Individual modes and patterns of rational and intuitive decision-making by purchasing managers

Lutz Kaufmann[a,*], Claudia M. Wagner[a], Craig R. Carter[b]

[a] SCM Group, WHU - Otto Beisheim School of Management, Burgplatz 2, 56179 Vallendar, Germany
[b] W.P. Carey School of Business, Arizona State University, USA

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ABSTRACT

This study extends the literature on decision modes in purchasing. While decision modes have traditionally been divided broadly into *rational* and *intuitive* processing modes (dual-process approach), following the tenet of recent psychology research, we further differentiate the latter into experience-based and emotional processing (multiple systems approach). Previous decision-making research has been inconsistent in its findings about the relationship between decision modes and performance. Using the purchasing manager's supplier selection decision process as our unit of analysis, we first investigate the relationship between *individual decision modes* and the financial and non-financial performance of the selected supplier. Hierarchical regression analyses indicate that rational processing is positively related to both financial and non-financial performance, while emotional processing is negatively related to financial performance, and the interaction of rational and emotional processing is positively related to both performance outcomes. Because recent cognitive psychology assumes that some combination of rationality and intuition is commonly used, we then apply a configuration approach and develop a taxonomy of decision-making modes surrounding supplier selection. Cluster analysis results show five *decision-making patterns* that are related to the performance of the selected supplier.

1. Introduction

Purchasing research traditionally characterizes decision-making processes as analytical, or rational, processes that include extensive information-gathering and detailed analyses (Riedl et al., 2013; Weber et al., 1991). For example, the comprehensive supplier selection literature, which can be grouped into two major categories (Carter et al., 2010; for a recent review see Igarashi et al. (2013)) – (1) selection criteria (e.g., Choi and Hartley, 1996; Sharland et al., 2003) and (2) decision models (de Boer and van der Wegen, 2003; Singh, 2014) – typically assumes rational behavior.

In practice, however, the increasing external volatility and complexity, on the one hand, and the internal time pressures and resource constraints on the other hand, make gathering, structuring, and extensively analyzing data before making a purchasing decision often difficult if not impossible (Ellis et al., 2010; Mantel et al., 2006).

In that vein, a large body of literature rooted in cognitive psychology, "demonstrates that individuals are boundedly rational, use heuristics for decision-making, and suffer from systematic biases" (Bendoly et al., 2010, p. 439). The still nascent behavioral operations management (BOM) and the more specific behavioral supply manage-

ment (BSM) streams therefore argue that a behavioral perspective is also necessary for the supply chain management (SCM) discipline (Bendoly et al., 2010; Carter et al., 2007; Gino and Pisano, 2008). Recent findings from the general human judgment and decision-making (HJDM) research further point to the need to investigate both the risks *and* the benefits of the use of non-rational decision-making modes, such as intuition (Ariely, 2010; Kahneman and Klein, 2009).

While intuition as a phenomenon has a long-standing history in the general HJDM research, it has typically been rooted in psychology (e.g., Bendoly et al., 2010; Kahneman and Klein, 2009) and has only recently become a focus in business studies (e.g., Dayan and Di Benedetto, 2011; Kaufmann et al., 2014; Khatri and Ng, 2000). Findings about the relationship between intuition and outcome variables generally have been mixed. One explanation might be the heterogeneous conceptualization and operationalization of the intuition construct (Akinci and Sadler-Smith, 2012). Another explanation might be that until this point, studies have either investigated intuition in isolation (Khatri and Ng, 2000), or they have treated rationality and intuition simply as polar ends of a continuum (Dayan and Di Benedetto, 2011). However, recent decision-making research concedes that both can be used together in a complementary fashion (e.g., Hodgkinson et al., 2009): "A purely

intuitive strategy relying only on pattern matching would be too risky because sometimes the pattern matching generates flawed options. [But] a completely deliberative and analytical strategy would be too slow (…)." (Klein, 2008, p. 458). Hence, a combination of rational and intuitive modes seems to be an effective approach.

The assumption of rationality and intuition as distinct but interacting cognitive systems is the central tenet of dual-process and dual-systems theories (Dane and Pratt, 2007; Epstein, 2010; Evans, 2010; Healey et al., 2015). However, the terms "*dual*-processing" and "*dual* systems" (for simplicity, in the remainder of the paper we use the term *dual-process*) might in fact be misleading because recent psychological research assumes the involvement of *several* decision-making dimensions or systems involving complex interactions that combine rational and intuitive processing (Evans, 2014). We therefore conceptualize *intuition* as a two-dimensional construct consisting of *experience-based* and *emotional processing* (Leybourne and Sadler-Smith, 2006; Sinclair and Ashkanasy, 2005; Stanczyk et al., 2015). These dimensions describe the processes of (a) linking new cues to experiences stored in memory, thus influencing the current action, and (b) perceiving positive or negative gut feelings that guide the decision process. We conceptualize *rationality* following Simon's (1978) concept of procedural rationality, which involves the processes of defining relevant decision criteria, gathering information, and making analysis-based decisions.

Recent behavioral purchasing research (Kaufmann et al., 2014) has investigated the use of *rational and intuitive* processing in the context of cross-functional sourcing *teams*. But, one might raise the question of whether this research has jumped too far ahead, considering recent psychology research that emphasizes the importance of investigating the interplay of *multiple cognitive systems* at the level of the *individual decision maker* (e.g., Evans, 2014). Therefore, this study focuses on the *multiple systems approach* starting with the *purchasing manager* as the *individual* decision maker, and examines (a) the *impact of several* decision modes (rational, experience-based, and emotional) on the outcome of a supplier selection decision, (b) the *interaction* among these three modes, and (c) how *patterns* of the decision modes are related to supplier performance.

