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Competitive Intelligence in the Digital Economy: Understanding Market Sensing Capabilities in Data-Rich Business Environments

Chen Hao^{1*}, Liu Fang¹, Zhao Lin²

Abstract

In the data-rich digital economy, organizations face unprecedented volumes of market signals that demand rapid interpretation and strategic action. Traditional competitive intelligence approaches, rooted in periodic environmental scanning, are increasingly inadequate for capturing real-time digital signals and converting them into sustainable advantage. This paper synthesizes recent advances in market sensing capabilities and data-driven competitive intelligence to address a critical gap: the lack of an integrated conceptual architecture that links digital signal capture, intelligence interpretation, and strategic decision-making in continuous feedback loops. The analysis reveals how big data analytics, dynamic capabilities, and real-time monitoring systems reshape organizational sensing processes. The paper introduces the Adaptive Market Sensing Intelligence Framework—a novel conceptual model comprising six interlocking layers that enable firms to transform raw digital signals into actionable strategic insights. The framework advances theory by bridging market sensing and competitive intelligence literatures and offers practical guidance for managers seeking to build resilient intelligence systems in volatile, data-saturated environments. Implications for strategic management and information systems research are discussed, emphasizing the need for continuous, adaptive sensing mechanisms.

Keywords Market sensing capabilities, Competitive intelligence, Big data analytics, Digital economy, Data-driven decision-making, Strategic sensing

*Correspondence:

Chen Hao

chen.hao@outlook.com

¹ Department of Digital Enterprise Systems, Zhejiang University, Hangzhou, China

² Department of Innovation and Strategic Analytics, Nanjing University, Nanjing, China

Introduction

The digital economy has fundamentally reconfigured the competitive landscape, ushering in an era of unprecedented velocity, complexity, and unpredictability. For contemporary organizations, the ability to detect, interpret, and respond to market shifts is no longer a periodic strategic exercise but a continuous, organization-wide imperative [1, 2]. This transformation is driven by the proliferation of high-velocity data streams from a vast, interconnected digital ecosystem. Sources such as social media platforms, the Internet of Things (IoT), mobile

applications, e-commerce transaction logs, and real-time sensor networks generate an overwhelming volume of structured and unstructured data [3–7]. Consequently, firms now operate within environments where actionable signals are embedded in constant “noise,” demanding a fundamental rethinking of traditional competitive intelligence (CI) practices [3].

Historically, competitive intelligence relied on structured, periodic methodologies, including manual environmental scans, competitor reports, and episodic market research, which often resulted in lagging indicators and reactive

strategies [1, 8, 9]. In the current context, such approaches are inadequate. CI must evolve into a dynamic, technology-enabled capability—one that is proactive, predictive, and deeply integrated into strategic decision-making processes [3, 10–19]. Central to this evolution is the concept of market sensing capabilities. Defined as the organizational routines and processes for acquiring, interpreting, and utilizing market information to sense and shape opportunities and threats [6, 20], market sensing has long been recognized as a cornerstone of strategic agility. However, in the digital era, its nature is being profoundly augmented. The infusion of big data analytics, artificial intelligence (AI), and advanced information systems is transforming market sensing from a primarily human-centric, episodic activity into a technologically mediated, continuous, and often automated capability [4, 8, 17].

Despite the growing recognition of these shifts, scholarly inquiry into the intersection of CI, market sensing, and digital transformation remains fragmented, hindering both theoretical development and managerial application. Existing research streams often operate in silos. For instance, a substantial body of literature on CI systems focuses predominantly on internal processes, technological infrastructure, and data security, often treating the external information environment as a static input [1, 9]. Concurrently, the market sensing literature, particularly within the dynamic capabilities framework, has traditionally emphasized how firms build and deploy sensing capabilities in relatively stable or moderately dynamic settings, with less attention paid to the unique demands of hyper-digitalized, real-time contexts [6, 18, 20]. Furthermore, studies on big data analytics often highlight technical capabilities and data management but frequently lack a clear articulation of how these technical processes translate into strategic market intelligence and, ultimately, into organizational action [4, 21–28]. This fragmentation creates a critical gap: no integrated framework explicitly links the capture of digital signals, their real-time interpretation through analytical systems, and the subsequent feedback-driven strategic responses within a cohesive, cyclical process. This theoretical lacuna leaves organizations without a clear blueprint for developing the integrated capabilities necessary to navigate the complexities of fast-moving digital markets, rendering them vulnerable to competitive blind spots, missed opportunities, and strategic surprises [2, 7, 21, 22].

