Artificial intelligence ambidexterity, adaptive transformation capability, and their impact on performance under tumultuous times

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Abstract. Over the past two years, scholars have increasingly paid attention to firms' capability to adapt to their increasingly turbulent business ecosystem environments. This study embraces the dynamic capabilities theory, uses ideas from the accelerated corporate transformation, and posits that adaptive transformation capability, driven by ambidextrous artificial intelligence (AI) use, i.e., routine and innovative use in practice, serves as a mechanism for firms to gain superior organizational performance under COVID-19. Using a composite-based structural equation model (SEM) approach, we use survey data from 257 C-level practitioners with key decision-making roles and experience in AI and digital transformation initiatives. We used this data to analyze the theorized relationships. Outcomes show that the ambidextrous use of AI positively enhances a firm's adaptive transformation capability. This capability, in turn, fully mediates the impact of AI ambidexterity on competitive performance during COVID-19. These outcomes have important theoretical and practical implications.

Keywords: Artificial intelligence, ambidexterity, dynamic capability, adaptive transformation capability, competitive performance, COVID-19, composited-based SEM, PLS-SEM

1 Introduction

During the COVID-19 crisis, social, technological, demographic, political, and economic changes accelerated rapidly. Under these stressful conditions, contemporary firms should shape their adaptive capabilities to address customer behavior and market dynamics changes. Adaptive capabilities enable firms to evolve rapidly and serve as a foundation for organizational change and transformation [1, 2]. Incumbent firms use new innovative technologies to enhance their business operations and adapt. One of those technologies is artificial intelligence (AI), or "the next era of analytics," as Davenport denotes it [3].

AI is a broad term encompassing various advanced analyses, applications, and logic-based techniques that mimic human behavior, decision-making, and activities like learning and problem-solving [4]. AI in business is not new, as the field originated in the 50s of the last century [5]. However, AI solutions offer firms many opportunities to transform their business across various industries, typically part of the digital transformation [6]. For example, consider using AI-driven decision-making regarding loans, credit decisions, or sales forecasting [6]. Furthermore, AI can offer considerable advantages in automating previously manual processes [7] and enabling augmented processes where humans and AI interact mutually supportive [8].

According to a recent report from Gartner [9], senior executives regard analytics and AI as the key game changer to emerge stronger from the current pandemic. However, despite the excitement concerning the potential of AI, there is currently much scholarly debate about the adoption challenges and the competencies and capabilities needed for valuable results from AI [10-12]. Moreover, Forbes estimated that by 2023 34% of the employees expect their respective jobs to be replaced by AI solutions [13].

AI can bring substantial benefits to firms. However, when a major transformation is required, firms must articulate a compelling shared vision to adopt AI and enable a high impact that does not derail all the investments and effort [14-16]. Moreover, firms must leverage innovative and distinctive technologies like AI to develop adaptive transformation capabilities and sense and respond capabilities to drive innovation, improve service levels and customer experiences, and foster competitive performance [3, 17-19].

Thus, there is a clear need to unfold how AI is leveraged into the organizational fabric and how it aligns and drives business strategy. This objective becomes increasingly more complex when organizations face continuous shifts in their business environments and major disruptions due to unforeseen events, such as the COVID-19 pandemic.

The need for adaptive capabilities informs our approach to organizational change and transformation. We follow [20, 21] and define adaptive transformation capability as a firm's proficiency in identifying and capitalizing upon emerging market and technology opportunities and building organizational capabilities in parallel with implementing new strategic directions. In addition, this capability can be considered a dynamic capability, which can use and deploy organizational resources and competencies to achieve the desired result [22] and drive the firms' future entrepreneurial activities and business value opportunities [20]. However, currently, little is known about the equivocal capacity to routinely and innovatively use AI, i.e., AI ambidexterity, in firms and how this supports dynamic capabilities, especially how they collectively drive competitive performance under COVID-19 [16, 23, 24].

