Reconstructing Sensing in the Dynamic Capabilities View: A Configurational Capability Architecture for Opportunity Exploration

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ABSTRACT

Sensing is widely recognised as the initiating function of dynamic capabilities, yet its internal architecture remains under-specified in the Dynamic Capabilities View. Prior research often treats sensing as a broad higher-order capability, an aggregated sensing–seizing–transforming dimension, or a reflective bundle of scanning, monitoring, information acquisition, and digital routines. This creates conceptual ambiguity and weakens the explanation of how firms translate environmental signals into opportunity exploration. This conceptual paper reconstructs sensing as a capability architecture comprising intelligence, connectivity, and analytical capabilities. Intelligence capability detects and filters environmental signals; connectivity capability validates and integrates dispersed knowledge across organisational and inter-organisational actors; and analytical capability converts integrated information into opportunity-relevant insights. Learning capability is positioned outside the core sensing triad as a recursive-refinement mechanism that helps firms retain experience, revise assumptions, and improve sensing cycles. Drawing on configurational logic, the paper argues that opportunity exploration depends not on isolated capability strength, but on the alignment of detection, validation, interpretation, and learning-based refinement. The framework contributes to the Dynamic Capabilities View by returning sensing to Teece's foundational view of purposive search, interpretation, hypothesis testing, and assumption validation, while explaining how sensing operates, why it fails, and how it supports opportunity exploration under uncertainty.

Keywords: Dynamic capabilities; opportunity exploration; Intelligence Capability; Sensing capability; Connectivity capability; Organisational learning capability.

INTRODUCTION

Sensing capability is the entry point of the dynamic capabilities (DC) framework because it determines how firms notice, interpret, and respond to emerging change. It refers to the capacity to identify technological discontinuities, shifting customer needs, competitor movements, and environmental changes that may reshape competitive conditions (Helfat & Peteraf, 2015; Teece, 2018). In Teece (2007) tripartite architecture of sensing, seizing, and transforming (SST), sensing constitutes the initiating stage of adaptive renewal. It provides the informational and interpretive basis for subsequent resource commitment and structural reconfiguration; without effective sensing, later stages of DC enactment lack strategic direction.

The theoretical development of sensing, however, is embedded within a broader intellectual duality that has characterised the DC literature since its inception. The field emerged from two seminal but distinct streams: the evolutionary and orchestration-oriented perspective associated with Teece et al. (1997), and the process-oriented interpretation advanced by Eisenhardt and Martin (2000). The former conceptualises DC as higher-order integrative capacities rooted in managerial cognition and asset orchestration, whereas the latter emphasises identifiable organisational processes and routines that enable reconfiguration in response to environmental change. Although subsequent scholarship has identified areas of overlap between these perspectives, this foundational duality remains evident in how core DC constructs are framed and operationalised (Pitelis et al., 2024; Pundziene et al., 2023).

Consequently, under the higher-order capability view, sensing is treated as an integrative strategic capacity that enables opportunity recognition and interpretive framing. Under the process-oriented view, sensing is decomposed into observable routines, including environmental scanning, information acquisition, market

learning, and digital monitoring. This divergence affects not only conceptualisation but also structural specification: sensing is alternatively conceived as a unified meta-capability or as a bundle of discrete activities. As a result, its internal architecture, including the boundaries, sub-capabilities, and relational ordering of its components, remains under-specified (Joussen et al., 2025; Leemann & Kanbach, 2022; Stadtfeld & Gruchmann, 2024). The broader DC literature reflects similar patterns of conceptual plurality and structural instability, including definitional multiplicity, blurred distinctions between ordinary and DC, and weak causal specification. Ongoing debates over theoretical foundations, microfoundations, and adjacent constructs suggest that the field remains in flux rather than architecturally consolidated (Barreto, 2010; Pitelis, 2022). Collectively, these patterns indicate that the field has progressed without achieving architectural consolidation.

These structural issues become particularly salient in empirical treatments of sensing. A significant stream of empirical research adopts sensing, seizing, and transforming as first-order dimensions of a higher-order dynamic capability construct. Even validated scale-based approaches reflect this tendency: Kump et al. (2019), for instance, operationalise sensing primarily through general external-scanning and market-awareness indicators, thereby providing empirical measurability while leaving the internal sequencing and relational ordering of sensing activities less explicit. Within this dominant variance-based modelling approach, the internal interactions among these dimensions are rarely specified sequentially, configurationally, or recursively. Instead, dynamic capability is frequently operationalised as an aggregated index that directly and linearly affects innovation or performance outcomes, as illustrated by Supramono et al. (2025), Legg et al. (2025), and Corrales-Estrada et al. (2025). In such models, sensing is typically measured through generalised capacity-oriented indicators rather than through event-level enactment, and orchestration among stages is theoretically implied but not empirically demonstrated (Pfajfar et al., 2024). This modelling tendency transforms a processual and evolutionary construct into a composite predictor variable.

The result is a misalignment between measurement and ontology. The theoretical logic of sensing implies functional dependency, interpretive sequencing, and structured interaction with subsequent capability stages (Pfajfar et al., 2024; Pitelis et al., 2024). However, empirical operationalisations often treat sensing elements as interchangeable reflective indicators or additive components within higher-order constructs, as demonstrated in Hernandez-Perlines et al. (2025), Legg et al. (2025), Saputra et al. (2024), and Silva et al. (2025). When operational routines overlap with ordinary capabilities, boundary clarity weakens and construct inflation may emerge. These empirical tendencies reinforce broader concerns regarding conceptual plurality, causal ambiguity, and theoretical dilution identified in recent reviews (Pitelis, 2022; Pitelis et al., 2024; Schwaeke et al., 2025). The underlying issue, therefore, is not definitional diversity alone but architectural under-specification. While the DC literature has expanded substantially, it has not established a coherent internal structure for sensing that clarifies its constituent sub-capabilities and their relational logic. Without such specification, sensing oscillates between an abstract higher-order capacity and an aggregated routine bundle, limiting theoretical accumulation and constraining empirical precision (Barreto, 2010; Leemann & Kanbach, 2022).

This paper addresses this architectural gap by developing a structured conceptual framework of sensing capability that specifies its core sub-capabilities, intelligence generation, interpretive analysis, and proactive opportunity framing, and theorises their relational sequencing within the dynamic capabilities process. By clarifying the internal composition and functional ordering of the sensing system, the study seeks to strengthen conceptual coherence and provide a more aligned foundation for subsequent empirical modelling.

