

The Impact of IT Ambidexterity on Organizational Agility: The Mediating Role of Organizational Change Capacity

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Abstract

Background: Organizational agility (OA) is recognized as a vital capability for competitiveness in dynamic business environments. While IT capabilities are acknowledged as a potential source of OA, there is limited research on the agility-enabling role of IT ambidexterity (ITA), which is the dual pursuit of IT exploitation and IT exploration. In particular, the influence of ITA on market capitalizing agility (MCA) and operational adjustment agility (OAA), which are key agility dimensions, remains unexplored. Although prior work has argued that intermediary organizational capabilities may be required to translate IT capabilities into OA, no previous studies have considered the role of organizational change capacity (OCC), in the ITA-OA relationship. To address these gaps, we draw on the dynamic capability view and the IT-enabled agility literature to examine the relationships between ITA and MCA, OAA, and OA, and propose that OCC mediates these relationships.

Method: A comprehensive quantitative approach, involving the development of a robust research instrument, was used to empirically investigate the relationships between the constructs. Survey data was collected from 173 IT professionals. The analysis was performed using partial least squares structural equation modelling to assess the measurement model and to test the hypotheses.

Results: Our findings reveal that ITA has a direct positive impact on MCA, OAA, and OA, while OCC partially mediates the ITA-MCA, ITA-OAA, and ITA-OA relationships. All measurement and structural model assessment criteria were met, demonstrating the robustness of our conceptualized model.

Conclusion: The results highlight the importance of balancing IT exploitation and exploration to foster OA, particularly through OAA and MCA, and introduces OCC as an intermediary capability that facilitates the translation of ITA into OA, and its dimensions. The theoretical arguments and empirical evidence offer insights for future research and organizational practice into the direct and indirect role of ITA in developing organizational dynamic capabilities.

Keywords: IT Ambidexterity, Organizational Agility, Organizational Change Capacity, Organizational Capabilities, Dynamic Capability View.

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Introduction

Contemporary organizations operate in dynamic, complex, and uncertain business environments characterized by intense global competition, changing consumer demands, price volatility, and shifting trading regulations (Lee et al., 2021; Mikalef & Pateli, 2017; Tallon et al., 2019). In this environment, organizational agility (OA) has emerged as a crucial capability for swiftly adapting to environmental changes and seizing new opportunities (Teece et al., 2016; Walter, 2020). While OA can be influenced by organizational factors such as culture, structures, and workforce adaptability (Känsälä & Tokumaru, 2023; Sindhwani & Malhotra, 2017; Walter, 2020), research in the past two decades has increasingly focused on the role of IT capabilities in enhancing OA (Barlette & Baillette, 2022; Ghasemaghaei et al., 2017; Liang et al., 2022; Ravichandran, 2018; Sambamurthy et al., 2003; Tallon et al., 2019).

However, fostering OA through IT is a challenging, often long-term endeavor, requiring numerous IT-related capabilities (Lowry & Wilson, 2016; Queiroz et al., 2018). The challenge is intensified by the rise of digital transformation and new digital business models (Ameen et al., 2024; Del Giudice et al., 2021; Grass et al., 2020). The contemporary IT landscape demands that IT functions manage both traditional enterprise systems and services, while simultaneously developing digital business capabilities for innovation and digital value creation (Leonhardt et al., 2017; Vetter et al., 2023). Balancing the exploration of new opportunities in the digital business arena with the stable exploitation of existing IT resources presents a dual challenge, resulting in impeding tensions (Gregory et al., 2015; Syed et al., 2023).

Organizations resolve these tensions by developing IT ambidexterity (ITA), which is “*the dual capacity to explore and exploit IT resources and practices*” (Gregory et al., 2015; Lee et al., 2015, p. 398). The exploration of ITA in information systems (IS) research is crucial for aligning IT management with strategic business objectives in the digital era, highlighting its importance for enhancing IT competitiveness in technologically disruptive markets (Liang et al., 2022; Syed et al., 2020a; Syed et al., 2023; Vetter et al., 2023). For example, organizations such as the Haier group who pursued an ambidextrous IT approach, have seen improvements in flexibility, reliability, and response time, thereby enhancing their competitiveness (Huang et al., 2012; Lee et al., 2015). However, despite emerging circumstantial evidence, research on the potential performance benefits of ITA is limited (Syed et al., 2020b; Syed et al., 2023).

While ITA is recognized as a key enabler of agility (Syed et al., 2020a; Zhen, Xie, et al., 2021), a comprehensive exploration of its direct impact on the multifaceted dimensions of OA remains a significant gap in the literature (Lee et al., 2015; Liang et al., 2022). For instance, previous research has focussed on operational forms of agility (Syed et al., 2020b), which does not fully encompass the broader notion of OA (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017). Other scholars have explored the isolated effects of IT exploration and exploitation on OA (Zhen, Cao, et al., 2021; Zhen, Xie, et al., 2021), yet neglected the inherent paradoxical challenges posed by pursuing these capabilities concurrently (Gregory et al., 2015; Mithas & Rust, 2016). This gap in understanding the broader implications of ITA on OA necessitates a closer examination of its impact on specific OA dimensions vital in the current business environment. Liang et al. (2022) studied the influence of ITA on the sensing and seizing dimensions of OA, shedding light on its role, yet underscoring the necessity for a more exhaustive examination. OA is frequently conceptualized to encompass the dimensions of operational adjustment agility (OAA) and market capitalizing agility (MCA), which involves rapidly leveraging market opportunities and adapting operational processes (Lu & Ramamurthy, 2011; Madhala et al., 2023). Despite their significance, MCA and OAA remain underexplored in ITA research, prompting our novel investigation into ITA's impact on these specific dimensions and OA overall, aiming to enrich our understanding of ITA's broader impact.

To further explore the ITA-OA nexus, we examine the emerging literature on IT-enabled OA (Tallon et al., 2019). Multiple studies propose that IT capabilities play a pivotal role in directly bolstering agility (Ameen et al., 2024; Côte-Real et al., 2017; Hyun et al., 2020; Mikalef & Pateli, 2017; Ravichandran, 2018). Alternative viewpoints underscore neutral or potential obstructive impacts (Ghasemaghaei et al., 2017; Liang et al., 2017; van de Wetering, 2021). This dichotomy in findings has catalyzed a view emphasizing the role of intermediary organizational capabilities in translating IT capabilities, including ITA, into agility (Lee et al., 2021; Liang et al., 2022; Liu et al., 2020). For example, Ghasemaghaei et al. (2017) suggest that achieving OA through IT capabilities requires a strong alignment between firm tasks, analytical tools, data, and workforce competencies, while Liang et al. (2022) suggest that the IT-OA relationship is contingent on environmental dynamism. Liang et al. (2017) suggest that effective business coordination is instrumental in transforming IT alignment into OA. Analogously, Lee et al. (2015) found that operational ambidexterity acts as a bridge between ITA and OA, especially in fluid business environments. Despite these studies, there is still a significant gap in understanding how intermediary organizational capabilities can help organizations leverage and enhance their existing capabilities to improve performance.

Building on the premise that intermediary organizational capabilities are critical in translating IT capabilities into OA, we posit a novel exploration into the role of organizational change capacity (OCC) within the ITA and OA context. OCC is recognized as a key capability for the introduction and execution of strategically aligned change initiatives (Judge & Elenkov, 2005; Soparnot, 2011; Supriharyanti & Sukoco, 2023), and is deemed essential for revitalizing and enhancing existing competencies and nurturing new ones vital for sustained growth (Andreeva & Ritala, 2016; Judge, 2011; Judge & Douglas, 2009). Specifically, we propose that ITA can be instrumental in nurturing OCC by optimizing IT assets and techniques to bolster organizational efficiency (IT exploitation), and by promoting innovation and initiating novel resources and approaches (IT exploration) (Gregory et al., 2015; Lee et al., 2015; Syed et al., 2023). In turn, we posit that OCC can capture the extent to which an organization can “*agilely adapt to evolving conditions*” (Ameen et al., 2024; Mikalef & Gupta, 2021, p. 7). Inspired by its promise to enhance OA and the nascent viewpoint that distinct organizational capabilities might be instrumental in translating ITA into OA, we examine OCC's influence within the ITA-OA nexus—a relationship not yet explored in existing research.

To extend the understanding of the relationships among our constructs, we utilize the dynamic capability view (DCV) as our theoretical lens (Teece, 2007, 2018). This is a unique approach in the context of the ITA-OCC-OA relationship. While the DCV has been used to explain the relationship between lower-order IT capabilities and higher-order dynamic capabilities (DCs) (Ghasemaghahi et al., 2017; Lee et al., 2015; Queiroz et al., 2018), the interaction between ITA, OA and OCC through this lens remains unexplored, marking a gap in the literature. The DCV diverges from the resource-based view (RBV), which emphasizes a firm's inherent resources and capabilities as key drivers for competitive advantage (Steininger et al., 2022). While several IT-enabled OA studies are anchored on the RBV, it often fails to elucidate IT performance gains in dynamic environments (Irfan et al., 2019; Mikalef & Pateli, 2017). Conversely, the DCV, which highlights an organization's adaptability in changing environments (Peteraf et al., 2013; Teece, 2007), is well-suited for our analysis of OCC's role in the ITA-OA relationship, especially considering that OA and OCC offer performance improvements in such dynamic settings (Mikalef & Pateli, 2017; Soparnot, 2011). As such, we conceptualize ITA as a lower-order capability (Lee et al., 2015), OCC as a generic DC (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023), and OA as a higher-order DC (Teece et al., 2016), and contribute fresh insights on their interplay to enhance organizational performance.