Therefore, this study addresses the following research question: "*to what extent does AI ambidexterity accelerate the development of an adaptive transformation capability to ensure the business can meet the needs of an increasingly complex environment under COVID-19?*"

This research question builds on the growing use of AI to inform and adapt organizational operations. However, while today an increasing number of organizations are delving into such activities, there is little empirically supported evidence to guide them in the process. This study, therefore, attempts to understand how the ambidextrous use of AI can indirectly lead to competitive performance gains in turbulent conditions.

The remainder of this paper is structured as follows. First, the background to the theoretical context and proposition is discussed. Next, the research methodology and the developed model are presented.

2 Theoretical context and proposition

2.1 Artificial intelligence and its ambidextrous use

AI ambidexterity builds upon the foundation of the IT ambidexterity literature that concerns the equivocal capacity to innovate and explore IT resources and practices and, on the other hand, to routinize and exploit them [25, 26]. These practices are typically difficult-to-imitate as they are uniquely adopted, deployed, and used in a particular setting to create value [27, 28] and drive the formation of organizational capabilities [29, 30]. Routine use of AI describes how AI use is integrated as a normal part of the employees' work processes. This exploitation mode focuses on refining and extending current services and products, leading to incremental innovation [24, 31].

On the other hand, innovative use refers to embedding AI deeply and comprehensively in work processes and to "employees" discovering new ways to use AI to support their work [25]. This particular stance is sometimes called 'emergent use' [32] or "trying to innovate with IT" [33], or "creative IT use" [34].

The simultaneous use of these two AI modes, i.e., AI ambidexterity, allows firms to sense the business environment by analyzing real-time and high-volume data, identifying and capturing customer needs and trends, uncovering patterns, and extracting relevant information for decision-making processes [35, 36]. Specifically relevant for this study, the ambidextrous use of AI in firms will shape the firm's dynamic capabilities as AI is used to solve business issues and problems, identify creative solutions and ideas, contribute to the effectiveness of business operations integration and help accelerate change within the firm [14, 15, 37].

However, capturing the value from both opposing modes of operandi, i.e., routine vs. innovative use of AI, is not a straightforward process as different routines and capabilities and organizational routines. Instead, the literature argues that big data and

AI should be deployed as a critical organizational resource to strengthen the firms' dynamic capabilities to use their full strategic potential [38-41]. Moreover, stakeholders should be involved to get fully engaged, and commitment from all employees for the new improvement initiatives and alignment with the strategic direction across the organization is crucial [42, 43]. Therefore, firms' simultaneous alignment of 'routinization' and 'innovation' will provide superior and sustained business benefits and strong adaptive capabilities [31, 44, 45].

2.2 Adaptive transformation capability and competitive performance under COVID-19

Following Wang and Ahmed [1], we define dynamic capabilities as "…the firm's behavioral orientation constantly to integrate, reconfigure, renew and recreate its resources and capabilities and, most importantly, upgrade and reconstruct its core capabilities in response to the changing environment to attain and sustain competitive advantage." We consider adaptive transformation capability a dynamic capability that follows the philosophy of accelerated corporate transformations [46]. Hence, this capability can be regarded as an accelerator of rapid transformations that equips firms with the capacity to address possible transformation inhibitors by corresponding transformation accelerators [47].

Change initiatives provide opportunities to build a firm's ability to adapt and change. Therefore, change initiatives that facilitate and do not inhibit adaptive transformation capabilities are more likely to produce long-term results. However, unfortunately, various inhibitors become embedded in all organizations during transformation processes. Think, for instance, about disengaged employees, recalcitrant decision-makers, and business-as-usual processes [43].

Adaptive transformation capability addresses these inhibitors to overcome the transformation barriers and guides firms to orchestrate balanced transformation initiatives, engages the extended leadership team, and helps reshape the organization, its management, and resilience [48]. In addition, this capability drives healthy interfaces across organizational boundaries and collaborations within the firm that easily reconfigures and offers multiple paths for individual contribution. As such, adaptive transformation capability is crucial in enhancing competitive performance during tumultuous times, such as the COVID-19 pandemic [23].