The unit of analysis is the purchasing manager's supplier selection decision. Supplier selection is an appropriate context for behavioral purchasing decision research because B2B purchasing is traditionally assumed to be a rational process for which objective criteria and rational decision models have been developed and studied extensively. Supplier selection can therefore be assumed to be a tough environment for non-rational behavior. Findings from this context on the constructs and relationships of interest would consequently add to the external validity of the study. For instance, a purchasing manager might be responsible for selecting a new supplier for an automotive material procured on a regular basis. While combing through the information at hand and finding that the material price might lead to favor supplier A, the purchasing manager might experience a negative gut feeling about choosing that supplier without exactly knowing at first why. Therefore, she follows her instincts and looks extensively for further information before coming to a conclusion. Further, the purchasing manager detects parallels towards previous supplier selection decisions which she can use for focusing on specific aspects such as the company's credit status and employee structure. Finally, important aspects might be found that prove or disprove the gut feeling and after thorough analysis the final supplier selection decision is made.

Our research contributes to purchasing and supply management knowledge in two important ways. First, we examine the relationship among the three *individual* decision modes—rational, experience-based, and emotional processing—and two different dimensions of supplier *performance*—financial and non-financial performance. Second, we derive *patterns* of the *three* processing modes to delve more deeply into how they work together within the context of supplier selection (Evans, 2014). By investigating the mix of rational and

intuitive decision making modes on the level of the individual purchasing manager, we put forth the notion of using more than one decision mode in a complementary fashion in purchasing contexts, strengthening the assumption of multiple systems.

We now turn to developing the theory, describing the study, and then presenting and discussing our results. We conclude by outlining implications for managers and providing suggestions for future research.

2. Theory and hypotheses

2.1. Individual decision-making modes in supplier selection

We begin by theorizing about how *individual* modes of decision processing are related to supplier performance and to each other in supplier selection decisions.

2.1.1. Relationship between rational processing and supplier performance

Following Dean and Sharfman (1993, p. 589), we define procedural rationality as "the extent to which the decision process involves the collection of information relevant to the decision, and the reliance upon analysis of this information in making the choice." Information processing theories distinguish several elements or steps that are part of rational decision-making—for example, collecting relevant information, extensively analyzing the data using a set of criteria, evaluating several alternatives, and making probability assumptions about outcomes (Dean and Sharfman, 1993; Evans, 2010; Miller, 2008; Sadler-Smith and Shefy, 2004).

We differentiate our outcome variable—supplier performance—into financial and non-financial performance, as defined in previous research (Cai and Yang, 2008). Financial supplier performance strongly focuses on costs paid by the buyer (Talluri, 2002), while non-financial supplier performance includes buyer-relevant characteristics of the supplier such as quality of the delivered product, delivery time, and responsiveness (Carr and Smeltzer, 2000).

Using information processing approaches, recent supply management research has underscored the importance of procedural rationality in supplier selection processes in light of its capacity to substantially influence the decision outcome (Kaufmann et al., 2014). The reason is that the conscious analytical system of decision-makers is able to deal with high levels of abstraction, to identify complex cause–effect relationships, and to develop effective long-term strategies (Allen, 2011; Epstein, 2010; Evans, 2010; Miller, 2008). In addition, the activities of clarifying decision criteria, identifying a set of potential suppliers based on their strengths and weaknesses, and generating a list of alternative suppliers, can create greater negotiation power for the buying firm (Giunipero et al., 1999; Kaufmann et al., 2012). Further, the thorough evaluation of information gathered on individual suppliers and of overall supply and demand developments in the market helps purchasing managers to form a comprehensive view of the decision context; such a view is more likely to prevent the hasty (re) actions and cognitive biases that can lead to the selection of an underperforming (whether financially or non-financially) supplier (Carter et al., 2007; Glöckner and Witteman, 2010; Kaufmann et al., 2014). Thus, for the first *individual* decision-making mode, we posit the following:

Hypothesis 1a. Rational processing is positively related to the financial performance of the supplier.

Hypothesis 1b. Rational processing is positively related to the non-financial performance of the supplier.

2.1.2. Relationship between experience-based and emotional processing and supplier performance

Existing decision-making research conceptualizes *experience-based*

and *affect-initiated* decisions (Burke and Miller, 1999) by linking them to mental processes (Akinci and Sadler-Smith, 2012). Recent qualitative research in SCM also has identified two intuition dimensions: reliance on past experiences (justified intuition) and reliance on gut-feelings (creative intuition) (Stanczyk et al., 2015). In line with this research stream, we define intuition as a two-dimensional construct and describe the respective decision modes as experience-based processing and emotional processing.

The concept of *experience-based processing* is used to describe a process in which the decision-maker establishes a connection between the current and past situations. Simon (1992) specifies the process as one in which past situations offer the decision-maker cues, thereby giving "the expert access to information stored in memory" (p. 155). A similar situation in the present can activate this cue, and the relevant information from the past can be retrieved from memory to help guide the current decision (Koskinen, 2000; Salas et al., 2010). The process of establishing (technological) knowledge which enables the decision-maker to make predictions and causal associations such as understanding the effects of input on output variables, has also been emphasized in the management arena (Adler and Shenbar, 1990; Bohn, 1994). But in practice, "complete knowledge" of processes and the environment cannot be reached due to the degree of complexity.

In the case of *emotional processing*, we characterize positive and negative "gut feelings," "gut instincts," "hunches," or "growing excitement in the stomach," which are evoked in supplier selection decisions and guide the decision-making process (Barnard, 1938; Leybourne and Sadler-Smith, 2006; Sinclair and Ashkanasy, 2005). This dimension has a long-standing history in the broader decision-making literatures and is still a common conceptualization of intuition in recent research (Akinci and Sadler-Smith, 2012; Dayan and Di Benedetto, 2011; Giunipero et al., 1999; Khatri and Ng, 2000; Leybourne and Sadler-Smith, 2006).

The increasing dynamism and complexity in supplier selection can lead to limitations in analytical processing, including gathering, culling through and assessing, and interpreting relevant facts about suppliers (Ellis et al., 2010; Mantel et al., 2006; Sadler-Smith and Shefy, 2004). Specifically, in environments characterized by high degrees of uncertainty, business research has found an increased use of experience-based and emotional processing (Dayan and Di Benedetto, 2011; Khatri and Ng, 2000). But, managerial research about the *effects* of intuitive processing on decision outcomes is generally scarce, and results are inconsistent (Dane and Pratt, 2007). This inconsistency is not surprising, given opposing theoretical predictions: On the one hand, the heuristics and biases (HB) approach traditionally assumes that intuitive processing and heuristics can lead to biases and suboptimal decisions, while on the other hand, studies support the inevitability and upside potential of using intuition (Kahneman and Klein, 2009; Lee et al., 2009).