The present paper directly addresses this gap by developing a novel conceptual architecture that explicates

the mechanisms through which market sensing capabilities can be operationalized to enable effective competitive intelligence in the digital economy. The central research question guiding this inquiry is: How can organizations systematically integrate digital signal capture, real-time analysis, and strategic response into a unified market-sensing capability to enhance competitive intelligence? To answer this, the study undertakes a rigorous synthesis of empirical and theoretical insights from a curated selection of 29 peer-reviewed publications spanning 2017 to 2023. This body of literature is drawn from leading journals that represent the intersection of strategic management, information systems, and technology innovation, including the *Journal of Business Research*, *Information & Management*, *Journal of Strategic Information Systems*, *Technological Forecasting and Social Change*, and *Long Range Planning*. The selection criteria prioritized articles that empirically investigated or theoretically advanced the understanding of big data's role in environmental scanning [1, 3, 14], the contribution of real-time monitoring systems to strategic agility [8, 19, 23], and the critical organizational processes involved in transforming raw data into decision-relevant intelligence [4, 9, 28].

The synthesis of this literature reveals several recurring and interconnected themes. First, there is a consensus on the augmentative role of big data; it is not merely a source of more information but a fundamentally new type of asset that expands the scope, depth, and speed of environmental scanning, enabling organizations to detect weak signals and nascent trends that were previously imperceptible [1, 3, 14]. Second, the literature emphasizes the shift from periodic analysis to real-time monitoring as a cornerstone of strategic agility, where the capacity to sense and respond instantaneously becomes a source of competitive advantage in markets characterized by rapid shifts and fleeting opportunities [8, 19, 23]. Third, a critical theme is the challenge of transformation: converting vast, noisy data streams into structured, actionable intelligence. This requires not only sophisticated analytical algorithms but also robust organizational routines for interpretation, sense-making, and the effective communication of insights to decision-makers [4, 9, 28].

Building upon these synthesized foundations, this paper introduces the adaptive market sensing intelligence (AMSI) framework. This original conceptual model reconceptualizes CI as a layered, cyclical, and adaptive system rather than a linear process. The AMSI framework

is structured around four core, interconnected layers: (1) digital signal capture, which addresses the technological and procedural aspects of harvesting data from the digital environment; (2) real-time analytical interpretation, which focuses on the application of analytical tools (from descriptive to prescriptive) to filter, contextualize, and generate insights; (3) strategic decision integration, which examines the organizational and cognitive processes for embedding these insights into strategic choices; and (4) embedded strategic actions, which encompasses the execution of decisions and their subsequent market impacts. Crucially, the framework is underpinned by continuous learning loops that facilitate feedback from actions back into the sensing and interpretation layers, enabling the entire system to adapt and evolve. By focusing exclusively on the conceptual relationships between these layers rather than empirical testing, the AMSI Framework serves as a robust theoretical platform that generates testable propositions for future empirical research and provides a practical heuristic for managers seeking to build or audit their own digital market sensing capabilities.

In doing so, this paper makes several key contributions to the digital business and strategic management literatures. First, it offers a unified conceptual lens that synthesizes disparate streams of research on CI, market sensing, and big data analytics, thereby reducing theoretical fragmentation. Second, it introduces a novel, process-oriented framework that specifies the mechanisms and information flows required to transform a passive data environment into an active strategic asset. Third, it provides a clear departure from static models by embedding adaptability and continuous learning as core principles of the framework, reflecting the reality of modern digital markets. The following sections will first synthesize the conceptual foundations in greater detail, then present a comprehensive exposition of the AMSI Framework's architecture, components, and information flows, before concluding with a discussion of its implications for future research and managerial practice. **Table 1** delineates the structural shift from traditional competitive intelligence to adaptive, data-driven market sensing, highlighting how the AMSI framework reconfigures sensing into a continuous, strategically embedded capability.

Table 1. From traditional competitive intelligence to adaptive market sensing: a structural capability shift.

