Analysis or intuition?

Reframing the decision-making styles debate in technological settings

Ludovico Bullini Orlandi

Department of Business Administration, University of Verona, Verona, Italy, and

Paul Pierce

Department of Informatics, Lunds Universitet, Lund, Sweden

Abstract

Purpose – The debate over intuitive versus analytical decision-making styles began almost 40 years ago and had yet to deliver definite answers. The debate – however – has led to divergent theoretical stances and empirical results. The purpose of this study is to investigate the role of these information processing styles in customer-related decision-making in the context of mobile technologies.

Design/methodology/approach – The hypotheses are derived from the contrasting theoretical propositions and empirical evidence present in the debate around decision-making styles. The study also introduces and investigates the moderating role of environmental dynamism. Analyses and results are based on survey research that involves 251 managers with responsibility for organizational decision-making processes.

Findings – The study's findings suggest that both intuitive and analytical styles are relevant in the actual context characterized by mobile technologies. Intuition still plays a central role in managers' decision-making processes, but when the industry environment is highly dynamic analytical information processing also plays an essential role in supporting organizational responsiveness and performance.

Practical implication – This study can help managers in reconsidering the way in which they employ analytical or intuitive information processing activities inside their decision-making at different levels of environmental dynamism.

Originality/value – The novelty of this paper relies on testing hypothesis simultaneously developed by both the theoretical stances favorable to intuitive and to analytical information processing. Besides, it tests these hypotheses in the actual empirical context characterized by a transformed scenario in terms of data availability.

Keywords: intuition, analysis, environmental dynamism, mobile technologies.

Article Classification: research paper

1. Introduction

The debate about intuitive and analytical decision-making styles is a longstanding issue in management decision literature (e.g., Barnard, 1936) and it is still present and alive today (e.g., Patton, 2003; Okoli & Watt, 2018).

This discussion has been historically polarized by management scholars in two main sides. On the one hand, some scholars have supported the primacy of analytical information processing and decision-making over intuition (e.g., Meehl,1957; Lusk, 1979; Goll & Rasheed 1997).

On the other hand, in the same period, other scholars have investigated and supported that intuition is a more effective information-processing and decision-making style due to the lack of complete information and adequate analytical tools (e.g., Agor, 1984; McCarthy, Spital, & Lauenstein, 1987; Eisenhardt,1990).

The debate mentioned above is evolved and rekindled by the exponential increase of business-related data available to managers (Erevelles, Fukawa, & Swayne, 2015) and the development of business analytics practices (Chen et al., 2012) providing managers with new and efficient tools to collect and analyze information. Above all, the tools help managers make decisions based on analytical information processing in an easier way than ever before. Therefore, also in recent years, the debate about employing analytical or intuitive information processing styles is still open in several management-related fields, such as crisis management (Okoli & Watt, 2018), new venture evaluation (Huang & Pearce, 2015), and also in traditional strategic decision-making (Levenson, 2018).

Nevertheless, the literature still seems to lack studies that empirically test both the theoretical stances simultaneously to verify how they interact, as well as studies that reframe the issue in the actual empirical setting characterized by over-abundance of real-time and location sensitive information deriving from mobile technologies (Ghose et al., 2013; Shankar et al., 2016).

Today firms' investments in mobile technology are increasing rapidly and have recently reached as much as a quarter of their entire digital budgets (Shankar, 2016). Besides, mobile technologies are so widespread "that there are more people with mobile devices than there are with toothbrushes in the world" (Shankar et al., 2016, p. 37).

The diffusion of mobile technologies represents an organizational challenge because of the fragmentation of market channels and the rapid growth of customer touch points (Day, 2011). Today customers have the chance to "perform a number of activities and make decisions on the move" (Shankar et al., 2016, p. 38). They can search and collect information and carry out their decision-making process about an object of interest in real time and often in physical proximity to the object itself.

On the other hand, the increase in mobile technology adoption has created a scenario of possibilities linked with the real-time and location-sensitive nature of mobile customer data (Chen et al., 2012; Ghose et al., 2013). Indeed, organizations facing a high-velocity market characterized by high dynamism need access to real-time information to react quickly to changes and to gain a competitive advantage (Eisenhardt & Martin, 2000).

This research is an effort to study the evolution of the role of analytical and intuitive information-processing inside contemporary organizations characterized by customer information utterly different from the past. Namely today organizations can rely on exhaustive, even over-abundant, real-time and location sensitive information to support their customer-related decision-making processes at organizational level.

This study seeks to contribute to the debate on analytical versus intuitive information processing by empirically verifying the hypotheses, derived by both streams of the literature, in the organizational setting of customer-related decision-making.

The empirical testing relies on 251 cases of organizational deployment with both analytical customer information-processing activities based on mobile customer data analysis and intuitive activities that are more prone to a holistic and subjectivist interpretation of customer information.

The contribution of the paper to the previously mentioned debate and the related literature is threefold.