We assume that in the focal supply management context of this research, purchasing managers have to deal with increasingly disruptive technological change, supply disruption risk, and demand volatility (Ro et al., 2016). Further, they need to consider multiple criteria such as service, quality, and price when making a selection decision (Carter et al., 2010). When confronted with complex, risky and volatile situations in their selection of suppliers, purchasing managers increasingly face new situations for which stored patterns, as precondition for using experience-based processing, might not be readily available or fitting (Hodgkinson et al., 2009). We further assume that a predominant reliance on gut-feelings might lead to decision-making biases and flawed choices in such situations because purchasing managers might make hasty, non-optimal decisions (Carter et al., 2007; Kaufmann et al., 2012; Snijders et al., 2003).

The theorizing of negative effects of intuition on decision outcomes is based on the HB approach, which underlines the use of heuristics in intuitive processing to allow for simplification of complex data, focusing on less information and leading to a faster but potentially

unfitting solution (Dane and Pratt, 2007; Elbanna et al., 2013). Initial supply management studies have investigated the effects of decision biases, such as the availability bias (e.g., overestimation of facts due to higher availability of relevant memories), confirmation bias (e.g., information processing based on the decision-maker's preconception), and presentation bias (e.g., tendency to recall first mentioned facts (primacy effect) or last listed data (recency effect) rather than middle items in a series, all of which can negatively affect decision outcomes (Carter et al., 2007; Mantel et al., 2006). Research in strategic decision-making also found that intuition increases decision disturbance (Elbanna et al., 2013) and is negatively related to organizational performance in stable environmental conditions (Khatri and Ng, 2000). Thus, for the second and third *individual* decision-making modes, we therefore tentatively put forth the following hypotheses:

Hypothesis 2a. (i) Experience-based processing and (ii) emotional processing are negatively related to the financial performance of the supplier.

Hypothesis 2b. (i) Experience-based processing and (ii) emotional processing are negatively related to the non-financial performance of the supplier.

2.1.3. Interaction of rationality and intuition

Existing empirical decision-making research in business contexts has focused primarily on *either* rationality *or* intuition, the two decision-making styles that have been distinguished by Simon (1987), and thereby has failed to examine both styles simultaneously. Conceptually, the issue of how rationality and intuition interact has been examined using several theories, which can be summarized under the term *dual-process theories*. Although known by different names, all dual-process theories treat rationality and intuition as discrete, interacting, information-processing systems (Dane and Pratt, 2007; Epstein, 1973; Evans, 2010; Healey et al., 2015). Thus, they do not seek to answer the question of whether rationality *or* intuition (polarity perspective) is used but theorize that several complex interactions of rationality *and* intuition (a two-system perspective) exist. More specifically, they assume one rather slow, conscious, and deliberative mode and one automatic, unconscious processing mode. These theories propose "a rejection of a long-standing dichotomy that holds that cognition is either analytical or intuitive" (Doherty and Kurz, 1996, p. 130) and agree that decision-makers often make use of both rational and intuitive processing. One example is Epstein's (1973) cognitive-experiential self-theory (CEST), which distinguishes between "two information-processing systems: an experiential system, which is an automatic, associative learning system, and a rational/analytic system, which is a verbal reasoning system" (Epstein, 2010, p. 298). Both systems interact with each other and guide behavior.

Dual-process theories make different assumptions about the interaction of rationality and intuition. One assumption is that both systems interact in a temporal sequence (default interventionist view) where, for instance, initial non-rational decisions are justified post-hoc or overridden using extensive analyses (Evans, 2010; Pareto, 1935). A competing assumption is that both systems function in parallel and process information at the same time (Healey et al., 2015; Sloman, 1996; Smith and DeCoster, 2000). Other research, in turn, posits that both parallel and sequential interactions of rationality and intuition occur (Epstein, 2010). Accordingly, several directions, both sequential and parallel, might be possible—for instance, a sequence starts with intuition, then rationality moderates the initial intuition, and finally, parallel processing of both leads to the point of decision (Allen, 2011). We assume that, in our investigated context of supplier selection, rationality functions in this complex interplay as a "controlling mechanism" that checks every important decision step before a final supplier is selected.

Especially when patterns of previous experiences seem to match the current situation, decision biases can emerge and need to be mitigated

through extensive rational analysis (Evans, 2010; Kaufmann et al., 2012; Miller, 2008). For instance, experienced decision-makers might recognize patterns or experience gut feelings when interacting with potential suppliers during negotiations or site visits, creating an initial impression that is then evaluated in greater depth through analytical processing to examine whether the intuitive decision is acceptable and can be executed (Epstein, 2010; Salas et al., 2010).

Thus, we assume that rational processing moderates experience-based and emotional processing in supplier selection, guiding the purchasing manager to choose a supplier whose financial and non-financial performance is sound. We therefore tentatively posit:

Hypothesis 3a. Rational processing will positively moderate the relationship between experience-based processing/emotional processing and financial performance.

Hypothesis 3b. Rational processing will positively moderate the relationship between experience-based processing/emotional processing and non-financial performance.

