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► **To cite this version:**

Issam Laguir, Shivam Gupta, Indranil Bose, Rebecca Stekelorum, Lamia Laguir. Analytics capabilities and organizational competitiveness: Unveiling the impact of management control systems and environmental uncertainty. *Decision Support Systems*, 2022, 156, pp.113744. 10.1016/j.dss.2022.113744 . hal-03636923

**HAL Id: hal-03636923**

**<https://hal.science/hal-03636923v1>**

Submitted on 22 Jul 2024

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## **Analytics capabilities and organizational competitiveness: Unveiling the impact of management control systems and environmental uncertainty**

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# **Analytics capabilities and organizational competitiveness: Unveiling the impact of management control systems and environmental uncertainty**

## **Abstract**

In this study, we investigated how management control systems (MCS) aid in translating analytics capabilities (AC) generated insights into enhanced organizational competitiveness under conditions of environmental uncertainty. The survey data from 405 manufacturing firms offers several unique contributions. First, it reveals that the link between AC and organizational competitiveness is not necessarily direct and may occur through MCS. Thus, it offers interesting insights concerning the mechanisms through which AC can generate value and competitiveness. Second, this study borrows from Simons' (1995, 2000) levers of control (LoC) framework and offers a holistic and more in-depth understanding of the connections between AC, MCS, and organizational competitiveness. Third, by considering the nonlinear moderating role of environmental uncertainty, it offers a response to recent calls for research on the circumstances under which AC-generated insights can lead to organizational competitiveness. It also provides a response to recent calls for further research on AC - MCS relationships. Fourth, the study draws on a dynamic capabilities perspective to analyze how MCS can help translate AC-generated insights into improved organizational competitiveness. While this perspective has proven its worth in the information systems literature, it has received less attention with regards to management control processes.

**Keywords:** Analytics Capabilities; Dynamic Capabilities View; Environmental Uncertainty; Management Control Systems; Organizational Competitiveness.

## **1. Introduction**

In this global and digital era, organizations have access to huge quantities of data from a wide range of stakeholders (Mikalef et al., 2019; Raffoni et al., 2018). Firms are therefore prompted to engage in a fervent quest for organizational competitiveness and value creation through the exploration and use of analytics capabilities (AC) (Luo et al., 2015). Indeed, with AC, companies have the ability to collect, save and analyze considerable volumes of unstructured data, often reaching valuable insights that can

create value and generate organizational competitiveness (Srinivasan and Swink, 2018). The ability to produce these data-generated insights is extremely important, particularly for those firms evolving in complex and uncertain environments in which informed decision-making is crucial (Mikalef et al., 2019). Yet, extant research on the competitive advantage generated by AC is still in the preliminary stage, and knowledge is lacking on the mechanisms by which such advantage is generated (Côte-Real et al., 2020; Mikalef et al., 2020). Sharma et al. (2014), for example, noted that, despite the evidence that AC can indeed generate value, deeper analysis is still needed. Günther et al. (2017) emphasized that more extensive empirical study would help better understand the mechanisms for disseminating AC in order to enhance organizational competitiveness. Following this line of argument, it can be observed that the mere use of technology will have no effect if it is not supported by management accounting systems that turn AC from a resource to a capability. Indeed, management control systems (MCS) provide ways to translate AC-generated insights into organizational competitiveness. As decision support activities, these systems are central to strategy-making (Gond et al., 2012; Henri, 2006) because they “shape the process of strategy emergence and support the implementation of deliberate strategies” (Gond et al., 2012, p.206), which ultimately creates value for the firms. In this vein, firms can mobilize AC-generated insights to identify emergent behaviors and priorities, to fix acceptable and off-limits activities, to explore new indicators to assess and monitor outcomes, and to sense strategic uncertainties and emergent opportunities. In doing so, AC bolster MCS that enable firms to promote shared core values, to foster information exchange, to decrease the risk of off-limit activities, to manage environmental uncertainties and promote the adoption of opportunity-seeking behaviors. This ultimately allows firms to generate organizational competitiveness.

Information systems (IS) studies have recently begun focusing on AC and the value organizations can create by successfully rooting these capabilities in managerial accounting tasks (Rikhardsson and Yigitbasioglu, 2018). However, research on the use of AC to bolster MCS and ultimately generate organizational competitiveness is still sporadic, with fragmented and disparate findings. For example, Sharma et al. (2015) have proposed a research agenda to analyze linkages among business analytics,

decision-making processes and organizational performance. O'Connor and Martinsons (2006) have proposed an integrative cost-benefit framework in order to investigate outsourcing, chargebacks, business process re-engineering and amelioration, and decision support. They have also emphasized that accounting research can provide significant insights to knowledge on IS. Vallurupalli and Bose (2018) have provided a new framework that is process-based to allow end-to-end analysis of the technology shaping performance measurement systems through a case-based study of a big manufacturing company located in India. Last, Raffoni et al. (2018) have proposed a broad model that can be used to operationalize analytics for diagnostic and interactive performance management systems and, using an action research approach, have designed a framework comprising five steps for application to a construction company. This brief review reveals that no study has yet investigated whether MCS are able to translate AC into enhanced organizational competitiveness. Therefore, to address this literature gap, our first research question (RQ1) is as follows: *To what extent can AC be used to bolster MCS and generate organizational competitiveness?*

Research has shown that turbulent and uncertain environments can affect the competencies of organizations (Gligor, 2016). Along the same line, Schilke (2014) has pointed out that firm capabilities are in great part dependent on the context of deployment. Other scholars have found that efficient organizational adaptation depends on environmental forces, and they have also emphasized that environmental uncertainty may well be a significant contextual variable (Helfat and Winter, 2011; Schilke, 2014). Here, we investigate the role of environmental uncertainty in terms of demand, manufacturing and supply (Chen and Paulraj, 2004; Sreedevi and Saranga, 2017). Indeed, Chen and Paulraj (2004, pp. 122-123) argued that “there are three different sources of uncertainty that plague supply chains: supplier uncertainty, arising from on-time performance, average lateness, and degree of inconsistency; manufacturing uncertainty, arising from process performance, machine breakdown, supply chain performance, etc.; and customer or demand uncertainty, arising from forecasting errors, irregular orders, etc.” In other words, uncertainty in demand refers to unknowns related to product or environmental characteristics that render the prediction and control of the demand for a final product

difficult. Uncertainty in manufacturing refers to factors in the manufacturing process that are unpredictable and uncontrollable and that emerge from process performances, machine breakdowns, supply chain performances, and so on (Chen and Paulraj, 2004). Last, uncertainty in supply refers to failing to deliver according to the customer's needs due to issues of on-time performance, average lateness, degree of inconsistency, etc. (Chen and Paulraj, 2004). In this regard, the literature has demonstrated that turbulent and uncertain environments can impact the competencies of organizations (Gligor, 2016), and researchers have found that efficient organizational adaptation depends on environmental forces, thus showing that environmental uncertainty might well be a significant contextual variable (Schilke, 2014). In this vein, the recent coronavirus outbreak (Covid-19) provides an example of how an uncertain and complex environment can hamper firms as well as all domains of economy and society. The Covid-19 pandemic has led to a huge economic breakdown, as customer demand and worldwide industry activity have collapsed (Giones et al., 2021; Choi and Sethi, 2021). During the second quarter of 2020, GDP declined by 12.1% within the EU zone, while it shrunk by 32.9% in the US (CNBC, 2020). Thus, another gap in the literature concerns the question of how AC benefit MCS under conditions of varying degrees of environmental uncertainty. To fill this gap, we sought to answer a second research question (RQ2): *In what way does environmental uncertainty impact the relationships between AC and MCS?*

This study offers several unique contributions. First, it reveals that the link between AC and organizational competitiveness is not necessarily direct and may occur through MCS. Thus, it offers interesting insights concerning the mechanisms through which AC can generate value and competitiveness. Second, this study borrows from Simons' (1995, 2000) levers of control (LoC) framework and offers a holistic and more in-depth understanding of the connections between AC, MCS, and organizational competitiveness. Third, by considering the nonlinear moderating role of environmental uncertainty, it offers a response to recent calls for research on the circumstances under which AC-generated insights can lead to organizational competitiveness (Mikalef et al., 2020; 2019). It also provides a response to recent calls for further research on AC–MCS relationships

(Rikhardsson and Yigitbasioglu, 2018). Fourth, the study draws on a dynamic capabilities perspective to analyze how MCS can help translate AC-generated insights into improved organizational competitiveness. While this perspective has proven its worth in the information systems literature, it has received less attention with regard to management control processes. The study thus offers unique insights and extends the literature in this area.