In summary, as a strategic capability, adaptive transformation capability facilitates firms to anchor the transformation agenda and serves as the foundation to achieve high performance under tumultuous times. Driven by AI ambidexterity, this dynamic capability enables firms to rapidly orchestrate the launch of the next development phase and implement necessary changes [24]. In a high-engagement manner, firms ensure that sustainable changes drive competitive performance and achieve breakthrough results in turbulent times.

Based on the above, we define the following:

Proposition 1: *Firms' adaptive transformation capability mediates the relationship between AI ambidexterity and competitive firm performance under COVID-19.*

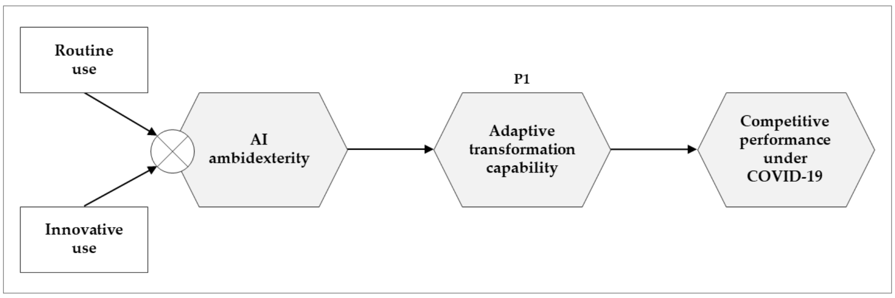

Fig. 1. Theoretical model and proposition.

3 Research methodology and dataset

3.1 Survey and data collection procedure

The target population of this study was C-level practitioners (i.e., innovation and business managers, IT managers) with key decision-making roles and experience in AI and digital transformation initiatives within the organization.

An initial survey was developed and was iteratively pretested by three Ph.D. students, one scholar, and two senior business professionals. The final survey data were collected between October 2021 and November 2021 as the practitioners completed an executive education course. The survey was also sent to colleagues within their professional network using the 'snowball' technique. After removing incomplete (N=25) or unreliable (N=21) responses from our sample, a total of 257 responses were used for the final analyses. All firms are operating in the Netherlands. Furthermore, we controlled, using a survey question, if all the respondents could address all items given their knowledge and experience. Finally, survey items were operationalized based on previous empirically validated scales (Table 1). We used a 7-point Likert scale for all items (1. strongly disagree to 7. strongly agree).

Most respondents worked in the private sector (54%) or the public sector (37%). In addition, 4% worked in Private-Public Partnerships and 5% for a Non-Profit Organization.

3.2 Measures and composite operationalization

We used previously validated measures for the constructs of AI ambidexterity. Hence, we used three measures for routine and innovative AI use. Items were drawn from [49]. We used the item-interaction of the respective constructs to measure ambidexterity following [44] as routine and innovative use of AI are interdependent and nonsubstitutable. Nine (multiplicative) items were used as a (reflective) latent construct for the operationalization.

For adaptive transformation capability, we build upon theoretical and practical work by Miles [43, 46]. Adaptive transformation capability is operationalized following the accelerated corporate transformation process architecture that identifies five levers that collectively drive transformations successfully and ensure that the business can meet customer demands during tumultuous times. These levers include strategic assessments to create a limited set of balanced transformation initiatives, high engagement and alignment at all levels, and disciplined monitoring, assessment, and readjustment throughout the transformation process. This construct is operationalized as an emergent (formative) construct.

Finally, building upon work by [38, 50], we used five items to reflect organizational performance during COVID-19. Items include increased customer satisfaction, enhanced customer loyalty, and increased profit during the past one and a half years during the COVID-19 crisis relative to competitors operating in the same industry. The organizational performance also follows the operationalization logic of a latent reflective construct. All items can be found in Table 1.