LITERATURE REVIEW

Teece (2007) and, later, Teece (2018) Conceptualise sensing as a bounded domain of purposive activities through which firms identify, interpret, and shape emerging technological and market opportunities. In this formulation, sensing is not a diffuse awareness capability but a structured activity domain involving directed search, environmental scanning, exploration of new technologies, assessment of customer needs, and evaluation of competitors' moves. These activities are selective rather than generic forms of information gathering, and they are bounded by managerial judgment and strategic intent. This distinction separates sensing from routine operational monitoring, as sensing focuses on identifying and interpreting opportunities that may require strategic renewal (Chen, Liu, et al., 2023; Vu, 2020).

Importantly, sensing operates through iterative cycles rather than one-off detection events. Opportunity recognition unfolds through repeated scanning, conjecture formation, interpretation, reassessment, and renewed search. Firms generate hypotheses about technological trajectories or market evolution, test these through engagement and experimentation, refine their interpretations, and adjust subsequent search directions. Sensing is therefore embedded in evolutionary feedback loops connecting perception, interpretation, and renewed exploration (Dayangan & Aykol, 2024; Stadtfeld & Gruchmann, 2024; Xu & Abdullah, 2025).

Sensing is therefore positioned as an intentional and evolutionary process through which firms shape and refine opportunity exploration. This ontological positioning becomes particularly important in the contemporary digital context. The rapid diffusion of artificial intelligence, big data analytics, and advanced information infrastructures has encouraged an implicit equation of technological sophistication with sensing capability (Mikalef et al., 2021). Nonetheless, the possession of AI systems or large-scale data platforms does not, in itself, constitute sensing. Technology may expand computational capacity and accelerate pattern detection (Chen, Khan, & Iftikhar, 2023; Stadtfeld & Gruchmann, 2024). Without structured search direction, integrative validation across actors, and evaluative framing of relevance, digital systems generate informational abundance rather than adaptive insight. In contrast, sensing, within the DC framework, remains an organisational and managerial process of purposive search, interpretive judgment, and strategic conjecture under uncertainty (Teece, 2007; Teece, 2017).

The paradox, therefore, lies in the assumption that more data or more advanced analytics automatically imply stronger sensing, when sensing depends on the disciplined orchestration of these tools within an intentional evolutionary process (Xiang et al., 2024). This logic implies three differentiated but interconnected functional mechanisms. First, sensing requires intelligence activities that systematically collect and detect environmental signals. Second, sensing requires connectivity activities that communicate, circulate, and coordinate these signals across the relevant organisational and inter-organisational actors. Third, sensing requires analytical activities that interpret circulated information and convert it into strategic insight. These mechanisms then feed learning capability, which sustains the recursive refinement of future sensing cycles (Jenkinson et al., 2024; Mezger, 2014; Randhawa et al., 2021; Vu, 2020; Xu & Abdullah, 2025).

This structured view is partially reflected in empirical operationalisations of DC. Kump et al. (2019), in developing a validated 14-item DC scale based on Teece's SST framework, operationalise sensing primarily as the firm's capacity to systematically and reliably acquire strategically relevant external information. Their sensing items capture knowledge of market best practices, awareness of current market conditions, systematic search for market information, access to new information, and monitoring of competitors' activities. This scale reinforces the view of sensing as a bounded external scanning and intelligence capability rather than diffuse organisational awareness. However, it also demonstrates a key limitation of dominant empirical measurement: sensing is often captured through information acquisition and market awareness, whereas interpretive sequencing, opportunity framing, and recursive learning are less explicitly specified.

Subsequent research expands the sensing construct by linking it to multiple organisational capabilities. Digital and technological capabilities support environmental scanning and early signal detection through analytics and interconnected information systems (Ciacci & Penco, 2023; Magableh et al., 2024). Analytical capabilities support the interpretation of complex information streams (Jenkinson et al., 2024; Schaffer et al., 2022). Managerial capabilities contribute to the cognitive acuity and strategic foresight necessary for evaluating uncertain signals (Basile & Faraci, 2015; Čirjevskis, 2017). Relational and connectivity capabilities embed firms in knowledge networks, thereby enabling the validation and enrichment of detected signals (Elnaggar & Elsayed, 2023). Learning capability sustains the iterative refinement process by institutionalising feedback and experimentation (Malik et al., 2022; Roaldsen, 2014). Across these contributions, sensing emerges as a micro-foundational architecture of purposive search, interpretive evaluation, and exploratory engagement operating within recursive feedback cycles.

However, as sensing operates through this integrated architecture, its challenges are correspondingly systemic. Coordination failures may arise when intelligence generation, interpretive analysis, and relational engagement are misaligned. Advanced digital systems may generate large volumes of data without adequate analytical depth (Mueller-Saegebrecht & Walter, 2025; Witschel et al., 2022). Managerial foresight may rely on conjecture unsupported by structured evidence (Liao & Xie, 2024). External network access may exceed the organisation's absorptive and interpretive capacity (Liu et al., 2025). The presence of multiple capabilities does not guarantee effective sensing; coherence among them is required.

In addition, the iterative nature of sensing introduces temporal and cognitive constraints. Repeated cycles of scanning and reassessment require organisations to question prior assumptions and revise strategic hypotheses. Cognitive biases and dominant logics may distort the interpretation of weak signals, especially when these contradict established trajectories. Structural rigidity may delay collective sensemaking, and information overload may increase noise rather than clarity (Mielcarek & Dymitrowski, 2022; Mueller-Saegebrecht & Walter, 2025; Mustikasari & Ciptono, 2025). These constraints demonstrate that sensing effectiveness depends on the structured orchestration of its components within recursive cycles.