To address the highlighted gaps in understanding the direct and indirect effects of ITA on OAA, MCA, and OA overall, through OCC, we pose a crucial and timely research question: How does OCC impact the relationship between ITA and OA? We evaluate this through a novel nomological model that amalgamates the constructs and undertake a rigorous empirical analysis based on structural equation modeling of 173 online survey responses. The results indicate that ITA significantly influences MCA, OAA, and OA overall, with OCC serving a complementary role in translating ITA into agility. This study broadens the understanding of both the direct and indirect effects of IT capabilities on the development of organizational DCs. By elucidating the distinct mechanisms through which ITA and OCC interact and affect OA, our study not only enriches the academic knowledge base but also introduces a unique perspective on the dynamic interplay of these capabilities. This integration of constructs within a singular framework offers a comprehensive understanding of their collective impact, providing actionable insights for organizations aiming to enhance their adaptive capabilities in dynamic environments. These contributions underscore the importance of considering intermediary capabilities for IT-enabled agility, informing both theory and practice.

Theoretical Foundation and Research Model

The Dynamic Capability View (DCV)

Our theoretical underpinning draws on the DCV (Teece, 2007, 2018), which evolved from the RBV (Mikalef & Pateli, 2017; Steininger et al., 2022). While the RBV suggests that organizations can gain a competitive edge through the value, rarity, and non-replicability of their resources, the DCV contends that to maintain competitiveness in dynamic markets, continual refinement of resources and capabilities is essential (Peteraf et al., 2013; Teece, 2018). According to the DCV, the essence of DCs lies in their ability to renew and adapt organizational resources and processes, thereby ensuring sustained competitiveness (Steininger et al., 2022; Teece et al., 2016). This adaptability enhances an organization's ability to navigate environmental changes without succumbing to rigidity (Girod & Whittington, 2017; Mikalef & Pateli, 2017).

While IS research on the underlying processes that lead to the emergence of DCs remains in its formative stages (Conboy et al., 2020; Mikalef et al., 2021; Protogerou et al., 2012), prevailing theories posit that IT capabilities either enable DCs or are embedded in them (Li & Chan, 2019; Steininger et al., 2022). In the embedded perspective, IT capabilities mesh with DCs, ensuring digital strategies become central to businesses.

Conversely, the enabler perspective perceives IT capabilities as supporting the development of DCs, either as a direct result or as an intermediary leading to performance outcomes (Steininger et al., 2022). This perspective suggests that organizational DCs arise from a hierarchical capability-building process (Ayabakan et al., 2017; Grant, 1996; Lee et al., 2015; Sambamurthy et al., 2003).

The hierarchical capability perspective delineates capabilities across different layers, starting from lower-order (functional) capabilities, necessary for efficient current operations, to higher-order DCs focused on strategic activities, namely sensing, seizing, and transforming to ensure adaptability and external fitness (Teece, 2007, 2018; Teece et al., 2016). The hierarchy includes generic DCs, considered universal for all other DCs within an organization, which serve as a source of organizational dynamism and long-term sustainability (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023). In the capability-building process, the development and reconfiguration of functional IT capabilities (i.e., lower-order capabilities) can lead to the enablement of higher-order (Lee et al., 2015; Mikalef & Pateli, 2017; Park et al., 2017) and generic DCs (Andreeva & Ritala, 2016).

Accordingly, we conceptualize the constructs in our study within the hierarchical capability-building viewpoint of the DCV. Specifically, we conceptualize ITA as a lower-order IT capability that can enhance operational efficiency, and that can enable higher-order DCs, such as agility and knowledge processes, thereby enabling organizations to dynamically reconfigure their IT management (Lee et al., 2015; van de Wetering & Versendaal, 2021). Consistent with the literature, OA is conceptualized as a higher-order DC (Park et al., 2017; Queiroz et al., 2018; Teece et al., 2016) that can enable firms to strategically sense and seize opportunities in dynamic environments (Barlette & Baillette, 2022; Tallon et al., 2019). Lastly, following emerging literature, OCC is conceptualized as a generic DC that can cultivate the adaptation and evolution of other DCs embedded within an organization by helping organizations manage change processes, adapt to external shifts, and sustain competitiveness over time (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023).

Through this approach, we aim to reveal how functional capabilities such as ITA support the development of strategic capabilities such as OA and OCC. This provides a comprehensive understanding of their interrelated roles within organizations and elucidates the interconnectedness among the constructs across different levels of the capability hierarchy.

Organizational Agility (OA)

In the dynamic contemporary business environment, OA is regarded as a higher-order DC enabling firms to anticipate and capitalize on opportunities with foresight and dexterity (Barlette & Baillette, 2022; Lee et al., 2021; Tallon et al., 2019; Teece et al., 2016). Agile organizations have an expanded range of possible competitive actions to respond to new opportunities and can better manage environmental pressures (Barlette & Baillette, 2022; Sambamurthy et al., 2003). They are better positioned to increase their revenue and usually benefit from higher profitability (Chen et al., 2014; Ghasemaghaei et al., 2017; Queiroz et al., 2018), making OA a rewarding capability for organizations to pursue (Teece et al., 2016). For example, the platform company Tencent exemplifies OA by adapting to evolving market trends and consumer demands, utilizing data analytics to tailor user experiences across its diverse platforms, thereby boosting its market responsiveness and competitive advantage (Murmann & Zhu, 2021).

The OA literature highlights various characteristics, such as proactiveness, radicalness, responsiveness, and adaptiveness (Lee et al., 2015), as well as various dimensions including customer, partnering and strategic agility (Ameen et al., 2024; Queiroz et al., 2018; Ravichandran, 2018; Sambamurthy et al., 2003), and OAA and MCA (Lu & Ramamurthy, 2011). Among these, OAA and MCA offer a holistic view of OA, by encompassing the agility needed for rapid execution and innovative strategies inherent in several other facets of the notion (Ghasemaghaei et al., 2017; Mao et al., 2020; Mikalef & Pateli, 2017). OAA empowers organizations to swiftly modify their internal operations in response to market dynamics or demand shifts (Lu & Ramamurthy, 2011; Sambamurthy et al., 2003). Conversely, organizations with MCA monitor the business environment for opportunities and act swiftly to capitalize on them by improving their products or services (Ghasemaghaei et al., 2017; Mikalef & Pateli, 2017). Combined, MCA and OAA, represent unique but complementary facets of an organizational capability, with MCA preparing organizations for “entrepreneurial actions”, and OAA for the “*swift implementation and reconfiguration of necessary processes*” (Mikalef & Pateli, 2017, p. 4). However, while the pursuit of OA is crucial, there is limited understanding of the underlying mechanisms that can enhance agility through these dimensions.

Information Technology Ambidexterity (ITA)

Ambidexterity theory, grounded in organizational theory, suggests that organizations can achieve superior performance by balancing exploratory and exploitative activities (O'Reilly & Tushman, 2013; Snehvrat et al., 2018). Exploitative activities aim to optimize current operations within existing paradigms, while exploratory

activities focus on innovation, experimentation, and adapting to environmental changes for long-term growth (Del Giudice et al., 2021; Raisch & Birkinshaw, 2008; Snehvrat et al., 2018). This balance, known as organizational ambidexterity, can be conceived as *“an organization's ability to be aligned and efficient in its management of today's business demands while simultaneously being adaptive to changes in the environment”* (Raisch & Birkinshaw, 2008, p. 375).

Drawing on ambidexterity theory and the potential advantages of balancing strategic exploration with operational exploitation (O'Reilly & Tushman, 2013; Raisch & Birkinshaw, 2008; Snehvrat et al., 2018), there is a nascent stream of IS literature emphasizing an ambidextrous approach to IT (Lee et al., 2015). While a unanimous definition of ITA remains elusive (Syed et al., 2020a, 2020b), there is congruence within the IS field that it represents an organizational capability, highlighting the ability to harmonize the paradoxical yet interconnected demands of exploration and exploitation placed upon modern IT functions (Gregory et al., 2015; Mithas & Rust, 2016; Syed et al., 2023). ITA is considered as a lower-order functional IT capability that can lead to specific higher-order DCs such as OA and knowledge processes (Lee et al., 2015; van de Wetering & Versendaal, 2021). Specifically, ITA can be viewed as *“the ability of firms to simultaneously explore new IT resources and practices (IT exploration) as well as exploit their current IT resources and practices (IT exploitation)”* (Lee et al., 2015, p. 398). IT exploitation represents the ongoing refinement and adaptation of existing IT practices and resources, while IT exploration epitomizes the development of new IT solutions and practices through innovation and experimentation (Mithas & Rust, 2016; Syed et al., 2020b).

Prior research suggests three modes of ambidexterity to manage IT in the organizational context: sequential, structural, and contextual (O'Reilly & Tushman, 2013; Raisch & Birkinshaw, 2008; Syed et al., 2020a). Sequential ITA involves the IT function concentrating sequentially on either IT exploitation or exploration (Syed et al., 2020b). Structural ITA designates IT exploration and exploitation tasks to distinct IT sub-divisions, whereas contextual ITA integrates these tasks harmoniously (Snehvrat et al., 2018; Syed et al., 2023). In the latter approach, organizations can benefit from the coexistence and complementary learning mechanisms of the dual pursuit of IT exploration and exploitation, which is deemed necessary given the incessant technological advances in the IT environment (Syed et al., 2020a; Syed et al., 2023). Yet, there is a scarcity of explicit conceptualization and empirical investigation concerning the direct influence of contextual ITA on OA (Lee et al., 2015), which we aim to address by empirically investigating how contextual ITA, operationalized as a second-order construct encompassing both IT exploration and exploitation, influences OA.

The Relationship between ITA and OA

Previous research emphasizes IT capabilities such as cloud computing, data analytics and enterprise architecture to enable OA (Côte-Real et al., 2017; Ghasemaghaei et al., 2017; Hyun et al., 2020; Liu et al., 2018; van de Wetering, 2021). However, there is limited focus on ITA's impact on agility. For example, Syed et al. (2020b) focused on the impact of ITA on operational agility, overlooking the market capitalizing dimension of OA (Lu & Ramamurthy, 2011). While Lee et al. (2015) did not explicitly hypothesize on ITA's direct impact on OA, their results suggest a link mediated by operational ambidexterity. Liang et al. (2022) examined the direct relationship between ITA and OA but did not construct OA to encompass MCA and OAA (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017), leaving these dimensions underexplored. Other studies indicate that IT exploration and exploitation, both dimensions of ITA, influence OA (Zhen, Cao, et al., 2021; Zhen, Xie, et al., 2021). However, these studies did not account for the concurrent existence and the paradoxical challenges associated with balancing IT exploration and exploitation (Mithas & Rust, 2016; Syed et al., 2023), when fostering OA, nor did they investigate the impact of ITA on MCA and OAA, which are key dimensions of the overall notion of OA (Lu & Ramamurthy, 2011; Madhala et al., 2023; Mao et al., 2020).

