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Agentic AI and Circular Procurement Performance: An Empirical Study

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ABSTRACT

Organizations that practice circular procurement in this rapidly changing world face many uncertainties. However, emerging digital technologies, such as agentic AI, can help manage resources and improve responsiveness to better serve both internal and external customers. Drawing on resource-orchestration theory, this study aims to understand the impact of adopting agentic AI in industrial purchasing on circular procurement performance. Data for this study were collected from a developing nation, and the analysis was conducted using covariance-based SEM and a Process analytical method. The results show that firms are most likely to benefit from agentic AI adoption when three prerequisites are present: (i) structured resource scanning and evaluation processes, (ii) integrated cross-functional procurement systems, and (iii) established supplier collaboration routines. This study is the first to theorize the relationship between organizations' agentic AI adoption and circular procurement performance. The findings will help purchasing and supply managers formulate policies and standard operating procedures to effectively manage circular procurement performance in this rapidly changing world.

1 | Introduction

Industrial procurement is undergoing a significant transformation as firms strive to align their sourcing activities with the objectives of the circular economy, operating in increasingly volatile material markets (Farooque et al. 2024). Circular procurement involves creating circular specifications, identifying suppliers capable of recycling materials, sourcing stable second-hand materials, handling reverse logistics, and integrating procurement, engineering, logistics, and sustainability functions (Kristoffersen et al. 2021; Rejeb and Appolloni 2022; Jia and Chen 2024; Laukkanen et al. 2026). These activities demand continuous sensing and rapid decision-making.

Digital technologies have emerged as a transformational tool in industrial operations, enabling companies to remain responsive and integrate circular procurement ideas into sourcing-related decisions (Bag et al. 2025; Petrik et al. 2025). The IoT, blockchain, cyberphysical systems, and sophisticated analytics technologies help in traceability (Van Veldhoven and Vanthienen 2022) and help close material loops by boosting the quality and flow of data throughout product life cycles (Bag et al. 2021; Vaezinejad et al. 2025). Empirical research also reveals that analytics skills supplement a firm's capability to identify and arrange resources and implement circular practices, resulting in improved performance outcomes (Palmié et al. 2021; Gusmerotti et al. 2025). Thus, digital tools help generate visibility into the data required for circular sourcing.

Although prior procurement digitalization research has largely focused on analytics, blockchain, IoT, and platform technologies, these tools primarily enhance visibility, traceability, and decision support (Liu et al. 2023). They remain fundamentally human-directed systems in which managers interpret dashboards, evaluate trade-offs, and initiate actions. In contrast, agentic AI represents a qualitatively different technological paradigm. Agentic systems are autonomous, goal-directed, and capable of executing multistep reasoning processes with limited human intervention (Hughes et al. 2025). Rather than purely providing insights, they can sense environmental changes, generate alternative sourcing strategies, simulate trade-offs, and implement adjustments within predefined governance boundaries. In procurement settings, this means that AI agents can continuously monitor supplier markets, evaluate sustainability criteria, reconfigure sourcing portfolios, and trigger workflow changes in near real time (Xu et al. 2024). This distinction is not incremental but architectural. Traditional analytics optimizes within decision episodes; agentic AI operates across decision cycles (Hughes et al. 2025). Earlier digital tools are reactive and human-in-the-loop. Agentic systems enable human-on-the-loop supervision. Whereas dashboards enhance information processing, agentic AI expands decision execution capacity (Hughes et al. 2025). These differences are particularly important in circular procurement, where managers must simultaneously evaluate cost, recyclability, compliance, material availability, and ecosystem collaboration under high volatility (Mondal et al. 2025). The move from decision support to delegated orchestration, therefore, marks a fundamental shift in procurement capability development. Accordingly, the focus is moving to agentic AI, which is an autonomous, goal-directed system that is able to interpret dynamic indicators, start analyses, run multistep processes, and coordinate among units of an organization with a small degree of human interaction. Agentic AI is capable of predicting risk, restructuring sourcing portfolios, and making autonomous changes to allocations when market conditions change (Aylak 2025). Nonetheless, it is not enough to implement agentic AI. Technology provides value when companies possess the complementary capabilities to acquire, integrate, and leverage AI-enabled assets (Podrecca et al. 2024).

Resource Orchestration Theory (ROT) offers an important perspective to explain how agentic AI may play a role in circular procurement performance (CPP). ROT proposes that the key to obtaining competitive advantage is not the availability of resources but how the manager structures, bundles, and leverages resources over time (Sirmon et al. 2007; Sirmon et al. 2011). In the case of circular procurement, structuring is the process of selecting proper suppliers, sustainability data, and AI-ready infrastructure, whereas bundling is the process of integrating these elements, digital tools, expertise, and workflows into cohesive capabilities, whereas leveraging is the process of applying these capabilities to work with suppliers and achieve circular goals. Despite increasing interest in digital transformation, empirical evidence on how agentic AI develops specific capabilities that drive circular procurement, such as resource acquisition, resource integration, and collaborative innovation (COI), is limited, despite digital and analytics capabilities being recognized to support circular economy initiatives (Andersén 2023).

Three interrelated gaps motivate this study. First, procurement digitalization research has largely examined analytics, platforms, and visibility tools, with limited attention to autonomous AI agents capable of delegated decision execution (Bienhaus and Haddud 2018; Bag et al. 2021; Zeiss et al. 2021; Meena et al. 2025). Second, circular procurement research acknowledges the importance of digital enablers but treats them primarily as background infrastructure rather than as orchestrators of capability development. Third, although ROT emphasizes sequential structuring, bundling, and leveraging of resources, there is little empirical evidence explaining how AI-enabled systems contribute to these stages in sustainability-oriented procurement contexts (Papert et al. 2024). This study examines agentic AI adoption through a structured capability chain involving resource acquisition, integration, and COI. This study addresses the above gaps and advances understanding of how autonomous technologies such as agentic AI reshape CPP. Hence, the study is guided by two research questions:

- *RQ1:* How does agentic AI adoption influence circular procurement performance in industrial purchasing?
- *RQ2:* How do resource acquisition, resource integration, and collaborative innovation mediate the relationship between agentic AI adoption and circular procurement performance?

These questions emerge at a crucial juncture for digital and sustainable procurement research and practice. The relevance of agentic AI is amplified by recent shifts in both regulatory and technological landscapes. Regulatory regimes such as extended producer responsibility, carbon disclosure mandates, and circularity reporting requirements are increasing the informational and coordination burdens placed on procurement functions. At the same time, volatility in secondary-material markets and geopolitical supply disruptions have exposed the limitations of traditional sourcing strategies. These conditions demand continuous sensing and adaptive reconfiguration rather than periodic optimization. Parallel to these pressures, enterprise software providers and consulting firms have accelerated the commercialization of AI agents embedded in procurement and supply chain platforms. Major technology vendors now deploy AI agents capable of supplier scouting, automated contract analysis, ESG screening, and scenario simulation within integrated ERP environments. Industry reports increasingly frame agentic AI not as experimental, but as a strategic infrastructure layer for procurement transformation. This convergence of regulatory complexity, market volatility, and maturing AI-agent architectures makes the present moment particularly appropriate for scholarly examination.

The Sustainable Development Agenda has made circular economy strategies popular among firms worldwide. Circular procurement is gaining recognition as a driver of financial and environmental performance, but existing digital tools remain too slow, siloed, and reactive to support the real-time sensing, coordination, and decision-making needed for circular economy strategies (Kristoffersen et al. 2021; Guida et al. 2023). Circular procurement relies on continuous material-flow monitoring, quick sustainability trade-off assessments, and close supplier collaboration capabilities that traditional or rule-based systems cannot reliably deliver (Podrecca et al. 2024). These limitations highlight an urgent need for autonomous, adaptive, and highly responsive technologies. Understanding how agentic AI can fulfill this need, and through which capability pathways it can enable better CPP, is therefore both practically vital and theoretically significant.

The rest of the section is organized as follows. Section 2 provides the literature background and theory; Section 3 provides the theoretical framework and research hypotheses. Section 4 details the empirical methodology. Section 5 presents the covariance-based structural equation modelling (CB-SEM) and process-driven data analysis. The discussion of the findings is laid out in Section 6. The final section covers the concluding remarks.

2 | Theoretical Underpinning

Recent advances in AI further contextualize the emergence of agentic systems. Although earlier AI applications in supply chains primarily focused on predictive analytics and optimization (Dubey et al. 2020). However, recent work highlights the growing role of generative AI and large language model-based systems in supporting decision-making, knowledge integration, and circular innovation (Banh and Strobel 2023; Du et al. 2026; Malhotra and Manzoor 2026; Xia et al. 2026). Emerging evidence also shows how AI-driven systems are being applied in domain-specific contexts such as automated waste recognition, circular construction practices, and end-of-life processing, thereby enhancing sustainability-oriented decision capabilities (Chen et al. 2026; Soomro et al. 2026; Tian and Sarkis 2026). Building on these developments, agentic AI represents a further shift toward autonomous, goal-directed systems capable of initiating and executing multistep decisions within defined governance structures. This evolution reflects a transition from assistive intelligence toward delegated orchestration in organizational and supply chain contexts.

This study integrates literature from information technology, circular economy, and procurement management areas (see Figure 1).

2.1 | The Circular Economy and Agentic AI

Circular procurement (CP) is a set of practices that apply the principles of the circular economy to the purchasing process and emphasize resource efficiency, waste management, material reuse, and working with suppliers to establish closed-loop supply chains (Rejeb and Appolloni 2022). The application of conventional digital tools is popular in automating, optimizing, and minimizing the environmental impact of supply chain operations (Bienhaus and Haddud 2018; Bag et al. 2021; Petrik et al. 2025). These tools are good at providing visibility but lack responsiveness.