2.2. Decision-making patterns in supplier selection

The approach taken so far of investigating the performance effects of *individual* decision-making modes is limited in that it cannot handle the complicated human decision process from a holistic perspective that would reveal how the three processing dimensions actually interact and influence each other. Recent psychology research points to the need to analyze the interaction of *multiple cognitive systems* when examining human decision-making (e.g., Evans, 2014). As previously outlined, purchasing managers combine several decision-making approaches such as thorough rational analyses based on recognized parallels to previous supplier selection decisions. So far, however, our approach does not consider the potential interplay among the three different processing modes. For this reason, the configuration approach (Miller, 1986) can be employed to provide such a holistic view of organizational structures and processes and is able to analyze more deeply how decision-making styles interact and influence each other, rather than just focusing on pairwise relationships. It handles *co-alignment* and *fit* among various factors, labeled as configurations or gestalts, and deals with their complex relationships (Drazin and Van De Ven, 1985; Flynn et al., 2010). Based on an inductive analysis, a taxonomy of decision-making styles can be developed that might be consistent with the assumption of heterogeneity among supplier selection decisions (Child and Hsieh, 2014; Flynn et al., 2010).

Because companies typically require purchasing managers to follow certain guidelines, routines, and formalizations, we expect that most supplier selection decisions involve at least a certain level of rational processing and that decisions differ instead in terms of (a) the balance of rational and intuitive processing and (b) the strength of the intuition modes used. To better understand the interplay of rationality and intuition in supplier selection contexts and how it relates to decision outcomes, we assume that different configurations of rational, experience-based, and emotional processing can be distinguished. Thus, we offer the following hypothesis:

Hypothesis 4. An emergent taxonomy of decisions in supplier selection can be developed based on the patterns of rational, experienced-based, and emotional decision processing.

In line with the human judgment and supply management decision-making literature, we further assume that a combination of several processing dimensions is more commonly used and might be more effective than either the use of only rational processing (Doherty and Kurz, 1996; Frantz, 2003; Katsikopoulos and Gigerenzer, 2013) or even the use of intuitive processing alone. Therefore, we posit that the identified configurations of rational, experience-based, and emotional processing are related to the performance of the selected supplier:

Hypothesis 5a. The processing patterns that are developed will be related to the financial performance of the supplier.

Hypothesis 5b. The processing patterns that are developed will be related to the non-financial performance of the supplier.

3. Methodology

3.1. Sampling and data collection

Using contact information from a leading international business contact service company, we sent 628 invitations to purchasing managers. Respondents were asked to complete an online survey referring to a specific supplier selection decision that fulfilled the following five criteria: (1) the supplier selection was made within the past three months (to reduce retrospective bias); (2) the purchase item was procured on a regular basis (no one-off items, such as capital investments), so that respondents could assess the quality, service, and delivery performance of the supplier; (3) a new supplier was chosen for a specific item (i.e., a prior long-term relationship could be neglected); (4) the supply base was large enough to ensure sufficient alternatives (no supplier was a priori the obvious choice); and (5) the respondent was the main decision maker (purchasing was not in a consulting/internal service provider role).

We received 117 usable responses from purchasing managers who possessed, on average, 11–15 years of experience in supplier selection, resulting in an effective response rate of 18.6%. This figure is in line with related research designs in the supply chain management literature (Flynn et al., 2010; Kaynak and Hartley, 2008). Prior to collecting these data, we conducted interviews with three general managers and a pre-test with eight purchasing managers responsible for supplier selection decisions to ensure that the survey was clear, realistic, concise, and specific (Podsakoff et al., 2003). Based on the experts' feedback, adjustments were made before the main survey was launched. Detailed sample characteristics of the main study are illustrated in Table 1.

3.2. Measurement

We measured all latent independent variables using a seven-point Likert-type scale ranging from "strongly disagree" to "strongly agree", and ranging from "needs improvement" to "superior performance" for both performance scales (see Table 2 for detailed items). In line with previous research, we used reflective measurement models (e.g., Kaufmann et al., 2014).

3.2.1. Decision processing
Participants were asked to indicate how they made their decision during a supplier selection process in the past three months. Specifically, we examined *procedural rationality* (Simon, 1978) using a four-item measure (M=5.44, SD=1.20) based on Kaufmann et al. (2014). We measured intuitive processing using two scales. We used four items to measure *experience-based processing* (Kaufmann et al., 2014), including the linking of perceived stimuli to past experiences stored in memory (Across the main sample, this scale had a mean score (M) of 4.30 and a standard deviation (SD) of 1.43). We also developed five items to measure *emotional processing* (e.g., Burns and D'Zurilla, 1999), including gut feelings that guide the decision process (M=2.01, SD=0.92).

3.2.2. Supplier performance
The performance of the selected supplier is typically measured through financial outcome variables (e.g., item costs) and non-financial outcome variables (e.g., responsiveness of the supplier) (Cai and Yang, 2008; Riedl et al., 2013; Shin, 2000). Therefore, we measured *supplier performance* using both a financial measure and a non-financial measure. Because financial performance has a strong focus on costs

Table 1
Sample characteristics.

Industry	33.3% Automotive & industrial goods; 20.5% Consumer goods; 16.2% Chemicals; 5.1% Pharmaceuticals; 12.0% Logistics; 12.0% IT & telecommunications; 0.9% Other non-manufacturing
Purchase item type	29.9% indirect materials; 27.4% raw materials; 16.2% packaging materials; 26.5% services
Gender	66.7% male; 33.3% female
Age	11.1% under age 30; 16.2% ages 30–35; 17.9% ages 36–40; 20.5% ages 41–45; 15.4% ages 46–50; 12.8% ages 51–55; 6.0% over age 55
Education	28.2% High school graduates; 15.4% B.A./B.Sc. degrees; 42.7% M.A./M.Sc. degrees; 13.7% Ph.D. degrees

(Talluri, 2002), we used two items, "low item price" and "total cost of ownership," to measure *financial performance* (M=5.11, SD=1.64). We measured *non-financial performance* using three items: item quality, on-time delivery, and responsiveness of the supplier to requests for changes (M=5.50, SD=0.96) (e.g., Weber et al., 1991; Wu et al., 2010). Both scales were developed based on the supplier selection criteria identified by Weber et al. (1991) and the supplier performance measure developed by Wu et al. (2010). Participants were asked to indicate how well the selected supplier performed in comparison to their expectations.