These intertwined challenges reveal a deeper issue. Since Teece (2007) defines sensing as a bounded and distinct activity domain embedded in iterative processes, its internal composition and relational ordering must be explicitly specified. Without structural clarification, sensing risks becoming either an overloaded composite of loosely connected activities or a diffuse proxy for general adaptability (Pitelis et al., 2024; Stadtfeld & Gruchmann, 2024). Nevertheless, the literature has yet to consolidate the internal architecture of sensing. Instead, it has progressively expanded to encompass heterogeneous capabilities without clarifying their structural relationships. Studies associate sensing with digital analytics, managerial foresight, relational networks, organisational agility, learning orientation, cultural openness, and strategic posture (Chen, Liu, et al., 2023; Joussen et al., 2025; Leemann & Kanbach, 2022; Mueller-Saegebrecht & Walter, 2025; Schmidt & Scaringella, 2020). While each may contribute to environmental awareness, the literature rarely specifies whether it functions as a constitutive sub-capability, an enabling condition, a contextual moderator, or a complementary mechanism. The result is conceptual layering without architectural differentiation.

This absence of structural specification gives rise to three ambiguities. First, the constitutive boundaries of sensing remain unclear. When heterogeneous elements are aggregated without distinction, the originally articulated bounded logic is diluted, and the construct absorbs adjacent domains of organisational capability (Vu, 2020; Xu & Abdullah, 2025). Second, relational ordering among elements is undertheorized. Teece's logic implies interdependence and iteration; nonetheless, many studies treat sensing-related elements as parallel dimensions rather than as components within a structured sequence (Barreto, 2010; Pitelis, 2022). Third, architectural expansion weakens the clarity of the boundary between ordinary and DC. Routine monitoring or incremental adjustments are frequently subsumed under sensing without demonstrating how they contribute to higher-order opportunity framing (Murmann & Vogt, 2023; Shiferaw & Amentie Kero, 2024).

Consequently, Sensing oscillates between abstraction and aggregation, lacking an explicit internal structure that preserves its restrictive logic. Addressing this structural specification gap requires identifying the core sub-capabilities that constitute sensing and clarifying the relational sequencing that connects them within iterative cycles. Accordingly, only mechanisms that directly perform the core functions of intelligence generation, interpretive analysis, and proactive opportunity framing can be considered constitutive sub-capabilities. Mechanisms that facilitate, amplify, or accelerate these functions without performing them should be treated as enabling conditions rather than as elements of sensing itself.

With that in mind, two criteria guide this distinction. First, a constitutive sub-capability must directly execute one of the purposive sensing activities identified in Teece's formulation. Sensing is not merely about collecting data; it is fundamentally an intelligence-generating, interpretive, and opportunity-framing activity (Teece, 2007). Second, it must participate in the recursive logic through which search informs interpretation and interpretation, in turn, reshapes subsequent search. Capabilities that support sensing indirectly, such as culture, general agility, or broad strategic orientation, may influence effectiveness but do not perform sensing themselves. Applying these criteria reveals three constitutive sub-capabilities.

Configurational Approach

A configurational approach provides stronger explanatory value for conceptualising sensing because sensing does not operate as a single isolated capability, an additive bundle of activities, or a fixed linear sequence. In Teece's (2007) logic, sensing requires firms to search across technologies, customers, competitors, suppliers, complementors, and external knowledge domains, while also filtering, shaping, and calibrating opportunity conjectures under uncertainty. This means that sensing effectiveness depends on the alignment among multiple interdependent functions rather than on the independent strength of any one activity. Alternative approaches, such as treating sensing as environmental scanning, market sensing, business intelligence, or a reflective higher-order dimension, capture important parts of the phenomenon but do not explain how these parts combine to produce opportunity exploration (Warner & Wäger, 2019). A firm may possess strong scanning routines but remain trapped in narrow local search; it may have broad external linkages but suffer from information overload; or it may possess advanced analytical systems but interpret incomplete or poorly validated signals (Helfat & Peteraf, 2015; Loon et al., 2020). A configurational approach is therefore more appropriate to explain sensing as the joint fit among detection, knowledge access, validation, interpretation, and calibration. It also explains sensing failure as a misalignment among these elements, rather than simply the absence of a single capability. In this way, the configurational approach preserves Teece's (2007) view of sensing as a purposive, entrepreneurial, and interpretive process while offering a stronger explanation of how sensing mechanisms combine to support opportunity exploration.

Configurational theory provides the relational logic for explaining sensing as an architecture of interdependent mechanisms. It explains organisational outcomes through combinations of conditions rather than through the independent effects of single variables, emphasising conjunctural causation, non-linearity, equifinality, and causal asymmetry (Furnari et al., 2021; Meyer et al., 1993). This perspective complements the DCV because the effectiveness of DCs depends not only on the presence of sensing-related activities but also on how these activities are aligned within organisational and environmental contexts (Fainshmidt et al., 2019). The DCV explains the substantive function of sensing: transforming ambiguous environmental signals into opportunity exploration. Configurational theory explains how the mechanisms supporting this function combine. Intelligence capability, connectivity capability, and analytical capability are therefore treated as complementary conditions rather than isolated predictors or interchangeable indicators. While learning capability is positioned as a connected refinement mechanism that supports the recursive adjustment of the sensing configuration. Prior studies similarly show that different combinations of capabilities may generate alternative pathways to opportunity recognition, innovation, adaptation, and performance (Cheng & Miao, 2025; Khan et al., 2023; Mostafiz et al., 2023).

Applied to sensing, configurational theory explains opportunity exploration through three premises. First, conjunctural causation holds that opportunity exploration arises from the joint presence and alignment of sensing mechanisms rather than from the independent effect of any single capability. Intelligence capability may expand the firm's perceptual field by detecting weak signals, technological discontinuities, customer shifts, and regulatory changes, but such signals remain fragmented unless they are connected to relevant knowledge sources and validated across organisational and inter-organisational actors (Jenkinson et al., 2024; Liu et al., 2025). Connectivity capability may expose the firm to customers, suppliers, partners, platforms, and ecosystem actors, but openness alone does not constitute sensing if the firm lacks a disciplined intelligence logic to filter relevant signals or an analytical capability to interpret their strategic meaning (Chen & Yu, 2023; Jenkinson et al., 2024). Analytical capability may process large volumes of structured and unstructured data, but its value depends on the quality, relevance, and diversity of the signals made available through intelligence and connectivity (Balta et al., 2024; Liu et al., 2025). Thus, opportunity exploration does not arise from scanning, networking, or analytics in isolation. It emerges from the configuration in which intelligence defines what the firm should attend to, connectivity determines how dispersed signals are accessed and validated, and analytical capability converts these signals into opportunity-relevant interpretations.