First, this paper reviews and summarizes the main literature (see Tables 1a and 1b) about the analytical versus intuitive decision-making debate derived from all the research fields related to management decision studies (organizational behavior and psychology, management of information systems, marketing, and strategic management); this allows the authors to draw the fundamental hypotheses from both theoretical stances.

Second, most of the literature mainly focuses on the individual level of information processing without clarifying the impact at the organizational level. Instead, this study conceptualizes information processing at the organizational level and its impact on firms' performance.

Finally, no studies test these hypotheses in the context of real-time and location sensitive data. We argue that these new features of organizational information assets could affect the effectiveness of analytical information processing in terms of both speed and accuracy.

The article is structured as follows. Section 2 provides the theoretical framework for the study and outlines the hypotheses of the two polarized perspectives. Section 3 presents the data collection, methodology, and analyses. Section 4 presents the results, and Section 5 is devoted to discussion and conclusions.

2. Literature review and hypotheses

The debate over decision-making styles in organization and management fields dates back to the end of the 1970s and the 1980s (Agor, 1984; Kirton, 1976; Lusk, 1979; Prietula & Simon, 1989; Simon, 1987). However, even older contributions exist that introduced the main elements of the debate.

Chester Barnard, in *The Functions of the Executive* (1938), claimed that some decisions are made without an evident reasoning process, and the activity beyond the decision is “so unexplainable that we call it ‘intuition’” (Barnard, 1938, p. 305).

In the 1980s and 1990s, most authors in the management decision-making field (see Table 1b) were favorable to intuition as a way to cope with a highly dynamic environment characterized by incomplete information (e.g., Harper, 1988; McCarthy, Spital, & Lauenstein, 1987). Intuition was viewed as a way to accelerate the decision-making process (Prietula & Simon, 1989) and to manage the trade-off between decision-making speed and accuracy (Khatri & Ng, 2000). Another common issue is that executives and senior managers should use their intuition given the complexity and lack of complete information about problems at hand (Agor, 1984; Isenberg, 1984, Patton, 2003). During the same period, however, some studies claimed that for individual-level tasks analytical information processing generated more effective decision-making (e.g., Meehl, 1957; Lusk, 1979).

The discussion about analytical versus intuitive information-processing styles has been recently revitalized, particularly in the management and marketing literature related to organizational analytics tools (Erevelles, Fukawa, & Swayne, 2015; Persson & Ryals, 2014; Rusetski, 2014). It is due to the growth of digital data available to organizations and the development of analytical tools to manage complex managerial issues, which has completely changed the previous informative scenario characterized by lack of data and of sufficiently powerful analytical tools (Chen et al., 2012; George et al., 2014; Van Knippenberg, Dahlander, Haas, & George, 2015).

2.1 Analytical customer information processing: Mobile data and analytics

One of the first contributions, which explicitly states the superiority of analytical information processing over the intuitive option, dates back to the 1950s with the work of Meehl (1957).

Additionally, at the end of the 1970s, when most contributions were favorable to intuitive information processing, some authors used empirical studies to support the concept that a highly analytical approach to decision making led to higher task performance (Benbasat & Dexter, 1979; Lusk, 1979).

Interest in the deployment of an analytical information-processing style is growing fast in the contemporary context characterized by a "deluge of data" available to organizations (Day, 2011). An overabundance of customer data derives from the digitalization of marketing channels, the proliferation of digital media, and the fragmentation of customer touch points (Day, 2011). Managerial decision-making is now supported by the collection, storage, analysis, and visualization of extremely large, unstructured, and complex data sets (Chen et al., 2012; George et al., 2014; Xu, Frankwick, & Ramirez, 2015).

The availability of such data, generated and potentially analyzable in real-time, has set the stage for testing theoretical propositions about the impact of analytical information processing over organizational performance in a scenario wholly transformed in terms of information availability (e.g. Day, 2011) and intensity of environmental dynamism (Elbanna, Child, & Dayan, 2013).

When the market is highly dynamic, firms can benefit from real-time information and, consequently, from real-time decision-making processes, thus achieving competitive advantage (Eisenhardt & Martin, 2000; George et al., 2014; Ricciardi, Zardini, & Rossignoli, 2016). To do so, organizations must rely on data produced in real-time, a feature that today characterizes the data produced in digital channels such as the Web, social media, and mobile devices (Fan & Gordon, 2014; George et al., 2014; Shankar, Venkatesh, Hofacker, & Naik, 2010). Moreover, real-time data can be employed to gain insights useful for the customer decision-making process if organizations deploy analytical processes to make sense of the data and to use them strategically (Chen et al., 2012; Watson et al., 2006; Xu et al., 2015).