Dimension	Traditional competitive intelligence	Digital market sensing capability	AMSI framework advancement
Temporal orientation	Periodic and retrospective	Continuous and real-time	Recursive adaptive cycles with feedback loops
Data sources	Structured and limited (reports and surveys)	High-volume and heterogeneous (IoT, social, and transactions)	Multi-source signal ecosystem including weak signals
Analytical mode	Descriptive and manual	Predictive and algorithmic	Hybrid AI-human interpretive architecture
Signal sensitivity	Focus on strong and visible signals	Detection of emerging and weak signals	Systematic amplification and filtering of weak signals
Organizational integration	Siloed CI units	Cross-functional analytics integration	Enterprise-wide intelligence orchestration
Decision linkage	Indirect and lagged influence	Increasingly embedded	Formalized decision integration mechanisms
Learning mechanism	Minimal or ad hoc	Data-driven improvement	Explicit feedback loops enabling dynamic capability renewal
Strategic role	Support function	Enabler of agility	Core driver of adaptive competitive advantage

Literature Synthesis and Conceptual Foundations

Recent scholarship underscores the transformation of competitive intelligence from static information gathering to dynamic, data-driven market sensing. Foundational work demonstrates that big data analytics serve as a core enabler for building organizational CI, allowing firms to process vast unstructured datasets and generate timely insights [1, 4, 14]. For instance, analytics capabilities have been shown to strengthen market performance by supporting disruptive business models and intensifying competitive responses [2]. Complementary studies extend this view to strategic marketing, revealing how big data augments dynamic capabilities and enables proactive opportunity identification [3, 7].

Market sensing capabilities occupy a pivotal position within this landscape. Defined as the organizational ability to detect and interpret market signals, these capabilities are increasingly viewed through a digital lens. Research on small and medium-sized enterprises highlights a positive relationship between market sensing and new product performance, mediated by knowledge-creation processes [6]. In industrial marketing contexts, sensing and analytics capabilities jointly influence performance outcomes, with digital capabilities acting as important moderators [8]. Broader reviews confirm that big data-augmented trend identification and environmental scanning have become essential for strategic foresight [7, 9].

A parallel stream examines the mechanisms of digital signal capture and interpretation. Digital data streams create continuous flows of real-time information that organizations must capture, integrate, and analyze to maintain competitive vigilance [21, 23]. Advanced information systems facilitate this by supporting environmental scanning and real-time market monitoring [13, 15]. Strategic information systems research further emphasizes how such systems contribute to value creation by improving decision-making and fostering organizational ambidexterity [9, 14, 19].

Dynamic capabilities theory provides the overarching conceptual anchor. Sensing, as one of Teece's microfoundations, is amplified in digital contexts where market signals are abundant yet ambiguous [18, 20]. Studies on digital transformation illustrate how firms build sensing routines to renew strategic capabilities, particularly through big data and artificial intelligence [17, 19, 28]. Real-

time monitoring systems and business intelligence platforms have been linked to higher-quality strategic decisions, reinforcing the feedback mechanisms essential for adaptive learning [27, 29].

Orchestrating Adaptive Sensing and Intelligence Fusion: The AMSI Framework

The AMSI framework is proposed as a novel conceptual architecture for systematically embedding market sensing capabilities into competitive intelligence (CI) systems operating in data-rich digital environments. Recognizing the limitations of linear, stage-gate models of intelligence gathering [1, 9], the AMSI framework conceptualizes CI as a dynamic, interconnected ecosystem rather than a sequential process. It is structured as a layered, cyclical system that continuously converts high-velocity, heterogeneous digital signals into sustainable strategic advantage. The framework's core logic is predicated on the principle of adaptive orchestration—the deliberate coordination of technological assets, analytical routines, and human cognitive processes to sense, interpret, and act upon market information in real time. Comprising six core components arranged in sequential yet recursive flows, the AMSI Framework is distinguished by its explicit integration of feedback and learning loops, ensuring that the system is not merely reactive but perpetually self-refining and evolving in response to environmental changes [18, 20].

The following subsections detail each of the six components, elucidating their constituent elements, operational mechanisms, and theoretical underpinnings.

Digital signal capture layer

The digital signal capture layer constitutes the foundational input stage of the AMSI Framework, addressing the critical capability of systematic environmental scanning in a hyper-connected world. Traditional CI scanning methods, often reliant on structured reports, periodic competitor audits, and manual media monitoring, are ill-equipped to handle the volume, velocity, and variety of data characterizing digital markets [7, 23]. This layer, therefore, focuses on systematically acquiring heterogeneous market signals from a broad range of digital sources. These sources include, but are not limited to, unstructured text from social media platforms (e.g., Twitter, LinkedIn, specialized forums), real-time telemetry from IoT sensors and

connected devices, transactional data from online platforms and e-commerce systems, and structured data from public repositories and government APIs [8, 23].