Second, equifinality means that different sensing configurations may generate opportunity exploration under different organisational and environmental conditions. A digital platform firm may explore opportunities through broad digital connectivity, real-time behavioural data, and advanced analytical capability that identifies emerging patterns in user behaviour (Lin et al., 2020). In contrast, a manufacturing firm operating in a more specialised industrial context may rely less on algorithmic breadth and more on deep intelligence capability, supplier relationships, customer proximity, and managerial interpretation of technical signals (Fang, 2023). Both pathways may support opportunity exploration, but they do so through different configurations of detection, connection, and interpretation. This means that there is no single universal sensing formula. The relative importance of intelligence, connectivity, and analytical capability depends on the firm's technological intensity, ecosystem position, market dynamism, and knowledge base (Jingwen et al., 2025). Configurational theory, therefore, allows sensing to be understood as a context-sensitive architecture rather than a uniform linear sequence.

Third, causal asymmetry means that the conditions that produce successful opportunity exploration are not simply the inverse of those that produce sensing failure. A firm may fail not because it lacks all sensing mechanisms, but because one mechanism is misaligned with the others. High connectivity without sufficient analytical capability may generate information overload, cognitive dispersion, and strategic paralysis. Strong analytical capability without connectivity may produce sophisticated but narrow interpretations based on incomplete or outdated data (Gretzinger et al., 2024; Liu et al., 2025). Strong intelligence capability without cross-boundary validation may reinforce internal assumptions and dominant logics rather than reveal genuinely novel opportunities. Conversely, reducing information overload or improving data quality does not automatically create effective sensing unless the firm also configures intelligence, connectivity, and analytical capability into a coherent opportunity-exploration system (Christofi et al., 2024; Randhawa et al., 2021; Schwaeke et al., 2025). This asymmetry is important because it shifts the explanation of sensing from the possession of capabilities to their configuration: the question is not whether the firm has more data, stronger networks, or better analytics, but whether these mechanisms fit together in ways that transform environmental signals into strategically meaningful opportunities for exploration.

Intelligence Capability

Intelligence capability constitutes the perceptual function of sensing. It refers to the firm's capacity to acquire and use information about external events, trends, and relationships to support managerial understanding of the organisation's future course of action (Jorosi, 2008). Within the sensing architecture, the intelligence capability performs the directed search function. It enables firms to scan markets, monitor technological trajectories, track competitor movements, identify regulatory shifts, and detect emerging or unarticulated customer needs. Its purpose is not merely to accumulate information, but to expand the firm's perceptual field and identify signals that may indicate potential opportunities for exploration (Bérard & Cloutier, 2024; Tajeddini et al., 2026).

In this sense, intelligence capability operates as the firm's market-sensing radar. It filters the external environment by directing attention toward strategically relevant signals while reducing exposure to irrelevant noise (Christofi et al., 2024). Firms with stronger intelligence capability are better able to detect weak signals, recognise shifts in customer behaviour, monitor technological discontinuities, and anticipate changes in industry conditions (Dasgupta, 2019). This makes intelligence capability central to opportunity exploration because unexplored opportunities rarely appear as fully formed strategic options. They are usually embedded in fragmented market signals, emerging technologies, competitor actions, regulatory developments, or changing customer expectations (Balta et al., 2024). Intelligence capability, therefore, provides the initial informational basis for opportunity exploration.

In the digital era, intelligence generation is increasingly supported by data-rich infrastructures and information-processing tools. Data is now widely treated as a strategic asset that shapes competitiveness and innovation capacity (Liu et al., 2025) . Business intelligence systems, news mining, natural language processing, real-time reporting, digital audience segmentation, and social media analytics can help firms extract relevant information from large public and proprietary datasets, identify emerging trends, and anticipate shifts in consumer behaviour and market demand. These tools enhance the reach, speed, and precision of intelligence generation by allowing firms to monitor complex market dynamics more systematically (Mostafiz et al., 2023; Tajeddini et al., 2026).

However, digital infrastructures and analytics tools should not be equated with intelligence capability itself. They may support intelligence generation, but the constitutive element lies in the purposive search process through which firms decide what to monitor, which signals matter, and how external information should be related to strategic opportunity exploration. Without this directed search logic, data accumulation may increase informational volume without improving sensing effectiveness (Al Kurdi et al., 2022; Jingwen et al., 2025). Intelligence capability, therefore, depends on disciplined environmental scanning, strategic attention, and systematic signal filtering rather than on technological sophistication alone (Cano-Marin et al., 2024).

Through this function, intelligence capability generates structured inputs about markets, technologies, competitors, customers, regulations, and ecosystems. Yet raw signals do not become strategically meaningful by detection alone. Information must be circulated, connected, validated, and contextualised across organisational and inter-organisational boundaries. This integrative function is performed by the connectivity capability.

Connectivity Capability

Drawing on Brass et al. (2004), connectivity capability refers to the firm's capacity to establish, coordinate, and mobilise networks of actors and communication ties so that relevant information circulates to the appropriate decision-makers in a timely manner. These networks consist of nodes or actors, including individuals, work units, organisations, customers, suppliers, partners, platforms, and knowledge institutions, as well as the ties among them, such as communication, collaboration, workflow, and knowledge-exchange relationships (Brass et al., 2004). Within the sensing architecture, the connectivity capability performs the circulatory and integrative functions. It ensures that signals generated through intelligence activities are not isolated within specific units or data systems, but are shared, validated, and contextualised across the actors capable of interpreting them (Gretzinger et al., 2024; Jayakumar et al., 2024).

Connectivity capability therefore acts as the firm's boundary-spanning sensing network. It opens organisational boundaries and links the firm to external ecosystems where early signs of technological change, customer shifts, competitor movement, and market reconfiguration often emerge (Liu et al., 2025). Through collaborative networks, digital platforms, IoT-enabled infrastructures, supplier relationships, customer interfaces, and open innovation arrangements, firms gain access to heterogeneous information that cannot be generated internally alone (Gretzinger et al., 2024). This makes connectivity central to opportunity exploration because emerging opportunities are rarely visible from a single organisational location. They are often distributed across customers, partners, suppliers, competitors, regulators, technologies, and industry communities (Chen & Yu, 2023).