The consultancy/industry reports indicate that AI has evolved through distinct functional paradigms that differ in purpose, autonomy, and role in organizational decision-making. Early forms of AI, including predictive and traditional rule-based systems, primarily focus on identifying patterns in historical data to support forecasting and optimization, thereby enhancing decision-making but remaining dependent on human initiation and interpretation. More recent developments in generative AI extend these capabilities by enabling the creation of new content such as text, images, or code through large-scale pattern learning, typically in response to user prompts. Although generative AI enhances creativity and analytical support, it remains largely reactive and input-driven in nature.[1]

In contrast, agentic AI represents a qualitatively distinct paradigm characterized by goal-directed autonomy and delegated execution.[2] Rather than purely supporting or generating outputs, agentic AI systems are designed to perceive, reason, act,

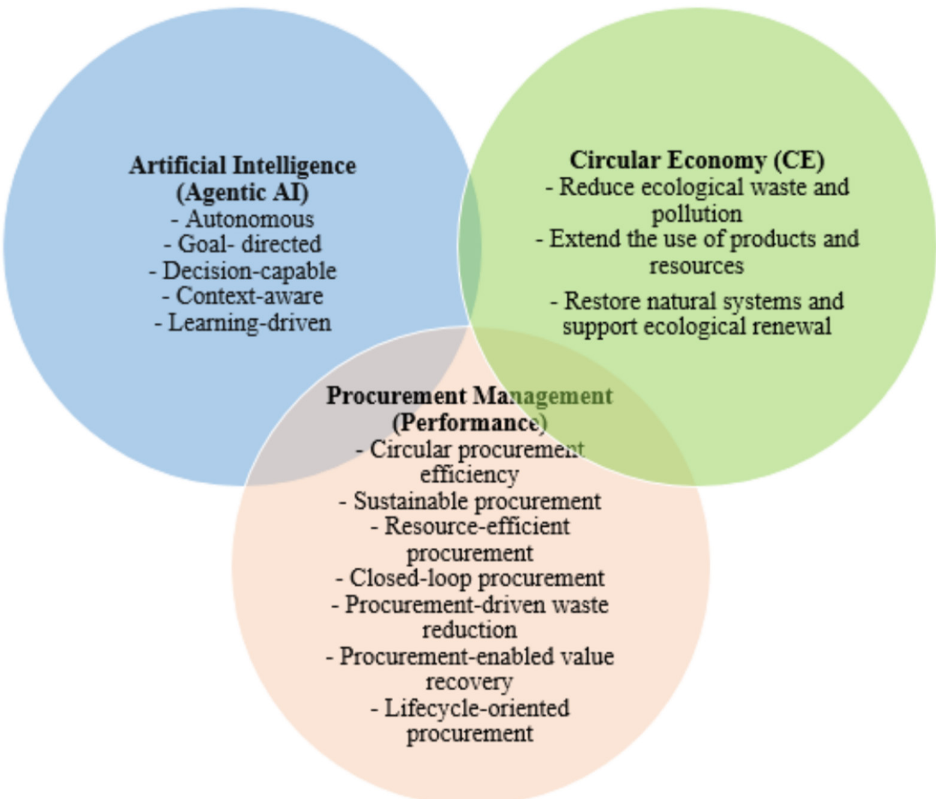

FIGURE 1 | Key concepts of our study (Source: Authors' own work).

and learn in pursuit of defined objectives, often with limited human intervention. These systems integrate large language models with machine learning, natural language processing, and external tools to initiate analyses, evaluate alternatives, and execute multistep decisions within predefined governance boundaries. Notably, agentic AI operates proactively, adapting to dynamic environments and coordinating actions across tasks and functions, thereby extending organizational decision-making from human-in-the-loop support toward human-on-the-loop supervision.[3,4]

This distinction is critical for procurement contexts. Whereas predictive and generative AI enhance information processing and content generation, agentic AI enables delegated orchestration of sourcing decisions, including continuous supplier monitoring, evaluation of circular trade-offs, and execution of adjustments in response to changing conditions. Accordingly, agentic AI is conceptualized in this study not simply as a digital capability, but as an autonomous, goal-directed system that expands the scope of organizational decision execution, thereby fundamentally differentiating it from adjacent AI constructs.

The literature also indicates that agentic AI is conceptually distinct from conventional AI or analytics systems (Dubey et al. 2020; Hughes et al. 2025). Predictive analytics and decision-support tools provide recommendations that require human interpretation and execution; agentic AI systems possess autonomy, goal-directed reasoning, and delegated execution capacity. They are capable of independently initiating analyses, evaluating alternative actions, executing multistep decision sequences, and adapting behavior based on feedback within defined governance parameters (Hughes et al. 2025). In procurement contexts, this implies that AI agents do not merely inform buyers but can autonomously monitor markets, reconfigure sourcing options, trigger workflow adjustments, and coordinate actions across functions (Xu et al. 2024). This autonomy and delegated action capacity define the "agentic" nature of the construct and distinguish it from general digital tool adoption (Hughes et al. 2025).

Agentic AI is rapidly advancing, but its application in the procurement and supply chain context remains nascent. For example, SustAI-SCM, as illustrated by Aylak (2025), is a transformer-based agentic AI that can effectively reduce costs and carbon footprint by learning from past procurement trends and carbon footprint history. There is industry evidence to suggest that agentic AI is becoming a viable option. According to EY and SAP, agentic AI can continuously scan markets, assess suppliers in terms of sustainability and circularity, and automatically suggest lower footprint and recycled products or take back options, thereby transforming procurement into a more active process that aligns with circular sourcing (EY 2025[5]; SAP 2025[6]). Thus, agentic AI has the capability to limit material use and handle the complexity and dynamism of circular procurement.

However, we must understand that agentic AI is not a binary phenomenon but rather varies in terms of autonomy and decision scope. Research on human–automation interaction emphasizes that autonomy exists along levels, from systems that merely inform or recommend actions to systems that execute decisions with human supervision ("human-on-the-loop") and, at the highest levels, operate with delegated authority under governance constraints. This autonomy gradient is important because higher levels imply broader delegation, reduced human intervention during execution, and stronger system initiative, which can materially alter organizational decision architectures and coordination patterns (Endsley and Kaber 1999; Parasuraman et al. 2000). Relying with this view, agentic AI in procurement can be conceptualized across (i) task agents that automate bounded activities (e.g., supplier screening), (ii) process agents that coordinate sequences of procurement tasks across systems, and (iii) orchestration agents that adaptively reconfigure sourcing options and coordinate decisions across functions and partners. These distinctions matter because the capability effects of agentic AI should scale with autonomy and cross-functional reach (Jannelli et al. 2025).

2.2 | Resource Orchestration and Managerial Capabilities

ROT posits that organizations can gain a competitive advantage by not just owning resources but also by how they structure, bundle, and leverage resources over time (Sirmon et al. 2007; Sirmon et al. 2011). ROT explains how resources can be converted into capabilities. There is evidence of the application of ROT in purchasing and sustainability research. Purchasing orchestration practices, an extension of ROT, are critical drivers of innovation performance (Schmelzle and Tate 2022). Andersén (2023) extended ROT to develop green resource orchestration capability, which is central to creating environmental and economic value in sustainability contexts. Kristoffersen et al. (2021) demonstrate that business analytics capabilities enhance firms' resource orchestration capabilities.

The ability of agentic AI to provide autonomous sensing, planning, and adaptive decision-making, thereby expanding and reconfiguring the resource base of firms in real time, aligns with the structuring processes in ROT (Sirmon et al. 2011; Aylak 2025). It provides a combination of digital, material, and relational resources through integrating data across the whole procurement, engineering, logistics, and sustainability in capabilities needed to achieve a circular procurement (Van Veldhoven and Vanthienen 2022; Schmelzle and Tate 2022). Using these capabilities, it is able to support COI through multiagent coordination and automated engagement with suppliers, which is essential to circular results in volatile ecosystems (Brown et al. 2020). Placing agentic AI in this context, thus, is theoretically coherent and new: Agentic AI may be seen as a resource that needs to be orchestrated as well as an orchestrator given its inherent capability, which can dynamically organize data, suppliers, and workflows in real time. This duality is particularly relevant to the focus of ROT on managerial orchestration, and it expands to include AI-enabled orchestration. It is of particular relevance to volatile, resource-constrained circular supply chains that require continuous structuring, bundling, and leveraging, rather than episodic approaches.

Agentic AI functions both as a resource to be structured and as an enabling mechanism that augments managerial orchestration capacity. It enhances sensing, accelerates bundling through cross-system integration, and facilitates leveraging via coordinated supplier interaction. In this sense, AI does not replace managerial agency but extends orchestration bandwidth under environmental complexity.

ROT emphasizes managerial actions rather than resource stocks (Sirmon et al. 2007; Sirmon et al. 2011). Structuring refers to acquiring and accumulating resources; bundling refers to stabilizing and integrating resources into capabilities; leveraging refers to mobilizing capabilities to achieve value creation. In this study, resource acquisition capability (RAC) reflects structuring actions, resource integration capability (RIC) reflects bundling processes, and COI reflects leveraging behaviors enacted through ecosystem coordination. Thus, the mediators are not treated as static firm attributes but as manifestations of ongoing orchestration activities.

2.3 | CPP

CPP measurement is used to determine how procurement processes minimize waste, ensure products have long life cycles, and support reuse and recycling through well-informed procurement decisions and effective supplier cooperation. The available literature suggests that circular supplier selection, digital sourcing of secondary resources, and take back or remanufacturing initiatives can play a crucial role in enhancing a firm's performance in a manufacturing environment (Zhou et al. 2024). Digital technologies like IoT, analytics, and platform-based procurement also improve CPP by facilitating transparency, connecting stakeholders, and coordination of circular flows via data (Papert et al. 2024; Kristoffersen et al. 2021). Studies on Industry 4.0 confirm that digital purchasing platforms can enhance circularity through increased visibility and efficiency (Bag et al. 2021).

The benefits notwithstanding, CPP is complex to realize in practice. Circular supply chains exhibit extremely unpredictable rates of material return, varying quality of secondary materials, and shifting regulatory requirements, all of which introduce uncertainty into procurement operations (Liu et al. 2022; Reike et al. 2018). Companies also struggle to obtain high-quality circularity data, integrate information across procurement, engineering, and sustainability roles, and align with various ecosystem stakeholders, such as recyclers, remanufacturers, and waste handlers, whose systems may not be interconnected (Guida et al. 2023). Other barriers include a lack of incentive alignment, a lack of commitment on the part of suppliers, and operational conflicts associated with the adoption of circular sourcing models (Bocken et al. 2016). These limitations prove that digital tools, which increase visibility, are not enough; CPP measurement tools need to have more autonomous, adaptive, and cross-functionally integrated decision-making capabilities.