The rest of this article is composed of five sections: the second section gives readers the background in terms of theory for our study and introduces our hypotheses. The third section sets forth our research method, sample selection, and variable measures. The fourth section presents the results. We discuss the findings in the fifth section and conclude in the last section.

## **2. Theoretical framework and hypothesis development**

### *2.1 Dynamic capabilities view (DCV)*

We theoretically developed the linkages between AC, MCS, and organizational competitiveness under environmental uncertainty by drawing on the dynamic capabilities view (DCV), which is essentially a prolongation of the resource-based view (RBV) from Teece et al. (1997) to investigate organizational competitiveness in turbulent markets and highly dynamic and uncertain environments (Teece, 2012). In this regard, Teece et al. (1997) have underlined the importance of fostering management capabilities and combinations of organization, function, and technology-related skills that are difficult to mimic. Teece (2012, p. 1395) have stated that dynamic capabilities refer to organizational abilities “to integrate, build, and reconfigure internal and external resources/ competences to address, and possibly shape, rapidly changing business environments”. More specifically, dynamic capabilities comprise the ability to (i) detect threats and opportunities, (ii) act on opportunities, and (iii) reconfigure firm resources (Eckstein et al., 2015). Sensing abilities comprise identifying, developing, co-developing, and evaluating technological opportunities for value creation. Seizing abilities refer to possessing the necessary resources to create value. Last, reconfiguration abilities include all those activities that “recombine bundles of resources and ordinary capabilities” (Fainshmidt et al., 2016, p. 2) in order to “innovate and respond to (or bring about) changes in the market and in the business environment more generally”

(Teece, 2014, p. 332). Scholars have argued that AC contribute to the sensing, seizing, and reconfiguring processes that ultimately improve organizational competitiveness (Mikalef et al., 2020; Tai et al., 2019). Indeed, these capabilities, which include using and combining different data sources, enable firms to generate useful insights that enhance the ability to perceive emerging threats and new business opportunities (Kiron, 2017). In addition, firms tend to use AC to handle unstructured and varied data sources over brief time cycles, which fosters the speed, effectiveness and efficiency of data-generated insights that can be used to seize opportunities (Sharma et al., 2014). Last, firms can use AC to learn about earlier failed or successful products/ services and thus reconfigure their abilities accordingly. Scholars have pointed out that dynamic capabilities are built in part when managerial and organizational processes facilitate the coordination of firm activities (Rehm et al., 2017; Teece et al., 1997). MCS can thus be considered as the set of processes that enable sensing, seizing, and reconfiguring firm activities. More specifically, firms can use the control features of boundary and diagnostic systems (i.e., rules and goals) to encourage employees to align with firm strategy and avoid emerging threats. They can also use the enabling aspects of interactive and belief systems to promote discussion and foster opportunity-seeking behaviors. In this regard, the use of these positive and negative forces creates dynamic tension between innovation and strategic renewal on one hand and targeted objective realization on the other hand, which should be properly dealt with to create an organizational competitive edge (Speklé et al., 2017; Kruis et al., 2016).

## *2.2 Analytics capabilities*

Analytics capabilities have increasingly come to the attention of both professionals and scholars (Srinivasan and Swink, 2018). Indeed, firms have increasingly promoted the use of AC as a way to generate the useful insights that will ultimately provide them with organizational competitiveness (Jha et al., 2020). However, scholars have pointed to the disagreements on what AC actually are, as they are conceptually at a nascent stage and have several definitions (Agarwal and Dhar, 2014; Srinivasan and Swink, 2018). In this study, we adopt the definition Srinivasan and Swink (2018, p. 1851), with AC understood to be a set of “tools, techniques, and processes that enable a firm to process, organize,



visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making, and execution”. Scholars have noted that a key distinction between AC and the conventional technologies to support decision-making relates to volume, variety, and velocity (McAfee and Brynjolfsson, 2012; Srinivasan and Swink, 2018). While scholars in IS relate AC solely to IT tools, the conceptual framework of Srinivasan and Swink (2018) have encompassed both tools and processes. More specifically, AC is related to “how firms use advanced quantitative techniques such as statistical methods, optimization, and simulation to arrive at usable information and insights in their decision-making process” (Srinivasan and Swink, 2018, p. 1852).

### *2.3 Management control systems*

This study used Simons’ (1995, 2000) LoC framework to help answer the research questions. Scholars have emphasized that the LoC framework has numerous strengths (Tessier and Otley, 2012) as it (i) focuses on MCS to shape strategic renewal and direct the attainment of strategic objectives (Henri, 2006; Simons, 1995), (ii) enables the intended strategies to be implemented and the exploration of emerging ones (Skærbækand and Tryggestad, 2010), and (iii) allows an analytical tool to examine how MCS are used to manage strategic uncertainty (Simons, 1995). Simons’ framework is based on the idea of managing the tensions of opposing forces “between freedom and constraint, between empowerment and accountability, between top-down direction and bottom-up creativity, between experimentation and efficiency” (Simons, 1995, p. 4). To handle the tension, Simons proposed what he called positive and negative control systems. Positive controls (i.e., interactive and belief systems) aim to motivate, reward, direct and foster learning, while negative controls (i.e., boundary and diagnostic control systems) aim to coerce, correct, prescribe and control (Tessier and Otley, 2012). These opposing forces have to coexist to ensure dynamic tensions and effective control. Indeed, the full potential of LoC is reached when they are mobilized together to help managers handle innovation, capabilities, and organizational learning and manage strategic objectives. As per Simons (1995, p.34), belief systems focus on the communication of an organization’s core values, being “the explicit set of organizational definitions that senior managers communicate formally and reinforce systematically to provide basic values, purpose, and direction for the

organization”. Interactive systems address strategic uncertainties/ opportunities and are “formal information systems that managers use to involve themselves regularly and personally in the decision activities of subordinates” (Simons, 1995, p. 95). Boundary systems help define the risks to be prevented and are “formal systems used by top managers to establish explicit limits and rules which must be respected.” (Simons, 1994, p. 170). Finally, diagnostic systems address the key performance indicators, being “formal information systems that managers use to monitor organizational outcomes and correct deviations from pre-set standards of performance” (Simons, 1995, p. 59).

#### *2.4 Environmental uncertainty*

Environmental uncertainty is a major factor in DCV (Schilke, 2014), which assumes that dynamic capabilities (AC and MCS) have different impacts on organizational competitiveness contingent on the degree of uncertainty in a company’s external environment (Chen et al., 2015; Henri and Wouters, 2019). Environmental uncertainty is therefore the concept of volatility and unpredictability present in the external environment (Henri and Wouters, 2019) that can be defined as “when the environment is ambiguous, firms can experience rapid, unpredictable changes in production technologies, customer demands, market competition, and other environmental factors” (Wang et al., 2020). Environmental uncertainty arises when information on future events and their outcomes is lacking (e.g., modifications in client demand, changes in competitor and supplier behavior, or technological development). Davis (1993) has proposed three sources of this uncertainty: (i) demand uncertainty, which is due to events such as forecasting errors and irregular orders (Chen and Paulraj, 2004; Sreedevi and Saranga, 2017), (ii) manufacturing uncertainty, which is due to poor process performances, machine breakdowns, and poor supply chain performances, among others; and (iii) supplier uncertainty, which is due to low on-time performance, high mean lateness, and high levels of incoherence. In line with Davis (1993), we have considered environmental uncertainty in terms of demand, manufacturing, and supply. Demand uncertainty is assessed in terms of fluctuations and changes in demand. Manufacturing uncertainty is measured in terms of fluctuations in manufacturing volume and the mix of products. Last, supply uncertainty is assessed in terms of fluctuations in supply requirements (volume and mix).