In this sense, connectivity capability does more than increase information access. It improves the circulation, comparison, and validation of signals across organisational and inter-organisational boundaries. Real-time data exchange, collaborative knowledge flows, and system interoperability allow firms to consolidate dispersed inputs and improve situational awareness (Gretzinger et al., 2024; Jayakumar et al., 2024). Evidence suggests that stronger connectivity improves decision-making speed and comprehensiveness by giving firms timely access to relevant information streams (Alzghoul et al., 2024). Similarly, IoT-enabled integration and digital interconnections can enhance coordination across actors, allowing firms to track subtle changes in operations, customer behaviour, and industry configurations (Bu et al., 2021; Li et al., 2023; Martínez-Ruedas et al., 2024).

Connectivity capability also reduces interpretive isolation. When signals remain confined to individual departments, technical teams, or external partners, they may be misunderstood, ignored, or interpreted narrowly. By embedding firms within interconnected knowledge ecosystems, connectivity capability enables cross-functional interpretation, external validation, and the integration of diverse perspectives (Bhaktiar et al., 2023; Setyawati et al., 2024). This is especially important under uncertainty, where weak signals require comparison across multiple knowledge domains before they can be recognised as meaningful cues to opportunity. Connectivity capability, therefore, strengthens the evaluative dimension of sensing by ensuring that intelligence outputs are exposed to broader organisational and ecosystem-level interpretation.

However, connectivity capability alone is not sufficient. Greater openness, broader networks, or more intensive data exchange do not automatically produce opportunity exploration (Liu et al., 2025). Without analytical capability, connected information may remain descriptive, fragmented, or excessive. In some cases, high connectivity may even increase ambiguity by exposing the firm to too many weak, conflicting, or strategically irrelevant signals (Saeed et al., 2023). The value of connectivity therefore depends on whether connected knowledge can be systematically interpreted, assessed, and converted into strategic insight. This transition from circulated information to opportunity-relevant interpretation is performed by analytical capability.

Analytical Capability

Analytical capability constitutes the cognitive sense-making function of sensing. It refers to the firm's ability to use tools, technologies, managerial cognition, and analytical processes to transform accumulated information into relevant insights (Bag & Rahman, 2023). It performs the evaluative function. converts detected and connected signals into meaningful opportunity frames by interpreting ambiguity, assessing strategic relevance, and determining whether emerging signals warrant further exploration (Eriksson & Heikkila, 2023).

Environmental signals are rarely clear, complete, or self-explanatory. They may be weak, fragmented, contradictory, or distributed across different data sources, actors, and organisational domains. Intelligence capability may detect these signals, and connectivity capability may circulate and validate them, but without analytical capability, they remain informational inputs rather than strategic insight. Analytical capability, therefore, represents the cognitive core of sensing: it assigns meaning to signals, identifies patterns, evaluates uncertainty, and converts dispersed information into opportunity-relevant interpretation (Ciacci & Penco, 2023; Daradkeh, 2023).

In contemporary organisations, analytical capability is increasingly supported by BDAC, AI, predictive modelling, and advanced information-processing systems. These tools allow firms to process large volumes of structured and unstructured data, detect hidden patterns, identify operational anomalies, anticipate customer behaviour, and generate forward-looking scenarios (Eriksson et al., 2022; Ghosh et al., 2023; Zheng et al., 2019). Empirical evidence suggests that analytical capability improves decision quality, reduces uncertainty, and supports the identification of growth opportunities and innovation trajectories (Bell, 2022; Jenkinson et al., 2024). It also enables firms to balance short-term pressures with long-term positioning by assessing alternative scenarios and evaluating the strategic implications of emerging signals (Sagala et al., 2024; Wu et al., 2024). However, analytical capability should not be reduced to technical data processing. Its value lies not only in processing more data, but in transforming information into strategically meaningful conjectures about possible futures. Deep analysis and insight generation enable decision-makers to recognise asymmetric competitive shifts, identify latent customer needs, detect emerging market spaces, and assess whether current business assumptions remain valid (Ciacci & Penco, 2023; Ciampi et al., 2021; Liao & Xie, 2024). In this sense, analytical capability does not simply describe the environment; it interprets it in relation to possible opportunities for exploration.

Providing that, analytical capability also reinforces the recursive nature of sensing. Once signals are interpreted, they generate opportunity hypotheses that guide exploratory experimentation, redirect intelligence activities, and reshape connectivity needs. For example, analytical interpretation may reveal that a weak customer signal requires deeper engagement with users, closer monitoring of a technological domain, or broader ecosystem collaboration. Thus, analysis does not terminate the sensing process. It produces forward-looking opportunity frames that feed back into renewed search, validation, and learning (Foss et al., 2023; Teece, 2017; Teece, 2018).

Learning Capability in the Sensing Process

The relational sequencing of sensing sub-capabilities (intelligence → connectivity → analytical) assumes that sensing is not a one-shot information event but an iterative capability cycle. What makes this cycle cumulative rather than merely repetitive is learning capability. Learning capability refers to the organisation's ability to acquire and translate knowledge from external sources, operations, experiences, and initiatives into improvement changes at the individual, group, and organisational levels (Alkaraeen & Al-Ashaab, 2021). It's therefore positioned as a recursive-refinement mechanism rather than as a constitutive sensing sub-capability.

This distinction is important. Intelligence capability detects and collects environmental signals; connectivity capability circulates and validates those signals across actors; and analytical capability interprets them into opportunity frames. Learning capability does not replace any of these mechanisms. Instead, it improves how they operate over time by embedding experience into search heuristics, knowledge-transfer routines, and interpretive schemas. In this sense, it enables the firm to "learn how to sense": it helps the organisation remember which signals proved meaningful, which knowledge sources were reliable, which interpretations were flawed, and which assumptions about opportunities required revision (Loon et al., 2020; Schmidt & Scaringella, 2020).

Learning capability also explains how sensing develops through experience. DCs evolve through repeated practice, feedback, and learning from prior successes and failures (Eisenhardt & Martin, 2017). In the sensing process, this means that previous cycles of signal detection, knowledge integration, and opportunity interpretation feed back into future sensing routines. Firms learn where to search, which actors to involve, how to validate weak signals, and how to avoid repeating ineffective interpretations. Without learning capability, sensing may become repetitive: firms may continue to scan the same sources, rely on the same networks, and interpret signals using outdated assumptions (Pavlou & El Sawy, 2011). With learning capability, sensing becomes evolutionary because each cycle improves the next.