3 | Theoretical Framework and Hypotheses

3.1 | Conceptual Model

Drawing on ROT, the proposed model is conceptualized (see Figure 2). It posits that agentic AI adoption (X) leads to RAC (M_1), RIC (M_2), and COI (M_3), which sequentially mediate the relationship between AI adoption (X) and CPP (Y). The three capabilities are defined as functionally distinct. RAC refers solely to the identification, access, and securing of internal and external resources. RIC refers to embedding, aligning, and coordinating acquired resources within organizational routines and cross-functional processes. COI refers to leveraging integrated resources through joint experimentation, codevelopment, and interorganizational coordination. None of these stages is interchangeable; acquisition expands resource availability, integration stabilizes configurations, and collaboration mobilizes value across boundaries.

Although ROT recognizes that structuring, bundling, and leveraging processes may evolve iteratively and recursively over time, the present model specifies a primary directional pathway for analytical clarity. Structuring logically precedes bundling, as resources must be acquired before they can be integrated. Similarly, integrated capabilities enable more sophisticated leveraging through COI. Although feedback loops may occur in practice, the sequential ordering reflects the dominant temporal logic of capability development rather than a rigid deterministic process.

ROT suggests that capabilities emerge in layered form rather than as independent mechanisms. Structuring activities expand the firm's resource base; bundling activities stabilize and embed these resources into coherent configurations; leveraging activities mobilize these configurations toward value creation (Sirmon et al. 2011). In this hierarchy, lower order capabilities serve as enabling conditions for higher order relational and innovation-oriented capabilities. Accordingly, RAC is conceptualized as foundational. Without acquiring appropriate suppliers, data, and technological assets, subsequent integration efforts lack substance. RIC represents a second-order coherence mechanism that embeds acquired resources into cross-functional routines. COI is positioned as a higher order leveraging capability that mobilizes integrated resources across organizational boundaries. Thus, the three mediators reflect escalating levels of orchestration maturity.

ROT conceptualizes orchestration as enacted by managers but manifested at the organizational level. Accordingly, although managerial actors initiate structuring, bundling, and leveraging processes, the resulting capabilities are organizational attributes. The present study measures these manifestations at the firm level rather than individual decision styles.

3.2 | Hypotheses

3.2.1 | Agentic AI Adoption and CPP

The digital capability provided by agentic AI is fundamentally different and can likely improve the performance of the circular procurement process through enhanced sensory, decision-making, and action processes of firms within a dynamic sourcing environment. Continuing evidence shows that evidence-based digital and analytics capabilities boost resource efficiency, reduce waste, and support sustainable supply chains (Kristoffersen et al. 2021; Bag and Rahman 2024). Recent research demonstrates that AI and big data analytics improve supply chain performance and manufacturing sustainability

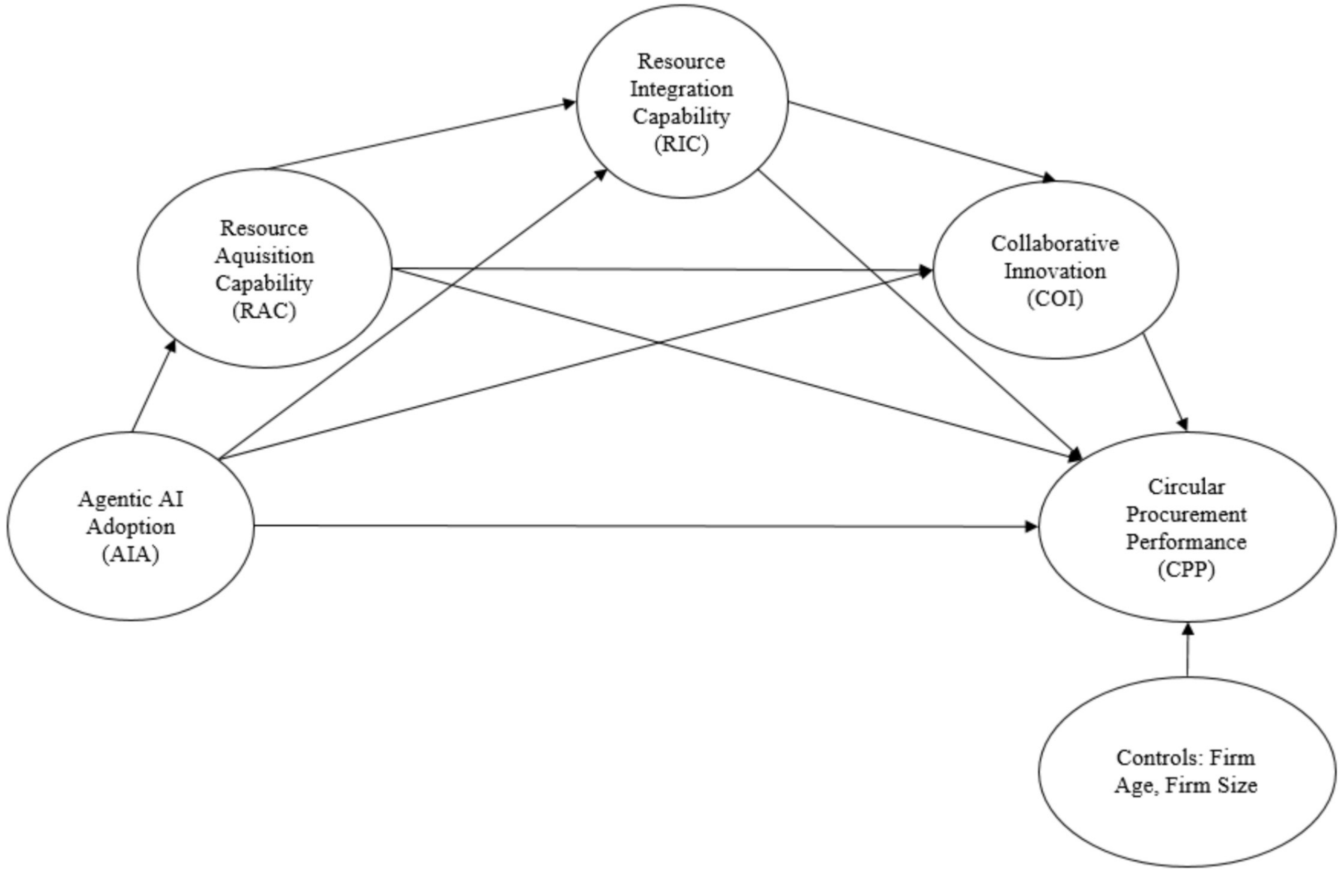

FIGURE 2 | Theoretical model (*Source:* Authors' own work). Note: a) Direct effect of AIA on CPP b) Indirect effect of AIA on CPP through RAC and RIC in serial c) Indirect effect of AIA on CPP through RAC and COI in serial d) Indirect effect of AIA on CPP through RIC and COI in serial d) Indirect effect of AIA on CPP through RAC, RIC, and COI in serial.

by ensuring resource optimization and minimizing waste (Yu et al. 2022). Studies on circular procurement also find that circular sourcing, supplier collaboration, and reverse-flow integration positively influence firm performance, yet they view digital tools mainly as background enablers rather than potential drivers (Bag et al. 2026). In contrast to traditional analytics, agentic AI is capable of identifying and evaluating suppliers on its own, has multistep processes that cut sourcing cycle times, and increases supplier relationships and procurement costs, which directly make procurement circular responsive and impactful, unlike traditional analytics. Meanwhile, the role of AI in sustainable and circular supply chains has been shown to increase environmental performance, reduce ESG decoupling, and strengthen the link between the circular economy and Industry 4.0, implying that advanced AI can contribute to operational and sustainability performance (Podrecca et al. 2024; Zhang et al. 2025).

ROT posits that resources create sustained value primarily through managerial structuring, bundling, and leveraging processes (Sirmon et al. 2007; Sirmon et al. 2011). Accordingly, the dominant mechanism through which agentic AI should influence CPP is expected to operate through capability development. However, certain technological resources may generate limited immediate efficiency spillovers prior to full orchestration. Agentic AI systems can automate information processing, reduce manual coordination burdens, and accelerate decision cycles. These efficiency-enhancing effects may directly improve aspects of procurement responsiveness, even before deeper resource acquisition, integration, and COI capabilities are fully developed. Such effects do not contradict ROT; rather, they reflect short-term operational spillovers that are not entirely captured by the structured capability chain. Therefore, although the primary performance impact of agentic AI is theorized to unfold through resource orchestration mechanisms, a residual direct effect may persist.

H1. *Agentic AI adoption (AIA) positively influences circular procurement performance (CPP).*

3.2.2 | Serial Mediation Through Acquisition and Integration

ROT suggests that new technologies do not provide value until the appropriate resources are first acquired by managers, then combined into coherent capability bundles, and leveraged by the manager to enhance performance (Sirmon et al. 2011; Fawcett et al. 2022). In the case of circular procurement, the adoption of agentic AI can be viewed as a structuring decision, which equips the firm with advanced digital resources such as autonomous agents, high-quality data, and analytics infrastructure that can be used for more effective searching, evaluating and selecting circular inputs and suppliers in order to strengthen its

RAC. Prior empirical work has shown that buyer-driven knowledge and digital engagement spur the development of acquisition capabilities, which then increase the outcomes of green and circular innovation, and prove that access to richer information and also external resources is a vital first step in the direction of sustainability-oriented performance enhancements (Awan et al. 2021). However, acquired resources only create value when they are combined and embedded into organizational processes, systems, and routines, i.e., when they are bundled into a RIC. Studies on digital and circular transitions find that business analytics and digital technologies mainly contribute to visibility of data but need automated cross-boundary integration mechanisms (Kristoffersen et al. 2021; Ströher et al. 2025). These findings imply a sequential process with adoption of agentic AI first improving RAC by increasing and enriching access to circular-relevant resources (e.g., suppliers, data, and technologies) and then improving RIC by supporting the systematic combination of these resources into procurement processes, platforms, and routines that support the circular sourcing and reverse flows of resources that ultimately enhance CPP. Accordingly, and consistent with ROT's structuring-bundling–leveraging framework, this study posits that:

H2. *Agentic AI adoption (AIA) positively influences circular procurement performance (CPP) through resource acquisition capability (RAC) and resource integration capability (RIC) in serial.*

3.2.3 | Serial Mediation Through RAC and COI

ROT suggests that new technologies initially expand a firm's access to valuable resources and then enable higher level collaborative processes that turn those resources into innovation and performance gains (Sirmon et al. 2011; Fawcett et al. 2022). In a circular procurement context, agentic AI adoption enhances RAC by autonomously scanning markets, mining ESG and circularity data, and identifying nonobvious partners such as recyclers, remanufacturers, and secondary-material suppliers. This broadens and deepens the pool of circular-relevant knowledge, materials, and technologies accessible to the buying firm. Empirical research on green and circular innovation indicates that buyer-driven knowledge and resource acquisition activities are critical for sustainability-oriented innovation: firms that strengthen their acquisition capabilities through buyer involvement and external knowledge sourcing achieve higher levels of green product and process innovation (Awan et al. 2021). However, merely accessing new resources is not enough; circular transitions typically require COI with ecosystem partners to redesign products, services, and business models around closing loops. Brown et al. (2020) argue that "collaborative circular oriented innovation" is essential for exploring and implementing circular strategies, however remains underresearched empirically. They show that effective COI depends on shared information, complementary resources, and trust-based relationships among firms. Recent studies on open and circular innovation also find that collaboration and resource sharing across stakeholders such as suppliers, customers, recyclers, and technology providers are crucial for achieving circular outcomes, especially when digital technologies facilitate knowledge and resource flows (Rajput and Singh 2019; Runiewicz-Wardyn 2023).