### *2.5 Organizational competitiveness*

Organizational competitiveness is the extent to which an organization generates and sustains a prevailing position over its competitors through value creation for stakeholders (Porter, 1985). In this regard, Porter (1985) has defined it as the way in which firms select and implement business strategies to enable/ retain competitive advantage. Organizational competitiveness encompasses those abilities that enable organizations to distinguish themselves from competitors as a result of crucial management decisions (Tracey et al., 1999). For example, a firm can derive organizational competitiveness by creating and developing sets of unique and strategic resources, competencies and/ or capabilities (AC or MCS) that it can control and exploit to gain competitive advantage (Barney, 1991). Like Fraj et al. (2015), we have considered organizational competitiveness in terms of cash flow from operations, operating profits, return on investment, capability to generate profits during periods of crisis, and ability to achieve economic objectives.

### *2.6 Relationships between analytics capabilities and organizational competitiveness*

The recent literature has shown that firms can derive value from AC as they pursue organizational goals (Mikalef, et al., 2019). Indeed, the focused mobilization of AC has helped firms identify threats and opportunities, produce key insights, and reconfigure their activities to fulfill stakeholder expectations in a competitive environment (Luo et al., 2012; Mikalef, et al., 2019). Thus, the main competitive differentiator that AC can generate is more informed decision-making (Abbasi et al., 2016). The growing attention to AC has been especially apparent in firms evolving in uncertain and fast-changing environments. Scholars have also observed that firms are increasingly mobilizing AC to shape their decisions and orient future strategies in order to achieve organizational competitiveness (Mikalef et al., 2020; Trkman et al., 2010). Moreover, Liu (2014) has highlighted that AC are major differentiators between high- and low-performing companies because they equip firms to be more proactive and faster in sensing emergent opportunities. They provide firms with the means to handle organizational contingencies through the assessment of alternatives aligned with the organization's strategic goals (Srinivasan and Swink, 2018). By rooting real-time insights generated from AC in organizational

decisions and fostering better solutions, firms can avoid costly actions (e.g., overtime production, lost sales, and inventory excesses or reductions) and achieve organizational competitiveness. In addition, AC provide firms with better insights on demand, which in turn improves resource assignments and product positioning decisions (Srinivasan and Swink, 2018). Furthermore, the critical insights generated by AC help firms take appropriate and accurate actions, such as modifying production levels and reconfiguring the product mix to meet customer expectations, and to achieve competitiveness (Côte-Real et al., 2020). We therefore offer the following hypothesis:

**H1.** AC are positively associated with organizational competitiveness.

### *2.7 Relationships between analytics capabilities, management control systems and organizational competitiveness*

AC can help organizations reach organizational competitiveness by strengthening intermediate organizational capabilities (Mikalef et al., 2020; Schryen, 2013). Indeed, AC are pivotal because they foster impacts that are complementary to those of intermediate organizational capabilities like MCS that ultimately generate competitive advantage (Mikalef et al., 2020). In managerial accounting, AC enable the development and evolution of effective MCS, and their roles can differ depending on their use (Raffoni, et al., 2018; Warren et al., 2015). More specifically, belief systems (e.g. credos, mission statements and purpose statements) enable employees to be involved in firms' core values and mission and direct their opportunity-seeking behaviors (Speklé et al., 2017). AC can thus support and bolster belief systems by identifying emergent behaviors, priorities, goals and/ or values to be incorporated into explicit firm statements. For example, using the web at work can be associated with learning and the pursuit of goals/ priorities, internal emails can be associated with the efficiency of internal business processes, and client service quality can be associated with vocalic cues gleaned from customer service calls (Warren et al., 2015). We thus hypothesize the following:

**H2a.** AC are positively associated with belief systems.

Simons (1990, p. 128) has argued that "Management control systems are used not only to monitor that outcomes are in accordance with plans, but also to motivate the organization to be fully informed

concerning the current and expected state of strategic uncertainties”. Accordingly, to generate organizational competitiveness, firms use MCS to foster staff involvement, promote coordinated actions, sense organizational goals and support their communication, and reduce uncertainties (Henri and Wouters, 2019). The use of MCS to generate competitive advantage varies depending on their nature. Through belief systems, firms foster shared core values that reflect a stable reference point for staff, especially when evolving in an uncertain and turbulent environment. In doing so, firms align employee behavior with their strategic orientation, enable a mutual foundation of understanding, promote the exchange of information between senior and junior staff members, and prevent conflicting interests and disagreements (Bedford, 2015). This in turn strengthens organizational competitiveness. Moreover, firms use belief systems to improve employee motivation in settings that need creativity (Simons, 1995). In this regard, the internalization of values and strategic intentions allows firms to direct employees’ creative efforts toward projects that generate value without displacing intrinsic impetus (Bedford, 2015). In hypothesis 2a, AC are linked to belief systems (hypothesis 2a), and research has shown that belief systems have a positive effect on organizational competitiveness. Accordingly, we expect AC to have indirect effects on organizational competitiveness by impacting belief systems. The following hypothesis is thus proposed:

**H2b.** AC positively influence organizational competitiveness through belief systems.

Firms can mobilize AC to bolster boundary systems. More specifically, boundary systems (e.g. codes of business conduct, strategic planning systems) enable firms to signal to employees the activities and practices they must avoid. Firms can thus use AC-generated insights to sense emergent standards and/ or acceptable and off-limits activities to be incorporated in explicit organizational parameters. For instance, firms can mobilize AC to monitor in-office behavior, email, and staff telephone calls in order to manage productivity risks. Firms can also monitor staff computers to produce activity logs that encompass data on time using productivity software, the web, and clickstreams (Warren et al., 2015) to identify adequate activities and sense the risks to be avoided. Drawing on the aforementioned argument, we offer the following hypothesis:

**H3a.** AC are positively associated with boundary systems.

Although boundary systems restrict employee latitude, this does not mean that motivation and empowerment decline (Bedford, 2015). Indeed, boundary systems enable firms to direct employee attention toward activities considered critical to competitiveness. More specifically, employees can become disheartened from constant searching for reconfigurations beyond timely and optimal solutions. Firms can likewise use boundary systems to lower the risk of off-limit activities that could hamper the efficiency and effectiveness of established processes (Bedford, 2015). Boundary systems foster strategic renewal and promote the adoption of new routines and frames of reference (Simons, 1994). This indicates that these systems contribute to strengthening organizational competitiveness. In hypothesis 3a, AC were connected to boundary systems. Subsequently, we argued that boundary systems support organizational competitiveness. Hence, we can hypothesize:

**H3b.** AC positively influence organizational competitiveness through boundary systems.

Firms can use AC to support diagnostic systems. More specifically, diagnostic systems (e.g. business plans and budgets) enable firms to motivate employees, monitor the outcomes of behaviors, and reward objective attainment. Critical AC-generated insights can thus be used to sense and explore emergent indicators to measure and monitor outcomes, direct corrective actions, and foster the implementation of intended strategies. AC can be mobilized to identify correlations, including linkages between adequate management performance and variables that have not been considered (Warren et al., 2015). Raffoni et al. (2018) have showed that AC can identify the causal effects between impact factors (qualitative/ non-financial) and strategic target measures. For instance, firms can use email and phone conversations provided by AC to shape indicators of staff morale (Warren et al., 2015). Moreover, the number of emails written by staff can be an indicator of productivity, whereas customers' body language as captured on video may indicate their satisfaction (Warren et al., 2015). This suggests that AC can bolster strategic and operational planning and measurement and strengthen day-to-day decision-making (Raffoni et al., 2018). Accordingly, we can hypothesize:

**H4a.** AC are positively associated with diagnostic systems.

Firms can use diagnostic systems to generate organizational competitiveness. Indeed, through diagnostic systems, firms provide clear and transparent organizational goals. In doing so, they promote mutual involvement, foster coordination, handle environmental uncertainties, and improve the effectiveness of finding solutions to task-related problems, which leads to higher competitiveness (Wang and Chen, 2006; Widener, 2007). Moreover, although diagnostic systems define the intended outcomes, they provide no indications about the procedures that should be followed (Bedford, 2015). These systems enable firms to provide adequate space and flexibility for employees to explore new reconfiguration of activities. Also, they enable assessment through goals, thus enhancing employee productivity and motivation and ultimately leading to improved competitiveness (Bedford, 2015). In hypothesis 4a, AC are associated with diagnostic systems. Above, we argued that diagnostic systems bolster organizational competitiveness. Accordingly, we can hypothesize:

**H4b.** AC positively influence organizational competitiveness through diagnostic systems.

AC can be used to bolster interactive systems. More specifically, interactive systems (e.g. works council, periodic meeting) enable firms to discuss objectives and action plans that shape firm activities, and to inform others about strategic priorities and uncertainties (Mundy, 2010). Firms can thus use AC-generated insights to sense and explore emergent strategies, strategic uncertainties, and potential opportunities to be incorporated in formal processes such as works councils, periodic meetings, and face-to-face meetings with operational staff. AC can be employed to foster the high level of information processing needed to deal with an uncertain and turbulent environment (Raffoni et al., 2018). Also, critical AC-generated insights can be debated and discussed in interactive exchanges with employees, thus fostering the shaping of emergent strategies, promoting the identification of new action plans, and prompting opportunity-seeking behaviors. Raffoni et al. (2018) have noted that bringing together multiple and varied sources of data may well promote information-sharing and discussion throughout the organization.

**H5a.** AC are positively associated with interactive systems.

Extant research has emphasized that interactive systems improve organizational competitiveness (Mikalef et al., 2020). Managers use these systems to keep themselves personally involved in subordinates' decision-making activities. In doing so, they ensure their own access to new activity patterns and foster adequate resource allocation to those activities with the greatest likelihood of generating competitive advantage (Bedford, 2015; Simons, 1995). Moreover, firms mobilize interactive systems to promote communication and discussion of implicit knowledge that is useful to guide opportunity-seeking behavior and gain competitiveness benefits from new markets and technologies. They use interactive systems to ensure an ongoing open space for dialogue, thereby appealing against the status quo, challenging actual action plans, and ultimately fostering competitiveness (Bedford, 2015; Simons, 1995). In hypothesis 5a, AC are linked to interactive systems. Since we argued that interactive systems support organizational competitiveness, the following hypothesis is therefore expected:

**H5b.** AC positively influence organizational competitiveness through interactive systems.

### *2.8 The moderating effects of environmental uncertainty*

The literature has emphasized the key role of the external environment to shape firm behavior (Bedford; 2015). Indeed, organizations deal with uncertainty caused by environmental change, manage the specialization or assignment of resources, and ultimately ensure organizational competitiveness (Wang et al., 2020). Gul and Chia (1994, p. 418) have found that “perceptions of uncertainty, rather than the actual uncertainty . . . influence the decision that managers make in response to their respective organizations' operating environments”. Moreover, scholars have noted that adaptation to the external environment differs for organizations evolving in a dynamic and uncertain environment compared to those evolving in a more stable environment (Mammassis and Kostopoulos, 2019). In this regard, when environmental uncertainty and informational needs tend to increase and/ or vary, the advantage of possessing further information from both AC and MCS is particularly relevant. More specifically, the use of MCS is likely to improve when firms dealing with growing environmental uncertainty have better AC-generated insights. Indeed, when environmental uncertainty increases, managers who receive and use timely AC-

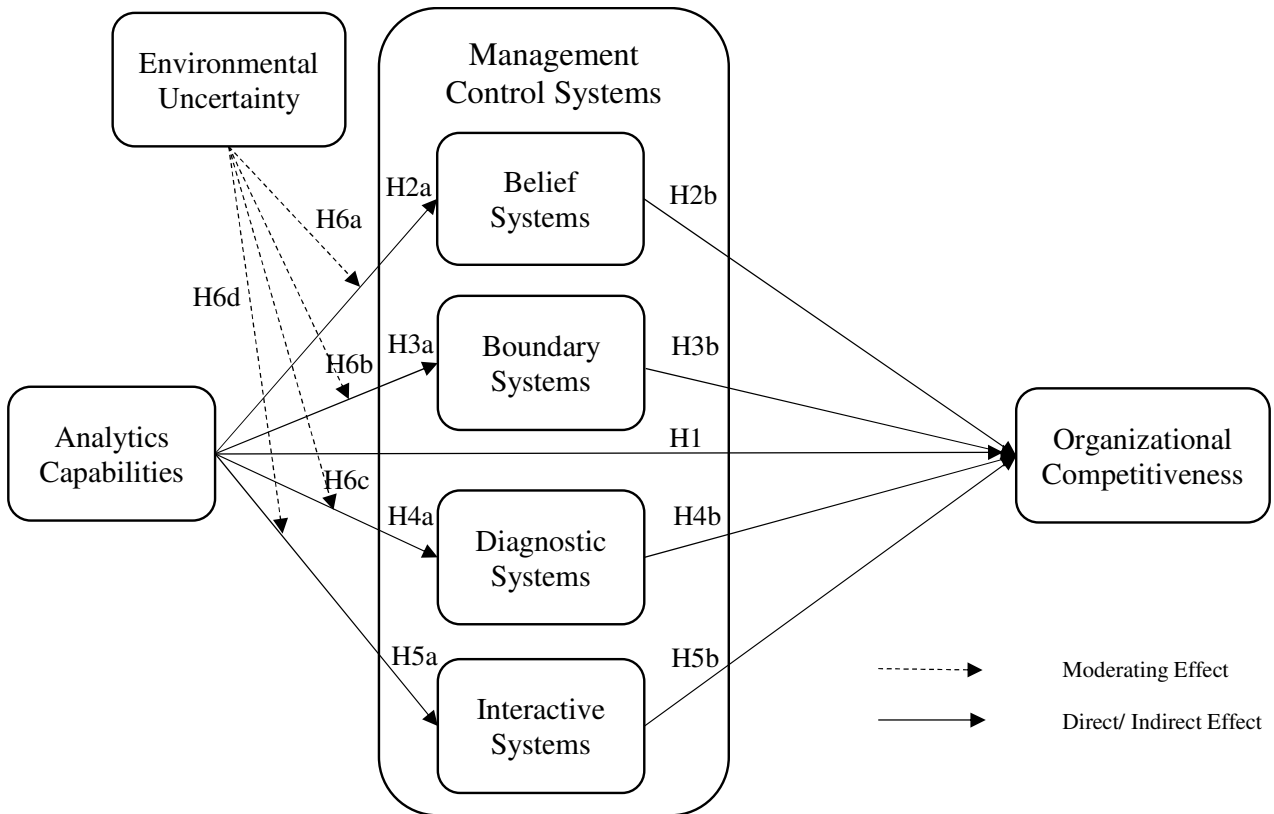


generated insights are more likely to make timely decisions that enhance the effectiveness of MCS.

Drawing on the aforementioned observations, we hypothesize the following:

**H6.** Environmental uncertainty has a beneficial moderating effect on the paths connecting AC and (a) belief systems, (b) boundary systems, (c) diagnostic systems, and (d) interactive systems.

Figure 1 provides a diagrammatic representation of the research model under study.



**Figure 1.** Research model

### 3. Research methods

#### 3.1 Study design

To investigate our research model, we employed a survey method based on a questionnaire as this permits simple replication, fosters the examination of a large number of items simultaneously, and enables the generalizability of results (Pinsonneault and Kraemer, 1993). We administered the survey from October 2019 to January 2020 to a random sample of 3000 manufacturing firms in France. To identify these firms, we used the DIANE database, which encompasses the key information about 28,986 licensed manufacturing firms in France. First, the survey was administered to academics and directors to

verify that all items were clear. We then proceeded to final modifications and identified an appropriate respondent in relevant departments through a direct company contact or LinkedIn. We sent an email to the senior managers of the firms explaining the objective of the study and attached the survey. Then we followed up with three email reminders. Respondents were assured of the confidentiality of any information shared with us. We received 405 completed surveys, indicating a 13.5% response rate.