3.2.3. Control variables

Contingencies may affect the employment and effectiveness of decision modes. We included a purchase item-specific dummy variable (0="product" in the case of indirect, raw, or packaging and 1="services) and an industry dummy variable (0=manufacturing and 1=non-man-

ufacturing) along with three ordinal variables assessing purchase item dynamism, purchase item complexity, and purchase item-related experience of the decision maker (Kaufmann et al., 2014; Kohli, 1989).

3.3. Bias evaluation

To control for unit non-response bias (Armstrong and Overton, 1977), we divided the data set into three groups: early, medium, and late respondents. The results of a non-parametric Kruskall-Wallis test showed no significant variance or differentiation ($p < 0.05$) among the responses in all three groups. To avoid common method variance, the surveys were presented to respondents as "research to improve the quality of the supplier selection process" and did not emphasize the focus on decision processing. In addition, we separated independent and dependent variables so that respondents would not develop their own theories about cause–effect relationships; to statistically control

Table 2
Scale items and reliability of constructs.

	Std. Factor Loading
Rational processing[a] (CR[b]=0.916, Variance Extracted=0.734)	
I followed a mostly analytical process in making decisions.	0.854
I looked extensively for information before making a decision.	0.915
I used a lot of quantitative analyses in making my decision.	0.801
I analyzed relevant information extensively before I came to a conclusion.	0.852
Experience-based processing (CR=0.865, Variance Extracted=0.681)	
I did not have time to decide analytically, so I relied on my experience.[c]	
I made a connection between the situation at hand and similar situations in the past and decided accordingly.	0.811
I decided based on experiences I had made with similar suppliers.	0.872
I recognized parallels to similar supplier selection and decided the same way.	0.791
Emotional processing (CR=0.802, Variance Extracted=0.510)	
I relied a great deal on my emotional perception to help me find the best way to decide.[c]	
I was not completely sure about how to decide, so I decided based on my gut feeling.	0.701
I had not worked with one/several suppliers before, so I decided based on my gut feeling.[c]	
My gut feeling said "something is wrong" so I declined a supplier.	0.684
To select a supplier, I mainly followed my instincts, rather than trying to reason things out.	0.756
Financial performance of supplier (CR=0.802, Variance Extracted=0.884) (1=needs improvement; 7=superior performance)	
Low total cost of ownership for the purchase item	0.893
Low purchase item price	0.985
Non-financial performance of supplier (CR=0.791, Variance Extracted=0.557) (1=needs improvement; 7=superior performance)	
High purchase item quality	0.793
On-time delivery of purchase item	0.724
Good responsiveness of supplier to requests for changes (volumes/specifications)	0.720

Control Variables

Purchase item dynamism: The item was subject to more technological changes than other items our organization has purchased.

Purchase item complexity: The item was technically complex.

Purchase item-related experience: I personally had a lot of experience with this item prior to this specific process.

Material (0=indirect material, raw material, or packaging, 1=services)

Industry (0=manufacturing, 1=logistics or other non-manufacturing)

Note: χ^2=88.11 (df=80), CFI=0.99, GFI=0.91, RMSEA=0.03, SRMR=0.05.
  [a] All items measured on a 1=strongly disagree to 7=strongly agree Likert-type scale unless otherwise noted in the table.
  [b] CR=Composite Reliability.
  [c] Item deleted due to high standardized residual.

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Table 3
Discriminant validity.

Construct					
	1	2	3	4	5
1. Rational processing					
2. Experience-based processing	–0.297[**]				
3. Emotional processing	–0.279[**]	0.212			
4. Financial performance	0.562[****]	–0.322[***]	–0.481[****]		
5. Non-financial performance	0.267[**]	0.042	–0.193	0.597[****]	

*$p < 0.05$.
[**] $p < 0.01$.
[***] $p < 0.001$.
[****] $p < 0.0001$.

for common method bias, we conducted a single method factor test (Podsakoff et al., 2003). We conducted confirmatory factor analyses (CFA) and compared the model fit of the one-factor model with the model fit of the measurement model. The fit of the one-factor model was significantly worse. Further, the addition of a common latent factor and an unrelated marker variable to our research model showed that the marker variable reduced the common variance of the variables (Lindell and Whitney, 2001). The results suggest a lack of common method bias.

4. Analysis and results

4.1. Model fit, reliability, and validity

To assess the model fit of our measurement model we conducted a CFA using the CALIS procedure in SAS, Version 9.4 and maximum

likelihood estimation (MLE). Following the procedures of Hu and Bentler (1999), we used the goodness-of-fit index (GFI), the Root Mean Squared Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Standardized Root Mean Square Residual (SRMR) as indicators of fit. These model fit indices were χ^2=(88.11, 80 *df*), GFI=0.91, CFI=0.99, RMSEA=0.03, and SRMR=0.05. All factor loadings were above 0.5 and significant at $p < 0.0001$. The average variance extracted (AVE) was above 0.50 for all scales, and composite reliability values ranged from 0.79 to 0.92. These values exceed the recommendations of Fornell and Larcker (1981), providing evidence of convergent validity (O'Leary-Kelly and Vokurka, 1998; Schermelleh-Engel et al., 2003).

To assess discriminant validity, we followed two procedures. First, we compared the restricted models (with an at-1 fixed factor correlation parameter) with the assumed unconstrained models. The chi-square difference tests conducted for all pairs of constructs were highly significant, resulting in a better model fit for the assumed models and thus indicating discriminant validity (Anderson and Gerbing, 1988). Second, we used the variance extracted test (Fornell and Larcker, 1981), in which we compared the variance extracted estimates to the squared construct correlation for each pair of constructs. None of the squared correlations were greater than the variance extracted for the associated constructs, providing additional support for discriminant validity (Table 3).

4.2. Results of individual decision-making modes in supplier selection

We calculated two separate hierarchical regression analyses, one with financial supplier performance and one with non-financial supplier performance, to test Hypotheses 1 through 3. Before we calculated OLS regression analysis, we tested for the assumptions of linearity and additivity (a lack of multicollinearity of independent variables), homo-

Table 4
Hierarchical regression results: financial performance of supplier.