This recursive role is reinforced by knowledge articulation and codification. Dynamic capabilities develop when organisations collectively discuss, evaluate, and codify what worked and what failed in prior routines (Zollo & Winter, 2002). Applied to sensing, learning capability enables firms to articulate why particular signals were missed, why certain sources proved valuable, or why specific interpretations were inaccurate. It also allows these lessons to be codified into updated scanning routines, revised market intelligence practices, improved knowledge-sharing processes, and more disciplined analytical criteria. Consequently, it transforms experience into more reliable sensing routines.

Further, it supports organisational unlearning. In turbulent environments, firms may be constrained by dominant logics, outdated success beliefs, and prior assumptions about customers, technologies, or markets. These cognitive commitments can distort sensing by filtering out weak signals that contradict established expectations. Learning capability helps firms question and revise these assumptions, discard obsolete interpretations, and update the cognitive frames through which environmental signals are evaluated. This prevents analytical capability from becoming trapped in historical path dependencies and enables the firm to refine opportunity exploration as conditions change.

Accordingly, learning capability occupies a connected but analytically distinct position in the sensing architecture. It supports the conversion of intelligence outputs into usable knowledge, improves the quality of cross-boundary integration enabled by connectivity, and enhances analytical interpretation by incorporating feedback from prior sensing cycles (Dayangan & Aykol, 2024; Pigola et al., 2023; Schwaeke et al., 2025). It does not constitute the immediate sensing triad itself; rather, it sustains the recursive refinement of that triad. This positioning preserves the restrictive architecture of sensing by confining constitutive status to intelligence, connectivity, and analytical capability, while explaining how the sensing system learns, adapts, and improves over repeated cycles.

FRAMEWORK DEVELOPMENT

Teece's (2007) and Teece's (2018) conceptualisation of sensing provides the theoretical basis for the proposed capability architecture. In the dynamic capabilities framework, sensing is the first pillar of the sensing, seizing, and transforming process because it enables firms to identify, develop, and calibrate technological opportunities, customer needs, and strategic challenges under conditions of uncertainty. Sensing is not a passive or static exercise of gathering environmental data. Rather, it is an active, entrepreneurial, and interpretive process through which firms search beyond existing markets, scan the core and periphery of their business ecosystems, engage external knowledge sources, and filter ambiguous signals into opportunity-related conjectures. Teece's microfoundations of sensing therefore include processes for tapping supplier and complementor innovation, directing internal research and development, identifying target market segments and changing customer needs, accessing exogenous science and technology, and using analytical systems and managerial cognition to learn, sense, filter, shape, and calibrate opportunities.

Building on this logic, the present study reconstructs sensing as a capability architecture comprising three constitutive mechanisms: intelligence, connectivity, and analytical capabilities. These mechanisms are selected because each corresponds to a direct and non-substitutable function within Teece's sensing logic. Intelligence capability captures the directed-search and signal-detection function by identifying and filtering relevant information from technological, market, customer, competitor, and regulatory environments. Connectivity capability captures the ecosystem-wide, boundary-spanning function by enabling firms to access, circulate, and validate dispersed knowledge among customers, suppliers, complementors, partners, and external knowledge domains. Analytical capability captures the interpretive and calibration function by converting detected and validated signals into opportunity-relevant insight. Accordingly, the proposed architecture does not add arbitrary dimensions to sensing; rather, it reorganises Teece's (2007) sensing microfoundations into a clearer configurational structure of detection, validation, and interpretation.

This study conceptualises sensing as a capability architecture through which firms transform ambiguous environmental signals into opportunity exploration. As shown in Figure 1.1, sensing comprises three core mechanisms: intelligence capability, connectivity capability, and analytical capability. Intelligence capability performs the detection function by identifying and filtering relevant environmental signals (Pigola et al., 2023; Rashidirad & Salimian, 2020; Xiang et al., 2024). Connectivity capability performs validation and integration functions by circulating these signals among organisational and inter-organisational actors; however, connected information remains descriptive rather than analytically interpreted (Daradkeh, 2023; Schwaeke et al., 2025). Analytical capability converts integrated information into opportunity-relevant insight, but its value depends on the relevance and validity of the signals generated and circulated through intelligence and connectivity (Ciacci & Penco, 2023; Leemann & Kanbach, 2022). Accordingly, sensing is not the additive sum of isolated capabilities, but an aligned configuration of detection, validation, and interpretation (Schmidt & Scaringella, 2020).

Learning capability is positioned outside the core sensing triad as a recursive-refinement mechanism. It strengthens the architecture by helping firms retain experience from prior sensing cycles, revise search routines, update knowledge-sharing patterns, and improve interpretive assumptions (Christofi et al., 2024; Mezger, 2014; Zollo & Winter, 2002). In this way, learning explains how sensing evolves over time rather than how sensing is constituted at a single point. Consequently, opportunity exploration is treated as the outcome of an aligned sensing configuration. It emerges when firms detect relevant signals, validate them across knowledge sources, and interpret them into strategic opportunity frames. The framework therefore explains how firms move from environmental ambiguity to opportunity exploration through detection, validation, interpretation, and learning-based refinement.

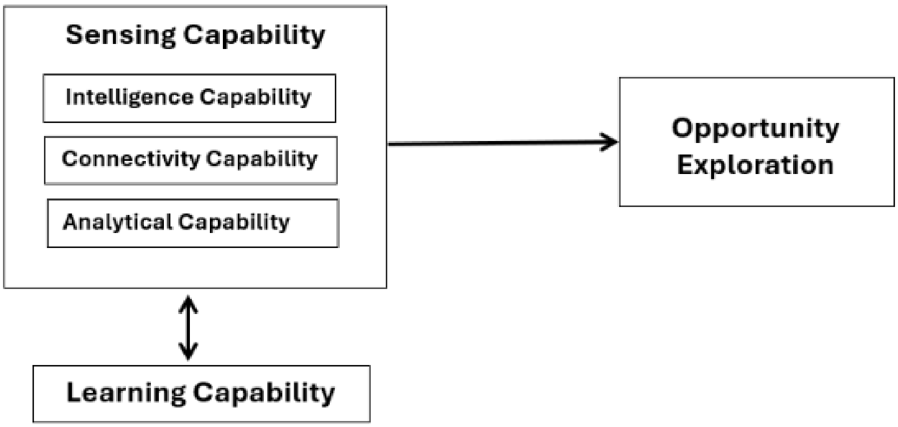

Figure 1. Sensing and Opportunity Exploration framework

Proposition 1: Opportunity exploration is more likely when intelligence, connectivity, and analytical capabilities are jointly aligned as complementary mechanisms for detection, integration, and interpretation within sensing capability.