We checked sample size adequacy via ‘a priori’ and post-hoc power analyses with the G\*Power tool (Faul et al., 2009). Thus, the minimum R<sup>2</sup> value was 0.10, the statistical power was 95%, and we had five predictors (the organizational competitiveness construct had the highest number of predictors). The ‘a priori’ G\*Power results indicated that we would need a sample size of 184. Also, the post-hoc G\*Power results for a minimum R<sup>2</sup> of 0.10, a sample size of 184, and five predictors indicated that the statistical power was 0.95. This indicates that our sample size was sufficient.

To ensure the validity of the data, we analyzed the non-response bias. We based our evaluation on the work of Werner et al. (2007) and did not find any significant differences between early and late responders (N=203 and N=202 respectively) for industry (t=1.521; p=.129). Accordingly, non-response bias did not pose a problem. Furthermore, the comparisons of respondents and non-respondents with regards to ownership characteristics showed no significant differences (Panel B, Table 1). Thus, the non-response analyses indicated that the sample was representative, and the likelihood of non-response bias was low. A summary of the sample characteristics and non-response test can be found in Table 1.

**Table 1.** Sample characteristics and tests of non-response

<b>Panel A: Characteristics of respondents (sample=405)</b>	<b>Numbers</b>	<b>Percentage</b>
<b>Respondents’ job titles</b>		
Logistics department manager	132	32.59%
CEO	90	22.22%
Purchasing department manager	74	18.27%
Production department manager	38	9.38%
Commercial or marketing department manager	36	8.88%
Others	35	8.64%
<b>Experience</b>		
[0-5[	69	17.03%
[5-15[	109	26.91%
[15-25[	130	32.09%

>25	97	23.95%
<b>Gender</b>		
Male	306	75.55%
Female	99	24.45%
<b>Industry</b>		
Food, beverage and tobacco products	77	19,01 %
Chemicals and petrochemicals	25	6,17 %
Wood and furniture	26	6,41 %
Pharmacy	24	5,92 %
Building materials	20	4,93 %
Rubber and plastics	37	9,13 %
Metal machinery and engineering	95	23,45 %
Textiles and apparel	16	3,95 %
Electronic products and electrical appliances	73	18,02 %
Publishing and printing	12	2,96 %
<b>Ownership</b>		
Joint-stock company	217	53,6 %
Limited joint-stock company	108	26,6 %
Limited liability company	58	14,3 %
Others	22	5,4 %
<b>Number of employees</b>		
[0-10[	27	6,66 %
[10-50[	111	27,40 %
[50-250[	134	33,08 %
>250	133	32,83 %

<b>Panel B: Non-response analysis for size and ownership characteristics of firms</b>	<b>Respondents (n = 405)</b>	<b>Non-respondents (n = 60)</b>	<b>Mann-Whitney-U-Test</b>
<b>Ownership</b>			
Joint-stock company	232.07	239.25	Z = -0.447 (p = 0.655)
Limited liability company	234	226.25	Z = -0.547 (p = 0.584)
Limited partnership	234.3	224.25	Z = -0.906 (p = 0.365)
Others	232.13	238.88	Z = -0.896 (p = 0.370)

### 3.2 Common method variance

This study employed self-reported and cross-sectional data. Consequently, common method variance (CMV) might have raised issues related to the robustness of the structural relationships between the model constructs. To handle these issues, we referred to Podsakoff et al. (2003) and used procedural

design and post-hoc analyses. More specifically, to ensure a procedural design, the survey was constructed with the input of senior academics. Also, we adopted a pre-test study in a limited group of manufacturing firms and exerted a counterbalancing effect on question order by splitting the survey sections on analytics capabilities, boundary systems, belief systems, interactive systems, diagnostic systems, environmental uncertainty and organizational competitiveness (Podsakoff et al., 2003). We thus ensured that measurement items were concise and clear. We used Harman's (1967) one factor test and Malhotra et al.'s (2006) marker variable approach for the post-hoc analysis of CMV. More specifically, the one factor test by Harman (1967) was applied to the dataset. The eigenvalue unrotated exploratory factor analysis solution showed six factors, with the greatest share of the variance being explained by a single factor of 35.64%. The likelihood that CMV would be an issue for this study was thus low, as most of the variance was not due to a single factor (Fraj et al., 2015). Moreover, the marker variable approach was used with the steps indicated for PLS-SEM (Lee and Hallak, 2017). In this vein, we the structural model was run with and without a marker construct as an exogenous variable predicting each construct. The legal form of firm was employed as the marker variable that was assessed by the following proxy: "The legal form of the firm is 'Joint-stock company'? (Yes/No)." The marker variable was collected simultaneously and in the same manner as the focal variables. The results demonstrated that the correlations between the marker construct and the model constructs (analytics capabilities: 0.105, belief systems: 0.064, boundary systems: 0.063, diagnostic systems: 0.056, interactive systems: 0.036, environmental uncertainty: -0.031, and organizational competitiveness: 0.053) were quite low, and its effect on the endogenous construct (organizational competitiveness:  $\beta = 0.021$  n.s.) was also low and nonsignificant, indicating that it was a suitable marker construct. Moreover, we compared the results between the structural models with and without the marker construct and did not find any significant differences, with all theorized paths reflecting similar path values and statistical significance levels. Accordingly, CMV was not likely to have been a problem in this study.

### *3.3 Construct measures*

All measures were based on well-documented items in extant literature. The full list of survey items is provided in Appendix A. Scholars have pointed out that size is a relevant control variable (Sharma, 2000). Accordingly, we included it as the main control variable. Size was measured through a polychotomous variable, coded 1 for companies with < 10 employees, 2 for companies with 10-49 employees, 3 for companies with 50-249 employees, and 4 for companies with > 250 employees.

### 3.4 Data analysis

We investigated our model through variance-based structural equation modeling (partial least squares: PLS-SEM) and using SmartPLS (v.3.2.7). We preferred this method for several reasons: (i) it is a predictive method that deals with complex models (Sarstedt et al., 2014), which was the case for this study with seven constructs; (ii) it provides more flexibility, thus avoiding the issues of factor indeterminacy and inadmissible solutions (Fornell & Bookstein, 1982); and (iii) it can be used with small samples (Sarstedt et al., 2014). We followed a two-step approach: (i) evaluating the validity and reliability of the measurement model, and (ii) examining the structural model (Chin, 2010).

## 4. Results

### 4.1 Measurement model

To ensure the adequacy of the measurement model, we assessed (i) item loadings and composite reliabilities, (ii) convergent validity (AVE), and (iii) discriminant validity. The reliability of the survey items was confirmed, as all outer loadings exceeded the 0.50 threshold (Hair et al., 2012) and both Dillon-Goldstein's rho (composite reliability) and Cronbach's  $\alpha$  values turned out to be higher than the minimum threshold of 0.60 (Hair et al., 2017) (Table 2). Furthermore, the convergent validity values for all constructs were higher than 0.50 (Table 2).

**Table 2.** Estimation of the measurement model parameters

Constructs/measures	Loading	Cronbach's alpha ( $\alpha$ )	Composite reliability	Average variance extracted (AVE)
<b>Analytics capabilities (AC)</b>		0.907	0.931	0.73
AC1	0.838			
AC2	0.818			

AC3	0.891			
AC4	0.88			
AC5	0.842			
<b>Belief systems (BELC)</b>		0.865	0.908	0.711
BELC1	0.835			
BELC2	0.852			
BELC3	0.869			
BELC4	0.816			
<b>Boundary systems (BOUNDC)</b>		0.891	0.924	0.754
BOUNDC1	0.858			
BOUNDC2	0.892			
BOUNDC3	0.856			
BOUNDC4	0.866			
<b>Diagnostic systems (DIAGPMS)</b>		0.883	0.919	0.74
DIAGPMS1	0.864			
DIAGPMS2	0.867			
DIAGPMS3	0.875			
DIAGPMS4	0.834			
<b>Interactive systems (INTERPMS)</b>		0.94	0.951	0.737
INTERPMS1	0.804			
INTERPMS2	0.852			
INTERPMS3	0.899			
INTERPMS4	0.891			
INTERPMS5	0.888			
INTERPMS6	0.889			
INTERPMS7	0.779			
<b>Environmental uncertainty (UNC)</b>		0.842	0.891	0.672
UNC1	0.807			
UNC2	0.802			
UNC3	0.749			
UNC4	0.913			
<b>Organizational competitiveness (ORGCOMP)</b>		0.917	0.937	0.749
ORGCOMP1	0.838			
ORGCOMP2	0.884			
ORGCOMP3	0.861			
ORGCOMP4	0.862			
ORGCOMP5	0.882			

Size SIZE	1	1	1
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We ensured discriminant validity using the Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations (HTMT). According to the Fornell-Larcker criterion, the square root of AVE for each construct should be larger than its correlation with all other constructs. In Table 3, we see that this criterion was satisfied for all constructs. Moreover, we used HTMT to assess discriminant validity. The acceptable values for HTMT should be at least below the threshold of 90% (<0.90) (Henseler et al., 2015). In this study, the HTMT values for all constructs ranged from 0.046 to 0.721 (Table 3), therefore providing support to the discriminant validity of the constructs.