Indeed, mobile devices represent one of the most promising technologies in terms of real-time interactions between customers and organizations (Ghose et al., 2013; Shankar et al., 2010). Different features characterize mobile devices when compared with other digital technologies. These devices are portable and permit individuals to ubiquitously access the Internet (Ghose et al., 2013; Shankar et al., 2016). This characteristic also drives other, equally important, characteristics, such as searching for information from any location and permitting the retrieval of information on anything with geographical proximity to the objects of interest (Ghose et al., 2013). Likewise, individuals can create and share user-generated content, such as comments on social media – once again, in proximity to the object – or the phenomenon involved in this interaction. In this technological scenario, organizations can collect, analyze, and decide how to interact with individuals in a location sensitive and real-time mode (Shankar et al., 2016). Given the aforementioned features of mobile data, this study employs mobile data analytics processes as representations of highly analytical information processing at organizational level. The following hypothesis development relies on the literature review (see Table 1a), which upholds that the deployment of highly analytical information processing has a positive impact on responsiveness (i.e., Bhatt, Emdad, Roberts, & Grover, 2010; Davenport, 2006; Day, 2011) and organizational performance (i.e., Germann et al., 2014, 2013; Goll & Rasheed, 1997; McAfee & Brynjolfsson, 2012). Accordingly, we develop the two following hypotheses:

H1. Analytical information processing is positively related to organizational responsiveness.

H2. Analytical information processing is positively related to organizational performance.

In the literature favorable to intuition information processing, one of the main critiques of highly analytical decision making relates to the boundary condition of environmental dynamism. As it emerges from the literature review, severe limitations to the deployment of analytical information processing exist in turbulent, fast-changing, and uncertain environments, and intuition is considered more effective in such environments (Agor, 1984; Dane & Pratt, 2007; Elbanna & Fadol, 2016; Khatri & Ng, 2000).

In particular, the following criticisms are identified: (1) the opportunity to collect all needed data given time constraints; (2) the doubtful disposability of necessary data; and (3) the information unreliability caused by the changing nature of environmental conditions (Khatri & Ng, 2000; Prietula & Simon, 1989). Nevertheless, in more recent developments of the literature about management analytics, several authors emphasize the importance of deploying intense and highly analytical information processing in fast-changing and dynamic environments (i.e., Bhatt et al., 2010; Day, 2011; Germann et al., 2013; Goll & Rasheed, 1997).

This stance is supported theoretically in the framework of Dynamic Capabilities (Eisenhardt & Martin, 2000; Teece, 2007). As Teece (2007) pointed out, analytical systems are fundamental elements of the "ecosystem framework for 'sensing' market and technological opportunities" (Teece, 2007, p. 1326).

In a highly dynamic and competitive environment, firms need a strong market and customer knowledge to sense new market trends (Bruni & Verona, 2009) and respond to changes in customer needs for new products or services (Barrett, Davidson, & Vargo, 2015). Then, organizational analytical infrastructures and processes are important antecedents to support organizational sense- and response- capabilities in unpredictable and changing environments (Wang, Hu, & Hu, 2013).

Furthermore, also from an empirical point of view, the moderating effect of environmental dynamism in the relation between analytical information processing and organizational performance is partially verified (Germann et al., 2013; Goll & Rasheed, 1997). This means that we elect to develop the following hypotheses:

H3. Environmental dynamism positively moderates the relation between analytical information processing and organizational responsiveness.

H4. Environmental dynamism positively moderates the relation between analytical information processing and organizational performance.

[Insert Table 1a here]

2.2 Intuitive customer information processing: A holistic approach to customer data

On the other side of the “fence,” several contributions exist that criticize analytical information processing and support intuitive one.

The earliest evocation of the concept of “paralysis through analysis” (Peters & Waterman, 1982, p. 31) suggested that too much analysis slows down the decision-making process (Eisenhardt, 1990). Additionally, Prietula and Simon (1989) suggested that analytical information processing is attention- and time-consuming.

In a highly dynamic and unstable environment, certain constraints exist in using analytical and data-intensive decision-making processes: (1) time constraints; (2) collection of a high volume of data to manage instability; (3) data reliability; and (4) data and knowledge incompleteness (Khatri & Ng, 2000; Persson & Ryals, 2014).

An intuitive decision-making style is considered the best way to cope with the speed of technological development, the complexity of managerial problems, and the incompleteness of data and information needed to deploy analytical processes (Agor, 1984; Dane & Pratt, 2007; McCarthy et al., 1987; Okoli &Watt, 2018).

Intuition is also characterized by “affectively charged judgments that arise through rapid, nonconscious, and holistic association” (Dane & Pratt, 2007, p. 33). The consequence of deploying intuition is the chance to quickly and effectively synthesize information (Dane & Pratt, 2007).

In the previous paragraph about analytical style, customer-related analytical information processing is delineated at an organizational level. Therefore, given the aim of this study, which is to compare customer-related analytical and intuitive information processing, a need exists to conceptually define the latter.

As Agor (1984) underlined, managers, who deploy an intuitive decision-making process, are more interested in solving problems by looking at the whole in a more informal and collegial manner. At the organizational level, inter-functional communication and meetings support the employment of an intuitive decision-making style (Agor, 1984). In addition, managers’ decision-making processes often rely on different information sources, such as talking and relating to people inside the organization, and data comes from different places and conversations (Khatri & Ng, 2000; Leonard et al., 1999).