The operational logic of this layer is grounded in the principle of multi-source, real-time monitoring. Rather than relying on a single or a few predetermined sources, it advocates for a portfolio approach to signal acquisition to capture a holistic view of the market environment. This includes both the “loud” signals of well-documented competitor moves and the “weak” signals—nascent trends, subtle shifts in consumer sentiment, or emerging technological discontinuities—that often precede disruptive change [3, 14]. To operationalize this, the layer emphasizes the deployment of automated scraping tools, application programming interfaces (APIs), and continuously operating sensor networks, enabling organizations to move from episodic scanning to a state of persistent environmental vigilance. The theoretical significance of this layer lies in its departure from bounded rationality assumptions in traditional CI; by systematically expanding the scope and speed of signal capture, it aims to reduce organizational blind spots and enhance the raw material available for subsequent analytical stages [7].

Data integration and analytics layer

The second component, the data integration and analytics layer, addresses the critical challenge of transforming a disparate collection of raw signals into a coherent, analyzable asset. The sheer heterogeneity of data captured in the first layer—ranging from unstructured text to structured numerical data—presents significant technical and organizational hurdles [2, 4]. This layer, therefore, aggregates captured signals into unified data repositories (e.g., data lakes or warehouses) and applies rigorous big data analytics techniques to clean, structure, normalize, and detect initial patterns. It encompasses the data engineering and data management processes that ensure data quality, consistency, and scalability [1, 14].

Beyond aggregation, this component is responsible for the initial analytical processing that renders the data amenable to deeper interpretation. This includes applying algorithmic techniques such as natural language processing (NLP) for sentiment extraction from textual data, time-series analysis for detecting anomalies in transactional streams, and network analysis for mapping influence structures in social media data [2, 4]. Crucially, this layer is not merely a technical pipeline but also an organizational one. It requires

establishing data governance protocols, interoperability standards, and the technical infrastructure (e.g., cloud computing resources) to handle the scale and computational demands of real-time data processing. Drawing on established research on analytics capabilities, this layer underscores that the value of digital signals depends on the organization's ability to render them into formats that are both analytically tractable and interpretable by human decision-makers [4, 14].

Intelligence interpretation mechanisms

The third component, the intelligence interpretation mechanisms, represents the critical juncture where data is transformed into meaning. While the previous layer provides structured data and initial analytics, it is within this component that raw analytical outputs are interpreted within specific strategic contexts. This addresses the core cognitive challenge of digital signal overload: the risk that increased data volume leads to paralysis rather than insight [3, 9]. The mechanisms within this layer combine advanced computational routines with human-augmented sense-making to filter, contextualize, and evaluate signals for their strategic relevance [21].

This layer operates through a dual-process architecture. First, algorithmic interpretation employs pattern recognition and anomaly detection algorithms to surface statistically significant deviations, correlations, or clusters that warrant attention. Second, and more critically, human-augmented interpretation involves cross-functional teams of analysts, strategists, and domain experts who engage in iterative sense-making routines. These routines include techniques such as “red teaming” to challenge assumptions, dialectical inquiry to explore opposing interpretations, and the application of strategic frameworks (e.g., scenario planning) to assess the competitive implications of identified patterns [3, 9]. The interplay between computational power and human judgment is paramount; algorithms can identify anomalies, but it is human cognition—informed by contextual knowledge and strategic intuition—that determines whether an anomaly represents a transient noise or a significant market shift [21]. This component thus serves as the cognitive engine of the AMSI Framework, directly addressing the translation problem inherent in converting data into intelligence.

Strategic insight generation layer

The fourth component, the strategic insight generation layer, synthesizes the interpreted intelligence from the previous stage into forward-looking, actionable insights. Whereas interpretation answers the question, “What is happening and what does it mean?”, insight generation addresses the more prescriptive questions: “What does this mean for our strategy, and what should we do about it?” [6, 19]. This layer bridges the outputs of analytical and interpretive processes with the organization’s existing knowledge bases, strategic priorities, and resource configurations.