Therefore, this body of work supports a sequential pathway where agentic AI adoption first enhances RAC by enabling firms to identify and secure circular-relevant resources and partners. This increased RAC then supports richer COI with these partners (e.g., codeveloping circular sourcing solutions, take back schemes, or closed-loop business models), ultimately improving CPP. In line with ROT's structuring-leveraging approach and the evidence on acquisition-driven COI, this study proposes:

H3. *Agentic AI adoption (AIA) positively influences circular procurement performance (CPP) through resource acquisition capability (RAC) and collaborative innovation (COI) in serial.*

3.2.4 | Serial Mediation Through RIC and COI

ROT posits that technology provides competitive advantage only when managers not only acquire new resources but also integrate them into coherent capability bundles and then leverage those bundles through coordinated actions with partners (Sirmon et al. 2011; Fawcett et al. 2022). In a circular procurement context, agentic AI adoption improves the integration capability of resources (RIC) by enabling firms to integrate newly acquired digital and circular resources (e.g., supplier sustainability information, traceability information, and secondary material options) into procurement processes, IT systems, and routines. Empirical studies on circular economy show that the circular implementation and performance of firms are improved by digital and analytics capabilities, mainly by providing better capabilities of firms to orchestrate and integrate data, tools, and partner resources across functions and product life cycles (Kristoffersen et al. 2021; Liu et al. 2022). Nonetheless, the value of such integrated resource bases is usually realized through COI with ecosystem partners: Brown et al. (2020) demonstrate that circular-oriented innovation almost always requires structured collaboration to develop circular value propositions, align on shared goals, and codesign circular business models. They note that empirical research on these collaborative processes remains limited. Other recent works in digital and circular supply chains also observe that digital technologies and platforms can support the collaborative redesign of resource loops between waste operators, suppliers, and manufacturers such as joint recycling, take back, and remanufacturing alliances, noting that an integrated digital infrastructure is a precondition of successful collaboration (Liu et al. 2022; Papert et al. 2024). In general, this literature confirms a progressive process according to which the adoption of agentic AI can initially improve RIC by introducing the relevant data, tools, and procedures in a circular way into procurement systems. This improved integration then facilitates deeper COI with suppliers and other circular partners (such as codeveloping circular procurement criteria, shared traceability solutions, and closed-loop contracts), ultimately improving CPP. Drawing on ROT's bundling-leveraging logic and emerging evidence on digital-enabled collaboration for circular outcomes, this study therefore proposes:

H4. *Agentic AI adoption (AIA) positively influences circular procurement performance (CPP) through resource integration capability (RIC) and collaborative innovation (COI) in serial.*

3.2.5 | Three Serial Mediators

ROT suggests that managers create advantage by sequentially structuring, bundling, and leveraging resources, rather than through isolated actions (Sirmon et al. 2011; Fawcett et al. 2022). Applied to agentic AI in circular procurement, this logic indicates that AI's performance effects should develop through a linked process: Firms must first acquire suitable resources, then integrate them, and finally leverage them collaboratively with partners. Agentic AI adoption enhances RAC by enabling firms to identify and secure new circular-relevant resources more broadly and efficiently than human buyers alone, thereby strengthening the structuring phase of resource orchestration (Bag et al. 2021; Meena et al. 2025). Empirical studies of green and circular innovation have shown that acquisition capabilities developed through external knowledge search and buyer engagement are crucial antecedents of sustainability-oriented innovation (Awan et al. 2021; Andersén 2023). However, only acquired resources provide value when integrated into organizational processes and systems in the form of coherent configurations, which is why Kristoffersen et al. (2021) show that business analytics capability enhances circular economy implementation and firm performance fully as a result of improved resource orchestration capability; the focus on digital resources is that to provide value to the firm, they must be bundled and embedded before they influence outcomes.

In circular supply chains, recent research also shows that digital technologies facilitate circular strategies by helping companies incorporate various information flows, processes and contributions from partners into reinvented resource loops (Liu et al. 2022). Once resources are integrated, it becomes easier for firms to utilize them for COI with other actors in the ecosystem. Brown et al. (2020) demonstrated that the process of circular-oriented innovation often requires collaboration to develop joint circular propositions, harmonize goals and co-develop circular business models with process steps in building circular business models from initial opportunity framing to joint implementation. Open circular innovation research similarly emphasizes that integrated resource bases and information flows enable deeper stakeholder collaboration and shared development of circular solutions (Runiewicz-Wardyn 2023). The literature supports a three-stage serial mechanism in which agentic AI adoption first enhances RAC, which then improves RIC, enabling richer COI with suppliers and other circular partners, ultimately leading to superior CPP. The sequencing reflects increasing levels of resource maturity. Acquisition expands the resource base but does not guarantee coordination. Integration stabilizes and embeds resources across functions, enabling coherence. Only once coherence is achieved can firms effectively leverage these integrated resources in COI with ecosystem partners. This maturation logic aligns with dynamic capability hierarchies, where lower order capabilities enable the development of higher order relational capabilities.

H5. *Agentic AI adoption (AIA) positively influences circular procurement performance (CPP) through the sequential chain of resource acquisition capability (RAC), resource integration capability (RIC) and collaborative innovation (COI).*

4 | Methodology

4.1 | Survey Design

A cross-sectional survey was administered to collect data for this study. The questionnaire measures constructs such as agentic AI adoption, the three mediators (RAC, RIC, and COI), CPP, and control variables (firm age and firm size). Items were adapted from past studies. Constructs such as agentic AI adoption were operationalized to capture autonomy, delegated execution, and goal-directed reasoning rather than general digitalization intensity. Items were carefully formulated to reflect the degree to which AI systems independently initiate analyses, evaluate alternatives, and execute procurement actions within governance constraints. Although agentic AI differs in autonomy and decision scope, this study models adoption as an organizational-level "delegated orchestration capacity" in procurement, capturing the overall extent to which AI agents are embedded with authority to initiate, recommend, and execute procurement actions under supervision, consistent with established autonomy-level theorizing.

The construct, RAC, includes items that assess the ability to obtain data, technologies, and supplier relationships, adapted from absorptive capacity and digital capability scales. RIC includes items that measure the integration of AI insights into procurement routines and cross-functional processes. COI encompasses items that gauge the joint development of circular solutions with suppliers. Although COI may be influenced by broader firm policies, the measurement items were designed to capture enacted coordination behaviors within procurement functions rather than formal strategic declarations. Respondents evaluated the extent to which procurement actively engages suppliers in joint experimentation, problem-solving, and circular solution development. These behaviors reflect leveraging actions consistent with ROT rather than static policy commitments.

Lastly, CPP includes items capturing reuse, recycling rates, waste reduction, and emissions reduction.

The questionnaire was slightly modified based on expert opinion. Furthermore, the modified questionnaire was pretested with 150 managers in India with experience in digital and circular purchasing and supply management. After verifying the validity and reliability criteria, we found them satisfactory and used the tested scale (See Table A1) in the main survey.

4.2 | Sampling and Data Collection

The target population consists of manufacturing and service firms in India engaged in digital and circular procurement activities. We applied purposive sampling of firms. We identified firms via professional bodies and databases. For instance, we considered the Confederation of Indian Industry, Federation of Indian Chamber of Commerce and Industry, NASSCOM, supply chain associations, and LinkedIn to identify company lists when selecting samples in India. We selected firms operating in India as the empirical context because manufacturing and service firms in the country have embarked on significant digital and sustainable initiatives aligned with the national policy priorities. Programs such as *Digital India, Make in India, and the Mission Life* sustainability campaign have accelerated the adoption of advanced analytics, AI-based procurement tools, and circular economy practices across industries. Moreover, India is the fourth-largest economy today and one of the fastest growing manufacturing and service hubs. This makes India an ideal setting for our empirical data collection to examine how agentic AI adoption influences CPP. The diversity, scale, and technological momentum of firms in India provide a meaningful and relevant context for this study.[7]

As per our sampling plan, we decided on the following inclusion criteria at the firm level, such as including firms operating in India. Moreover, the firm must have a formal procurement/purchasing and supply management function. The firm must be engaged in ongoing sourcing of goods and services. Moreover, the firm must have some degree of digitalization in procurement, such as the use of e-procurement tools, agentic AI pilots, or other digital plans. At the respondent level, the participant must be employed in a procurement, purchasing, supply chain role, or a senior executive role. They should have a minimum of 5 years of experience in digital (AI) and circular procurement/supply chain in the industry.

Although responses were collected from individual managers, the unit of analysis is the procurement function at the organizational level. Samples were selected based on their seniority and cross-functional exposure to ensure they possessed sufficient knowledge of firm-level procurement processes. Items were phrased to reflect organizational practices (e.g., "our procurement function") rather than individual behavior. This approach aligns with prior capability and resource orchestration research that relies on knowledgeable key informants to capture organizational-level constructs (Teece 2007; Sirmon et al. 2011).