Often, organizations want to collect less quantitative and more subjective data, such as what a customer thinks about a firm’s products or reputation. To do so, they can rely on methods like focus groups to elicit the communication of such information (Plax & Cecchi, 1989).

As Wibeck, Dahlgren, and Öberg (2007) underlined, intuition is central in discussions and focus groups to successfully facilitate the debate, to elicit information from customers, and to achieve a holistic view of an issue (Morgan, 1996; Plax & Cecchi, 1989; Wibeck et al., 2007). This is a fundamental trait of an intuitive information-processing approach (Isenberg, 1984; Khatri & Ng, 2000).

Intuition also plays a significant role in managers' and staffs' meetings and interactions, as Simon (1987) suggested: day-to-day manager–coworker interactions are loosely structured, intuitive, and qualitative (Simon, 1987).

Finally, the deployment of more qualitative information-gathering techniques that are not based on numerical data, such as focus groups and meetings, involve experience, judgment, and intuition (Wright & Geroy, 1991).

A theoretical conceptualization of intuitive information processing with the features mentioned above can be derived from the seminal literature on customer information processing (see, i.e., Day, 1994; Glazer, 1991; Kohli & Jaworski, 1990).

Intuitive customer information processing can be conceptualized as a subset of the activities that characterize the customer knowledge process (Jayachandran et al., 2004, Kohli & Jaworski, 1990; Li & Calantone, 1998), selecting activities that involve a high level of intuition, subjectivity, and a holistic approach. Then, intuitive customer information processing can be conceptualized as the process of acquiring, interpreting, and exploiting customer information inside the organization through activities such as marketing meetings and discussions, customer interviews and focus groups, and inter-functional meetings (Kohli & Jaworski, 1990; Li & Calantone, 1998).

The development of the hypotheses related to intuition is rooted in the literature review (see Table 1b) that presents both the theoretical and the empirical studies supporting the positive effects of deploying intuitive information processing.

The two main outcomes of intuition refer to different types of positive organizational performance (e.g., Agor, 1984; Cannella & Monroe, 1997; Dayan & Elbanna, 2011; Khatri & Ng, 2000) and to organizational responsiveness (e.g., Dane & Pratt, 2007; Eisenhardt, 1990; Prietula & Simon, 1989). With these outcomes in mind we develop the following hypotheses:

H5. Intuitive information processing is positively related to organizational responsiveness.

H6. Intuitive information processing is positively related to organizational performance.

As in the case of analytical information processing, also in the reviewed literature about intuitive information processing (see Table 1b), the environmental dynamism is considered a fundamental variable that moderates the relation between intuition and organizational outcomes.

Fast-changing and turbulent environments are typically what is referred to as the reasons why executives and managers should rely on intuition instead of on analytical processes (Elbanna & Fadol, 2016; Eisenhardt, 1989; McCarthy et al., 1987; Okoli & Watt, 2018). Technological changes are too rapid and extensive to obtain complete information about them and to deploy a full analytical plan; the CEO must rely on intuition and experience (McCarthy et al., 1987).

In unstable environments, different constraints exist on employing analytical information processing, such as time constraints in data collection, the need for large amounts of information to account for instability (Khatri & Ng, 2000), and sometimes the lack of "formulas" (Kleinmuntz, 1990) or adequate quantitative data (Harper, 1988) necessary to solve very complex managerial issues. In all of the previously mentioned situations, intuition is considered the best information processing style to face environmental dynamism and uncertainty (Elbanna & Fadol, 2016; Okoli & Watt, 2018). Furthermore, the positive moderating effect of environmental dynamism in the relation between intuitive information processing and organizational performance has been partially empirically verified in previous research (Dayan & Elbanna, 2011; Khatri & Ng, 2000). Then, we develop the following hypotheses on the moderation effect of environmental dynamism:

H7. Environmental dynamism positively moderates the relation between intuitive information processing and organizational responsiveness.

H8. Environmental dynamism positively moderates the relation between intuitive information processing and organizational performance.

[Insert Table 1b here]

3. Methods

3.1 Sample and data collection

This study identified managers who have roles of responsibility in Marketing or related activities as potential respondents because they are the most involved in and informed about customer information-processing activities.

The data for this research were obtained by employing a random sample from the AIDA-Bureau Van Dijk database, the most important database of all Italian limited companies.

The resulting sample consists of 1,200 potential respondents from a broad range of industries, geographical locations, and organizational dimensions.

The respondents were assured anonymity and the use of aggregated data to comply with Italian privacy law. A total of 251 responses were received, for a response rate of 20.9%. Of these, only 156 responses were fully completed and 95 were partially completed.

Organizational respondents represented a broad and equilibrated variety of industries: services (14%); information and telecommunications (13.6%); fashion and clothing (12%); manufacturing (8%); and food and beverage (6%). The firm sizes in the sample are measured following the EU Commission's size classes (2003/361/EC). Our sample displays 10.2% of micro firms with the number of employees between 0 and 9; 23.6% of small firms (10–49 employees); 29.6% of medium firms (50–249 employees); and 36.6% of large firms (>250 employees)

3.2 Preliminary data analysis

To decrease common method variance (CMV), this study followed best practices and procedural remedies (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) during the survey design and data collection phases.