The key function of this layer is to distill complex, interpreted intelligence into concise, decision-relevant formats that highlight emerging opportunities, nascent threats, and critical strategic gaps. It supports forward-looking activities such as scenario planning, foresight exercises, and the formulation of strategic options [7, 19]. For instance, interpreted data indicating a competitor’s supply chain disruption could be synthesized into an insight into a potential market-share opportunity, which then informs a strategic option to accelerate production or launch a targeted marketing campaign. This layer also involves codifying insights into organizational memory, ensuring that intelligence is not siloed within a single team or lost after a single decision. By moving beyond descriptive and diagnostic analytics to prescriptive and predictive insights, this component elevates CI from a reactive reporting function to a proactive strategic partner [6, 7].

Decision integration processes

The fifth component, decision integration processes, addresses a perennial challenge in CI and strategic management: ensuring that generated insights are not merely intellectual outputs but are effectively embedded into organizational action. This component focuses on the formal and informal mechanisms through which strategic insights are channeled into core decision-making routines [27–29]. Without deliberate integration, even the most sophisticated intelligence can fail to influence strategic outcomes, leading to a gap between sensing and responding [6, 20].

This layer encompasses aligning intelligence outputs with specific organizational processes, including capital allocation, innovation portfolio management, merger and acquisition evaluation, and competitive positioning. It requires establishing decision architectures that mandate

consideration of CI inputs at key junctures. For example, formal processes such as stage-gate innovation reviews or quarterly resource allocation meetings can be redesigned to include a mandatory “intelligence briefing” derived from the AMSI system [28, 29]. Furthermore, this component involves cultivating a strategic culture that values and leverages intelligence, facilitated by executive sponsorship and clear accountability for acting on insights. The effectiveness of this layer depends on the relational links between intelligence functions and C-suite executives, ensuring that insights are communicated in a timely, credible, and actionable format that resonates with decision-makers’ cognitive frames and strategic priorities [27].

Feedback and adaptive learning loops

The sixth and final component, the Feedback and Adaptive Learning Loops, serves as the framework’s self-correcting and evolutionary mechanism. Unlike linear CI models, which conclude with decision implementation, the AMSI Framework posits that the final step in one cycle serves as the foundational input for the next. This component explicitly closes the cycle by systematically feeding decision outcomes, performance metrics, and environmental responses back into the earlier sensing, interpretation, and insight generation layers [18, 20]. It embodies the principles of dynamic capabilities by ensuring that the organization’s market sensing system is not static but continuously refines itself based on experience [6, 18].

This component operates through structured processes of after-action reviews, competitive outcome analysis, and the recalibration of analytical models. For instance, if a strategic decision based on a predicted competitor move yields an unexpected outcome, this information is fed back to refine the signal-detection parameters in the first layer or recalibrate the interpretive heuristics in the third layer [20]. These loops serve multiple functions: they enhance the accuracy of future signal detection by filtering out previously misinterpreted “noise,” they refine analytical algorithms through machine learning techniques, and they improve organizational agility by shortening the cycle time between sensing and responding. By institutionalizing learning as a core component of the CI system, the AMSI Framework ensures that the organization’s capacity for market sensing becomes a source of sustainable, difficult-to-imitate competitive advantage, built on path-dependent, evolving routines and tacit knowledge [18]. **Figure 1**

depicts the AMSI Framework as a multi-layered circular model.

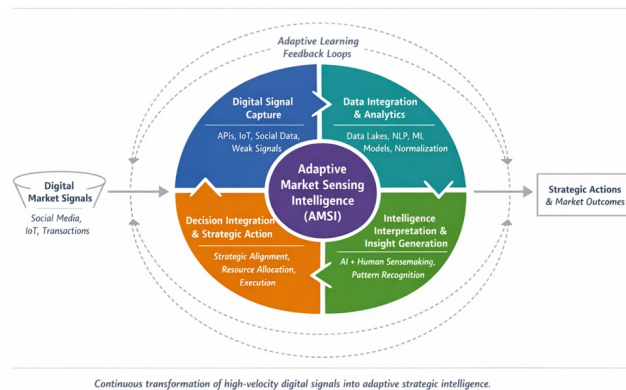


Figure 1. Conceptual architecture of the AMSI framework

The AMSI framework advances prior work by providing an explicit, operationalizable architecture that integrates previously siloed streams of research on CI systems, market sensing, and big data analytics. It is intended to guide both theoretical development and managerial design of intelligence capabilities in the digital economy.