We have five latent variables and 37 observed variables. We considered a 5% probability level. According to Danielsoper's recommended calculation (Soper 2025), the minimum sample size to detect a 30% effect is 188. Hence, the goal was to collect at least 188 usable responses to ensure 90% statistical power for serial mediation analysis (Cohen 2013; Westland 2010). The survey was started in December 2024, and it took almost a year to collect 500 complete responses from 500 firms. We followed institutes ethical guidelines to conduct the survey. Informed consent was completed by all participants. The demographic details of participants are presented in Table A2.

4.3 | Bias Countermeasures

We controlled and tested nonresponse bias (NRB) and common method bias (CMB) in this study to enhance the rigor of the empirical findings. NRB was assessed using the widely accepted extrapolation method proposed by Armstrong and Overton (1977). Responses received during the first 2 weeks were considered "early responses," whereas those received in the last 2 weeks of data collection were considered "late responses." Independent sample *t*-tests were performed across all constructs. The results indicated no statistically significant differences between early and late respondents. This strengthens our confidence that the sample is representative of the target population.

We collected data using a survey questionnaire; therefore, CMB was carefully addressed following procedural guidelines by MacKenzie and Podsakoff (2012) and Podsakoff et al. (2024). Several ex ante remedies were incorporated, including assuring respondents of anonymity and confidentiality. We also clarified that there are no right or wrong answers to our questions. In addition to procedural controls, we also performed some statistical tests. For instance, we conducted a full-collinearity test (Kock et al. 2021). The computed VIFs for all latent constructs were below the recommended threshold of 3.3, indicating the absence of collinearity. We also tested Harman's single factor test and the unrotated factor solution shows that the first factor accounted for 35.66% of the total variance. Furthermore, we used a marker variable test and did not find any major changes after adding these variables. These procedural and analytic checks confirmed that the data is not influenced by NRB or CMB.

5 | Results

The measurement model was examined using CB-SEM (Bagozzi and Yi 1988). The reason is due to the study uses reflective constructs that must be checked against their theoretical structure. This approach allows the factor loadings, error terms, and interconstruct correlations to be evaluated together while also providing global fit statistics. These features enable the determination of whether the indicators accurately represent their intended latent variables and whether the measures demonstrate adequate reliability and validity. Once the measurement properties were established, the analysis moved to the structural phase. Serial mediation was estimated with PROCESS, which relies on regression-based path estimation and uses bootstrapping to generate confidence intervals for indirect effects (Hayes 2017, 2018). This method is suitable since we expected the three mediators (Neyişçi et al. 2022) to operate in a particular sequence, and when the aim is to understand how the influence of the predictor (AIA) flows through each mediator (RAC, RIC, and COI).

5.1 | Validity and Reliability of Constructs

Given the conceptual distinction between agentic AI and other digital tools, particular attention was given to construct validity. Items were designed to capture autonomous sensing, goal-directed reasoning, and delegated execution, which constitute the defining features of agentic systems. This ensures alignment between the theoretical framing of agentic AI as an autonomous orchestrator and its empirical operationalization.

The measurement model was assessed through reliability, convergent validity, and discriminant validity following established guidelines (Gaskin et al. 2025). We used the CB-SEM approach to analyze the measurement model (see Figure 3).

Table 1 presents the factor loadings, Cronbach's alpha, composite reliability, and average variance extracted for all constructs.

All constructs exhibited strong internal consistency. Cronbach's alpha and composite reliability values are above the recommended threshold of 0.70 (Hair et al. 2018). The results indicate

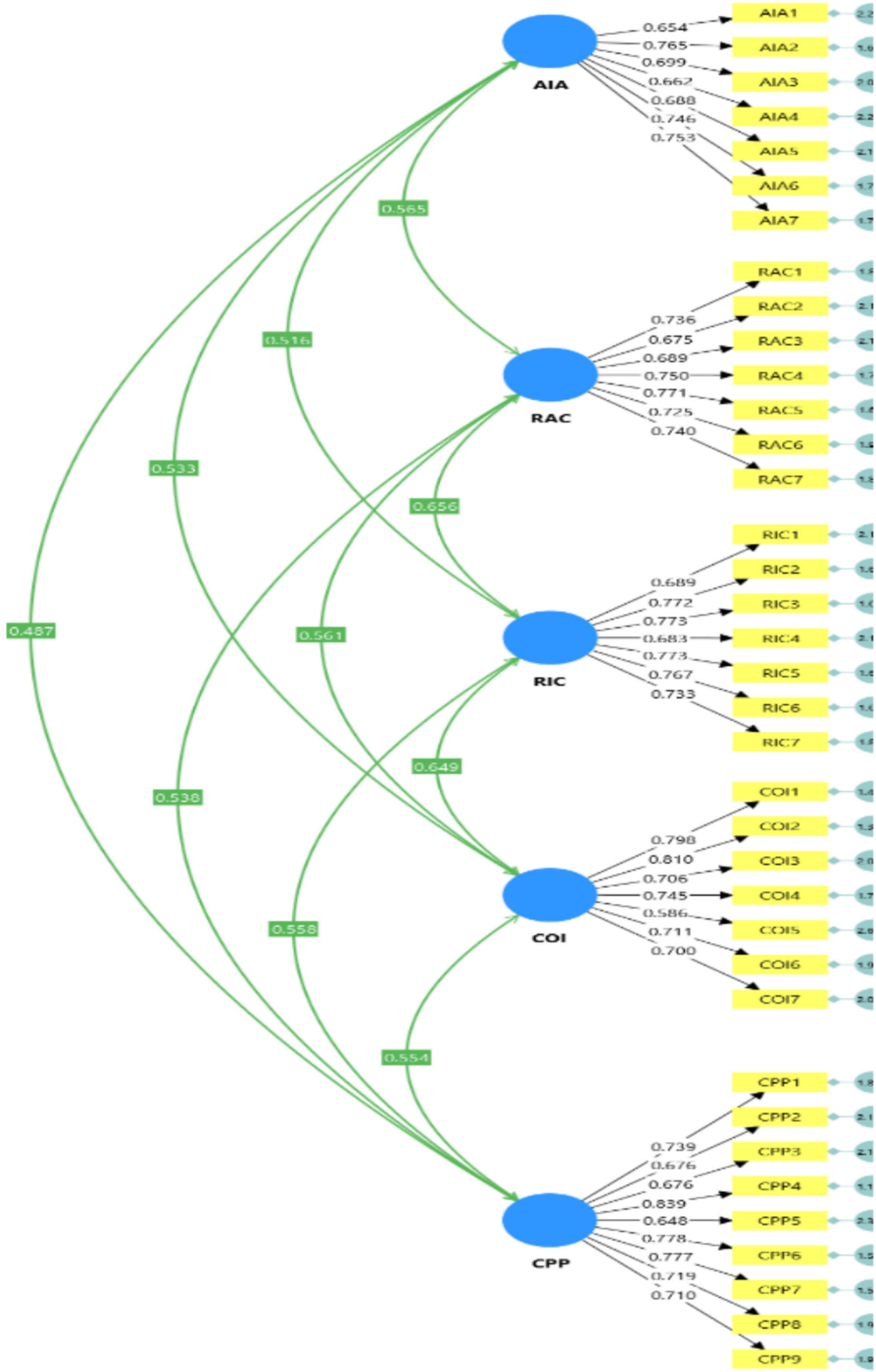

FIGURE 3 | Measurement model analysis (Source: Software output using CB-SEM).

TABLE 1 | Convergent validity.

Constructs	Items	Loadings	Cronbach's alpha (CA)	Composite reliability (CR)	Average variance extracted (AVE)
Agentic AI adoption in purchasing and supply management (AIA)	AIA1	0.654	0.876	0.877	0.505
	AIA2	0.765			
	AIA3	0.699			
	AIA4	0.662			
	AIA5	0.688			
	AIA6	0.746			
	AIA7	0.753			
Resource acquisition capability (RAC)	RAC1	0.736	0.886	0.887	0.529
	RAC2	0.675			
	RAC3	0.689			
	RAC4	0.750			
	RAC5	0.771			
	RAC6	0.725			
	RAC7	0.740			
Resource integration capability (RIC)	RIC1	0.689	0.895	0.895	0.551
	RIC2	0.772			
	RIC3	0.773			
	RIC4	0.683			
	RIC5	0.773			
	RIC6	0.767			
	RIC7	0.733			
Collaborative innovation (COI)	COI1	0.798	0.884	0.885	0.526
	COI2	0.810			
	COI3	0.706			
	COI4	0.745			
	COI5	0.586			
	COI6	0.711			
	COI7	0.700			
Circular procurement performance (CPP)	CPP1	0.739	0.911	0.911	0.535
	CPP2	0.676			
	CPP3	0.676			
	CPP4	0.839			
	CPP5	0.648			
	CPP6	0.778			
	CPP7	0.777			
	CPP8	0.719			
	CPP9	0.710			

that the scale items consistently represent their respective latent constructs.

Convergent validity was evaluated using factor loadings and AVE. All loadings exceeded 0.60 (Hair et al. 2018). AVE values surpass the acceptable threshold of 0.50, confirming that each construct explains more than half of the variance of its indicators. Therefore, these results validate adequate convergent validity (Table 1).

Discriminant validity was examined using the Fornell–Larcker criterion (Fornell and Larcker 1981) and the HTMT ratios (Henseler et al. 2015). Table 2 shows that the square root of AVE for each construct was greater than the intercorrelations. This indicates satisfactory discriminant validity.

HTMT ratios ranged from 0.485 to 0.659, which is below the recommended cut-off value of 0.85 for conceptually distinct constructs (see Table 3). This indicates that acquisition, integration, and COI represent empirically distinct orchestration stages rather than overlapping dimensions of a single construct.

The results indicate an excellent model fit. Chi-square value is significant and chi-square/degrees of freedom is 1.106 and within the recommended limit of 3.0. Additional fit indices all exceeded accepted thresholds: RMSEA = 0.015 (90% CI: 0.004–0.021), SRMR = 0.028, CFI = 0.993, TLI = 0.992, NFI = 0.932, GFI = 0.933, AGFI = 0.924, and PGFI = 0.822. Hence, all indices confirm the appropriateness of the measurement specification.