**Table 3.** Discriminant validity coefficients

	AC	BELC	BOUNDC	DIAGPMS	INTERPMS	UNC	ORGCOMP	SIZE
AC	<b>0.854</b>	0.501	0.499	0.578	0.554	0.097	0.263	0.318
BELC	0.566	<b>0.843</b>	0.632	0.412	0.606	0.065	0.361	0.077
BOUNDC	0.553	0.721	<b>0.868</b>	0.490	0.503	0.118	0.299	0.145
DIAGPMS	0.646	0.469	0.551	<b>0.860</b>	0.573	0.035	0.309	0.167
INTERPMS	0.597	0.674	0.551	0.626	<b>0.859</b>	0.106	0.354	0.031
UNC	0.105	0.081	0.126	0.052	0.113	<b>0.820</b>	-0.040	-0.035
ORGCOMP	0.282	0.398	0.324	0.335	0.373	0.063	<b>0.866</b>	0.065
SIZE	0.334	0.082	0.151	0.179	0.046	0.054	0.064	<b>1.000</b>

Diagonal elements (bold) represent the square root of the variance shared between the constructs and their indicators (AVE). The correlations between the construct values are above the diagonal elements. The HTMT values are below the diagonal elements.

#### 4.2 Structural model

The PLS-SEM procedure was chosen to estimate the Stone-Geisser-Criteria ( $Q^2$ ), coefficients of determination ( $R^2$ ), the standardized root mean square residual (SRMR), and path coefficients. Table 4 indicates that the Stone-Geisser  $Q^2$  values were  $>0$ , thus demonstrating the predictive relevance of the model (Hair et al., 2017). Furthermore, predictor variables explained 0.174 of the organizational competitiveness, reflecting adequate explanation (Hair et al., 2017). Last, the SRMR was 0.049 ( $<0.080$ ), which indicated a good model fit (Hair et al., 2017).

**Table 4.** Quality of the structural model

Constructs	$R^2$	$Q^2$	SRMR
BELC	0.251	0.166	-

<b>BOUNDC</b>	0.254	0.175	-
<b>DIAGPMS</b>	0.335	0.230	-
<b>INTERPMS</b>	0.310	0.208	-
<b>ORGCMP</b>	0.174	0.115	0.049

The structural model results are shown in Table 5. They revealed no significant relationship between AC and organizational competitiveness, thus rejecting H1. Moreover, positive and significant relationships were found between AC, on one hand, and belief, boundary, diagnostic, and interactive systems, on the other hand, thus supporting H2a, H3a, H4a and H5a. Results also indicated positive and significant effects of AC on organizational competitiveness through the belief, diagnostic and interactive systems, whereas no significant effect was found through boundary systems. These results provide support to H2b, H4b and H5b, while rejecting H3b. Last, the findings show no significant moderating effect of environmental uncertainty on the paths bringing AC and MCS together. These results reject H6a/b/c/d.

**Table 5.** Standardized results of the structural equation model

Description on main paths	Hypothesis	Direct effects		Specific indirect effects		Result
		Path coeff.	T statistics	Path coeff.	T statistics	
Analytics capabilities → Organizational competitiveness	H1	-0.026	0.688	-	-	Rejected
Analytics capabilities → Belief systems	H2a	0.501	11.347***	-	-	Supported
Analytics capabilities → Belief systems → Organizational competitiveness	H2b	-	-	0.101	2.981***	Supported
Analytics capabilities → Boundary systems	H3a	0.499	11.902***	-	-	Supported
Analytics capabilities → Boundary systems → Organizational competitiveness	H3b	-	-	0.021	0.669	Rejected
Analytics capabilities → Diagnostic systems	H4a	0.578	16.595***	-	-	Supported
Analytics capabilities → Diagnostic systems → Organizational competitiveness	H4b	-	-	0.075	1.987**	Supported
Analytics capabilities → Interactive systems	H5a	0.554	14.311***	-	-	Supported
Analytics capabilities → Interactive systems → Organizational competitiveness	H5b	-	-	0.083	2.265**	Supported
Analytics capabilities* Environmental uncertainty → Belief systems	H6a	-0.024	0.492	-	-	Rejected
Analytics capabilities* Environmental uncertainty → Boundary systems	H6b	-0.022	0.473	-	-	Rejected
Analytics capabilities* Environmental uncertainty → Organizational competitiveness	H6c	-0.021	0.415	-	-	Rejected



uncertainty → Diagnostic systems					
Analytics capabilities* Environmental uncertainty → Interactive systems	H6d	-0.019	0.377	-	-
Size → Organizational competitiveness	Control variable	0.025	0.525	-	-

\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.10

### 4.3 Post-hoc analysis

We expected that environmental uncertainty would have a positive moderating effect on the paths bringing AC and MCS together. This assumption stemmed from extant literature emphasizing that linkages between dynamic capabilities (AC and MCS) are strengthened when environmental uncertainty increases (Henri and Wouters, 2019; Mammassis and Kostopoulos, 2019). However, our hypotheses H6a/b/c/d were rejected. To investigate these surprising results in greater detail, we conducted a post-hoc analysis and investigated the nonlinear moderating effects of environmental uncertainty on the linkages between AC and MCS. We utilized ordinary least squares (OLS) regression for this purpose drawing on the procedure proposed by Jaccard et al. (2003) and used by Schilke (2014). With the latent variable scores from SmartPLS 3 as the input, we calculated the square of the moderating variable (environmental uncertainty), estimated the linear and squared product terms, and lastly assessed the regression equations given below:

$$BELC = \alpha_0 + \beta_1 AC + \beta_2 UNC + \beta_3 (UNC)^2 + \beta_4 AC * UNC + \beta_5 AC * (UNC)^2 + \beta_6 SIZE + \varepsilon \quad (1)$$

$$BOUNDC = \alpha'_0 + \beta'_1 AC + \beta'_2 UNC + \beta'_3 (UNC)^2 + \beta'_4 AC * UNC + \beta'_5 AC * (UNC)^2 + \beta'_6 SIZE + \varepsilon \quad (2)$$

$$DIAGPMS = \alpha''_0 + \beta''_1 AC + \beta''_2 UNC + \beta''_3 (UNC)^2 + \beta''_4 AC * UNC + \beta''_5 AC * (UNC)^2 + \beta''_6 SIZE + \varepsilon \quad (3)$$

$$INTERPMS = \alpha'''_0 + \beta'''_1 AC + \beta'''_2 UNC + \beta'''_3 (UNC)^2 + \beta'''_4 AC * UNC + \beta'''_5 AC * (UNC)^2 + \beta'''_6 SIZE + \varepsilon \quad (4)$$

According to Schilke (2014), a significant coefficient of the squared moderator product term (here  $\beta_5$ ,  $\beta'_5$ ,  $\beta''_5$ ,  $\beta'''_5$ ) reflects the presence of quadratic moderation, which suggests that the independent variable - outcome relationship varies as a nonlinear function of the moderator. In this regard, a positive

coefficient implies a U-shaped pattern and a negative coefficient suggests an inverse U-shaped pattern. With respect to our research model, we found an inverse U-shaped pattern between analytics capabilities and boundary/ interactive systems as a function of environmental uncertainty. Table 6 summarizes the regression results. Model 1 includes BELC as the outcome variable, model 2 includes BOUNDC as the outcome variable, model 3 includes DIAGPMS as the outcome variable, and model 4 includes INTERPMS as the outcome variable. We calculated variance inflation factors (VIFs) when we estimated our base regression models to test for signs of multi-collinearity among variables and found that no VIF was greater than 10 (the highest VIF is about 3.45). Therefore, multi-collinearity was not problematic in our base regression models (Hair et al., 2006).