Proposition 2: Intelligence capability contributes to opportunity exploration when signal-detection activities are supported by connectivity capability that validates dispersed information and analytical capability that interprets signals into opportunity-relevant insight.

Proposition 3: Connectivity capability contributes to opportunity exploration when knowledge-access and validation activities are aligned with intelligence capability and supported by analytical capability for strategic interpretation.

Proposition 4: Analytical capability contributes to opportunity exploration when interpretive activities are supported by relevant signal detection and validated knowledge flows.

Proposition 5: Learning capability supports the sensing configuration by enabling experience retention, assumption revision, feedback integration, and recursive refinement across repeated sensing cycles.

DISCUSSION

Teece's foundational view positions sensing as the initiating function of DCs. Sensing is not a passive awareness activity or a general information-gathering routine, but a purposive, interpretive, and hypothesis-oriented process through which firms search for technological discontinuities, identify emerging customer needs, monitor competitive shifts, and form conjectures about possible opportunities under uncertainty. It provides the cognitive and informational foundation for seizing because firms cannot commit resources to opportunities that have not first been detected, interpreted, tested, and framed as strategically meaningful (Teece, 2007; Teece, 2018).

However, subsequent research has often moved away from this foundational logic. Sensing is frequently treated as a broad higher-order capability, an aggregated SST dimension, or a reflective bundle of scanning, monitoring, information acquisition, digital, and market-learning activities (Kump et al., 2019; Rashidirad & Salimian, 2020; Witschel et al., 2022). In other studies, AI, BDAC, digital platforms, and information systems are implicitly treated as evidence of sensing capability (Balta et al., 2024; Jenkinson et al., 2024). Although this work shows the relevance of sensing to innovation, performance, and adaptation, it often underdevelops Teece's conjectural and validation-based logic. As a result, sensing becomes conceptually stretched, and its internal architecture remains unclear.

Building on this critique, the framework does not depart from the DCV; rather, it clarifies how sensing operates internally through three key mechanisms. Intelligence capability restores the directed-search function by explaining how firms identify and filter relevant environmental signals. Connectivity capability restores the validation and circulation function by explaining how dispersed signals are exchanged, contextualised, and tested across organisational and inter-organisational actors (Daradkeh, 2023; Liu et al., 2025; Schwaeke et al., 2025). Analytical capability restores the interpretive and conjectural function by converting integrated information into opportunity-relevant insight and preliminary assumptions about possible courses of action (Ciacci & Penco, 2023; Leemann & Kanbach, 2022; Loon et al., 2020). Together, these mechanisms clarify sensing as an architecture of detection, validation, and interpretation rather than as a single undifferentiated capability.

This architecture also reframes sensing effectiveness as a matter of configurational fit rather than isolated capability strength. The issue is not whether a firm possesses more data, broader networks, or stronger analytical tools, but whether its search routines, knowledge connections, interpretive processes, and learning-based refinement mechanisms reinforce one another. Learning capability is central to this interpretation, but not as a fourth constitutive sensing mechanism. It provides the recursive-refinement logic that keeps sensing evolutionary by embedding experience, revising assumptions, strengthening knowledge-transfer routines, and codifying lessons from prior search and interpretation cycles (Christofi et al., 2024; Mezger, 2014; Zollo &

Winter, 2002). This aligns with Teece's view of sensing as a learning-oriented, hypothesis-testing process, in which opportunity conjectures must be validated, revised, or abandoned as new information emerges.

This configurational view also explains why sensing may fail in different ways. First, sensing may fail when data lacks direction, where firms generate market intelligence but lack strategic or managerial alignment to channel that data toward coherent opportunity priorities (Liao & Xie, 2024; Mustikasari & Ciptono, 2025).Second, sensing may fail through connectivity without interpretation, where firms build broad networks, partnerships, and digital linkages but lack the analytical capability to filter and interpret incoming information. This may create information overload, conflicting knowledge inputs, and high coordination costs (Chen et al., 2016; Liu et al., 2025; Roaldsen, 2014). Third, sensing may fail through analytics in the absence of relevant signals, where firms invest in BDAC and advanced analytical systems but lack the intelligence and connectivity needed to source diverse external signals. In this case, analytics may optimise existing routines while weak signals from the broader ecosystem remain unseen (Dayangan & Aykol, 2024; Liu et al., 2025; Pang et al., 2023; Stadtfeld & Gruchmann, 2024). Fourth, sensing may fail through repeated sensing without learning, where firms continue to scan, connect, and analyse but interpret new information through outdated cognitive frames and historical success beliefs. This produces cognitive lock-in and constrains the exploration of opportunities (Liao & Xie, 2024; Mustikasari & Ciptono, 2025).

These failure patterns reinforce a broader boundary issue: not every mechanism that supports sensing should be treated as sensing itself. This is especially important in digital contexts, where AI, BDAC, platforms, IoT systems, and information infrastructures may increase the speed, scale, and precision of data capture and analysis. However, they do not constitute sensing capability on their own. Technology can generate data, detect patterns, and expand access to information, but sensing requires purposive search, cross-boundary validation, managerial interpretation, and assumption refinement. Without these organisational and managerial mechanisms, digital tools may produce informational abundance without opportunity exploration (Balta et al., 2024; Ciacci & Penco, 2023; Jenkinson et al., 2024; Li et al., 2024).

RESEARCH CONTRIBUTION

Theoretical Contribution:

The first theoretical contribution to the DCV is to address the architectural under-specification of sensing. By returning to Teece's foundational view from Teece (2007) till Teece (2023) , this study repositions sensing as a purposive, interpretive, and evolutionary capability process rather than as passive scanning, general monitoring, or broad information processing. The contribution lies in showing that this foundational view requires a clearer internal architecture. Accordingly, the framework specifies how sensing operates through differentiated but interdependent mechanisms that move firms from environmental ambiguity to opportunity exploration. In doing so, the study strengthens the DCV by clarifying the internal process through which the first stage of DCs operates.