The Relationship between ITA and MC

As a second-order construct encompassing IT exploration and IT exploitation, ITA can enhance firms' MCA. IT exploration of new technologies and methodologies can equip organizations with the foresight to identify emerging market trends and opportunities (Lowry & Wilson, 2016; Zhen, Cao, et al., 2021). This innovative approach can allow firms to anticipate environmental shifts and align IT strategies with future growth trajectories (Chen et al., 2014; Lee et al., 2015). For example, organizations with a strong innovation capacity can develop digital platforms adept at sensing and swiftly responding to market dynamics and consumer preferences (Ravichandran, 2018). Concurrently, exploiting IT resources and practices can enable organizations to gather IT-centric data, enhancing the integration of IT assets and facilitating faster responses to market fluctuations (Ghasemaghaei et al., 2017; Joshi et al., 2018; Zhen, Cao, et al., 2021). This can strengthen collaboration with business partners and align business processes with IT capabilities, improving product quality and consumer contentment (Gregory et al., 2015; Zhen, Xie, et al., 2021). For example, exploiting predefined configurable IT systems can allow organizations to proactively respond to market opportunities, enhancing their agility in capitalizing on market conditions (Lee et al., 2015). Through the simultaneous integration of IT exploration and

exploitation, which are unique, yet mutually reinforcing, ITA modeled as a second-order construct, can empower organizations to proactively sense emerging opportunities and swiftly adapt to dynamic markets (Benitez et al., 2018; Lee et al., 2015; Syed et al., 2020a). As such, it is plausible that ITA can enhance MCA, leading to the hypothesis that:

H1a: ITA will have a positive effect on MCA

The Relationship between ITA and OAA

ITA, through its first-order dimensions of IT exploitation and exploration, can allow firms to foster OAA. IT exploitation initiatives, such as digitizing procurement and supply chain systems, can enable organizations to adjust internal operations to support expansion and meet evolving market demands (Huang et al., 2012; Syed et al., 2020a). IT exploitation can also enhance operational capabilities through the efficient utilization of existing IT resources, leading to increased efficiency and precision (Lee et al., 2015; Syed et al., 2023; Tan et al., 2019). For example, IT exploitation can streamline the creation of new products and services, thereby elevating customer satisfaction and profitability (Syed et al., 2020a, 2023). Concurrently, IT exploration can enable organizations to integrate external knowledge, proactively realign internal operations, and enhance organizational resilience in dynamic markets (Benitez et al., 2018; Syed et al., 2020a; Zhen, Xie, et al., 2021). For instance, exploring and integrating new IT resources and practices can promote the transition to new operational processes to make organizations more flexible to respond to market changes (Benitez et al., 2018). By synergistically leveraging the interdependent capabilities of IT exploration and exploitation through ITA, organizations can agilely adjust their internal operations to capitalize on market opportunities (Lowry & Wilson, 2016; Syed et al., 2023; Zhen, Cao, et al., 2021). It is therefore proposed that ITA can support OAA, leading to the hypothesis that:

H1b: ITA will have a positive effect on OAA

The Direct Relationship between ITA and OA

It has already been hypothesized that ITA can foster MCA, and OAA. Though distinct, MCA and OAA are inherently synergistic dimensions of the broader concept of OA (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017; Ravichandran, 2018). Given MCA and OAA's interdependence, examining ITA's integrative role in enabling OA is warranted. For instance, ITA can enable organizations to deliver prompt and relevant IT responses to consumer demands, allowing them to adapt existing operations (i.e., OAA) in the face of market opportunities (i.e., MCA) (Lee et al., 2015; Syed et al., 2023; Teece et al., 2016). When harmoniously cultivated through ITA, organizations can leverage the symbiotic relationship between the market capitalizing and operational adjustment dimensions of OA (Lu & Ramamurthy, 2011; Park et al., 2017; Ravichandran, 2018). Consequently, it is plausible that ITA enhances OA, leading to the hypothesis:

H1: ITA will have a positive effect on OA

Organizational Change Capacity (OCC)

Addressing dynamic and uncertain environments requires organizations to instigate change. However, these initiatives often falter due to inadequate change management (Judge, 2011; Supriharyanti & Sukoco, 2023). Developing an organization's capacity to change is therefore essential (Judge & Elenkov, 2005; Soparnot, 2011), with OCC increasingly being considered a generic DC that can nurture the transformation of other DCs within an organization (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023). More formally, OCC can be described as "an organization's ability to upgrade or revise existing organizational competencies, while cultivating new competencies that enable the organization to survive and prosper" (Judge, 2011, p. 14). Distinct from OA, which focuses on rapidly responding to market changes to build resilience (Teece et al., 2016), OCC supports the initiation and execution of change initiatives that harmonize with the organization's strategic goals, thereby enhancing sustained competitive advantage (Andreeva & Ritala, 2016; Judge et al., 2015; Judge & Elenkov, 2005). For example, the role of companies such as Baidu and Alibaba in China's Belt and Road Initiative, exemplify their leveraging of OCC to strategically position themselves to exploit emerging markets and digital infrastructure opportunities, ultimately enhancing their global competitiveness (Su & Flew, 2021).

Previous studies suggest that OCC incorporates both individual and organizational characteristics vital for devising and implementing change endeavors (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023). OCC involves the capacity and commitment of an organization's human resources to strategize and actualize change initiatives at the individual level, and organizational learning to foster the assimilation of fresh insights during periods of organizational transformation (Andreeva & Ritala, 2016; Soparnot, 2011; Supriharyanti & Sukoco,

2023). OCC also incorporates the capabilities associated with the change process and the change context. The former is characterized by support mechanisms such as practices, values, and structures, while the latter addresses the broader organizational context, such as the political environment, which can facilitate continual change (Judge & Elenkov, 2005; Supriharyanti & Sukoco, 2023).

Drawing on these multi-dimensional OCC attributes, contemporary IS research has begun to streamline the focus on OCC aspects that enable organizations to plan and manage change, thereby minimizing the frictions and inertia that often accompany it (Besson & Rowe, 2012; Mikalef & Gupta, 2021). In both managerial and IS domains, the ability to plan and manage change is considered essential for leveraging digital transformation and deriving overall business value (Besson & Rowe, 2012; Mikalef & Gupta, 2021; Robey et al., 2013). In this context, OCC involves disrupting organizational norms by introducing new practices, values, and organizational structures (Grover et al., 1995; Mikalef & Gupta, 2021). As such, recent IS research has begun to conceptualize and measure OCC to encompass these facets as a single construct (Ameen et al., 2024; Mikalef & Gupta, 2021; Mikalef et al., 2022, 2023). However, a clear articulation of OCC's influence on OA, based on these dimensions, remains unexplored.

The IT-Agility Contradiction

The organizational capabilities hierarchy is growing in importance as a potential resolution to the IT-agility contradiction (Ghasemaghahi et al., 2017; Liu et al., 2018). While IT capabilities play a role, they might not exclusively drive OA (Tallon et al., 2019); other intermediary capabilities could be instrumental in this translation. For example, Ghasemaghahi et al. (2017) highlighted the importance of fit in translating data analytics into OA, while Hyun et al. (2020) showed how collectivistic culture moderates the OA and data analytics relationship. Liang et al. (2017) posited that the relationship between IT alignment and OA was mediated by business-IT coordination; however, contrarily organizational inertia did not mediate the relationship between intellectual alignment and OA. Although research directly exploring ITA's influence on OA is sparse (Lee et al., 2015; Liang et al., 2022), extant studies suggest that moderating or mediating capabilities may be necessary to facilitate the translation of the relationship. For instance, Syed et al. (2020b) demonstrated that ITA had a direct effect on operational agility, but that market complexity moderated this relationship. Similarly, empirical evidence from Lee et al. (2015) not only implied a direct relationship between ITA and OA but also highlighted the mediating role of operational ambidexterity and the moderating role of environmental dynamism in the ITA-OA relationship. Observed inconsistencies suggest that different organizational capabilities may exert differential effects or have varying contributions on the transition of IT capabilities into OA, potentially due to their varying positions in the organizational capability hierarchy (Benitez-Amado & Walczuch, 2012; Liu et al., 2020). While OCC is emerging as a generic DC that can potentially underpin the evolution of other organizational DCs (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023), its role in translating ITA into OA has not been previously examined. Discerning the mediating role of OCC in the ITA-OA relationship is crucial, as it has the potential to enhance this relationship (Mikalef & Gupta, 2021), providing a more comprehensive understanding of how intermediary organizational capabilities contribute to cultivating OA.

The Mediating Role of OCC

Existing literature underscores the significance of IT capabilities in driving organizational change. Robey et al. (2013) classified this body of work as the "IT impact" literature, suggesting a direct link between IT and organizational change (Chua et al., 2019). Extending this notion, we suggest that ITA, which is a functional IT capability (Lee et al., 2015; Syed et al., 2020a), influences OCC, which we conceptualize as a generic DC (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023). OCC embodies the ability to cultivate innovation and establish novel resources, methodologies, practices, and frameworks (Grover et al., 1995; Mikalef & Gupta, 2021) to advance organizational outcomes (Judge et al., 2015). IT exploration is congruently associated with the commitment of organizational resources to understand and trial various nascent IT resources and practices, with the objective of identifying suitable technologies poised to beneficially "*impact current and future business operations*" (Lee et al., 2015, p. 401). Through the exploration of innovative IT resources and methodologies, organizations can ensure that fresh insights and expertise are transferred to innovation and change capacity-shaping processes (Liu et al., 2013; Mao et al., 2020). This supports the assertion that "*technological innovation is associated with organizational change*" (Robey et al., 2013, p. 380).