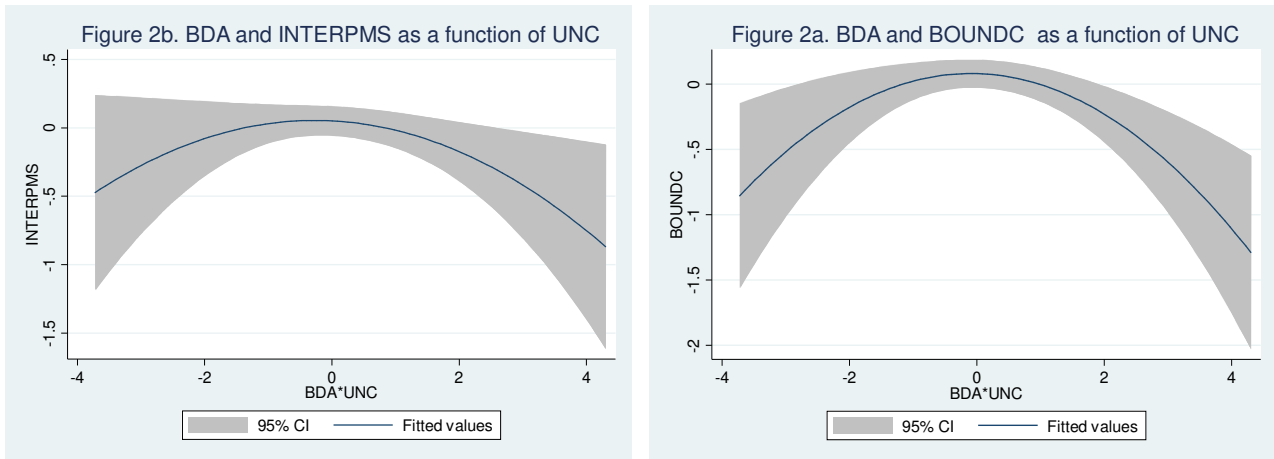
As Table 6 shows, the significant and negative coefficients of the squared product terms in models 2 and 4 indicated that the relationships between AC and both boundary and interactive systems varied across the degrees of environmental uncertainty in a quadratic manner. The types of interaction are shown in Figure 1. The graphs reflect the associations between AC and both boundary (Figure 2a) and interactive (Figure 2b) systems across the degrees of uncertainty. To establish these graphs, the regression equations were analyzed for different degrees of uncertainty, using the margins command in STATA. The proposed inverse U-shaped relationships between AC and boundary/interactive systems across increasing environmental uncertainty are evident from both graphs. As Figures 2a/2b show, for organizations facing low or high degrees of environmental uncertainty, the coefficients for the regressions of boundary/interactive systems on AC were comparatively low. Nevertheless, at intermediate degrees of environmental uncertainty, the associations were significant and positive.

**Table 6.** OLS estimations

	Model 1 BELC	Model 2 BOUNDC	Model 3 DIAGPMS	Model 4 INTERPMS
AC	0.536*** (0.060)	0.572*** (0.060)	0.630*** (0.056)	0.679*** (0.056)
UNC	0.014 (0.043)	0.075* (0.043)	-0.019 (0.041)	0.048 (0.041)
UNC <sup>2</sup>	0.058 (0.040)	-0.007 (0.040)	0.108*** (0.038)	0.057 (0.038)
AC*UNC	0.012 (0.041)	-0.029 (0.041)	-0.037 (0.039)	-0.042 (0.039)
AC*(UNC) <sup>2</sup>	-0.001 (0.037)	-0.074** (0.037)	-0.031 (0.035)	-0.070** (0.035)
SIZE	-0.084* (0.037)	-0.003 (0.037)	-0.007 (0.035)	-0.146*** (0.035)

	(0.045)	(0.046)	(0.043)	(0.043)
Constant	-0.059	0.0009	-0.108**	-0.063
	(0.058)	(0.058)	(0.055)	(0.043)
R-squared	0.263	0.261	0.351	0.344
Adjusted R-squared	0.252	0.250	0.341	0.234

Standard errors in parentheses. \*Significance at the .10 level; \*\* Significance at the .05 level; \*\*\* Significance at the .01 level



**Figure 2.** The relationship between analytics capabilities and boundary/ interactive systems as a function of environmental uncertainty (with 95% confidence interval). (a) AC and BOUNDC as a function of UNC. (b) AC and INTERPMS as a function of UNC.

This study revealed that AC had the strongest positive impacts on boundary/ interactive systems for intermediate degrees of environmental uncertainty, whereas their effects were comparatively weaker when environmental uncertainty was low or high. According to Schilke (2014), there are three degrees of environmental uncertainty: (i) environments with low uncertainty, where changes are rare and often anticipated by the market players; (ii) environments with intermediate uncertainty, characterized by regular and predictable changes; and (iii) environments with high uncertainty, characterized by quick, discontinuous and hardly predictable changes. When environmental uncertainty is low, developing AC

implies significant costs, thus hampering their potential value for boundary/ interactive systems. Indeed, when change is not as necessary, opportunity for AC to bolster both boundary and interactive systems becomes less likely. More specifically, organizations need to use their AC repeatedly in order to generate significant insights for boundary/ interactive systems. Accordingly, the positive effects of AC on a firm's boundary/ interactive systems are comparatively low when environmental uncertainty is low. Moreover, when environmental uncertainty is high, AC also have relatively weak effects on boundary/ interactive systems. Indeed, although highly uncertain environments offer a wide range of opportunities for resource reconfiguration, the high rate of new situations and the need to handle discontinuous organizational changes make AC less appropriate (Schreyogg and Kliesch-Eberl, 2007). More specifically, when there is a high level of environmental uncertainty, matching unfamiliar circumstances with organizational change is hard and might provoke the implementation of inappropriate AC. Also, in highly uncertain environments, AC adaptations that are based on experience are frequently linked with inertial forces that hamper the use of less local and more path-breaking changes (Schilke, 2014). This implies that the positive effects of AC on a firm's boundary/ interactive systems are comparatively low when environmental uncertainty is high. In contrast, when uncertainty is intermediate, environments are uncertain enough to offer possibilities for change but stable enough for firms to sense the frequent problems related to structure and leverage solutions that are present in the organizational memory (Schilke, 2014). This suggests that when the degree of environmental uncertainty is intermediate, organizational change and the ability to make use of the routinized practices that form the basis of AC have the potential to strengthen boundary/ interactive systems.

#### *4.4 Endogeneity concerns*

AC may be endogenously influenced by the firm's organizational competitiveness. Indeed, firms with improved AC can generate enhanced organizational competitiveness (Srinivasan and Swink, 2018). In parallel, firms with better organizational competitiveness are able to invest more in AC. Thus, it is unclear if the direction of causality runs from AC to firm's organizational competitiveness or vice versa. We thus complemented our previous analyses with an instrumental variables approach (2SLS) using

industry-average AC as an instrument. The logic is that the firm's AC is influenced by its membership in a given industry. Indeed, AC in a specific firm is systematically influenced by the AC of other firms within the same industry (i.e., industry-wide average AC). However, it is extremely improbable that the industry-wide average AC is related to organizational competitiveness of a given firm as there are many firms in each industry. More specifically, to account for a potential endogeneity between organizational competitiveness and AC we used Durbin-Wu-Hausman test (e.g., Li et al., 2020). The results validated the null hypothesis of no endogeneity (Durbin (score)  $\chi^2(1) = 0.344$  ( $p = 0.557$ ); Wu-Hausman  $F(1,402) = 0.342$  ( $p = 0.558$ )). Accordingly, we conclude that PLS-SEM may not lead to biased and inconsistent estimates in our sample.