The second theoretical contribution lies in generating new knowledge about the internal architecture of sensing. Prior DCV research recognises sensing as a foundational capability, but it often leaves its internal composition under-specified (Joussen et al., 2025; Leemann & Kanbach, 2022; Stadtfeld & Gruchmann, 2024). This study addresses this limitation by identifying three key sensing capabilities: intelligence, connectivity, and analytical capabilities. Intelligence capability explains how firms detect and filter environmental signals; connectivity capability explains how firms validate and integrate dispersed knowledge; and analytical capability explains how firms interpret information into opportunity-relevant insights. By identifying these key sensing capabilities, the study moves sensing research beyond broad descriptions of scanning, monitoring, or information acquisition and provides a more precise explanation of how sensing operates as a capability architecture.

The third theoretical contribution is that the study advances DCV's understanding of sensing by explaining it in terms of alignment, misalignment, and construct boundary clarity. Rather than treating sensing capabilities as isolated predictors with independent effects (Barreto, 2010; Pitelis, 2022; Pitelis et al., 2024; Schwaeke et al., 2025), the study shows that sensing depends on the coherent configuration of detection, validation, interpretation, and learning-based refinement. This shifts the explanation of sensing from the possession of capabilities to their fit. It also explains why sensing may fail even when firms possess strong data systems, broad networks, or advanced analytical tools, because failure may result from misalignment among sensing mechanisms rather than from the absence of one activity.

Further, this contribution improves construct clarity within the DCV by separating sensing from its empirical proxies and technological enablers. Sensing is not equivalent to general scanning, additive information-processing indicators, or the possession of AI, BDAC, platforms, and information infrastructures. Rather, these elements contribute to sensing only when they are embedded in purposive search, validation, interpretation, and learning-based refinement. This clarification reduces construct inflation and advances the explanatory power of the DCV by showing how sensing operates and why it may fail under uncertainty.

Practical Contribution

This study also offers practical contributions for managers seeking to strengthen sensing capability. First, the framework provides a diagnostic tool for identifying where sensing breaks down. Rather than assessing whether the firm has sensing capability in general, managers can examine whether weaknesses lie in intelligence, connectivity, analytical capability, or learning. Each weakness requires a different response: stronger signal detection, better boundary-spanning knowledge exchange, improved interpretation routines, or mechanisms for retaining experience and revising assumptions.

Second, the framework guides managers to build sensing as an integrated system rather than as isolated activities. Investments in market research, digital platforms, analytics tools, partnerships, or customer feedback systems create value only when they are connected. Managers should therefore design sensing routines that link what the firm searches for, who validates information, how signals are interpreted, and how lessons are fed back into future opportunity exploration. Third, the framework has practical relevance for digital transformation. AI, BDAC, IoT systems, and digital platforms may improve data access and analytical speed, but they do not automatically create sensing capability. Their value depends on whether they are embedded in organisational routines that convert data into opportunity-relevant insight.

Finally, the framework supports more disciplined opportunity exploration by helping managers avoid common sensing failures: data without direction, connectivity without interpretation, analytics without relevant signals, and repeated sensing without learning. This enables firms to move beyond fragmented scanning or technology-led experimentation toward a more coherent approach to identifying, validating, and refining emerging opportunities under uncertainty.

CONCLUSION

By returning to Teece's foundational view, this paper reconstructs sensing as a processual and evolutionary capability architecture. The central argument is that sensing should not be reduced to environmental scanning, information acquisition, digital sophistication, or the possession of advanced analytical tools. Sensing is a purposive organisational and managerial process through which firms search, interpret, validate assumptions, and refine opportunity conjectures under uncertainty. This boundary clarification is central to the paper's contribution. AI, BDAC, platforms, IoT systems, and information infrastructures may support sensing by expanding access to data and accelerating analysis, but they do not constitute sensing capability in themselves. Their strategic value depends on whether they are embedded within a coherent architecture of purposive search, cross-boundary validation, managerial interpretation, and learning-based refinement. Without this architecture, digital tools may increase informational abundance while leaving opportunity exploration weak, fragmented, or misdirected. The paper therefore positions sensing as more than a technological or information-processing function. It is an evolutionary capability architecture that becomes effective only when its mechanisms are coherently configured toward opportunity exploration. This distinction strengthens the explanatory precision of the DCV by clarifying what sensing is, what it is not.

Limitation and Future Research

This study is conceptual in nature, and its framework requires empirical validation. Although the proposed architecture clarifies sensing through intelligence, connectivity, analytical, and learning-based refinement capabilities, the relationships among these mechanisms have not yet been tested empirically. Future research should examine whether these key sensing capabilities operate as complementary mechanisms in explaining opportunity exploration. Quantitative studies could test the proposed framework across different organisational contexts, while qualitative case studies could examine how intelligence, connectivity, and analytical capabilities unfold sequentially in real sensing processes and how learning capability refines these transitions over repeated cycles. In addition, this study focuses specifically on sensing rather than the full SST process. This focus is necessary because sensing remains architecturally under-specified, but it also means that the transition from sensing to seizing is not fully examined. Future research should therefore investigate how opportunity exploration produced through sensing becomes linked to opportunity commitment, resource mobilisation, and business model design during seizing. This would help explain how firms move from identifying and validating opportunity conjectures to allocating resources and implementing strategic action.

Third, the framework identifies key sensing capabilities conceptually, but further work is needed to establish appropriate measurement scales. Future research should seek to develop and validate scales that match the processual and configurational ontology of sensing while remaining aligned with Teece's foundational view. Fourth, the framework does not fully account for contextual variation, particularly regarding digital transformation. The relative importance of intelligence capability, connectivity capability, analytical capability, and learning-based refinement may differ across industries, firm sizes, technological intensity, ecosystem complexity, and environmental turbulence. Future research should examine how different contexts shape sensing configurations and when digital technologies strengthen or weaken them. Although AI, BDAC, IoT systems, platforms, and digital infrastructures may enhance signal detection and analytical speed, they may also create information overload, narrow algorithmic attention, or false confidence in data-driven interpretation. Understanding these conditions would provide a more nuanced explanation of the relationship between digital transformation and DCs.

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