Variables	β	t	Adj. R^2	F	R^2	ΔR^2
Block 1 (Controls)			0.028	1.67	0.070	–
Material	–0.1312	–1.25				
Industry	–0.0714	–0.68				
Purchase Item Dynamism	–0.1555	–1.57				
Purchase Item Complexity	–0.0351	–0.35				
Purchase Item-Related Experience	0.0657	0.71				
Block 2 (Processing Modes)			0.414	11.24	0.454	0.384[****]
Material	–0.1099	–1.34				
Industry	0.0109	0.13				
Purchase Item Dynamism	–0.1280	–1.60				
Purchase Item Complexity	–0.1275	–1.63				
Purchase Item-Related Experience	0.0974	1.31				
Rational Processing (RP)	0.4786	6.24[****]				
Experience-Based Processing (EXP)	–0.1313	–1.70				
Emotional Processing (EP)	–0.2450	–3.05[**]				
Block 3 (Interaction Effects)			0.465	9.40	0.520	0.066[**]
Material	–0.1154	–1.45				
Industry	0.0121	0.14				
Purchase Item Dynamism	–0.1493	–1.91				
Purchase Item Complexity	–0.1027	–1.36				
Purchase Item-Related Experience	0.0751	1.02				
Rational Processing (RP)	0.4972	6.29[****]				
Experience-Based Processing (EXP)	–0.1309	–1.76				
Emotional Processing (EP)	–0.2419	–2.79[**]				
RP×EXP	–0.0904	–1.13				
RP×EP	0.3629	3.37[**]				
EXP×EP	0.0883	1.05				
RP×EP×EXP	–0.1388	–1.24				

Note: *($p < 0.05$), ***($p < 0.001$).
[**] ($p < 0.01$).
[****] ($p < 0.0001$).

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Table 5
Hierarchical regression results: non-financial performance of supplier.

Variables	β	T	Adj. R^2	F	R^2	ΔR^2
Block 1 (Controls)			−0.018	0.58	0.026	–
Material	−0.1261	−1.18				
Industry	−0.0465	−0.43				
Purchase Item Dynamism	−0.0284	−0.28				
Purchase Item Complexity	−0.0291	−0.29				
Purchase Item-Related Experience	−0.0079	−0.08				
Block 2 (Processing Modes)			0.024	1.35	0.091	0.065
Material	−0.1306	−1.24				
Industry	0.0019	0.02				
Purchase Item Dynamism	−0.0224	−0.22				
Purchase Item Complexity	−0.0696	−0.69				
Purchase Item-Related Experience	−0.0302	−0.31				
Rational Processing (RP)	0.2391	2.45[*]				
Experience-Based Processing (EXP)	0.1090	1.09				
Emotional Processing (EP)	−0.0942	−0.91				
Block 3 (Interaction Effects)			0.060	1.62	0.157	0.066
Material	−0.1135	−1.07				
Industry	−0.0242	−0.22				
Purchase Item Dynamism	−0.0614	−0.59				
Purchase Item Complexity	−0.0553	−0.55				
Purchase Item-Related Experience	−0.0539	−0.55				
Rational Processing (RP)	0.2588	2.47[*]				
Experience-Based Processing (EXP)	0.1132	1.15				
Emotional Processing (EP)	−0.1412	−1.23				
RP×EXP	−0.0797	−0.75				
RP×EP	0.4068	2.85[**]				
EXP×EP	0.1137	1.02				
RP×EP×EXP	−0.2712	−1.82				

Note: ***($p < 0.001$), ****($p < 0.0001$).
[*] ($p < 0.05$).
[**] ($p < 0.01$).

scedasticity, and correct specification of the research model including exogeneity. Symmetrically distributed points around the diagonal of plots of observed versus predicted values and residuals versus predicted values did not provide evidence of nonlinearity. Further, all variance inflation factors were below 1.10 (Hair et al., 2006). Residual plot analysis of residuals versus predicted values did not indicate issues related to heteroskedasticity or error term distribution.

To test for H1 through H3, we entered all variables and interaction effects in three different blocks in two separate hierarchical regression analyses: one for financial performance and one for non-financial performance. In the first step, we included the control variables: material, industry, purchase item dynamism, purchase item complexity, and purchase item-related experience. None of the control variables showed any significant relationships with our outcome variables. In the second step we entered the three main effect variables: rational processing, experience-based processing, and emotional processing. And in the third step we entered the two-way and three-way interactions (in order to avoid potential multicollinearity issues, all independent variables were mean-centered (Aiken and West, 1991)). The results are shown in Tables 4 and 5. We used the change in variance explained (ΔR^2) to determine the effects of decision processing on financial and non-financial supplier performance.

Hypothesis 1a posits a positive relationship between rational processing and financial performance. In our regression analysis, rational processing was positively related to financial performance, *supporting* H1a (b=0.4972, $p < 0.0001$, Block 3). Hypothesis 2a posits that experience-based processing and emotional processing are nega-

tively related to the financial performance of the supplier. Our results suggest that experience-based processing is not related to financial performance (b=−0.1309, $p > 0.05$), while emotional processing (b=−0.2419, $p < 0.01$) was significantly negatively related to financial performance. These results provide *partial support for* H2a. Hypothesis 3a posited that rational processing moderates the relationship between experience-based/emotional processing and financial performance. Adding the interaction terms further significantly increased the predictive power of the regression model (ΔR^2=0.066, $p < 0.01$). In particular, there is a significant, positive interaction effect between rational processing and emotional processing (b=0.3629, $p < 0.01$), although none of the other interaction terms were significantly related to financial performance. Thus, H3a is only *partially supported*.

Hypothesis 1b posited that rational processing is positively related to non-financial performance. Our regression analysis showed that rational processing was positively related to non-financial performance (b=0.2588, $p < 0.05$, Block 3), providing *support for* H1b. Hypothesis 2b posited that experience-based processing and emotional processing are negatively related to the non-financial performance of the supplier. The regression weights for experience-based and emotional processing were not significant; thus H2b was *not supported*. Hypothesis 3b posited that rational processing positively moderates the relationship between experience-based/emotional processing and non-financial performance. As was the case with financial performance, only the two-way interaction of rational and emotional processing was significantly positively related to non-financial performance (b=0.4068, $p < 0.01$); no other interaction terms were significantly related to non-financial performance. Thus, H3b is also only *partially supported*.