The survey was pre-submitted to eight experts from both academia and business. They reviewed the survey items and helped in the development of the scale used to measure mobile analytics activities.

Other remedies followed were to assure respondents' anonymity and to avoid items' social desirability, demand characteristics, and ambiguity (Podsakoff et al., 2003).

Once data was collected, common method bias was tested employing Harman's single-factor test (Podsakoff et al., 2003; Woszczynski & Whitman, 2004).

The variance explained by the one factor in the unrotated factor matrix is 27.9%, largely lower than the suggested 50% threshold. This result indicates that common method bias is not a significant problem in this study.

To check for non-response bias, the different groups of early and late respondents were tested with ANOVA. No significant differences were found between the two groups, indicating that non-response bias is not a major concern for this study.

Regarding missing data, a preliminary analysis using Little's MCAR test indicated a missing completely at random (MCAR) mechanism (Chi-square (83) = 75.47, p = .71). Given the missing MCAR mechanism, this study applied list-wise deletion as the treatment for missing data, which is considered unbiased under the MCAR condition (Newman, 2014).

3.3 Measures

Table 2 lists the presented items, Cronbach's alpha scores, and factor loadings of each construct. In the preliminary data analysis, an exploratory factor analysis (EFA) with principal axis factoring and oblique rotation was employed to verify the new scale (analytical information processing) and the general items' loadings. All factor loadings are higher than 0.5, suggesting adequate item reliability.

To further explore the validity and reliability of the model employed, a CFA analysis shows adequate results: CFI = .97, TLI = .96, RMSEA = .05, and SRMR = .06.

For each construct, the average variance extracted (AVE) is greater than the squared correlation coefficient of the respectively paired constructs (see Table 3), providing support for discriminant validity (Fornell & Larcker, 1981).

Analytical Customer Information-processing (ACIP): This scale is developed to measure the organizational-level activities of customer-related analytical information processing based on mobile technologies. Employing both the literature review and six expert interviews, the items on mobile analytics information processing are developed. The items, tested using EFA, demonstrate consistent loading on one factor, and the only item showing a low loading is the reverse item.

Intuitive Customer Information-processing (ICIP): This scale is adapted from Jayachandran et al. (2004) and Li and Calantone (1998) selecting the items more closely related with the intuitive customer-information processing (i.e., customer meetings, interdepartmental meetings, discussions about customer needs…). This items selection is also submitted for evaluation and discussed with the eight experts: the three chosen items are the results of the previous consultation process.

Environmental Dynamism and *Customer Responsiveness:* These two scales' items are respectively derived from Jayachandran et al. (2005) and Homburg et al. (2007) rejecting, in a parsimonious logic, the items that don’t reach the threshold of 0.5 of factor loadings in the EFA or that contribute negatively to the Cronbach’s alpha scores.

Market Performance: this scale is applied with no adaptation from Homburg et al. (2007).

Control variables: Firm sizes are measured using seven ranges of numbers of employees, based partially on the EU SME classification.

Additionally, business longevity is considered by employing the common log of business age. To control for industry, three dummy variables are introduced to account for the most represented industries (ICT, services, and fashion).

[Insert Table 2 here]

[Insert Table 3 here]

4. Results

The results of multiple regression and multiple moderated regression are presented in Table 4. The moderator variable used, Environmental Dynamism (ED), and the other two independent variables are centered to reduce multicollinearity before computing the different interaction terms (Aiken & West, 1991). Model 1 to Model 4 are used to test the hypothesis involving customer responsiveness (CR), and Model 5 to Model 8 use market performance (MP) as the dependent variable.

Models 1 and 5 consider control variables only; Models 2 and 6 present the multiple regression with independent variables and the moderator; Models 3 and 7 also consider the interaction terms between independent variables and the moderator; lastly, Models 4 and 8 present parsimonious models without considering control variables. Hypotheses 1 and 2 claim that analytical customer-related information processing (ACIP) is positively related to both the outcomes MP and CR, but all models suggest no significant correlation between them.

Instead, the relationships between intuitive customer-related information processing (ICIP) and both CR (B = .33, $p < .001$) and MP (B = .26, $p < .05$) are positive and significant; this evidence confirms Hypotheses 5 and 6.

Then Models 3, 4, 7, and 8 are employed to verify the hypothesis concerning the ED role as a moderator in the relationship between dependent variables and both outcomes.

Hypotheses 7 and 8, which claim a positive moderation effect of ED in the relationships between ICIP and both outcomes, have no empirical support. The interaction term ICIP x ED is not significant in any of the models.

One of the most interesting pieces of evidence regards Hypotheses 3 and 4. Models 3, 4, and 7 show that the interaction term ACIP x ED is positive and significant ($p < .05$), which supports Hypotheses 3 and 4. This would indicate that in highly dynamic environment analytical information processing has a positive impact over the considered organizational outcomes.