OCC not only embodies an organization's ability to realign its competencies in a dynamic environment, but it also signifies the proficiency to adapt processes to implement requisite changes that improve organizational performance (Soparnot, 2011; Supriharyanti & Sukoco, 2023). Organizations possessing pronounced levels of OCC are poised to conceptualize solutions fostering intrinsic evolution, whilst being able to respond to the external environment through the realization of internal change (Soparnot, 2011). Congruently, IT exploitation facilitates maximizing the potential of organizational IT resources and practices, repurposing them across different business operations, whilst enhancing organizational efficacy through the assimilation of new ancillary

resources with established business processes (Lee et al., 2015). By capitalizing on IT assets and methodologies, IT exploitation can provide pertinent technical infrastructures and platforms, such as internal corporate networks and external client databases (Lee et al., 2015; Mao et al., 2020), that enhance internal operations and develop new product or service solutions addressing external demands (Lee et al., 2015; Tan et al., 2019). By integrating both IT exploitation and exploration, organizations can leverage their IT resources to optimize operations while enabling the flexibility needed to adapt to market shifts (Liang et al., 2022; Syed et al., 2023), contributing to their capacity to change. As such, it is conceivable that pursuing ITA simultaneously through IT exploitation and exploration can contribute to OCC.

In turn, organizations possessing the capacity for change can swiftly and seamlessly (i.e., agilely) adjust to evolving conditions (Ameen et al., 2024; Mikalef & Gupta, 2021; Najrani, 2016). In particular, the organizational learning facet of OCC (Supriharyanti & Sukoco, 2023) resonates with the sensing DC attributes of OA (Lee et al., 2021; Park et al., 2017; Teece, 2007). For instance, organizations engaged in continuous learning by monitoring both internal and external environmental shifts, can assimilate, comprehend, and employ novel insights throughout the change process (Soparnot, 2011; Supriharyanti & Sukoco, 2023), strengthening their sensing capabilities (Lee et al., 2021). By continuously acclimatizing and updating their knowledge base, these organizations can be better prepared to recognize and act on emerging opportunities, ensuring a proactive approach to capitalizing on market demands (Barlette & Baillette, 2022; Mao et al., 2020; Teece et al., 2016). As such, continual development and adaptation through OCC can enhance an organization's foresight (Supriharyanti & Sukoco, 2023), which is congruent with the inherent sensing capability of MCA (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017). Thus, building on the argument that ITA can influence OCC, it is plausible that OCC can, in turn, influence MCA, leading us to hypothesize that:

H2a: OCC mediates the relationship between ITA and MCA

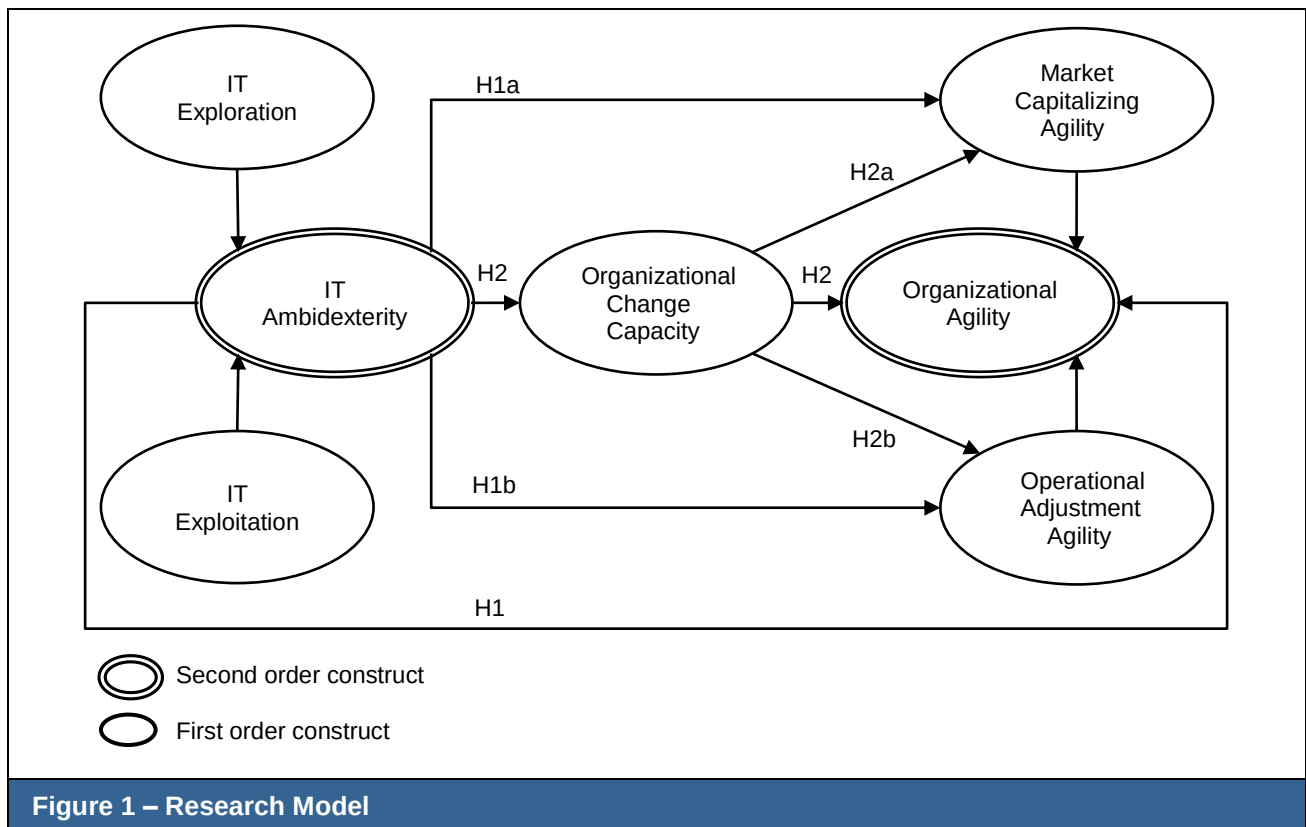
Similarly, organizations with a high OCC can proactively and rapidly (i.e., agilely) respond to evolving conditions (Mikalef & Gupta, 2021; Najrani, 2016). Specifically, the change process execution facet of OCC (Supriharyanti & Sukoco, 2023) aligns with the seizing DC attribute of OA (Lee et al., 2021; Park et al., 2017; Teece et al., 2016). Organizations that can adapt their internal support mechanisms, encompassing structures, processes, and systems, can initiate changes when new market opportunities or threats emerge, analogous to the seizing characteristics of OAA (Mao et al., 2020; Teece, 2007; Teece et al., 2016). For example, OCC can enable organizations to efficiently reconfigure internal structures and deploy resources in a manner that enhances their ability to seize emerging opportunities (Judge, 2011; Judge et al., 2015), which is a core characteristic of OAA (Mikalef & Pateli, 2017; Tai et al., 2019). More specifically, organizations that can anticipate potential organizational resistance to change and factor in both organizational politics and human resource strategies during change endeavors (Grover et al., 1995; Mikalef & Gupta, 2021; Mikalef et al., 2022), can adjust their operations rapidly and effectively in response to internal and external demands. This is congruent with the inherent seizing capability of OAA (Barlette & Baillette, 2022; Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017). ITA may therefore influence OCC, which has the potential to foster OAA, prompting us to hypothesize that:

H2b: OCC mediates the relationship between ITA and OAA

Building on these arguments, ITA, through its dimensions of IT exploitation and exploration (Lee et al., 2015; Syed et al., 2023), can lead to OCC. In turn, OCC which includes the facets of organizational learning and change process execution (Soparnot, 2011; Supriharyanti & Sukoco, 2023) can lead to MCA and OAA, which are aligned with the sensing and seizing capabilities inherent in the overall notion of OA (Lu & Ramamurthy, 2011; Park et al., 2017; Teece et al., 2016). Despite MCA and OCC each contributing unique and indispensable dimensions to OA, they are intrinsically synergistic and mutually dependent (Ghasemaghaei et al., 2017; Mikalef & Pateli, 2017; Ravichandran, 2018). Hence, it is plausible that OCC can lead to OA through these dimensions. As such, we hypothesize that:

H2: OCC mediates the relationship between ITA and OA

Figure 1 presents an overview of the conceptual framework, illustrating the hypothesized relationships and measurement model, with first-order constructs shown in single circles and second-order constructs in double circles.



Research Methodology

Data Collection

A quantitative methodology was used, consistent with other IS research on IT capabilities, which predominantly employs quantitative methods to assess broader business value by providing insights into how IT impacts organizational performance across industries (Abbasi et al., 2016; Steininger et al., 2022). Data was collected through a mono-method questionnaire-based survey, selected for its efficiency in capturing data from a large, dispersed sample, while ensuring replication and promoting the generalization of findings (Daneshvar et al., 2021; Pinsonneault & Kraemer, 1993). The survey was directed at senior technology officials, including CIOs, CTOs, and IT managers, responsible for overseeing IT infrastructures or involved in data analytics within their organizations, as ascertained through a qualifying question (Ghasemaghahi et al., 2017). These key informants were chosen due to their understanding of IT capabilities and their pivotal role in implementing IT strategies, ensuring their insights are representative of the organizational perspective of the constructs studied.

Before disseminating the survey, a pilot study involving ten senior IT professionals was undertaken to ensure the instrument's clarity and validity (Köhler et al., 2017). A voluntary, confidential, and anonymous electronic survey, available for three months, was then disseminated to approximately 4000 technology professionals primarily in South Africa, as identified through various channels. To boost participation, we engaged with a third-party data collection provider, through which the survey was distributed to 3630 technology professionals sourced from a B2B database. We also employed convenience sampling, reaching out to potential respondents through South African business directories, academic repositories, and professional forums. This sampling strategy was chosen to target IT professionals, aligning with the target population of the study. Respondents were primarily drawn from the manufacturing sector, which is crucial in South Africa due to its substantial potential to drive economic growth (Barnes, 2023; Kruse et al., 2022). The focus on South Africa, an important emerging market, sought to explore its unique and dynamic IT landscape, offering insights into IT capabilities within the context of the region's distinct socio-economic dynamics (Sutherland, 2020).