5.2 | Hypothesis Testing

Data is analyzed using PROCESS. Although SEM can be used to estimate mediation relationships, this study employs the PROCESS (Model 6) for hypothesis testing because the proposed framework involves a sequential three mediation structure that directly aligns with Hayes' (2017, 2018) specification. The serial multiple mediation model estimates the indirect effects of AIA on CPP through each mediator alone and in sequence (see Figure 4). Bootstrapping (5000 resamples) is used to test the significance of indirect effects. The structural model results provide strong empirical support for all hypothesized relationships (Figure 3 and Table 4). AIA was found to positively influence CPP directly, supporting H1. However, consistent with the theoretical framing, this effect is interpreted as residual relative to the mediated pathways. The magnitude of the indirect effects through resource acquisition, integration, and COI indicates that capability development constitutes the dominant mechanism linking agentic AI to CPP.

AIA also exhibited significant positive effects on each capability in the mediating chain, i.e., RAC, RIC, and COI, providing a foundation for the serial mediation effects. The indirect effect results confirmed that H2, H3, H4, and H5 were all significant, demonstrating that AIA enhances CPP through multiple pathways. Specifically, the sequential paths, i.e., AIA → RAC → RIC → CPP; AIA → RAC → COI → CPP; and AIA → RIC → COI → CPP were all statistically supported. The full chain with triple mediators, AIA → RAC → RIC → COI → CPP, was also significant. The control variables, firm age, and firm size did not exhibit significant effects on CPP, indicating that the results are robust across firms of different maturities and sizes.

The indirect effects are statistically significant, although their sizes differ across pathways. This is expected in a serial mediation model, where the impact is distributed across multiple stages rather than concentrated in a single link. The combined indirect effect, especially through the full sequence of resource acquisition, integration, and COI represents a meaningful contribution to CPP. This indicates that the impact of agentic AI unfolds gradually through capability building, and even relatively small individual effects can accumulate into practically important improvements.

Although the direct and partial mediation effects remain statistically significant when certain mediators are omitted, such results do not invalidate the hierarchical orchestration logic. ROT does not imply that lower order structuring or bundling actions are irrelevant in isolation; rather, it posits that sustained and scalable performance gains require cumulative orchestration. The triple-chain pathway captures this cumulative effect, representing the most theoretically complete mechanism through which agentic AI influences CPP.

We conducted a post hoc endogeneity test using the Gaussian copula approach. The copula terms were constructed for the independent variable (agentic AI adoption) and included in the regression-based mediation models. The results indicate that the copula terms are not statistically significant, and the inclusion of these terms does not materially change the magnitude, direction, or significance of the hypothesized relationships.

We conducted additional robustness analyses by examining alternative mediation configurations, including reduced and alternative ordering of mediators. The results indicate that although some alternative indirect pathways remain significant, the

TABLE 2 | Fornell–Larcker criterion.

	AIA	COI	CPP	RAC	RIC
AIA	0.711				
COI	0.533	0.725			
CPP	0.487	0.554	0.731		
RAC	0.565	0.561	0.538	0.727	
RIC	0.516	0.649	0.558	0.656	0.742

TABLE 3 | HTMT ratios.

	AIA	COI	CPP	RAC	RIC
AIA					
COI	0.525				
CPP	0.485	0.549			
RAC	0.568	0.563	0.541		
RIC	0.516	0.652	0.558	0.659	

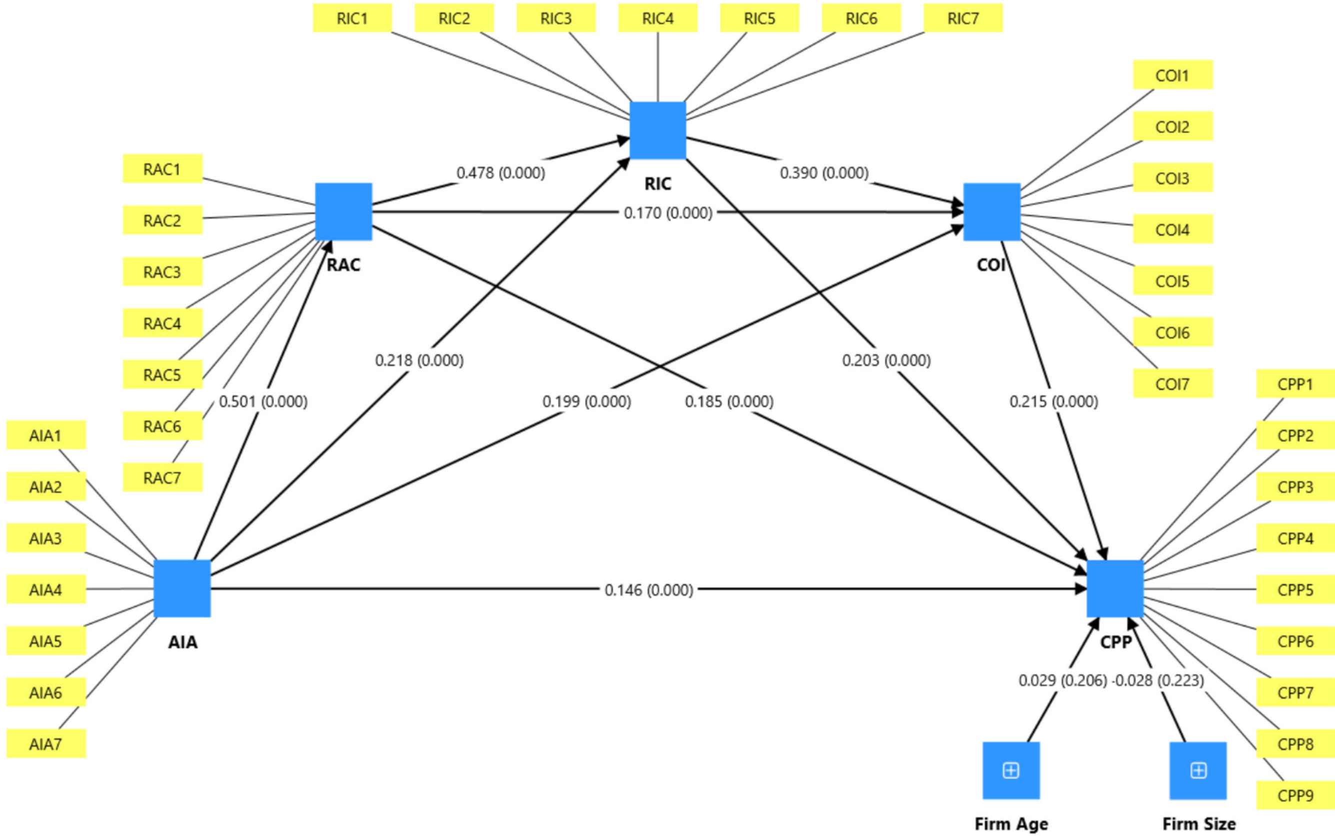

FIGURE 4 | Tested model (Source: PROCESS output).

TABLE 4 | Hypothesis testing results.

Hypothesis	Path	Path coefficient (β)	*t*-value	*p*	95% Bias-corrected and accelerated CI	Supported/ Not Supported
H1	AIA → CPP (direct)	0.146	3.334	0.000	[0.074, 0.216]	Supported
H2	AIA → RAC → RIC → CPP (serial)	0.049	3.680	0.000	[0.028, 0.073]	Supported
H3	AIA → RAC → COI → CPP (serial)	0.018	2.583	0.005	[0.009, 0.032]	Supported
H4	AIA → RIC → COI → CPP (serial)	0.018	3.116	0.001	[0.011, 0.030]	Supported
H5	AIA → RAC → RIC → COI → CPP (full chain)	0.020	3.563	0.000	[0.012, 0.031]	Supported

full serial mediation chain (AIA → RAC → RIC → COI → CPP) provides the most theoretically coherent and empirically consistent pattern of relationships. This finding aligns with the structuring-bundling-leveraging logic of ROT.

6 | Discussion

The results of our study support all hypotheses, providing empirical evidence in favor of agentic AI adoption as a key digital driver of CPP. The study also highlights that the true impact of agentic AI may be realized through capability development, thus confirming and extending previous studies in the areas of digital transformation in procurement and circular economy. H1 illustrates how agentic AI has a direct and positive impact on CPP, which is consistent with research showing that digital and analytics capabilities are positively associated with implementing the circular economy and improving firm performance by enhancing resource efficiency and data-driven decision-making in supply chains (Kristoffersen et al. 2021; Bag et al. 2021). This direct connection is also aligned with the research on Industry 4.0 and AI that highlighted digital technologies as a major facilitator of the circular practice and green procurement, especially in the manufacturing and construction domains, where the data volume and coordination complexity are high (Rejeb and Appolloni 2022). However, by distinguishing agentic AI from conventional digital capabilities, the study extends prior insights and shows that autonomous, goal-directed AI systems can produce more pronounced and rapid improvements in circular procurement than earlier analytics-driven technologies.

The study supports serial mediation H2, H3, and H4, which extend ROT into the domain of AI-enabled circular procurement by demonstrating that the performance effects of agentic AI operate through specific capability chains, rather than through undifferentiated IT resources or static capabilities. ROT posits that managers create competitive advantage by structuring, bundling, and leveraging resources in a sequential manner (Sirmon et al. 2011; Fawcett et al. 2022). H2 validates a RAC-RIC serial pathway, showing the way forward where agentic AI first enhances RAC by increasing access to circularly relevant suppliers, data, and technologies. This enriched resource base is then integrated into procurement systems and routines through a RIC, ultimately improving CPP. This finding is consistent with work that suggests knowledge acquisition and digital tools are important antecedents of green and circular innovation, but that their value emerges only when these resources are integrated into processes and capabilities (Awan et al. 2021; Kristoffersen et al. 2021). H3 and H4 add a leveraging layer by showing that both RAC and RIC feed into COI with ecosystem partners, suppliers, recyclers, and service providers, which is the mechanism through which integrated resources are transformed into circular outcomes. This supports and extends circular-oriented innovation research, which argues that collaboration is essential for closing loops and developing circular offerings but has lacked quantitative evidence on how underlying resource capabilities enable such collaboration (Brown et al. 2020).

