competitive intelligence process is in place), it is primarily a matter of constructive dialogue between company management and CI managers (or analysts). These professionals support the organization in addressing three fundamental areas: (1) strategic decision-making and actions, (2) early warning, and (3) comprehensive analysis of key players (Francis 2001; Herring 1999). A detailed initial CI audit can then be used to plan specific activities that help companies better understand their external environment, including identifying both opportunities and risks. Our study addresses this research gap and presents the possibilities of AI regarding the creation of KITs and KIQs as critical components of the initial phase, utilizing prompt engineering and large language models. Simultaneously, we aim to demonstrate effectiveness in preparing intelligence requirements based on real input data from management meetings using AI.

## 2. Methodology

Our research employs a mixed-method approach focusing on qualitative aspects of defining the initial phases of competitive intelligence driven by large language models (LLMs). We qualitatively evaluate the relevance of key intelligence question identification, including collection phase design with information source suggestions, followed by a quantitative evaluation of similarities among LLM responses.

Despite their underlying architecture of next-token prediction, LLMs exhibit emergent capabilities in structured reasoning, summarization, contextual mapping, and problem decomposition — all of which are central to CI tasks. By framing CI tasks (e.g., KIT/ KIQ development, situational analysis) within clearly defined prompts, LLMs can simulate the analytical heuristics of CI professionals. We acknowledge that LLMs are generative models that produce outputs based on their training data and contextual interpretation capabilities. This study does not aim to demonstrate the substitutability of competitive intelligence professionals; rather, it illustrates how LLMs can augment their internal reasoning processes, expand their strategic analysis capabilities, and reduce time spent on routine, labor-intensive tasks. The study begins with the AI-driven transcription of real-world, publicly available board of directors' meetings from an organization focused on patient care across three large hospital sites. Following this, we developed and tested prompts designed to extract critical problems and consequent evolving needs. The prompt construction process involved determining the industry/domain from the transcribed text, providing initial contextual elements for the LLMs, assigning the role of a competitive intelligence expert, and implementing a chain-of-thought approach divided into specific steps.

The analytical process instructed the models to analyze contextual information from the initial transcript to define organizational objectives, including identification of risks and opportunities. Models were then directed to define broader yet precisely framed challenges as KITs. Subsequently, they were tasked with designing KIQs transformed into Intelligence Requirements, including suggested information sources for collection phases.

We implemented the developed prompt across seven large language models: Claude Sonnet 3.7, DeepSeek R1, Gemini Pro Experimental 2.5, Grok 3, ChatGPT o1, LLaMA 3.3 and Qwen 2.5. For quantitative comparison of the responses, we collected and uploaded all generated outputs into an analysis framework employing cosine similarity measures with Claude Sonnet 3.7. This mathematical technique represents text data as vectors in a multidimensional space and calculates the cosine of the angle between these vectors, resulting in similarity scores ranging from -1 to 1, with higher values indicating greater semantic similarity. By applying this analysis to the collected responses, we quantitatively assessed the degree of convergence or divergence in how different LLMs approached the competitive intelligence tasks, complementing our qualitative evaluation of their performance.

This combined approach allows us to not only evaluate the quality of competitive intelligence insights generated by each model individually but also to systematically compare their outputs to identify patterns of similarity and difference across models, providing valuable insights into the reliability and consistency of LLM-driven competitive intelligence processes.

As part of our evaluation, we aim to compare the efficiency of LLMs in relation to our conceptual approach to the definition of KITs and KIQs. For this task, we employed self-consistency prompting, focusing on the following three qualitative metrics:

- **Precision of Industry/Domain Identification** – the degree to which the model accurately and specifically identified the healthcare context.
- **Relevance of KITs and KIQs** – assessed in terms of relevance, concrete impact, and actionability of the proposed intelligence topics and questions.
- **Sophistication of Information Sources** – the relevance, specificity, and comprehensiveness of the recommended data collection sources.
- **Methodology** – how the models have applied competitive intelligence best practices.

The evaluation metrics—industry/domain precision, KITs/KIQs relevance, source quality, and methodology adherence—reflect structured intelligence principles adopted by the U.S. intelligence community. They align with the Key Intelligence Questions Evaluation Process (KEP), particularly through practices such as domain framing, outside-in thinking, formulation of essential questions for decision-makers, quality of information checks, and the Analysis of Competing Hypotheses (ACH)—all emphasized in official CIA intelligence products (CIA 1979; CIA 1984; Tradecraft Primer 2009). These criteria ensure that LLM outputs are not only linguistically coherent but also analytically rigorous and decision-relevant within the competitive intelligence context. Each metric is evaluated using five levels of consistency with a final overall consistency calculation.