Table 1. Constructs, items, sources, and reliability statistics

Construct	Survey item	Source	Reliability statistics
Nature of constructs: latent construct, reflective			
Routine use of AI	(RUA1) The use of AI has been incorporated into our regular work practices of the organization	[49]	CA:0.83 CR:0.90 AVE:0.75
	(RUA2) The use of AI is pretty much integrated as part of our normal work routines within the organization		
	(RUA3) The use of AI is now a normal part of our work		
Innovative use of AI	(IUA1) Our organization has discovered new uses of AI to enhance our work performance	[49]	CA:0.77 CR:0.87 AVE:0.69
	(IUA2) Our organization has used AI in novel ways to support our work practices		
	(IUA3) Our organization has developed new applications based on AI use to support work processes		
Nature of construct: emergent, formative			
Adaptive transformation capability	(ATC1) We concentrate on upfront strategic and organizational assessments to create a limited set of balanced transformation initiatives	[43, 46]	Weights are sign. (*P*<0.05) $VIF_{Atc1\text{-}5}$ < 3.0
	(ATC2) We have a high engagement planning process with the extended leadership team and high accountability and alignment across the organization		
	(ATC3) We achieve agile alignment of individuals and departments with commitments from all employees		
	(ATC4) We established disciplined monitoring, assessment, and readjustment process throughout the transformation process		
	(ATC5) We provide an opportunity to build capabilities in parallel with implementing new strategic directions		
Nature of construct: latent construct, reflective			
Performance	(P1) Increase market share	[38, 50]	CA:0.84 CR:0.89 AVE:0.61
	(P2) Increase customer satisfaction		
	(P3) Increase profit		
	(P4) Enhance business brand and image		
	(P5) Enhance customer loyalty		

4 Model specification and analyses

4.1 A Composite-based SEM

As can be gleaned from the operationalization of the measures, we use composite-based SEM as the preferred approach to estimate our model and the study's central hypothesis [51]. The composite approach supports exploratory research contexts [52] and is most appropriate when using reflective and formative constructs in the research model [52]. Hence, we use latent and emergent constructs to operationalize our focal concepts.

We use SmartPLS for Windows version 3.3.6 [53] (http://www.smartpls.com) to run the analyses. When using a composite-based SEM approach, it is essential first to evaluate the reliability and validity of the measurement model, including both the latent and emergent constructs [52]. Hence, for the latent constructs, i.e., routine and innovative AI use and organizational performance under COVID-19, we assessed the psychometric properties of the theoretical model. Thus, we evaluated the latent constructs' internal consistency reliability through the use of Cronbach's alpha and the complementary composite reliability measure, convergent validity through the assessment of the AVE (average variance extracted), to identify the degree of variance captured by the latent construct), and discriminant validity [52].

After running the PLS-SEM algorithm, all latent constructs' outcomes showed reliable results (see Table 1). In addition, for the emergent construct, i.e., adaptive transformation capability, the variance inflation factor (VIF) values and the significance of the indicator (regression) weights were assessed. The VIF was used to check for possible collinearity of the formative measures. All obtained values were well below three as a threshold, and all items showed significant results [54].

4.2 Proposition testing

This section examines whether firms' adaptive transformation capability mediates the relationship between AI ambidexterity and competitive firm performance under COVID-19, i.e., proposition 1.

Outcomes for overall model fit showed that the Standardized Root Mean Square Residual (SRMR) was 0.06 [55], and thus proposition can now be tested as well as the coefficient of determination (R^2) and associated predictive power values (Stone-Geisser values, Q^2). We used a non-parametric bootstrapping procedure for the analyses using 5000 replications in SmartPLS to get stable statistical estimates. Outcomes of the bootstrapping procedure show that AI ambidexterity positively influences adaptive transformation capability (β =.54; t = 11.31; p < .0001) that subsequently significantly influences organizational performance under COVID-19 (β =.59; t =11.52; p < .0001).

Also, after following a systematic mediation procedure [56], results show that the impact of AI ambidexterity is fully mediated by adaptive transformation capability as the indirect effect (AI ambidexterity —› performance), among other affirmative results, was non-significant (β =.03; t = .47; p = .64). These outcomes confirm the main proposition of this work. Finally, included control variables (size and industry) showed non-significant results, excluding confounding issues. Also, the model explains 29.6% (R^2 = .30) of the variance for adaptive transformation capability and 35% (R^2 = .35) for organizational performance under COVID-19.