After screening 390 initial responses to ensure alignment with our target population and a completion rate greater than 50% (Schafer & Graham, 2002), we obtained a qualified sample of 173 respondents (Table 1). Informed by the sample size determination principles outlined by Memon et al. (2020), we performed a priori power analysis using a fixed model linear multiple regression F test in G*Power to ascertain the adequacy of the sample size (Faul et al., 2009). Adhering to the conservative guidelines proposed by Benitez et al. (2020), we employed an expected conservative effect size of 0.15, and included the two predictors for OA, which had

the highest number of arrows pointing to a construct in our model. This was done with a 95% confidence level and a desired statistical power of 80%. The analysis indicated that a minimum sample size of 68 was required to estimate the model with sufficient statistical accuracy. The sample size of 173 was therefore deemed suitable for the subsequent partial least squares structural equation modelling (PLS-SEM) (Hair Jr et al., 2020; Hair, Risher, et al., 2019).

Table 1 – Sample Demographics (n=173)		
Firm size	n	%
1-100	30	17.34
100-499	23	13.29
500 - 999	28	16.18
1000 or more	89	51.45
Unknown	3	1.73
Position	n	%
Entry level	5	2.89
Intermediate	18	10.4
Middle mgmt.	54	31.21
Senior mgmt.	58	33.53
Executive	38	21.97
Country	n	%
South Africa	162	93.64
Other	9	5.2
Unknown	2	1.16
Industry sector	n	%
Primary industry sector: Manufacturing	124	71.68
Automotive	50	28.9
Food and Beverages	12	6.94
Utilities and Energy	11	6.36
Petroleum and Chemicals	10	5.78
Manufacturing Other	41	23.7
Other industries: Manufacturing support	49	28.32
Transportation and Logistics	10	5.78
Technology Services	39	22.54

Measures, Construct Operationalization and Model Specification

The survey consisted of both demographic and Likert-style questions, designed to measure the control variables and key study constructs, as illustrated in Tables 1 and 2. All the measures and items used in this study, were adopted from prior empirical research. OA was envisaged as a second-order formative construct (Ghasemaghahi et al., 2017), encompassing both OAA and MCA (Lu & Ramamurthy, 2011). The choice of these dimensions is grounded in the construct's demonstrated applicability and validation in recent IT-driven agility research (Ghasemaghahi et al., 2017; Mao et al., 2020; Mikalef & Pateli, 2017). OAA emphasizes the importance of flexible business operations capable of rapid adaptation, whereas MCA focuses on leveraging market uncertainties for organizational advancement (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017). Notwithstanding their synergistic attributes, OAA and MCA each add unique and indispensable dimensions to OA (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017; Ravichandran, 2018), thereby warranting the examination of OA as a formative second-order construct using these dimensions (Ghasemaghahi et al., 2017). The operationalization of OAA and MCA, reflective in nature and totaling six items, follows the approach by Lu and Ramamurthy (2011), which is consistent with recent IT-driven agility research (Ghasemaghahi et al., 2017; Mao et al., 2020; Mikalef & Pateli, 2017). These items were conceptualized to be caused by their sub-constructs, are interchangeable, and share a common theme, which aligns with the constructs' original reflective conceptualization (Lu & Ramamurthy, 2011).

ITA, envisaged as a second-order formative construct (Benitez et al., 2018; Syed et al., 2020b), encompassed the dimensions of IT exploration and IT exploitation (Lee et al., 2015). IT exploration focuses on the investigation and experimentation with emerging technologies, whereas IT exploitation centers on maximizing the utility of existing technological assets for enhanced efficiency (Lee et al., 2015; Syed et al., 2020a, 2020b). The synergistic and integral nature of IT exploration and exploitation informs the contextual understanding of ITA, emphasizing the need for a balanced approach to IT management (Gregory et al., 2015; Syed et al., 2023). This viewpoint supports treating contextual ITA as a formative, second-order construct, where IT exploration and exploitation are not isolated activities but interconnected elements that collectively shape the broader notion

(Syed et al., 2020b). At the sub-construct level, IT exploration and exploitation were operationalized with six reflective items from Lee et al. (2015). This is consistent with recent ITA studies (Syed et al., 2023; Zhen, Xie, et al., 2021). These items encapsulate ITA's essence within organizations and align with contemporary measurement approaches, accurately reflecting their collective contribution to the broader concept of ITA (Syed et al., 2023). As such, a reflective-formative model was conceptualized (Abbasi, 2023; Sarstedt et al., 2019).

Despite its inherent multidimensionality, this study aligns with prevailing IS research on the organizational impact of IT capabilities by conceptualizing OCC as a single construct (Ameen et al., 2024; Mikalef & Gupta, 2021; Mikalef et al., 2022, 2023). The selected indicators, as delineated in Table 2, are pivotal given their potential to culminate in an organizational capacity that mitigates the frictions and inertia associated with change, enabling enhanced strategizing and execution of change initiatives across various organizational levels (Besson & Rowe, 2012; Mikalef & Gupta, 2021). The items for the OCC construct were modelled reflectively to capture its essence within organizations (Mikalef & Gupta, 2021; Mikalef et al., 2022).

All items were evaluated using a 7-point Likert scale to promote equivalence throughout the instrument and to maintain uniformity in the subsequent data analysis (Lee et al., 2015; Tabachnick & Fidell, 2013). A 7-point scale was chosen for its ability to capture greater variability and provide more nuanced responses, enhancing the precision of the data analysis, while also reaching the “*upper limit of the scale's reliability*” (Allen & Seaman, 2007, p. 64; Finstad, 2010). Two control variables (CVs), namely firm size, and industry sector (refer to Table 1), were also integrated due to their potential impact on an organization's responsiveness in nurturing OA (Lee et al., 2015; Lu & Ramamurthy, 2011). For example, larger firms may have more resources for OA, whilst industry-specific dynamics can shape how OA is deployed (Ravichandran, 2018); thus, these CVs were used to ensure that the results reflect the true impact of the constructs studied, independent of these factors.

Table 2 – Construct Operationalization, Indicator Squared Loadings and T-Statistics					
Measure		Abbrev.	Item	λ^2	t
IT ambidexterity (ITA) (Lee et al., 2015)	IT exploration (ITER)	ITER1	We acquire new IT resources (e.g., new generation of IT architecture, potential IT applications, critical IT skills)	0.743	28.34
		ITER2	We experiment with new IT resources	0.867	65.337
		ITER3	We experiment with new IT management practices	0.759	28.147
	IT exploitation (ITEI)	ITEI1	We make extensive use of the existing IT components	0.738	30.105
		ITEI2	We offer IT applications and services sufficiently	0.812	39.219
		ITEI3	We have a high level of IT-related skills	0.808	47.103
Organizational change capacity (OCC) (Grover et al.,1995; Mikalef & Gupta, 2021)		OCC1	We are able to anticipate and plan for the organizational resistance to change	0.696	25.388
		OCC2	We consider the politics of the business when reengineering efforts	0.548	11.73
		OCC3	We are capable of communicating the reasons for change to the members of our organization	0.696	25.373
		OCC4	We are able to make the necessary changes in human resource policies for process reengineering	0.627	19.343
		OCC5	Senior management commits to new values	0.648	24.346
Organizational agility (OA) (Lu & Ramamurthy, 2011)	Operational adjustment agility (OAA)	OAA1	We fulfil demands for rapid-response, special requests of our customers whenever such demands arise; our customers have confidence in our ability.	0.817	48.878
		OAA2	We can quickly scale up or scale down our production/service levels to support fluctuations in demand from the market.	0.861	67.838
		OAA3	Whenever there is a disruption in supply from our suppliers, we can quickly make necessary alternative arrangements and internal adjustments	0.799	40.161
	Market capitalizing agility (MCA)	MCA1	We are quick to make and implement appropriate decisions in the face of market/customer changes.	0.734	32.324
		MCA2	We constantly look for ways to reinvent/re-engineer our organization to better serve our marketplace.	0.830	51.727
		MCA3	We treat market-related changes and apparent chaos as opportunities to capitalize quickly.	0.834	48.164

Approach to PLS-SEM

PLS-SEM was employed due to its proficiency in estimating the direct, indirect and total effects in hypothesized relationships, making it particularly well-suited for mediation models, combined with its distinguished predictive accuracy and explanatory capabilities (Benitez et al., 2018; Hair Jr et al., 2021; Hair, Sarstedt, et al., 2019). A further major advantage of utilizing PLS-SEM is its flexibility, allowing for the unrestricted use of formative measures, thereby enhancing its suitability to our reflective-formative model (Abbasi, 2023; Hair, Risher, et al., 2019; Sarstedt et al., 2019). To rigorously apply PLS-SEM, we followed the established guidelines suggested in the PLS-SEM literature (Abbasi, 2023; Benitez et al., 2020; Hair Jr et al., 2020; Hair, Risher, et al., 2019). After specifying the reflective-formative model, we followed five steps: 1) Model fit and common method bias assessments; 2) Reflective and formative measurement model evaluation; 3) Structural model evaluation; 4) Mediation analysis; and 5) Predictive capability tests. All tests were completed using the SmartPLS software package (version 4.1.0.0; Ringle et al., 2022).

Results

Measurement Model Evaluation

Common Method Bias and Measurement Model Fit

Prior to validating the measurement model, we evaluated the data for common method bias (CMB), a prevalent concern in survey research (Hair Jr et al., 2017), which could have potentially been introduced by our key informant, cross-sectional approach (Chang et al., 2010). To test for CMB, we followed Abbasi (2023) and conducted Harman's single factor test (Podsakoff et al., 2003) and a multicollinearity assessment (Kock, 2015; Kock & Lynn, 2012). The results of Harman's single factor test indicated that no single factor accounted for more than 50% of the variance, suggesting minimal CMB in our dataset. For the multicollinearity assessment, we calculated the variance inflation factors (VIFs) for our model, as high multicollinearity can be an indicator of CMB (Kock, 2015). All VIF values were below the stringent threshold ($VIF < 3$), further supporting the absence of significant CMB (Hair Jr et al., 2020; Petter et al., 2007).