The following prompt was input into the LLMs with system default value of temperature:

Based on the board meeting records [MEETING], identify the main INDUSTRY/DOMAIN. Then, act as a seasoned competitive intelligence expert specializing in INDUSTRY/DOMAIN and think step-by-step to finalize the Key Intelligence Topics (KITs) and formulate the Key Intelligence Questions (KIQs) for our company's next strategic moves.

**Steps:**

**1. Analyze MEETING**

- Identify the context, problems, risks, opportunities, and overall objectives captured in the board meeting records.

**2. Develop Key Intelligence Topics (KITs)**

- Based on your analysis, list the most relevant KITs that align with the company's strategic objectives.

**3. Formulate Key Intelligence Questions (KIQs)**

- For each KIT, propose specific KIQs that will guide research, strategic planning, and decision-making.

**4. Define Intelligence Requirements and Sources**

- For each KIQ, formalize the intelligence requirements (IR) needed to address it.
- Suggest both primary and secondary sources where the required data or insights can be gathered.

**Output Format**

**1. Situational and Critical Commentary**

- For each KIQ, include a brief discussion of:
  - Conceptualization: What the KIQ aims to clarify
  - Level of Difficulty: How challenging it may be to answer
  - Update Frequency: How often the KIQ or its answers should be revisited
  - Retrospective Timeframe: The historical data window needed for context

**2. Formatted Table**

- Present a table containing the following columns:
  - KIQ
  - Defines Information Requirements (IR)
  - Suggested Sources

Your response should be concise, well-structured, and actionable, directly linking the insights from MEETING to the company's strategic objectives. When you are ready and understand the instructions, let me know, and I will upload the board meeting transcript.

**3. Results**

Our quantitative comparison of the seven LLMs' competitive intelligence frameworks performed in Claude Sonnet 3.7. revealed varying degrees of similarity in their approaches to analyzing the healthcare management scenario. Table 1 presents the pairwise similarity scores between all models.

**Table 1: Cosine Similarity Matrix of LLM Responses**

LLM	Claude Sonnet 3.7	DeepSeek R1 (671B)	Gemini Pro Experimental 2.5	Grok 3	ChatGPT o1	LlaAMA 3.3	Qwen QwQ 32B
Claude Sonnet 3.7	1.000	0.230	0.559	0.489	0.269	0.374	0.156
DeepSeek R1 (671B)	0.230	1.000	0.312	0.393	0.282	0.357	0.326
Gemini Pro Experimental 2.5	0.559	0.312	1.000	0.498	0.225	0.403	0.137
Grok 3	0.489	0.393	0.498	1.000	0.380	0.417	0.230
ChatGPT o1	0.269	0.282	0.225	0.380	1.000	0.125	0.202

LLM	Claude Sonnet 3.7	DeepSeek R1 (671B)	Gemini Pro Experimental 2.5	Grok 3	ChatGPT o1	LlaaMA 3.3	Qwen QwQ 32B
LlaaMA 3.3	0.374	0.357	0.403	0.417	0.125	1.000	0.204
Qwen QwQ 32B	0.156	0.326	0.137	0.230	0.202	0.204	1.000

Our analysis identified Gemini Pro Experimental 2.5 and Claude Sonnet 3.7 (0.6612) as producing the most similar competitive intelligence frameworks, suggesting significant alignment in their analytical approaches. Other highly similar pairs included LLaMA 3.3 and Claude Sonnet 3.7 (0.6348), followed by LLaMA 3.3 and Gemini Pro Experimental 2.5 (0.6031). These three models exhibited substantial content overlap and similar structural approaches. Conversely, Qwen QwQ 32B and Claude Sonnet 3.7 showed the lowest similarity score (0.3509), indicating considerably different analytical approaches. Similarly, Qwen QwQ 32B and Gemini Pro Experimental 2.5 (0.3854), along with Gemini Pro Experimental 2.5 and DeepSeek R1 (0.3853), demonstrated significant divergence in their respective analyses.

The similarity analysis (Table 2) reveals varying degrees of consensus among LLMs in their competitive intelligence approach. Grok demonstrated the highest average similarity (0.401), positioning it as the most representative of the general consensus, with Gemini Pro Experimental 2.5 (0.356) and Claude Sonnet 3.7 (0.346) also showing strong alignment with other models. In contrast, Qwen QwQ 32B and ChatGPT o1 had the lowest average similarity scores, indicating more distinctive approaches. DeepSeek R1 maintained the most consistent similarity across all models (lowest variance), while LLaMA 3.3, despite middling average similarity, scored highest in centrality, suggesting it represents a middle ground in competitive intelligence frameworks. Qwen QwQ 32B's combination of lowest average similarity and lowest centrality confirms it took the most unique approach among all models analyzed.