Activating AMSI in Practice: Transforming Digital Signals into Organizational Advantage

The true value of the AMSI framework emerges when organizations embed its six layers into daily operations, enabling continuous conversion of market signals into competitive actions. In data-rich environments, the Digital Signal Capture Layer operates as a multi-channel radar, ingesting unstructured inputs from social listening platforms, sensor networks, and transactional ecosystems at high velocity [7, 8, 23]. Firms that configure automated crawlers and API integrations within this layer achieve earlier detection of weak signals—such as shifting consumer sentiment or supply disruptions—than competitors reliant on periodic surveys [3, 14].

Once signals enter the data integration and analytics layer, machine-learning algorithms and cloud-based repositories harmonize disparate data formats, applying natural-language processing and predictive modeling to reduce noise [1, 2, 4, 14]. This step is critical because raw volume alone does not create intelligence; only structured, context-aware datasets feed the subsequent layers effectively [9,

21]. Interpretation Mechanisms then activate cross-functional teams and AI-augmented dashboards to apply sense-making heuristics, distinguishing noise from opportunity and assigning strategic valence to emerging patterns [3, 9, 21].

Strategic insight generation translates these interpretations into scenario-based narratives that inform portfolio decisions and innovation roadmaps [6, 7, 19]. For example, an insight identifying an accelerating digital substitution trend can trigger reallocation of resources toward complementary offerings before rivals recognize the shift. Decision integration processes ensure these insights reach executive forums through standardized protocols—such as dashboards, war rooms, or automated alerts—embedding intelligence directly into resource-allocation and competitive-positioning routines [27–29].

The feedback and adaptive learning loops represent the framework's distinctive cyclical power. Every strategic action generates outcome metrics (market share shifts, customer engagement deltas, competitor responses) that recalibrate capture thresholds, analytics models, and interpretation rules [18, 20]. Organizations implementing AMSI, therefore, evolve from reactive scanners to proactive intelligence organisms, continuously sharpening their sensing acuity in volatile digital markets [17, 19, 28]. This activation pathway demonstrates that AMSI is not merely descriptive but prescriptive: firms can audit existing CI systems against the six layers, identify gaps, and prioritize technology and process investments accordingly.

Sustaining Competitive Edge through AMSI-Driven Organizational Renewal

Beyond immediate activation, the AMSI Framework supports long-term organizational renewal by aligning market sensing with dynamic capabilities in the digital economy. The recursive nature of its feedback loops cultivates organizational ambidexterity—balancing exploitation of current intelligence with exploration of novel signals—thereby sustaining advantage amid technological disruption [9, 14, 19]. Research on digital transformation underscores that firms excelling in real-time sensing outperform peers in both innovation speed and resilience [17, 19, 28]. AMSI operationalizes this advantage by making sensing routines explicit, measurable, and scalable across business units.

Leaders can deploy the framework to redesign CI functions from siloed departments into enterprise-wide platforms, fostering cross-functional intelligence cultures [1, 4, 9]. For instance, marketing, R&D, and supply-chain teams share a common AMSI dashboard, reducing information asymmetry and accelerating coordinated responses [8, 23]. The framework also addresses ethical and governance considerations inherent in data-rich environments: the Integration and Interpretation Layers must incorporate privacy-by-design principles and bias-detection protocols to maintain legitimacy and regulatory compliance [2, 7, 14].

By institutionalizing these practices, organizations convert market sensing from a peripheral activity into a core strategic competence. The AMSI architecture thus provides a blueprint for building intelligence systems that are not only responsive but anticipatory, turning data abundance into a sustainable source of differentiation [18, 20, 29].

Forging the Future of Intelligence Systems in Data-Saturated Markets

The AMSI framework synthesizes fragmented streams of competitive intelligence and market sensing research into a cohesive, actionable architecture tailored for the digital economy. By delineating six interdependent layers connected through explicit information flows and adaptive feedback, AMSI offers scholars and practitioners a unified lens for understanding how organizations capture, interpret, and act upon digital signals [1, 3, 9, 14, 19, 28]. Its cyclical design extends dynamic capabilities theory by specifying the micro-mechanisms through which sensing, seizing, and transforming occur in real time [18, 20].

Future theoretical development can test AMSI's boundary conditions across industries, firm sizes, and regulatory contexts. At the same time, empirical extensions—though outside the scope of this conceptual work—could examine implementation barriers and performance outcomes. For managers, the framework supplies a diagnostic and design tool to elevate CI from tactical reporting to strategic orchestration, ensuring firms remain vigilant and agile in data-rich environments. Ultimately, AMSI reframes competitive intelligence as an ongoing, adaptive intelligence capability rather than a static function, positioning organizations to thrive amid continuous digital disruption.

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