In the assessment of the reflective-formative measurement model (i.e., the outer model), our initial evaluation focused on model fit, employing the Standardized Root Mean Square Residual (SRMR) index as the model fit metric (Benitez et al., 2020; Henseler et al., 2014). This index tests for model fit by measuring the discrepancy between "*the empirical correlation matrix and the model-implied correlation matrix*" and is increasingly being reported in the latest related studies that apply PLS-SEM (Benitez et al., 2018, p. 513). The measurement model yielded an SRMR value of 0.069, which is below the accepted threshold of 0.08, signifying an acceptable measurement model fit (Benitez et al., 2018; Benitez et al., 2020; Hair, Sarstedt, et al., 2019).

Confirmatory Composite Analysis

After establishing model fit, we conducted a Confirmatory Composite Analysis (CCA). CCA is a method for validating measurement models in PLS-SEM and involves a series of steps to confirm both reflective and formative measurement models, especially when adapting established measures to a new context (Abbasi, 2023; Hair Jr et al., 2020; Schuberth et al., 2020). Using the CCA approach, latent variable scores for lower (first-order) constructs are estimated and used to develop second (higher-order) constructs, simplifying complex models and aiding a parsimonious analysis (Abbasi, 2023). To develop the reflective-formative higher-order model, we utilized the two-stage approach for developing higher-order constructs in PLS-SEM (Sarstedt et al., 2019; Schuberth et al., 2020) to formulate OA and ITA as second-order constructs. Specifically, all indicators were first freely associated with their respective first-order latent constructs, and the resulting latent variable scores were used to create the second-order latent variables.

The two-stage approach streamlined the number of path models, while supporting the PLS-SEM necessary to assess both direct and indirect effects in the mediation analysis (Benitez et al., 2018; Sarstedt et al., 2019). By modeling first-order constructs (MCA, OAA, ITER, and ITEI) and second-order constructs (ITA and OA), we ensured that the relationships between ITA, OCC, and the specific dimensions of OA could be appropriately tested. Additionally, this approach facilitated the analysis of both reflective and formative constructs, supporting the methodological rigor of our mediation model (Becker et al., 2012). Using CCA, we first analyzed the reflective constructs and then proceeded with the formative composite model.

Reliability and Validity of the Reflective Model

To confirm the reflective model's reliability and validity, we executed tests for indicator (i.e., item) and construct reliability, whilst also testing for convergent and discriminant validity (Abbasi, 2023; Hair Jr et al., 2017; Hair Jr et al., 2020). We ascertained indicator and construct reliability by squaring the respective loadings (λ) and verifying if they surpassed the 0.5 threshold with t-statistics (t) greater than ± 1.96 . Table 2 shows that the lowest squared item loading (λ^2) was 0.548 ($t = 11.73$). Similarly, the lowest squared construct loading (λ^2) was 0.726 ($t = 16.926$). Thus, the reliability of the first and second-order indicators were confirmed.

Construct reliability was assessed by computing Cronbach's alpha (α) and composite reliability (CR) metrics, as shown in Table 3. α was used to assess internal consistency, while CR was used to better reflect construct reliability in cases where α may underestimate it (Hair, Risher, et al., 2019). All values for both tests were within the recommended upper (0.95) and lower (0.7) limits (Hair Jr et al., 2017), confirming the establishment of construct reliability. Concerns about redundancy, characterized by the assessment of indicators that evaluate the same construct and, in turn, reduce construct distinctiveness, were not an issue in this context (Hair, Risher, et al., 2019). These results show that each indicator contributes uniquely to its construct, avoiding overlap and preserving construct heterogeneity (Hair Jr et al., 2021; Hair Jr et al., 2017). Additionally, the correlations between the reflective constructs were all statistically significant ($p < 0.001$), with values ranging from moderate to strong, as expected for interchangeable reflective indicators (Hair Jr et al., 2020), as shown in Table 4.

Convergent validity, which is “the extent to which the construct converges to explain the variance of its items” (Hair, Risher, et al., 2019, p. 9), was ascertained through the average variance extracted (AVE) metric. All AVE values surpassed the prescribed threshold of 0.5, as detailed in Table 3. This demonstrates that more than 50% of the variance was captured between each construct and its corresponding indicators, establishing convergent validity (Hair Jr et al., 2020). Discriminant validity, which assesses the distinctiveness of constructs, was established using the Heterotrait-Monotrait (HTMT) ratio of correlations, which addresses the performance limitations associated with the Fornell-Larcker criterion (Hair, Risher, et al., 2019; Henseler et al., 2015). The HTMT ratio compares the mean correlations between items across different constructs to the geometric mean of the average correlations between items measuring the same construct (Hair, Risher, et al., 2019). All HTMT values, for the first-order constructs including the mediating variable, fell below the accepted threshold of 0.85-0.90 (Table 3), thus confirming discriminant validity (Hair Jr et al., 2020). These findings establish the robust fit, and the reliability and validity of the measurement model.

Table 3 – Reliability, Convergent (AVE) and Discriminant Validity (HTMT) Results

Construct	Reliability				Validity			
	α	CR - rho_a	CR - rho_c	AVE	HTMT			
					ITEI	ITER	MCA	OAA
ITEI	0.864	0.87	0.917	0.786				
ITER	0.866	0.873	0.918	0.79	0.772			
MCA	0.874	0.875	0.923	0.799	0.635	0.6		
OAA	0.895	0.901	0.934	0.826	0.487	0.492	0.856	
OCC	0.862	0.872	0.9	0.643	0.618	0.57	0.726	0.647

Table 4 – Correlations Matrix for Reflective Constructs

Construct	ITEI	ITER	MCA	OAA	OCC
ITEI	1.000				
ITER	0.672	1.000			
MCA	0.555	0.526	1.000		
OAA	0.431	0.440	0.763	1.000	
OCC	0.540	0.500	0.646	0.579	1.000

Reliability and Validity of the Formative Model

Measuring formative composite models differs from reflective models as they are linear combinations of indicators that form the construct and do not necessarily covary, with high correlations potentially causing issues with multicollinearity (Hair Jr et al., 2020). To evaluate the integrity of the formative measurement model, we first assessed multicollinearity by calculating the VIFs (Abbasi, 2023; Hair, Risher, et al., 2019). The VIF values ranged from 1.824 to 2.395, as detailed in Table 5. All values were below the stringent threshold ($VIF < 3$), confirming that multicollinearity was not an issue (Hair, Risher, et al., 2019; Petter et al., 2007).

We then evaluated the size and significance of the weights of the formative sub-constructs. ITEI and MCA had significant weights greater than the 0.5 benchmark (Hair, Risher, et al., 2019; Hair Jr et al., 2021), while ITER and OAA did not meet this criterion. We proceeded to evaluate their formative indicator loadings, as they illustrate an indicator's absolute contribution to its formative construct (Hair Jr et al., 2020). As shown in Table 5, the loadings were all significant, and exceeded the 0.5 benchmark, justifying their inclusion in the formative model. Together, these results confirm the robustness of our formative measurement model.

Table 5 – Weights, Loadings and VIF Values of the Formative Measurement Model

Path	Indicator weights		Indicator loadings		VIF
	Weights	Significance	Loadings	Significance	
ITEI → ITA	0.605	$p < 0.001$	0.933	$p < 0.001$	1.824
ITER → ITA	0.487	$p < 0.05$	0.894	$p < 0.001$	1.824
MCA → OA	0.811	$p < 0.001$	0.989	$p < 0.001$	2.395
OAA → OA	0.233	$p > 0.05$	0.852	$p < 0.001$	2.395

Structural Model and Hypotheses Tests

To assess the hypotheses, an initial examination of the structural model was conducted to ascertain if multicollinearity was a concern. We then scrutinized the standardized path coefficients (β), the explained variance in the endogenous variables (R^2), and the corresponding effect sizes (f^2), prior to undertaking a mediation analysis (Benitez et al., 2020; Hair, Risher, et al., 2019). For the multicollinearity assessment of the inner model, as shown in Table 6, all VIF values were below the stringent threshold ($VIF < 3$), thereby confirming the absence of multicollinearity in the structural model (Hair Jr et al., 2020; Petter et al., 2007).

Table 6 – Test for Multicollinearity

Path	VIF values
ITA → MCA	1.482
ITA → OAA	1.482
ITA → OA	1.482
ITA → OCC	1
OCC → MCA	1.482
OCC → OAA	1.482
OCC → OA	1.482

To evaluate the direct effects, bootstrapping with 5,000 resamples was used to establish the standardized path coefficients (β) and their significance, whilst 95% confidence intervals were further reported to support the estimates' robustness (Hair Jr et al., 2020). Consistent with our hypotheses, ITA demonstrated a positive and significant impact on MCA (H_{1a} : $\beta = 0.331$, $t = 3.915$, $p < 0.001$), OAA (H_{1b} : $\beta = 0.215$, $t = 2.408$, $p < 0.05$), and OA (H_1 : $\beta = 0.319$, $t = 3.838$, $p < 0.001$). The confidence intervals for all these relationships excluded zero, thereby further confirming their statistical significance (Hair, Risher, et al., 2019). The R^2 values were assessed to estimate the in-sample predictive power of the endogenous constructs, explaining 49.1% of the variance in MCA ($R^2 = 0.491$), 36.7% in OAA ($R^2 = 0.367$), and 50.2% in OA ($R^2 = 0.502$). Notably, the R^2 value for OA, the primary endogenous construct in this study, is within the moderate range (Hair Jr et al., 2017), and aligns with findings from similar ITA-OA studies (Lee et al., 2015), suggesting the model's satisfactory in-sample predictive ability (Benitez et al., 2020). The effect sizes, denoted by f^2 , were also assessed against benchmark values to estimate the contribution of the exogenous constructs to the variance of the endogenous latent variables R^2 (Hair Jr et al., 2020; Hair Jr et al., 2021). The f^2 values ranged from 0.049 (small effect) to 0.146 (large effect), indicating that the model has measurable predictive power within the sample, further affirming its in-sample predictive ability (Benitez et al., 2020; Hair Jr et al., 2020). The results are summarized in Table 7.