**Table 2: Average Similarity Scores (Highest to Lowest)**

LLM	Average Similarity Score
Grok	0.401
Gemini Pro Experimental 2.5	0.356
Claude Sonnet 3.7	0.346
DeepSeek R1 (671B)	0.317
LlaaMA 3.3	0.313
ChatGPT o1	0.247
Qwen QwQ 32B	0.209

The comparative analysis of LLM outputs (Table 3) revealed distinct strengths across models: Gemini Pro Experimental 2.5 delivered the most comprehensive and detailed framework with specific implementation guidance; ChatGPT o1 demonstrated the strongest operational focus with emphasis on immediate staffing and financial challenges; Claude Sonnet 3.7 maintained the most strategic outlook, particularly regarding system integration and long-term planning; LLaMA 3.3 presented the most generic approach with broadly formulated KIQs and minimal guidance; DeepSeek R1 and Grok achieved the best balance between immediate operational concerns and longer-term strategic planning; Qwen QwQ 32B offered the most unique perspective by explicitly addressing external market and policy analysis as a separate KIT; while Claude Sonnet 3.7 and Grok showed the strongest prioritization of core issues around workforce, quality, and system integration.

A comparative Table 4 analyzes how the seven LLMs approached situational analysis and source recommendations in their competitive intelligence frameworks. It reveals significant variation in how the LLMs approached these aspects: Gemini Pro Experimental 2.5 provided the most comprehensive situational analysis and most detailed source recommendations, with extensive health-specific context; Claude 3.7 and ChatGPT o1 both offered strong situational analyses and well-structured source recommendations with good categorization; LLaMA 3.3 showed the weakest performance in both situational analysis and source recommendations, providing only generic healthcare categories without any specific insights; Most models emphasized the importance of combining internal Trust data with regulatory information and sector-specific resources, though

with varying levels of specificity. This table complements the earlier comparison by focusing specifically on how well each LLM understood the situation and recommended appropriate information sources to address the intelligence needs.

The consistency analysis of seven large language models (LLMs) for competitive intelligence framework development (Table 5) reveals significant performance variations across key metrics including industry/domain precision, KITs/KIQs relevance, source quality, and methodology adherence. Gemini Pro Experimental 2.5 demonstrated exceptional consistency, achieving perfect scores across all dimensions with its comprehensive understanding of the NHS context, highly specific intelligence questions with clear decision-making connections, extensive source recommendations, and systematic methodological approach. Claude 3.7 followed closely with very good overall consistency (4.25/5), showing particular strength in methodology adherence while maintaining strong performance across other metrics. ChatGPT o1 achieved solid consistency (4.0/5) with an operational focus and effective implementation guidance. The middle tier included Grok (3.50/5) and Qwen QwQ (3.25/5), which showed good performance in certain areas but lacked the comprehensive depth of the leading models. DeepSeek R1 demonstrated more variable consistency (2.75/5) with acceptable industry identification but weaker information source quality. LLama 3.3 consistently underperformed across all dimensions (1.50/5), offering generic approaches lacking NHS-specific insights.

To ensure an objective perspective on the self-consistency test results, we conducted a qualitative human verification of individual outputs related to planning within the competitive intelligence process, including the alignment with intelligence requirements and the proposed data and information sources. We can confirm that the Gemini Pro Experimental 2.5 model provided not only a comprehensive perspective deconstructed into distinct topics and questions but also an optimal source foundation with demonstrated expertise. Regarding structure and reasoning from the perspective of utilizing alternative models, we can similarly affirm the relevance of KIQs/KITs including optimal sources, noting that Claude Sonnet 3.7 and ChatGPT performed with highly qualitative responses where the differences were minimal. This quantitative assessment confirms Gemini Pro Experimental 2.5 as the optimal model for healthcare competitive intelligence applications based on its exceptional consistency and depth across all evaluation metrics, with Claude 3.7 and ChatGPT o1 representing strong alternatives with slightly different emphases in their respective frameworks.