## **5. Discussion**

Our findings revealed that the impact on organizational competitiveness is indirect and contingent on how MCS are used under different degrees of environmental uncertainty. Our study revealed that firms invest in different AC, like advanced analytical techniques (e.g., regression, optimization and simulation), multiple data sources, and data visualization techniques (e.g., dashboards) to generate critical insights. These AC can be used to shape strategy, bolster MCS and, ultimately, improve organizational competitiveness. Our findings specifically indicated that organizational competitiveness is positively influenced by AC through three main MCS: belief, diagnostic, and interactive systems, whereas no significant effect was found through boundary systems. Firms use AC to sense emergent behaviors, identify new priorities, and sense emergent goals and/ or values to be incorporated in belief systems such as mission statements, strategic plans, and training sessions. This in turn allows them to promote shared core values, direct employee behaviors with strategic organizational goals, foster a mutual foundation of understanding, avoid conflicting interests and disagreements and, ultimately, enhance organizational competitiveness. Moreover, firms use AC to bolster diagnostic systems. Indeed, AC-generated insights enable firms to identify decision-facilitating indicators that promote outcome assessment and monitoring, identify causal effects, enrich feedback/ feed-forward controls, and improve corrective actions. This in turn enables firms to provide staff with concise and transparent goals; foster employee flexibility,

coordination and motivation; compare outcomes to expectations; monitor results; review key measures; and ultimately improve organizational competitiveness. The findings also revealed that AC-generated insights are used to strengthen interactive systems. In this regard, AC allow firms to sense new strategies, identify organizational uncertainties, and explore emergent opportunities. Also, AC-generated insights are debated interactively with employees to promote opportunity-seeking behaviors and reconfigure action plans. Firms thus foster discussions in meetings between managers, subordinates and peers; promote ongoing challenges to and discussion of the underlying data, assumptions and action plans; offer a common vocabulary and viewpoint; strengthen ties between managers and employees; prompt attention to common issues; promote focus on critical success factors, and ultimately generate enhanced organizational competitiveness. Our study revealed that AC are used to bolster boundary systems. AC-generated insights are used to identify potential standards and/ or activities deemed appropriate and those considered off-limits to be incorporated in formal processes such as audits and internal controls, ethics guides and codes of conduct. However, our findings also revealed that firms fail to translate AC-generated insights into enhanced organizational competitiveness through boundary systems. One explanation may be that excessive staff monitoring can lead to a backlash related to economic, legal, and ethical concerns. Furthermore, exorbitant tracking of employees can hamper their creativity, involvement and/ or productivity. This in turn can generate negative behaviors such as avoiding difficult problems and inadequate decision-making, ultimately hampering organizational competitiveness. Overall, our study revealed that the positive impact of AC on organizational competitiveness depends on the nature, implementation, and use of the MCS. Thus, our study extends the extant literature showing that AC positively affect firm organizational performance and competitiveness (Mikalef, et al., 2019) and provides further support for dynamic capabilities theory.

This study revealed that environmental uncertainty is a crucial factor in the linkages between AC and MCS. Indeed, the effects of AC on both boundary and interactive systems vary as a nonlinear function of environmental uncertainty. In particular we found that AC have the strongest positive impacts on boundary/ interactive systems when the degree of environmental uncertainty is intermediate, while their

effects are weaker when environmental uncertainty is low or high. Thus, our study provided support for the cost argument (Schilke, 2014) that stable environments do not offer enough possibilities to afford the costs related to implementation and development of AC and MCS. Our study also provided support for the familiarity/ discontinuity argument (Schreyogg and Kliesch-Eberl, 2007; Schilke, 2014) that experiential, rules-based routines are unsuitable for handling unfamiliar situations and the quick and frequent changes that characterize highly uncertain environments. The inverse U-shaped moderation we developed and tested in this study suggested that both arguments are effective and that the complexity of the interactions among AC, environmental uncertainty and MCS might be greater than the simple linear relationship considered by earlier research (Henri and Wouters, 2019).

### *5.1 Implications for theory*

This work offers multiple theoretical contributions to the literature. First, it draws on Simons' (1995, 2000) levers of control framework, which offers a holistic and in-depth comprehension of the linkages among AC, MCS, and organizational competitiveness. Second, it helps enrich our understanding of the mechanisms through which AC generate value and competitiveness. More specifically, this study provides empirical evidence on what MCS are improved through AC and what organizational capacities are needed to institutionalize AC. The study also used quantitative methods to investigate how AC are mobilized by different MCS. Third, by considering the nonlinear moderating role of environmental uncertainty, it offers a response to the recent requests for more research on the conditions under which AC investments can lead to organizational competitiveness (Mikalef et al., 2019). The study is also a response to recent calls for further research on AC - MCS linkages (Rikhardsson and Yigitbasioglu, 2018). Accordingly, it extends and links the IS and accounting literature, thus offering unique insights in these areas. Fourth, the study used a dynamic capabilities perspective to examine the role of MCS in translating AC-generated insights into enhanced organizational competitiveness under conditions of environmental uncertainty. Although this perspective has shown its worth in the IS literature, it has been given less attention with respect to the management control processes of firms. The study thus extends literature in this area.

## *5.2 Implications for practice*

Our study offers interesting managerial implications. Indeed, firms that invest in AC should implement and develop management control systems in order to create value and generate organizational competitiveness. Specifically, managers should promote the use of belief, diagnostic, and interactive systems to translate AC-generated insights into enhanced organizational competitiveness. An example can be illustrated by L'oréal, world number one in cosmetics, that has launched the production of hydroalcoholic gel, thus increasing the size of their cosmetic division related to health by 13.2% (LSA, 2020). Here, AC-generated insights can be used to foster belief, diagnostic, and interactive systems allowing firms to direct staff toward new objectives, i.e., production and development of hydroalcoholic gel, to promote exchanges about action plans that shape this new product, and to identify adequate indicators that foster the new product assessment and monitoring. Furthermore, managers should maintain an adequate balance and trade-off between AC-generated insights and boundary systems. They should use AC-generated insights carefully in order to avoid excessive employee monitoring and tracking and provide them with adequate space and flexibility to promote creativity and exploration, thus enhancing competitiveness. Managers should also take the degree of environmental uncertainty into account when they use AC-generated insights and MCS. Under intermediate environmental uncertainty, they should foster the use of AC-generated insights to bolster both boundary and interactive systems. Indeed, our findings revealed that these insights have the strongest positive effects on boundary/ interactive systems when the degree of environmental uncertainty is intermediate, with their effects being comparatively weaker when environmental uncertainty is low or high. Thus, in periods of crises like the Covid-19 outbreak, the use of AC-generated insights to strengthen both interactive and boundary systems can allow firms to improve exchanges and debate about organizational strategy, reshape existing action plans, manage workers' opportunity-seeking actions to avoid wasting resources, and ultimately, generate organizational competitiveness. This point can be shown by many innovative operational strategies



adopted by some companies in Hong Kong, including the use of WhatsApp as a tool to enhance retail operations and consumer shopping during city lockdown (Choi and Sethi, 2021).

## 6. Conclusion

In this study, we examined the role of MCS in translating AC-generated insights into enhanced organizational competitiveness under conditions of environmental uncertainty. To our knowledge, this is the first attempt to do so. The study revealed that the influence of AC on organizational competitiveness depends on the nature and use of MCS. Indeed, AC enable firms to improve organizational competitiveness through belief, diagnostic, and interactive systems, whereas boundary systems play no role in this regard. The study also revealed that inverse U-shaped relationship exist between AC and boundary/ interactive systems across increasing degrees of environmental uncertainty. The positive impact that AC have on boundary/ interactive systems is strongest under intermediate environmental uncertainty, while their effects are weaker by comparison when environmental uncertainty is low or high. This study has limitations that should be noted. First, it focused on the moderating role of environmental uncertainty. In future, researchers can study the moderating role of environmental uncertainty through the environmental dynamism, complexity, and magnificence. Taking into consideration other organizational capabilities (e.g., ecocentricity, supply chain complexity) might yield different findings. Moreover, it investigated the role of MCS in translating AC-generated insights into organizational competitiveness. Future research can easily extend the framework to explore the role of other capabilities such as organizational ambidexterity, organizational learning, and organizational resilience.

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