To further explore this evidence, this study employed the SPSS computational procedure PROCESS (Hayes, 2013), which allows for slope analysis at three moderator levels (high, moderate, and low). The analysis supports the presence of a moderation effect of ED in the relationship between ACIP and CR (B = .12, $p < .001$). In addition, the slope analysis in Figure 1 shows that the slope changes sign, passing from low to high levels of ED, which supports Hypothesis 3. The same analysis with MP as outcomes gives partial support to Hypothesis 4. In fact, for low and moderate ED (–1SD and mean), the bootstrapped confidence intervals contain zero and are not significant. With high levels of ED (+1SD = 1.14), the effect is significant and the bootstrapped confidence interval does not contain zero (B = .18, $p < .05$, LLCI = .01, ULCI = .35). Given this latter is partially non-significant we report only the slope analysis with CR as the outcome (see Figure 1).

[Insert Table 4 here]

[Insert Figure 1 here]

5. Discussion and conclusion

5.1 Theoretical implications

Theoretically, this study contributes to management decision literature, reframing the long-standing debate about analytical versus intuitive information-processing in the actual context of mobile technologies.

The contribution to the literature and scientific debate about information-processing and decision-making is threefold.

First, it provides management decision scholars with an up-to-date and in-depth literature review that organizes all the relevant studies published about analytical and intuitive information processing in different management-related fields.

Second, a literature gap is addressed conceptualizing and operationalizing the theoretical constructs of analytical and intuitive information-processing at organizational level and testing them with simultaneous models that take into account both the information-processing styles and their interaction effects with environmental dynamism.

Third and last, this is the first research that theoretically contextualized and empirically tested the issue in the contemporary organizational context characterized by mobile technologies.

These technologies have changed the organizational information-processing scenario, especially as a result of the real-time and location-sensitive nature of customer data. These data are not suitable for processing with intuitive activities given their quantity and complexity, and then they do not conceptually overlap with other types of customer data that are still processed using intuitive information processing.

The study also contributes to the scientific debate proposing the disentanglement of the two processes at the organizational level, allowing their relationships to be theoretically hypothesized in simultaneous and reciprocal relationships with organizational responsiveness and performance.

By employing a large-scale survey, this study finds evidence that reconciles the two polarized theoretical stances. The external Environmental Dynamism (ED) level works as a moderator in the relationship between analytical customer information processing and outcomes. At a high ED level, analytical approaches are positively related to both customer responsiveness and market performance. At moderate and low ED levels, this construct is not significant and only intuitive customer-related information processing displays positive relationships with outcomes.

In some sense, this evidence confirms Simon's claim: "The effective manager does not have the luxury of choosing between 'analytic' and 'intuitive' approaches to problems" (Simon, 1987, p. 63). Besides, the empirical results of this study support previous evidence from more qualitative studies suggesting that effective decision-making stems from the combination of intuitive and analytic information-processing styles (Selart et al., 2008).

5.2 Managerial implications

Two main managerial implications can be derived from this study and could be generalized to management decision in contexts characterized by real-time and location sensitive data (such as mobile analytics, Internet of Things, sensor-based analytics). One is that managers must be aware of the importance of intuitive customer information-processing that enhances related organizational-level activities. Even in an actual data-rich context, a holistic and intuitive approach to customer knowledge and decision-making still plays the most significant role in organizational responsiveness and performance.

Another implication is that managers who operate in highly dynamic and turbulent environments must also rely on analytical information-processing, especially when customers' real-time time data are available.

5.3 Limitations and future research

Despite its contributions, this study is constrained by some limitations. Employing self-reported perceptual data based on a single key informant could weaken the study's internal validity. Even if substantial precautions are taken to narrow common method variance, future research should provide a sampling of multiple respondents for each organization to check for inter-rater validity.

Furthermore, customer-related analytical information-processing is framed only in an empirical setting characterized by mobile technologies. Mobile data, as previously noted, have specific features, such as a real-time and location-sensitive nature, that enhances their value in the customer decision-making process. To enhance the generalizability of the empirical findings of this study, future research should address other types of customer data, such as user-generated content on social media, and other information processing subjects, such as technological developments and competitors, for both analytical and intuitive information-processing activities. Moreover, in order to provide useful implications in other scientific fields, besides business management, further research should also take into consideration non-profit and public firms.

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Table 1a.