#### 4. Limitations and Future Research

This study faces several limiting factors. The most significant constraint lies in the use of a single test dataset—albeit a real-world one—which consists of verbatim transcripts of individual members of a company’s management team. Due to the clear identification of each speaker within the meeting transcript, it was possible to structure the document without any significant issues. However, future testing will focus primarily on more complex and less structured recordings, including those with intricate dialogues, frequent speaker changes, and abrupt transitions. Subsequently, we aim to explore real-time transcription followed by immediate input analysis. It's clear that all above-mentioned methods must be conducted with the highest care regarding data protection, specifically personal and sensitive data such as names, contact information, locations, interior elements, and similar.

The overarching objective is the development and conceptualization of a Competitive Intelligence Agentic AI Ecosystem, in which autonomous agents, informed by initial Key Intelligence Topics (KITs) and Key Intelligence Questions (KIQs), will be capable of addressing specific tasks leading to informed decision-making. A notable limitation, already partially acknowledged, is the reliance on a single dataset. This is particularly significant in light of the need to compare different domains and observe how large language models (LLMs) respond to varying types of content.

**Table 3: LLM Competitive Intelligence Planning Framework Comparison**

LLM	Issue Prioritization	KITs/KIQs Specificity	Impact Prediction	Operational vs. Strategic
<b>Claude 3.7</b>	1) Workforce, 2) Quality/Safety, 3) Integration, 4) Sustainable Improvement	High: Detailed KIQs; Clear timeframes; 8 KIQs/4 KITs	Strong: Links to outcomes; Includes update requirements	Strategic (70/30): Long-term planning; System integration
<b>DeepSeek R1</b>	1) Workforce, 2) CQC Compliance, 3) Staffing Ratios, 4) ICS Alignment, 5) Financial	Medium-High: Targeted KIQs; Concise commentary; 10 KIQs/5 KITs	Moderate: Links to board concerns; Limited impact details	Balanced (50/50): Equal operational/strategic focus

LLM	Issue Prioritization	KITs/KIQs Specificity	Impact Prediction	Operational vs. Strategic
<b>Gemini 2.5</b>	1) Regulatory, 2) Workforce, 3) Clinical Service, 4) Governance, 5) Market Dynamics	Very High: Extensive detail; Comprehensive requirements; 8 KIQs/5 KITs	Strong: Detailed applications; Explicit connections	Strategic-Leaning (60/40): Long-term compliance; Some operational focus
<b>Grok</b>	1) Workforce, 2) Service Delivery, 3) Positioning, 4) Compliance	Medium-High: Concise KIQs; Structured ratings; 8 KIQs/4 KITs	Moderate: Links to planning; Limited application details	Balanced (50/50): Equal immediate/future focus
<b>ChatGPT o1</b>	1) Workforce/Staffing, 2) Quality/Compliance, 3) Market Dynamics, 4) Financial, 5) Culture	High: Clear KIQs; Detailed commentary; 10 KIQs/5 KITs	Strong: "Next Steps" section; Board-level ownership	Operational-Leaning (40/60): Immediate challenges; Real-time needs
<b>LLaMA 3.3</b>	1) Workforce, 2) Patient Safety, 3) Financial, 4) Governance, 5) Compliance	Low: Generic KIQs; Minimal commentary; 15 KIQs/5 KITs	Weak: General mentions; No timeframes; Generic requirements	Balanced but Generic (50/50): Low specificity overall
<b>Qwen QwQ</b>	1) Workforce, 2) Quality/Compliance, 3) Governance, 4) Market/Policy, 5) Resources	High: Detailed formulation; Clear timeframes; 10 KIQs/5 KITs	Strong: Strategic priorities; Regulatory connections	Strategic-Leaning (60/40): Long-term focus; Some immediate needs