4.3. Results of decision-making patterns in supplier selection

Hypothesis 4 postulates that an emergent taxonomy of decisions in supplier selection can be developed based on their patterns of experienced-based, emotional, and rational processing. A two-step cluster procedure was applied: We investigated the number of clusters using hierarchical clustering procedures and classified respondents into decision-making patterns using non-hierarchical clustering (Hair et al., 2006).

First, we undertook hierarchical clustering procedures using Ward's algorithm based on squared Euclidian distances to determine the number of clusters (Ward, 1963). Because large variances among variables can bias the results, we standardized their values by a standard deviation of 1 before we conducted the cluster analysis. We interpreted the dendrograms and plotted the number of clusters on the x-axis (starting with the one-cluster solution at the left) against the coefficients (distances at which clusters are combined) on the y-axis to develop a scree-plot to search for a distinctive elbow criterion (e.g., Mooi and Sarstedt, 2011). Based on the dendrograms, scree-plot, and theoretical reasoning of the number of clusters, a five-cluster solution best satisfied all criteria.

The use of both hierarchical and non-hierarchical cluster analyses has been shown to be a powerful combination for finding a robust cluster solution (Helsen and Green, 1991; Homburg et al., 2008). Therefore, in a *second* step, we used the Ward analysis as a starting solution and applied non-hierarchical clustering using K-means algorithms with quick-cluster to assign the cases to—in our case—five final clusters (Hair et al., 2006). In interpreting the results presented in Table 6 and Fig. 1, we distinguished between (a) the *balance* of rationality and intuition and (b) the *strength* of using emotional processing: All clusters differed in the balance of rationality and intuition, leading us to distinguish between one predominantly rational, two balanced, and two predominantly intuitive processing modes. Further, the clusters differed in terms of the strength with which emotional processing was used, with three clusters containing low values and two clusters containing medium values of emotional

Table 6
Cluster centroids and analysis of variance.

Cluster	Rational processing Mean (SD)	Experience-based processing Mean (SD)	Emotional processing Mean (SD)	Financial performance Mean (SD)	Non-financial performance Mean (SD)
Preferred rationality					
(1) Predominantly rational (N=25)	6.32 (0.49)	3.19 (0.58)	1.44 (0.46)	5.96 (0.91) [4][a]	5.72 (1.10)
Balanced processing					
(2) Rational–experience-based (N=47)	5.96 (0.61)	4.94 (0.67)	1.80 (0.74)	5.47 (1.22) [4]	5.92 (0.75) [4]
(3) Rational–emotional (N=16)	5.38 (0.80)	2.02 (0.64)	2.21 (0.73)	5.53 (1.20) [4]	6.00 (0.68) [4]
Preferred intuition					
(4) Experience-based–emotional (N=22)	4.18 (0.94)	5.33 (0.92)	3.17 (0.88)	3.09 (1.59) [1,2,3,5]	5.24 (1.00) [2,3]
(5) Predominantly experience-based (N=7)	2.93 (0.89)	5.95 (1.08)	1.33 (0.38)	5.00 (2.33) [4]	5.86 (1.36) [2,3]
F	55.824[****]	83.036[****]	21.979[****]	16.653[****]	2.447

*p < 0.05, **p < 0.01, ***p < 0.001.

[a] Numbers in brackets indicate the cluster(s) from which that cluster is significantly different in financial and non-financial performance at $p < 0.05$.
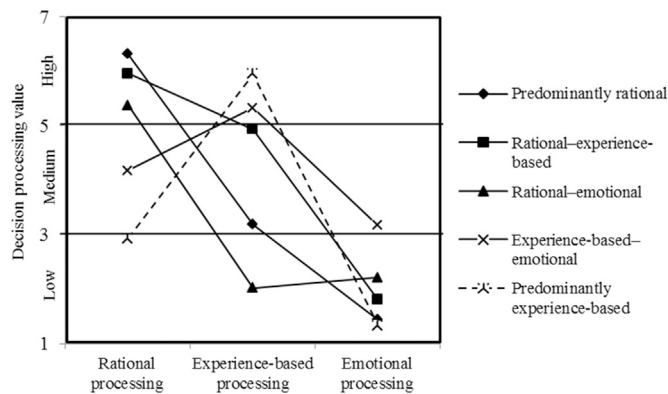
[****] $p < 0.0001$.

Fig. 1. Taxonomy of processing dimensions.

processing. Combining these findings on balance and strength, we labeled the five clusters as (1) predominantly rational, (2) rational–experience-based, (3) rational–emotional, (4) experience-based–emotional, and (5) predominantly experience-based.

We used canonical discriminant analysis to identify functions that characterized the configuration clusters. The results in Table 7 show that two functions had Eigenvalues larger than 1, which explained 93.9% of the variance.

The coefficients in Table 8 reveal that function 1 (explaining 71.2% of the variance) divided the clusters based on the *balance* of rational and intuitive processing used. Function 2 (explaining 22.8% of the variance) distinguished the clusters on the basis of their *strength* of emotional processing used. The cluster centers and their differences based on the discriminant functions are shown in Fig. 2. This illustration also shows the *balance* of rationality and intuition along the horizontal axis, where clusters with a clearly higher focus on rationality are positioned further to the left on the discriminant plane; clusters containing high or medium values of both rationality and intuition are in centered positions; and clusters with a predominant focus on intuition are further to the right. The *strength* of using emotional processing is shown along the vertical axis, with high (low) values for emotional processing leading to positions at the bottom (top) of the discriminant plane. Classification results revealed that 95.7% of the original cases and 94.0% of the cross-validated cases have been correctly classified, emphasizing the predictive ability of the functions and the independence of the scales. These cluster analyses thus allowed us to develop an emergent taxonomy of decision modes in supplier selection, based on their patterns of rational, experienced-based, and

emotional processing and differing in terms of (a) the balance of rationality and intuition and (b) the strength of emotional processing, thus providing *support for* Hypothesis 4.