Literature review about analytical information processing

Authors (years)	Information processing	Environmental conditions	Outcomes
Lusk (1979)	Analytical	Not defined.	(+) Higher task performance.
Benbasat & Dexter (1979)	Analytical	Not defined.	(+) Higher profitability and faster decision making.
Prietula & Simon (1989)	Analytical	Not defined.	(+/-) Support the intuitive process, but consumes attention and time.
Eisenhardt (1990)	Analytical (forecasting)	Fast-moving, high technology.	(−) Slow down responsiveness.
Goll & Rasheed (1997)	Analytical	Highly dynamic and highly munificent environment.	(+) Organizational performance.
Covin, Slevin, & Heeley (2001)	Analytical	Low technology. Predictable environment.	(+) Organizational performance.
Davenport (2006)	Analytical (deployment of analytics)	Not defined.	(+) Organizational performance and responsiveness.
Bhatt, Emdad, Roberts, & Grover (2010)	Analytical (information leveraging)	Dynamic environment.	(+) Organizational responsiveness.
Trkman, McCormack, De Oliveira, & Ladeira (2010)	Analytical (deployment of analytics)	Changing environment.	(+) Supply chain performance.
Day (2011)	Analytical (quasi-experiment with digital data)	Accelerating complexity, fragmentation, rapid changes.	(+) Organizational responsiveness and adaptation.
Barton & Court (2012)	Analytical	Not defined.	(+) Competitive advantage.
McAfee & Brynjolfsson (2012)	Analytical (data-driven decision making)	Not defined.	(+) Higher productivity and profitability.
Germann, Lilien, & Rangaswamy (2013)	Analytical (deployment of analytics)	Hyper-competitive and fast-changing environment.	(+) Organizational performance.
Germann, Lilien, Fiedler, & Kraus (2014)	Analytical (deployment of analytics)	Not defined.	(+) Organizational performance.
Erevelles, Fukawa, & Swayne (2015)	Analytical (employing Big Data analytics)	Hyper-competitive environment.	(+) Sustainable competitive advantage.
Levenson, A. (2018)	Analytical (employing workforce analytics)	Not defined.	(+) Strategy executions and organizational effectiveness.
Ortiz-Barrios, Herrera-Fontalvo, Rúa-Muñoz, Ojeda-Gutiérrez, De Felice, & Petrillo, (2018)	Analytical (employing Analytic hierarchy process)	High uncertainty.	(+) Assessment and control of risks.

Table 1b.

Literature review about intuitive information processing

Authors (years)	**Information processing**	**Environmental conditions**	**Outcomes**
Agor (1984)	Intuitive	Turbulent, rapid changes, complexity.	(+) Effective decision making in different functions (i.e., HR, Marketing…)
McCarthy, Spital, & Lauenstein (1987)	Intuitive (“gut feel”)	Fast-moving, high technology, uncertainty.	(+) Positive impact on technological developments decision making.
Harper (1988)	Intuitive	Lack of information, fast changing, uncertainty.	(+) Size new opportunities.
Prietula & Simon (1989)	Intuitive	Not defined.	(+) Speed up responsiveness, need less informative effort.
Eisenhardt (1990)	Intuitive	Fast-moving, high technology.	(+) Speed up responsiveness.
Cannella & Monroe (1997)	Intuitive	High level of ambiguity.	(+) Innovation outcomes.
Andersen (2000)	Intuitive	Not defined.	(+) Organizational effectiveness.
Khatri & Ng (2000)	Intuitive	Unstable.	(+) Positive impact over performance.
Khatri & Ng (2000)	Intuitive	Stable.	(−) Negative impact over performance.
Covin, Slevin, & Heeley (2001)	Intuitive	High technology. Changes in technological standards.	(+) Organizational performance.
Hayashi (2001)	Intuitive	Complex, ambiguous, turbulent.	(+) Effective strategic decision making.
Dane & Pratt (2007)	Intuitive	Environmental uncertainty.	(+) Fast and accurate decision making.
Dayan & Elbanna (2011)	Intuitive	Environmental turbulence.	(+) Market success of new product. Speed to market.
Elbanna, Child, & Dayan (2013)	Intuitive	Environmental turbulence, instability, hostility.	(+) Organizational performance. (not empirically confirmed)
Matzler, Uzelac, & Bauer (2014)	Intuitive	Not defined.	(+) Organizational innovativeness.
Huang & Pearce (2015)	Prevalent intuitive (+ formal analysis)	Extreme uncertainty.	(+) Positive correlation with new venture success.
Elbanna & Fadol (2016)	Intuitive	Environmental uncertainty and hostility.	(+) Support in making complex decision.
Okoli & Watt (2018)	Intuitive	High uncertainty of crisis situations.	(+) Effective responses to crisis situations.