Using SmartPLS's blindfolding procedure, we obtained Q^2 values to assess the model's predictive power. Hence, obtained Q^2 values were also well beyond 0, showing the model's predictive relevance.

5 Discussion and implications

This study aimed to investigate the contribution of AI ambidexterity in firms and how this supports the organization's adaptive transformation capability and competitive performance under COVID-19. To test the central proposition of this work, we used data collected from 257 senior professionals from firms operating in various industries.

We found support for this proposition. Therefore, AI seems crucial in shaping a firm's adaptive transformation capability and thus its ability to accelerate rapid transformations and drive performance under COVID-19. However, while this claim has been argued in several practice-based studies and many editorial and opinion articles, there has been limited empirical support to document whether AI can produce business value in the organizational context and through what means. In this empirical investigation, we have documented the effect and the mechanisms of action through a large-scale quantitative study. Doing so opens up several important theoretical and practical which are discussed further.

5.1 Theoretical and practical implications

This study makes three vital theoretical contributions. *First*, this is the first empirical study that unfolds the crucial role of adaptive transformation capability, facilitated by AI, in achieving competitive results during tumultuous times. Therefore, this study extends numerous conceptual and empirical studies that highlight the crucial role of AI in developing capabilities, driving innovation, and obtaining business benefits [11, 15, 18, 35, 39]. This is important as scholars can now use these results to investigate transformation agendas and evaluate sustainable organizational changes.

Second, our current work also indicates that digital technologies such as AI can allow organizations to navigate demanding and changing business conditions by building digital capabilities that are hard to replicate from the competition. Thus, our work contributes to the extant literature and answers the call for more foundational research regarding AI in shaping dynamic capabilities [10, 14, 16, 23, 24]. In doing so, we highlight the role of AI as an agile enabler of business. This study outcome also goes against claims that AI is often monolithic and challenging to adapt to changing conditions due to its long life-cycle times. However, what is essential is that firms can leverage AI to facilitate rather than impede adaptive transformation [10, 23, 24, 36]. Our study constructs offer insights on how to achieve this.

Third, we also show how AI ambidexterity is a crucial enabler of adaptive transformation capability. The conceptualization of AI ambidexterity builds upon the foundations of IT ambidexterity, and we, therefore, extend this current knowledge base [25, 30, 41]. While there has been significant theoretical discussion about the role of AI in facilitating exploration and exploitation [24, 35, 36], there is limited empirical knowledge about whether being able to leverage AI in this manner impacts the adaptive transformation capability of firms. Findings such as this indicate that digital technologies can facilitate organizational fluidity and adaptability when leveraged under certain conditions.

This work has various practical implications addressing how firms can leverage these results. Based on the outcomes of this work, we argue that decision-makers should focus on an ongoing strategy and capability-building process enabled by AI. This means, for example, that decision-makers within the organization should emphasize seeing the AI phenomenon through a more holistic approach that considers technology a core component of competitive strategies. In doing so, firms should actively invest in routine, and innovative AI uses to develop and further shape dynamic capabilities to look forward, inform and optimize decision-making, and adapt to changing market conditions and demands. These steps will ensure that the firm refocusses on several strategic growth and performance improvement initiatives, keeps up with competitors, and achieves high levels of organizational performance.

Despite the study's contributions, several limitations should be acknowledged. First, we only surveyed respondents from the Netherlands. It would be a valuable research opportunity to execute this research in different countries in Europe or even on other Continents. Second, as we used a cross-sectional approach, we only measured at a single point in time. Thus, we could not follow the development of AI and its contributions to adaptive transformation capability over a more extended period. Nevertheless, this could be a valuable area for future work that several in-depth case studies can strengthen. Third, future work could also embrace a configurational perspective and unfold possible factors and conditions under which firms can realize high levels of organizational performance while capitalizing on their dynamic capabilities [57].

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