Above all, the confirmation of H5 that agentic AI can impact CPP across the entire RAC-RIC-COI chain provides a more detailed model of the process compared to previous research, which either considers digital capability as a single construct or analyses individual mediators. Kristoffersen et al. (2021) demonstrate the idea that business analytics competence enhances the implementation of a circular economy through the coordination of resources, whereas the study on Industry 4.0-circular synergies demonstrates that digital technologies facilitate the achievement of a circular outcome by means of multiple dynamic capabilities, without specifying a particular set of steps to take (Kristoffersen et al. 2021). This study, by empirically illustrating a three-stage serial chain, elucidates that there is no immediate or parallel way for agentic AI to enhance circular procurement: Its impacts are conditional on managers initially deploying AI to purchase the right circular resources, and then on integrating such integrated resources into organizational systems and workflows (RIC), and finally, engaging those integrated resources jointly with partners into the process of cocreating circular solutions (COI). This way, the results not only conform to the logic of structuring, bundling, and leveraging, as developed by ROT, but also expand the latter into an AI-intensive, sustainability-oriented procurement setting, offering a theoretically informed, empirically proven blueprint of how advanced AI should be orchestrated to allow the CPP to be unlocked.

6.1 | Theoretical Implications

Each of the hypotheses is empirically supported and makes significant theoretical contributions to the ROT, research on digital transformation, and the study of the circular economy. The study is a novel implementation of ROT by analyzing the application of agentic AI to build capabilities in a circular procurement process and enhance performance. According to the findings, agentic AI triggers the full framework, bundling and leveraging as described in ROT and operates through RAC, RIC, and COI to improve the performance of circular procurement. Our study integrates the perspectives of the intelligent circular economy literature (Liu et al. 2022), and it becomes evident that the agentic AI implies the dual role whereby managers need to set up, integrate, and implement resources, whereas the orchestrator needs to coordinate suppliers, data flows, and workflows in real time. Such a dual identity enables ROT to expand beyond its conventional human scope but narrows its applicability in the current digital and sustainability-centered procurement environments.

The confirmation of the serial-mediation processes through H2 and H5 also promotes research on digital sustainability by outlining the process of capability building at the microlevel of operation, illustrating how AI-based resources support the performance of circular procurement. Although earlier studies have found direct or parallel impacts of digital tools on the results of the circular economy (Liu et al. 2022; Bag and Rahman 2024), this study reveals a hierarchically dependent pathway to capability: RAC is the structuring mechanism, extending the base of the circular resources, RIC is the bundling mechanism, facilitating the integration of the resources across the functions, and COI is the leveraging mechanism, transforming integrated resources into the procurement outcomes. This sequential procedure answers the demands of multistage theorizing at the digital-circular interface (Zeiss et al. 2021) and states that the introduction of agentic AI to the integration and innovation process is not automatic but relies on the breakthroughs made in resource acquisition in the past.

Moreover, our study recognizes agentic AI as a specific technological construct that is relevant to the AI scholarship pertaining to the supply chain and procurement research. In contrast to predictive analytics or decision-support systems, agentic AI exhibits its autonomy, adaptability, and goal-directed problem-solving, thereby transforming the concept of developing procurement capabilities. The powerful direct influence of agentic AI on the performance of the circle procurement in H1 and the triple serial mediating effect of H5 indicate that agentic AI does not work in the same direction as previous research on digital transformation has shown (Podrecca et al. 2024; Spreitzenbarth et al. 2024). Its dual function as both a resource and an orchestrator clarifies this divergence and highlights the suitability of agentic AI for volatile, resource-constrained, and cyclical contexts.

Thus, the approved RAC-RIC-COI sequence combines three previously discontinuous research fields, including ROT, smart circular economy literature, and digital transformation, into a single process. The following integrative framework serves as a template that can be applied in the generalization of resource restructuring, integration, and capitalization in the transition toward sustainability and in the case of emerging technologies. It provides a powerful framework for further research on agentic AI-enabled regenerative supply chains, circular ecosystem relationships, and procurement 4.0, contributing to the theoretical understanding of how businesses utilize autonomous technologies to achieve a circular and low-carbon solution.

TABLE 5 | Recommendations for stakeholders based on findings.

Stakeholder group	Link to study findings (RAC-RIC-COI Chain)	Key operational issue	Actionable recommendations	Expected outcome
Procurement managers	AIA → RAC	Limited visibility of circular suppliers and materials	Deploy agentic AI agents to autonomously scan supplier markets, monitor circularity indicators, and identify secondary or recycled material sources within defined governance boundaries	Expanded access to circular suppliers and improved sourcing responsiveness
Strategic sourcing teams	RAC (structuring stage)	Manual and episodic supplier evaluation	Configure agentic AI systems to evaluate and rank sourcing alternatives (cost, recyclability, and compliance) and generate sourcing scenarios for decision support and execution	More systematic and faster evaluation of circular sourcing options
Supply chain/ procurement leaders	RAC → RIC	Weak integration of sourcing intelligence into routines	Embed outputs from agentic AI agents into procurement workflows and cross-functional systems (ERP and supplier management), ensuring that AI-initiated actions are aligned with organizational processes	Improved coherence between sensing, decision-making, and execution
Engineering/product design teams	RAC–RIC interface	Disconnect between sourced materials and design feasibility	Engage with procurement to review agentic AI-generated sourcing alternatives and assess technical feasibility (material properties, recyclability, and life cycle compatibility) before adoption	Better alignment between circular sourcing and product design requirements
Production/operations managers	RIC (bundling stage)	Risk in using circular or variable-quality inputs	Provide operational constraints and feedback that can be incorporated into agentic AI decision rules and boundaries, ensuring that autonomous sourcing actions remain production feasible	Reduced risk of operational disruption from AI-initiated sourcing decisions
Planning/PPC managers	RIC → COI interface	Difficulty aligning dynamic sourcing with planning stability	Use outputs from agentic AI systems (e.g., reallocation signals and sourcing adjustments) as inputs into planning reviews, particularly under volatile material availability	More adaptive and informed production planning
Sustainability/ESG managers	COI (Leveraging stage)	Limited operationalization of circular metrics	Define circularity and sustainability criteria that guide agentic AI decision-making (e.g., thresholds for recycled content, emissions, and recovery value)	Stronger integration of sustainability objectives into procurement actions
Innovation/R&D teams	COI	Limited supplier collaboration for circular solutions	Use agentic AI-identified partners and opportunities to initiate joint experimentation (e.g., closed-loop sourcing, alternative materials, and take back systems)	More targeted and data-informed collaborative innovation

(Continues)

TABLE 5 | (Continued)

Stakeholder group	Link to study findings (RAC-RIC-COI Chain)	Key operational issue	Actionable recommendations	Expected outcome
IT/digital transformation teams	AIA → RIC	Lack of integration and governance of autonomous systems	Ensure interoperability of agentic AI agents with enterprise systems; implement governance mechanisms (human-on-the-loop oversight, audit trails, and decision boundaries) for autonomous execution	Reliable, controlled, and scalable deployment of agentic AI
Top management	Full RAC–RIC–COI chain	Viewing agentic AI as a standalone tool	Treat agentic AI as a capability-enabling infrastructure; invest sequentially in acquisition, integration, and collaboration capabilities; establish clear governance and accountability for AI autonomy	Sustained performance improvements through structured capability development
Suppliers/ecosystem partners	COI	Limited coordination in circular initiatives	Engage with buyer firms through data sharing and structured interaction protocols that can be utilized by agentic AI systems for monitoring, evaluation, and coordination	Improved collaboration and alignment in circular procurement activities
Technology providers (agentic AI vendors)	AIA (enabler)	Misalignment between agentic AI systems and procurement needs	Develop agentic AI solutions with delegated execution capabilities, explainability, and configurable governance boundaries suited to procurement workflows	Higher adoption and effective use of agentic AI in procurement
Policymakers/ regulators	Governance context	Lack of clarity on autonomous AI use in procurement	Develop regulatory guidance on agentic AI transparency, accountability, and human oversight, especially in sustainability-critical procurement decisions	Responsible and trustworthy deployment of agentic AI
Industry associations	Ecosystem coordination	Fragmented adoption practices	Facilitate best practices and standards for agentic AI use in circular procurement, including data-sharing protocols and governance norms	More consistent and scalable adoption across industries

6.2 | Practical Implications

The results of this study provide procurement executives with a clear, action-oriented representation of how they can apply agentic AI and enhance the performance of circular procurement. The study provides different pathways that help to decode the adoption of agentic AI for improving procurement performance. The accepted hypotheses from H1 to H5 suggest that agentic AI enhances the process of circular procurement not through one mechanism, but rather through a complex combination of managerial skills that reinforce each other over time. The implications also contain valuable advice to practitioners on how they should plan, prioritize, and govern their AI-enabled transformational activities in circles. The most significant implication is that resource acquisition ability (RAC), resource integration ability (RIC), and COI are all valuable resources that link agentic AI adoption to CPP. This will help procurement leaders in identifying where there may be weak links in their existing systems. In firms that struggle to identify circular suppliers, estimate the accessibility of recyclable materials, or monitor relevant dynamics in the secondary-material market, the RAC pathway recommends investing in AI-supported supplier discovery, market sensing, and automated tracking of regulatory changes at an earlier stage. When the primary bottleneck is not supplier availability but the fragmentation of data, systems, and processes, the RIC pathway suggests the need to centralize information flows, harmonize data structures, and integrate agentic AI with procurement, sustainability, and engineering platforms. On somewhat mature data systems and fragmented relationships with suppliers, agentic AI can be deployed using the COI approach, which implies joint experimentation, life cycle-aware sourcing, and data-driven cooperation with suppliers.

At the same time, the justification of the entire RAC-RIC-COI chain provides procurement leaders with a strategic roadmap for building circular procurement competencies over the years. According to the findings, agentic AI yields the highest payoffs in cases where companies initially expand their base of circular resources, followed by their incorporation into routines and platforms, and then utilize that platform to engage in innovation over time in partnership with suppliers and partners. This will align with the structuring-bundling-leveraging approach of the ROT, utilizing procurement transformation as an ability enhancement process rather than simply adopting a new technology. Before practitioners can become involved in more sophisticated joint innovations, they need to build capabilities sequentially, including developing circular, scaled-up supplier networks and integrating them.

Another implication of the results is the twofold purpose of agentic AI, as an asset that can be deployed in an organized way and as an organizer that brings data, suppliers, and workflows together on demand. This governance has two sides. Managers should have specific guidelines on how to deal with AI, including data quality guidelines, human-in-the-loop measures, interoperability guidelines, and standards of compliance. The possibility of agentic AI to simplify the process, anticipate disruption, and organize stakeholders cannot be realized in the absence of such structures.