Table 2.
Construct, Cronbach's alpha scores, items, and factor loadings

Construct	Items #	Scale items and factor loadings	Source
Analytical Customer Information-processing (α = .84)	ACIP 1	We habitually use mobile analytics tools to collect information about customer. (0.89)	Developed for this study
	ACIP 2	Information from mobile analytics are crucial in supporting customer-related activities. (0.90)	
	ACIP 3	We rarely employ information from mobile analytics to support forecasting about customers' needs and preferences. (0.59) (R)	
	ACIP 4	Decision making about customers is supported using mobile analytics information. (0.88)	
Intuitive Customer Information-processing (α = .67)	ICIP 1	We regularly meet customers to learn their current and potential needs for new products. (0.75)	Jayachandran et al. (2004), Li and Calantone (1998)
	ICIP 2	We have interdepartmental meetings regularly to discuss customers' needs. (0.65)	
	ICIP 3	Marketing personnel in our business unit spend time discussing customers' future needs with other functional departments. (0.74)	
Environmental Dynamism (α = .83)	EV 1	We are witnessing demand for our products and services from customers who never bought them before. (0.72)	Jayachandran et al. (2005)
	EV 2	The technology in our industry is changing rapidly. (0.82)	
	EV 3	Technological changes provide big opportunities in our industry. (0.82)	
	EV 4	A large number of new product ideas have been made possible through technological breakthroughs in our industry. (0.86)	
Customer Responsiveness (α = .89)	CR 1	We respond rapidly if something important happens with regard to our customers. (0.79)	Homburg et al. (2007)
	CR 2	We quickly implement our planned activities with regard to customers. (0.89)	
	CR 3	If our customer-related activities do not lead to the desired effects, we are fast at changing them. (0.80)	
	CR 4	We quickly react to fundamental changes with regard to our customers. (0.86)	
Market performance (α = .94)		In the last three years, relative to your competitors, how has your business unit performed with respect to:	Homburg et al. (2007)
	MP 1	Achieving the desired profit and revenue level?* (0.92)	
	MP 2	Achieving the desired growth?* (0.96)	
	MP 3	Achieving/securing the desired market share?* (0.94)	
		* Seven-points rating scale anchored by "clearly worse" [1], "competition level" [4], and "clearly better" [7]	

Table 3.
Means, standard deviations, inter-construct correlations, and discriminant validity

Constructs	Mean	S.D.	AVE	1	2	3	4	5
1. Analytical Customer Information-processing	4.13	1.64	.62	1				
2. Intuitive Customer Information-processing	5.15	1.13	.43	.26	1			
3. Environmental Dynamism	5.01	1.14	.58	.38	.27	1		
4. Customer Responsiveness	5.80	.97	.65	.18	.44	.06	1	
5. Market Performance	4.85	1.22	.83	.20	.29	.22	.26	1

AVE = average variance extracted; SD = standard deviation.
The underlined correlation is not significant; all the other correlations are significant at α = .05 (two-tailed)

Table 4.
Regression results on customer responsiveness and market performance

	Model 1 Customer Responsiveness B (s.e.)	Model 2 Customer Responsiveness B (s.e.)	Model 3 Customer Responsiveness B (s.e.)	Model 4 Customer Responsiveness B (s.e.)
Controls				
Constant	5.54 (.31)***	4.07 (.47)***	3.86 (.47)***	3.75 (.39)***
Number of employees (7 ranges)	-.15 (.05)**	-.12 (.05)*	-.12 (.05)*	
Log of business age	.43 (.21)*	.32 (.19) $^{+}$	.31 (.19)	
ICT	.49 (.26)$^{+}$	.42 (.25)$^{+}$	.36 (.25)	
Fashion	.24 (.25)	.17 (.23)	.21 (.22)	
Services	.62 (.24)**	.43 (.22)$^{+}$	.34 (.23)	
Independent variables				
ACIP		.05 (.05)	.06 (.05)	.06 (.05)
ICIP		.33 (.07)***	.33 (.07)***	.37 (.06)***
Moderator variable				
ED		-.07 (.07)	-.04 (.07)	-.04 (.07)
Interaction terms				
ACIP x ED			.09 (.04)*	.12 (.04)**
ICIP x ED			-.002 (.06)	.002 (.06)
F	4.16**	6.63***	6.06***	10.72***
Adjusted R^2	.09	.22	.25	.24
df	5	8	10	5
	Model 5 Market Performance B (s.e.)	Model 6 Market Performance B (s.e.)	Model 7 Market Performance B (s.e.)	Model 8 Market Performance B (s.e.)
Controls				
Constant	4.61 (.40)***	2.36 (.65)***	2.10 (.69)**	2.54 (.54)***
Number of employees (7 ranges)	-.06 (.07)	-.07 (.07)	-.07 (.07)	
Log of business age	.32 (.27)	.32 (.27)	.31 (.27)	
ICT	.002 (.35)	-.20 (.35)	-.28 (.34)	
Fashion	-.04 (.32)	-.32 (.31)	-.43 (.31)	
Services	-.08 (.32)	-.18 (.32)	-.13 (.31)	
Independent variables				
ACIP		.09 (.07)	.10 (.07)	.07 (.06)
ICIP		.26 (.09)**	.26 (.09)**	.26 (.09)**
Moderator variable				
ED		.13 (.09)	.16 (.09)$^{+}$	.13 (.09)
Interaction terms				
ACIP x ED			.11 (.05)*	.09 (.05)$^{+}$
ICIP x ED			.001 (.08)	-.02 (.08)
F	.35	2.88**	2,749**	4.34**
Adjusted R^2	-	.09	.10	.10
df	5	8	10	5

$^{+}$ $p < .1$
* $p < .05$
** $p < .01$
*** $p < .001$

Figure 1.
Hypothesis 3 Interactions Term Plot for Customer Responsiveness