Table 7 – Summary of the Direct Effects and Hypotheses Testing Results

Path	H	β	t	Sig.	Confidence Int.		R^2	f^2	Conclusion
					2.5%	97.5%			
ITA → MCA	H1a	0.331	3.915	$p < 0.001$	0.171	0.505	0.491	0.146	Supported
ITA → OAA	H1b	0.215	2.408	$p < 0.050$	0.049	0.398	0.367	0.049	Supported
ITA → OA	H1	0.319	3.838	$p < 0.001$	0.163	0.489	0.502	0.138	Supported

Furthermore, following Benitez et al. (2018), we added the CVs to the structural path of the model and carried out the bootstrapping procedure. Even though the sample predominantly included firms from the automotive sector and those with more than 1000 employees, our analysis showed that the CVs had a non-significant impact on OA (Firm size: $\beta = 0.090$, $t = 0.514$, $p > 0.1$; Industry: $\beta = 0.245$, $t = 0.980$, $p > 0.1$). This finding suggests that the impact of OA in our study is not significantly influenced by firm size and industry sector, indicating a degree of robustness in our conceptualization of OA across different contexts. Additionally, the SRMR fit index for the structural model was computed to determine if any important effects were erroneously excluded from the model (Benitez et al., 2020). The overall model achieved an SRMR value of 0.057, which is lower than the established threshold of 0.08 (Benitez et al., 2018; Hair Jr et al., 2017). Despite this result signifying a suitable model fit, global model fit metrics such as SRMR need to be interpreted cautiously, as these metrics are actively being developed within the context of PLS-SEM (Benitez et al., 2020; Hair, Sarstedt, et al., 2019).

Test for Mediation

To assess the mediating role of OCC in the ITA-OA relationship, we followed the established approach of Zhao et al. (2010). This approach has received significant attention recently and has been employed by “a very high number of recent studies published in the best IS and management journals” (Benitez et al., 2018, p. 515; Hair Jr et al., 2017). Specifically, we applied the bootstrapping technique utilizing 5,000 samples (Benitez et al., 2018; Li et al., 2024), an approach which is compatible with PLS-SEM since it does not necessitate any assumptions concerning the normality of the sample distribution (Hair Jr et al., 2017; Preacher & Hayes, 2008). Bootstrapping provided robust confidence intervals for all effects, enhancing the reliability of the estimates (Benitez et al., 2018; Hair Jr et al., 2021). This approach allowed us to test the direct, indirect, and total effects of ITA on MCA, OAA, and OA through OCC, as summarized in Table 8.

The analysis revealed statistically significant indirect effects of ITA on MCA (H_{2a} : $\beta = 0.261$, $t = 5.521$, $p < 0.001$), OAA (H_{2b} : $\beta = 0.260$, $t = 5.026$, $p < 0.001$), and OA (H_2 : $\beta = 0.272$, $t = 5.826$, $p < 0.001$), through the mediator OCC. This was complemented by statistically significant direct effects of ITA on MCA (H_{1a} : $\beta = 0.331$, $t = 3.915$, $p < 0.001$), OAA (H_{1b} : $\beta = 0.215$, $t = 2.408$, $p < 0.05$), and OA (H_1 : $\beta = 0.319$, $t = 3.838$, $p < 0.001$). The total effects of ITA on MCA ($\beta = 0.592$, $t = 8.703$, $p < 0.001$), OAA ($\beta = 0.476$, $t = 6.258$, $p < 0.001$), and OA ($\beta = 0.591$, $t = 8.604$, $p < 0.001$) highlight the robust, consistent influence of ITA on these outcomes, reinforcing the validity of the relationships. The absence of zero in the direct, indirect, and total effects confidence intervals further corroborates their statistical significance (Hair, Risher, et al., 2019). The significance of both the indirect and direct paths suggests that OCC serves as a partial mediator between ITA and MCA, OAA, and OA, as the direct effects remain significant even with the presence of the mediator (Hair Jr et al., 2021; Li et al., 2024). This validates the mediation hypotheses, demonstrating that OCC explains part of the relationships, but that ITA still maintains a direct influence on the endogenous latent variables. As the final step, we analyzed the product of the direct and indirect effects (Zhao et al., 2010), both of which were positive. This indicates that OCC acts as a complementary mediator, partially explaining the relationships while still allowing ITA to exert a direct influence, thereby strengthening these relationships without fully accounting for them (Hair Jr et al., 2021).

Table 8 – Summary of Mediation Results: Indirect, Direct and Total Effects

Path	Indirect Effect	t-stat [LCI, UCI]	Direct Effect	t-stat [LCI, UCI]	Total Effect	t-stat [LCI, UCI]	Conclusion
ITA→OCC→MCA	0.261 **	5.521 [0.166, 0.352]	0.331 **	3.915 [0.171, 0.505]	0.592 **	8.703 [0.450, 0.719]	Partial mediation
ITA→OCC→OAA	0.260 **	5.026 [0.162, 0.365]	0.215 *	2.408 [0.049, 0.398]	0.476 **	6.258 [0.330, 0.625]	Partial mediation
ITA→OCC→OA	0.272 **	5.826 [0.178, 0.363]	0.319 **	3.838 [0.163, 0.489]	0.591 **	8.604 [0.453, 0.722]	Partial mediation

LCI = Lower confidence interval;
 UCI = Upper confidence interval

Notes: * $p < 0.05$. ** $p < 0.001$.

With mediation established, we examined the model's in-sample explanatory power (Hair Jr et al., 2020). The R^2 values—0.325 for OCC, 0.491 for MCA, 0.367 for OAA, and 0.502 for OA—highlight the substantial variance explained by ITA in these constructs. The f^2 values—0.482 for ITA → OCC, 0.276 for OCC → MCA, 0.222 for OCC → OAA, and 0.308 for OCC → OA—further demonstrate the medium to large effect sizes of the exogenous constructs on the endogenous latent variables. These results reinforce the model's robust in-sample predictive ability (Hair Jr et al., 2020; Hair Jr et al., 2021).

Predictive Validity

We also examined the model's out-of-sample predictive capability, utilizing the PLSpredict algorithm, as outlined by Shmueli et al. (2016). This approach involves training the model on a specific subset of the data and evaluating its predictive performance using a separate, reserved sample (Hair Jr et al., 2021). Assessing the predictive capability of a model beyond the sample data is important especially *"when drawing conclusions that affect business practices and have managerial implications"* (Hair, Risher, et al., 2019, p. 3). To assess the out-of-sample predictive validity of the model, we computed the PLS-SEM root mean square error (RMSE) metric and compared it against a baseline naïve linear model (LM) (Hair Jr et al., 2021; Shmueli et al., 2019). As evident in Table 9, the prediction errors derived from the PLS-SEM model were consistently lower than those from the LM benchmark, illustrating the high predictive capability of our conceptualized model (Hair Jr et al., 2021).

Table 9 – PLS Predict Analysis for the Endogenous Variables			
Construct	PLS-SEM_RMSE	LM_RMSE	PLS-SEM < LM
MCA	0.826	0.827	Yes
OAA	0.900	0.905	Yes
OCC	0.835	0.836	Yes

Discussion

Recent contributions to the PAJAIS have highlighted the critical role of IT in fostering OA. This is evident across themes such as the interaction between agile methods and organizational culture (Känsälä & Tokumaru, 2023), and improving agility through big data analytics (Hyun et al., 2020), business intelligence (Ali et al., 2018), and enterprise architecture (van de Wetering, 2021). These PAJAIS contributions align with the journal's focus on the social and organizational aspects of IS (Jiang et al., 2019), and highlight the multifaceted nature of IT-enabled agility. This context underscores our study's relevance in the ongoing scholarly discourse, as we investigate the influence of ITA on OA, considering the mediating effect of OCC in the relationship.

Our findings reveal a direct positive impact of ITA on OA and its dimensions, OAA and MCA, which was not previously hypothesized in the literature. These results emphasize ITA's critical role in enhancing agile operations and market responsiveness, supporting the growing body of work advocating for a balanced approach to IT exploration and exploitation to foster OA (Lee et al., 2015; Zhen, Cao, et al., 2021; Zhen, Xie, et al., 2021). Although contradictions regarding IT's role in enabling agility are noted in the literature, our findings align with the view that IT capabilities directly enable OA (Ghasemaghaei et al., 2017; Hyun et al., 2020; Liang et al., 2022; Liu et al., 2018). Conversely, our findings contradict previous studies suggesting that IT capabilities have a neutral or negative impact on the notion (Ghasemaghaei et al., 2017; Liang et al., 2017; Liu et al., 2013; van de Wetering, 2021).

Moreover, the results demonstrate that OCC acts as a partial mediator in the relationship between ITA and both OA and its dimensions: MCA and OAA. The previously unexplored mediating role of OCC in the ITA-OA relationship supports emerging perspectives advocating for additional organizational mechanisms to effectively leverage IT capabilities for enhancing OA and its constituent sub-capabilities (Ghasemaghaei et al., 2017; Lee et al., 2021; Liang et al., 2017). Despite certain limitations, our research offers valuable insights for both theory and managerial practice, highlighting ITA's nuanced role in fostering OA directly and indirectly for organizations operating in the dynamic Asia Pacific region and competing globally.