Table 4: LLM Situational Analysis and Source Comparison

LLM	Situational Analysis	Source Relevancy & Specificity	Typical Sources Emphasized
<b>Claude 3.7</b>	High: Detailed health-sector context; Specific regulatory status; Referenced facilities	High: KIQ-specific sources; Balanced primary/secondary mix; Well-categorized	NHS Improvement resources; Clinical audit data; Board evaluations; Peer networking
<b>DeepSeek R1</b>	Medium-High: Workforce focus; Demographic risks; Limited opportunities discussion	Medium: Brief descriptions; Limited differentiation; Partial KIQ coverage	NHS retention pilots; CQC repositories; ICS workforce reports; Annual reports
<b>Gemini 2.5</b>	Very High: Comprehensive context; Specific metrics; Detailed problems/risks/opportunities	Very High: Extensive detailing; Multiple categories; NHS ecosystem-specific	CQC longitudinal analysis; NHS employer resources; Board papers; ICS documents
<b>Grok</b>	High: SWOT-like structure; Post-COVID context; Specific operational metrics	Medium-High: Good specificity; Internal/external mix; Limited application explanation	Internal data; NHS England guidance; HSJ reports; Financial statements
<b>ChatGPT o1</b>	High: Thorough analysis; Well-organized SWOT; Budget pressures; Morale issues	High: Detailed listings; Effective categorization; Data systems and stakeholders	E-roster platforms; CQC reports; Financial forecasts; Staff surveys
<b>LLaMA 3.3</b>	Low: Generic analysis; Minimal context; Standard categories; Limited NHS-specificity	Low: Generic categories; Non-specific sources; No internal/external distinction	Generic "Trust departments"; Unspecified reports and data sources
<b>Qwen QwQ</b>	Medium-High: Good KIT-level analysis; Specific issues; Clear regulatory context	High: Specific recommendations; Balanced internal/external; Detailed categories	HR reports; NHS workforce intelligence; Dashboard metrics; Financial modeling

Table 5: Self-Consistency Analysis of LLM Responses for Competitive Intelligence

LLM	Industry/Domain Precision	KITs/KIQs Relevance	Source Quality	Methodology	Overall Score
<b>Gemini 2.5</b>	5/5: Comprehensive organization's context; Detailed regulatory understanding	5/5: Highly specific KIQs; Clear decision-making links	5/5: Extensive specific sources; Primary/secondary balance	5/5: Strong CI practices; Systematic approach	5.00/5
<b>Claude 3.7</b>	4/5: Clear context; Good regulatory understanding	4/5: Well-structured; Strong conceptualization	4/5: Comprehensive sources; Good categorization	5/5: Strong methodology;	4.25/5

LLM	Industry/Domain Precision	KITs/KIQs Relevance	Source Quality	Methodology	Overall Score
				Professional structure	
<b>ChatGPT o1</b>	4/5: Thorough context; Good operational focus	4/5: Operationally-focused; Clear implementation	4/5: Well-structured sources; Good tool integration	4/5: Good methodology; Effective "Next Steps"	4.00/5
<b>Grok</b>	4/5: Clear identification; Good clinical focus	3/5: Well-balanced; Limited implementation detail	3/5: Appropriate mix; Limited application explanation	4/5: Systematic approach; Some depth limitations	3.50/5
<b>Qwen QwQ</b>	3/5: Good identification; Limited specifics	4/5: Well-organized; Good conceptualization	3/5: Balanced recommendations; Less comprehensive	3/5: Good organization; Some methodology gaps	3.25/5
<b>DeepSeek R1</b>	3/5: Correct focus; Limited details	3/5: Good alignment; Limited implementation	2/5: Brief descriptions; Partial coverage	3/5: Basic structure; Limited integration	2.75/5
<b>LLaMA 3.3</b>	2/5: Basic identification; Minimal context	1/5: Generic KIQs; Minimal conceptualization	1/5: Vague sources; No NHS-specific context	2/5: Limited application; Significant gaps	1.50/5

## 5. Conclusion

The presented study aimed to demonstrate the potential of large language models (LLMs) within the competitive intelligence (CI) process, specifically focusing on initial situational analysis and the subsequent formulation of Key Intelligence Topics (KITs) and Key Intelligence Questions (KIQs), including the proposal of relevant data and information sources. For this purpose, seven LLMs were selected: Claude Sonnet 3.7, DeepSeek R1, Gemini Pro Experimental 2.5, Grok 3, ChatGPT o1, LLaMA 3.3, and Qwen 2.5.

A critical component of the study was the construction of the input prompt, which each model used to respond to the transcript of a real-world management meeting within a public-sector organization. The findings suggest that LLMs can contribute effectively to the identification of key organizational challenges and the subsequent formulation of overarching intelligence themes (in the form of KITs), as well as the development of more specific intelligence questions (KIQs).

Moreover, the research offers a comparative analysis of the models in terms of similarity, relevance, and consistency of their responses. Based on the study's findings, the most effective models for CI-related processes, at the time of the research, appear to be Google Gemini Pro Experimental 2.5, Claude Sonnet 3.7, and ChatGPT o1.

**Ethics declaration** The author declares the study does not include any personal or sensitive data.

**AI declaration** The use of AI in this paper, particularly large language models, is fully documented in the Methodology section. Furthermore, Claude Sonnet 3.7 and ChatGPT 4o assisted the author in various stages of writing, including proofreading, language refinement, and bibliography formatting. All content was critically reviewed and edited by the author, who takes full responsibility for the final version of the manuscript.

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