The study's implications have direct application to major procurement activities. During supplier development, agentic AI can periodically assess the supplier's maturity in terms of circularity, identify areas for improvement, and evaluate capabilities for development. In the context of new product development, being able to effectively find circular materials that can be used in engineering applications thus leads to reuse, modularity, and minimization of waste. Supplier performance management AI dashboards will be able to transform classical metrics into circular indices. These insights are useful in helping identify agentic AI as a long-term strategic capability, enabling firms to better allocate resources, aim for realistic transformation phases, and improve responsiveness, supplier collaboration, and sustainability performance in increasingly resource-constrained markets.

The results directly impact key procurement initiatives. Agentic AI continuously evaluates circular maturity in supplier development, finds areas for improvement, and suggests focused capability building. It promotes reuse, modularity, and waste reduction by matching circular materials to engineering requirements for new product development. Supplier performance dashboards transform conventional indicators into circular indices, such as waste diversion and recyclability rates. In resource-constrained markets, these insights present agentic AI as a strategic capacity for resource allocation, progressive change, and improved responsiveness, collaboration, and sustainability.

Table 5 provides a structured set of actionable recommendations tailored to different stakeholder groups. These recommendations translate our findings (e.g., capability chain involving RAC, RIC, and COI) into actions for practice and policy.

7 | Conclusion

The entire world is working to combat climate change. Environmental issues are at the forefront of discussions in international conferences. Organizations are adopting circularity to reduce their environmental impact and the burden on Mother Earth. Managing circularity in this complex world, where the supply chain networks are spread across different geographies, is making the lives of procurement and supply chain professionals difficult. However, the advancement of digital technologies, such as AI, which brings new models, frequently proves to be useful in managing circular practices in this complex world. Nowadays, agentic AI is used in organizations that autonomously work and provide rich insights. Empirical applications of agentic AI and circular procurement remain scarce. Based on ROT, this study aims to understand how the introduction of agentic AI in industrial purchasing influences the performance of circular procurement. Data for this study were gathered from a developing nation, and empirical analysis was conducted. The results show that the use of agentic AI plays a role in improving the performance of circular procurement through three serial mediators: RAC, RIC, and COI. This study theorizes relationships between agentic adoption of AI by organizations and CPP. The research has demonstrated that agentic AI serves as both a strategic resource and an orchestrator of circular activities. The findings will help purchasing and supply managers formulate policies and standard operating procedures to effectively manage CPP in this rapidly changing world.

This study extends ROT by challenging its implicit assumption that orchestration is exclusively enacted by human managers. In the context of agentic AI, orchestration becomes partially delegated to autonomous, goal-directed systems capable of sensing, evaluating, and executing decisions within defined governance boundaries. This introduces a hybrid form of orchestration in which human actors and agentic systems jointly contribute to structuring, bundling, and leveraging processes. In this sense, agentic AI functions not only as a resource to be orchestrated but also as an orchestration-enabling mechanism that expands the scope and speed of decision execution. This contrast suggests that future research should reconsider the locus and nature of orchestration in digitally intensive environments, particularly where autonomous systems operate alongside human decision-makers.

The study has some limitations; e.g., it is a cross-sectional study, which may not capture changes over time, particularly with respect to mediating relations. However, agentic AI applications are in a nascent stage, and secondary data are difficult to obtain, so future researchers may be able to find and further test the model after a few years. Also, single-informant perceptual data are used in this study. Future research could strengthen measurement robustness by adopting multi-informant designs that capture perspectives from different functional areas within the same organization. In addition, the use of objective performance indicators would provide a more comprehensive assessment of CPP.

A further limitation is that agentic AI was modeled at an aggregate level, whereas real-world deployments vary in autonomy and decision scope. Future research could differentiate task agents versus orchestration agents and test whether higher autonomy levels strengthen specific capability pathways (e.g., integration and COI), building on established autonomy-level frameworks. Another limitation is that the study focuses on a developing nation like India, which is investing significantly in AI infrastructure and prioritizing circularity. However, future researchers can collect data from developed nations and perform comparative studies.

Author Contributions

Surajit Bag: writing – original draft, writing – review and editing, visualization, validation, supervision, methodology, formal analysis, data curation, conceptualization. **Susmi Routray**: writing – original draft. **Andrea Chiarini:** writing – original draft. **Rasem Qudaih:** writing – original draft.

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Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

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Appendix A

TABLE A1 | Constructs and measures.

Construct and source	Item no	Items
Agentic AI adoption in purchasing and supply management (AIA) (Jabbour et al. 2019; Yu et al. 2022; Aylak 2025; Hughes et al. 2025)	AIA1	Our procurement agentic AI systems can initiate sourcing analyses without requiring explicit human prompts.
	AIA2	Our procurement agentic AI systems independently monitor supplier markets and sustainability indicators.
	AIA3	Our procurement agentic AI systems autonomously identify and flag sourcing risks or circularity opportunities.
	AIA4	Our procurement agentic AI systems evaluate multiple sourcing alternatives based on predefined strategic and circular procurement objectives.
	AIA5	Our procurement agentic AI systems simulate trade-offs (e.g., cost, recyclability, and compliance) before recommending or initiating actions.
	AIA6	Our procurement agentic AI systems can trigger workflow adjustments (e.g., supplier reallocation, alerts, and contract modifications) within approved boundaries.
	AIA7	Certain procurement decisions are executed by agentic AI systems with minimal human intervention and within predefined authorization limits.
Resource acquisition capability (RAC) (Zahra and George 2002; Teece 2007; Sirmon et al. 2007)	RAC1	Our procurement function systematically identifies emerging technologies that can strengthen sourcing and supply capabilities.
	RAC2	Our procurement function continuously scans external markets for new suppliers, data sources, and technological resources.
	RAC3	We can rapidly secure access to new technological resources when required.
	RAC4	We effectively obtain external knowledge relevant to improving procurement decisions.
	RAC5	We successfully establish new supplier or partner relationships aligned with strategic sourcing needs.
	RAC6	We are capable of allocating financial and organizational resources to support new procurement initiatives.
	RAC7	Our procurement function effectively evaluates and selects new circular suppliers, technologies, or data sources before adoption.
Resource integration capability (RIC) (Flynn et al. 2010; Sirmon et al. 2007; Kristoffersen et al. 2021)	RIC1	We systematically embed agentic AI-generated insights into standardized procurement routines.
	RIC2	Information generated by agentic AI is formally shared and embedded across relevant functions (e.g., engineering and logistics).
	RIC3	Procurement processes are structurally aligned with other departments through shared systems and integrated workflows.
	RIC4	New digital tools are technically integrated with existing procurement IT systems and platforms.
	RIC5	Supplier data from multiple internal and external sources are consolidated into unified decision-support systems.
	RIC6	Internal and external data streams are systematically merged within procurement analytics platforms.
	RIC7	Procurement workflows are digitally interconnected with other functional systems (e.g., sustainability, logistics and finance).

(Continues)

TABLE A1 | (Continued)

Construct and source	Item no	Items
Collaborative innovation (COI) (Lee 2007; Cao and Zhang 2011; Batista et al. 2018).	COI1	We codesign circular sourcing solutions with key suppliers.
	COI2	We conduct joint experimentation with suppliers to develop sustainable material solutions.
	COI3	We jointly develop closed-loop sourcing initiatives with suppliers.
	COI4	We engage suppliers in formal joint innovation projects focused on circular procurement.
	COI5	We engage in structured joint problem-solving sessions with key suppliers to develop circular solutions.
	COI6	Our procurement function coinvests with suppliers in developing new circular technologies or processes.
	COI7	We jointly generate new circular sourcing practices through shared innovation workshops or pilot programs.
Circular procurement performance (CPP) (Potting et al. 2017; Stank et al. 2019; Howard et al. 2019; Kristoffersen et al. 2021; Bressanelli et al. 2022; Richey et al. 2022)	CPP1	Our procurement activities have reduced waste generation in the supply chain.
	CPP2	Our procurement decisions have increased the proportion of recycled or remanufactured materials in our inputs.
	CPP3	Our procurement function has improved material reuse rates across the supply chain.
	CPP4	Our procurement practices have enhanced overall resource efficiency in operations.
	CPP5	Our procurement initiatives have contributed to reducing the environmental footprint of our operations.
	CPP6	Our procurement strategies have improved the circular value recovery from products and materials.
	CPP7	Our procurement function has strengthened the long-term sustainability performance of our supply base.
	CPP8	Our procurement function has increased the recovery value derived from returned or end-of-life materials.
	CPP9	Our procurement decisions have contributed to extending the life cycle of sourced materials or components.

TABLE A2 | Demographic details of participants.

Current position	Frequency	Percentage
Director	45	9%
President/vice president	36	7%
General manager/assistant general manager	71	14%
Operations manager	64	13%
Supply chain manager	91	18%
Purchasing manager	81	16%
Information technology manager	40	8%
Sustainability/HSE manager	39	8%
Others	33	7%
Ownership type	**Frequency**	**Percentage**
Private	337	67%
Public	99	20%
Others	64	13%
Firm age category	**Frequency**	**Percentage**
< 10 years	43	9%
11–20 years	202	40%
> 20 years	255	51%
Firm size category	**Frequency**	**Percentage**
Small (< 50 employees)	115	23%
Medium (50–249 employees)	239	48%
Large (≥ 250 employees)	146	29%
Industry type	**Frequency**	**Percentage**
IT/ITES	70	14%
Food and beverage	59	12%
Automotive	57	11%
Chemicals	55	11%
Electronics	52	10%
Logistics	49	10%
Pharmaceuticals	47	9%
Renewables	43	9%
Textiles	42	8%
Others	26	5%

Biographies

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Andrea Chiarini received a Master's Degree in Electronic Engineering (100/100 cum laude) and a Post Graduate Diploma in Business Administration from Bologna University- Italy. He has also been awarded a Master of Arts (MA) in Social Science and Research Methods (Organisation and Management) and a PhD in "TQM and Business Excellence" subjects from Sheffield Hallam University, UK. He has been researching into Strategic Management, Operations Management, Industry 4.0, TQM, Lean Six Sigma, Logistics, Production Management, and CSR.

Rasem Qudaih is a Lecturer in Digital Business. Qudaih's research interests are centered on Big Data, Artificial Intelligence (AI), blockchain, and the Metaverse. He is particularly interested in how these technologies can drive innovation and create new opportunities across industries.