Theoretical Implications

This study presents three salient contributions to IS and organizational change research. Firstly, it advances empirical research by demonstrating ITA's direct impact on organizational capabilities, extending previous findings on new product development (Syed et al., 2023), operational ambidexterity (Lee et al., 2015), operational agility (Syed et al., 2020b) and firm performance (Mithas & Rust, 2016) to include MCA, OAA, overall OA, and OCC. It achieves this by demonstrating the in-sample predictive ability, explanatory strength, and out-of-sample predictive validity of the conceptualized research model. While the field of IS-enabled organizational transformation research continues to evolve (Barlette & Baille, 2022; Besson & Rowe, 2012), this study underscores the pivotal role of ITA in driving organizational change and cultivating an agile approach, through MCA and OAA. This agile approach can manifest in tangible performance gains and a more robust competitive positioning for organizations (Liang et al., 2022; Mithas & Rust, 2016; Teece et al., 2016).

Secondly, we reveal that OCC accounts for 32.5% of ITA's role in enabling OA, while also mediating the relationships between ITA and OA's specific dimensions, MCA and OAA. This provides early evidence for OCC as a generic DC that can impact other specific, higher-order DCs (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023). The result is significant, since OCC has the potential to enhance a firm's performance and sustained competitiveness by not only rejuvenating and fortifying existing competencies but also by fostering the development of new ones (Andreeva & Ritala, 2016; Judge, 2011; Judge et al., 2015). By introducing OCC as a mediator in the ITA-OA relationship, this study adds a fresh dimension to the literature on IT-enabled agility (Tallon et al., 2019), and supports emerging theoretical arguments on the potential of IT capabilities to enhance OA through organizational change (Barlette & Bailleite, 2022). Furthermore, this research responds to recent appeals for empirical investigations into the role of "OCC as a mediating variable" to produce both performance and non-performance-related organizational outcomes (Supriharyanti & Sukoco, 2023, p. 15). The empirical evidence supporting OCC's mediating role is consistent with the work of Lee et al. (2015), which found that operational ambidexterity was required to mediate the relationship, and with Mao et al. (2020), who found that absorptive capacity was crucial to translate IT capabilities into the specific OA dimensions of OAA and MCA. Our study elucidates the understanding on the ways in which intermediary organizational capabilities synergistically interact to transform IT capabilities, such as ITA, into OAA, MCA and overall OA (Lee et al., 2021; Liu et al., 2020; Ravichandran, 2018). This substantiates the growing scholarly consensus that IT "capabilities enable firms to generate performance gains through intermediate organizational capabilities" (Mikalef et al., 2021, p. 81; Steininger et al., 2022). Collectively, the results lend weight to nascent perspectives that highlight the necessity of considering both the direct and indirect influence of IT capabilities on the formation of organizational DCs (Lee et al., 2015; Li & Chan, 2019).

Thirdly, from a theoretical standpoint, grounded in the DCV (Steininger et al., 2022; Teece, 2007, 2018), this study enhances our comprehension of the interplay between lower-order IT capabilities and DCs within the organizational capability hierarchy (Ayabakan et al., 2017; Grant, 1996). The evidence suggests that ITA, viewed as a lower-order functional capability, appears instrumental in facilitating the evolution of OCC, delineated as a generic DC (Andreeva & Ritala, 2016; Supriharyanti & Sukoco, 2023), and OA, viewed as a specific higher-order DC (Park et al., 2017; Steininger et al., 2022; Teece et al., 2016). In contributing to scholarly discourse, this research elucidates the enabling role of IT capabilities in supporting the emergence of DCs, both as a mediating variable (OCC) and as an organizational outcome (OAA, MCA and overall OA) within the confines of the DCV framework. This perspective contrasts with the view that IT capabilities are intrinsically embedded within organizational DCs (Conboy et al., 2020; Steininger et al., 2022), and enhances our understanding of the underlying mechanisms that cause DCs to emerge (Mikalef et al., 2021; Protogerou et al., 2012). In conclusion, the study reveals promising avenues for future research, exploring the nuanced influence of IT capabilities on the fluidity and overall effectiveness of DCs in evolving organizational contexts.

Managerial Implications

This research, while conducted in South Africa, provides actionable insights for practitioners and management professionals across regions, including the Asia Pacific. The observed positive impact of ITA on OA, and its dimensions MCA and OAA, aligns with encouraging contextual evidence from organizations such as the Haier group (Huang et al., 2012; Syed et al., 2020a, 2020b), which found that balancing IT exploration and exploitation could enhance flexibility and response time, traits inherent to OA (Lee et al., 2021; Tallon et al., 2019). Despite the results indicating that IT exploitation had stronger weights and loadings compared to IT exploration, robust evidence emphasized the significance of both dimensions, as shown in Table 5. Drawing on this, IT practitioners should recognize that these two dimensions of ITA are intrinsically intertwined and depend on distinct structures, resources, and processes, leading to varied performance outcomes over time (Syed et al., 2020a). Similarly, although the model inferred that MCA explained 34% more of ITA's variance compared to OAA, we found evidence of the importance of both dimensions. Rather than pursuing one dimension, strategists should recognize the inherent synergy between MCA and OAA, despite their unique characteristics. Both dimensions contribute to OA by promoting a "continual readiness to change" (Lu & Ramamurthy, 2011, p. 933), and can facilitate performance gains in dynamic environments (Mikalef & Pateli, 2017; Teece et al., 2016). These findings corroborate circumstantial evidence from Asian Pacific firms such as Tencent, which have enhanced their responsiveness and competitiveness by adjusting their operations to meet evolving market trends and consumer demands (Murmman & Zhu, 2021).

The empirical evidence also supports the association between ITA and OCC, reinforcing the notion that "organizational change is a direct consequence of IT" (Chua et al., 2019; Robey et al., 2013, p. 380). Additionally, Table 8 corroborates that OCC can be instrumental in facilitating not only overall OA, but also its integral capabilities of MCA and OAA. These insights are relevant for business strategists and management executives tasked with cultivating organizational capabilities and spearheading change. For example, management professionals can consider employing the measures of the OCC construct as a diagnostic tool to evaluate organizational readiness for change (Weiner, 2009). Such evaluations are pivotal in bolstering the likelihood of

successful change initiatives (Andreeva & Ritala, 2016; Spaulding et al., 2017; Supriharyanti & Sukoco, 2023). By leveraging these indicators to assess the challenges and resistances inherent in change processes, professionals can enhance their strategic planning and execution of change initiatives. This is vital for achieving IS-driven organizational transformation and enhancing overall business value (Besson & Rowe, 2012; Mikalef & Gupta, 2021). The empirical results support circumstantial evidence from companies such as Baidu and Alibaba, whose strategic capacity to change has enabled them to seize new market and digital infrastructure opportunities in China's Belt and Road Initiative, thus enhancing their global competitiveness (Su & Flew, 2021). As such, strategically leveraging OCC has the potential to enable Asia Pacific firms to amplify their agility and responsiveness amid rapid technological and market changes (Murmann & Zhu, 2021).

Limitations and Recommendations

Despite encouraging results, this study's limitations suggest areas for future research. The measures used to evaluate OCC, while based on recent IS research (Ameen et al., 2024; Besson & Rowe, 2012; Mikalef & Gupta, 2021; Mikalef et al., 2022), might not fully encapsulate all the suggested dimensions of the overall notion, potentially affecting the mediation efficacy in our model. It would be beneficial for future research on the conceptualized model to construct a more encompassing representation of OCC, considering facets such as innovative culture and systemic organizational thinking capabilities (Judge & Douglas, 2009). Furthermore, this research is confined to a select set of variables, namely ITA, OCC, MCA, OAA and OA. Future research should incorporate additional determinants such as market complexity (Syed et al., 2020b) and environmental dynamism (Lee et al., 2015), which may influence the dynamics of the ITA-OCC-OA relationship. There is also an opportunity to refine the research model by introducing other mediating capabilities such as absorptive capacity and organizational ambidexterity, both of which hold the potential to facilitate the translation of IT capabilities into OA (Del Giudice et al., 2021; Mao et al., 2020).

The final qualified sample comprising 173 online respondents may not be representative of all organizations and industrial sectors. Future studies should aim to increase the sample size and diversify participant backgrounds from different industries and contexts to augment the generalizability of the results.

While the statistical tests did not find a significant effect of the control variables—firm size and industrial sector—on OA, future studies should explore potential heterogeneity through a multi-group analysis (Becker et al., 2013; Sarstedt et al., 2017). Given the potential for unobserved heterogeneity across groups, future research should also consider testing for measurement invariance to ensure that the constructs are measured consistently across different subgroups (Sarstedt et al., 2017). This is important as unobserved heterogeneity can considerably affect the results derived when using the PLS-SEM method, potentially leading to misinterpretations (Hair Jr et al., 2020). Advanced techniques such as finite mixture partial least squares (FIMIX-PLS) could identify latent groups within the sample, thereby augmenting the robustness and granularity of the insights (Hahn et al., 2002; Hair Jr et al., 2016, Hair Jr et al., 2017). Addressing this aspect would pave the way for results with a higher degree of validity, fostering a richer understanding of the intricate dynamics influencing OA.

The current study utilized a cross-sectional design, which inherently restricts the ability to infer causality; this limitation could be a factor in the absence of full mediation, since mediated models inherently suggest “*causal paths that imply the passage of time*” (Aguinis et al., 2017, p. 677). Future research should employ a longitudinal design to more clearly discern the causal relationships between ITA, OCC, OA, and its dimensions OAA and MCA. Such an approach would facilitate a deeper understanding of the ongoing dynamics and the evolutionary aspects of these relationships, which is vital in the ever-changing business environment (Lee et al., 2015; Syed et al., 2020a).

Conclusion

We endeavored to answer the question: How does OCC impact the relationship between ITA and OA? This was done through the empirical validation of a nomological network that modelled the relationships between ITA, OCC, OA, and its dimensions OAA and MCA. By uncovering the IT-enabled mechanisms that can facilitate the development of organizational DCs, this study lays the foundation for further research on the direct and indirect roles of IT capabilities in fostering agility. The empirical analysis reveals the practical significance of nurturing a harmonized approach to IT exploration and exploitation in the development of organizational capabilities. This balanced approach can foster more dynamic and adaptable capabilities, which, in turn, can enhance competitiveness. Importantly, our findings suggest a pathway for organizations to potentially leverage their IT capabilities strategically to enhance their change capabilities and agility in response to market demands and opportunities.

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