We used analysis of variance to test Hypotheses 5a and 5b. Hypothesis 5 posits that the processing patterns are related to (a) financial performance and (b) non-financial performance. The results presented in Table 6 show significant differences in financial performance ($p < 0.001$) and almost significant differences in non-financial performance (p was equal to, but not less than, 0.05) between the decision configurations, *supporting* H5a and providing *moderate support for* H5b. Fisher's Least Significant Distance (LSD) post-hoc analysis was used to further examine the performance differences between the configurations. The results showed that the experience-based emotional cluster differed significantly in financial performance from all other clusters, as well as in non-financial performance from the balanced processing clusters. Thus, significantly higher values of financial performance for clusters containing high values of rationality underscore the importance of maintaining rational procedures in supplier selection decisions. Higher values of non-financial performance for clusters that were balanced in intuition and rationality support the complementary assumption of dual-processing, particularly when more holistic decisions have to be made.

5. Discussion

We combined the HJDM and supply management literatures by distinguishing among rational, experience-based, and emotional processing and examining their interactions and relationships with the financial and non-financial performance of the supplier. Our results show that rational processing by the individual decision maker is positively related to financial and non-financial performance. This finding corroborates rational processing theories, which assume that extensive information gathering creates a deep comprehension of context variables, such as market developments and the pursuit of long-term strategies (Glöckner and Witteman, 2010; Miller, 2008), and that clear definitions of criteria help in choosing a high-performing supplier (Kaufmann et al., 2012). Through high procedural rationality, decision-makers also might be able to mitigate biases and therefore the potential downsides of using intuitive approaches (Carter et al., 2007). Thus, our findings underscore the key role of rationality in the supplier selection decision (Kaufmann et al., 2014; Miller, 2008).

Further, our findings show that experience-based and emotional processing, as two dimensions of intuitive processing, were used in several decisions, but that there was no relationship between these two

Table 7
Canonical discriminant analysis.

Function	Eigenvalue	% of variance	Cumulative %	Canonical correlation
1	4.653	71.2	71.2	0.907[****]
2	1.489	22.8	93.9	0.773[****]
3	0.397	6.1	100.0	0.533[****]

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
[****] $p < 0.0001$.

Table 8
Standardized canonical discriminant function coefficients.

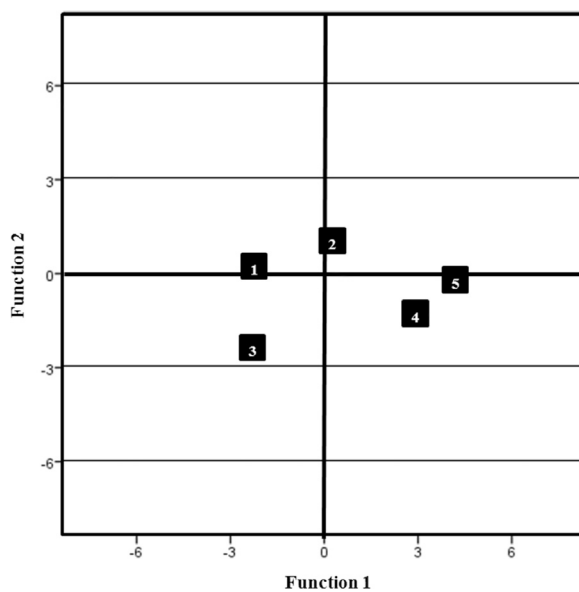|	Function 1	Function 2
Experience-based processing	0.796	0.624
Emotional processing	0.268	−0.585
Rational processing	−0.719	0.580

Fig. 2. Cluster centroids.

individual dimensions and financial and non-financial performance. This finding adds to our understanding of the HB approach, which emphasizes that the use of heuristics allows for faster decisions by ignoring some aspects but that it also is prone to fallacies and biases (Carter et al., 2007; Dane and Pratt, 2007; Elbanna et al., 2013; Snijders et al., 2003).

The upside potential of using intuition might rather be seen in its role as a complement/supplement to rationality. We found the interaction of rational and emotional processing to be positively linked with financial and non-financial performance, providing some evidence for dual-process theories. In that vein, a perceived positive or negative gut feeling might provide guidance in terms of which information should be further analyzed or neglected in the selection of a supplier (Akinci and Sadler-Smith, 2012). Rational procedures can help to override potential errors or misinterpretations that might influence initial gut-based decisions. None of the other interaction terms were significant, which might result from failing to consider the exact interplay between them. For this reason, we included the use of an inductive configuration approach to shed further light on the complex and heterogeneous relationships of *all three* processing modes (Child and Hsieh, 2014; Flynn et al., 2010).

In doing so, we corroborated dual-process theories (Epstein, 2010; Evans, 2010) by deriving five configuration patterns that can be characterized in terms of the balance of rationality and intuition used

(function 1) and in terms of the strength of emotional processing used (function 2). Described by discriminant function 1, rationality and intuition interact, leading to different processing modes that predominantly use either one or use a balance of both. Thus, a continuum perspective in which one processing mode rules out the other seems inadequate in explaining the emergence of the balanced clusters (e.g., Dayan and Di Benedetto, 2011).

Discriminant function 2 divides the clusters into those with medium or low values of emotional processing, with two clusters possessing medium values and three clusters possessing low values of emotional processing. While recent qualitative sourcing research has found that emotional processing (creative intuition) is negatively related to rational processing (Stanczyk et al., 2015) (e.g., cases with high values of procedural rationality revealed low values of creative intuition and vice versa), in our research we found clusters with high rational and low emotional processing, as well as a cluster with high rational and medium emotional processing. Moreover, while Stanczyk et al. (2015) found a negative relationship between experience-based and emotional processing (e.g., cases with high values of justified intuition revealed low values of creative intuition, and vice versa), our cluster analysis revealed clusters with high experience-based and low emotional processing, as well as clusters containing high experience-based and medium emotional processing. Thus, our in-depth analysis extends nascent BSM research by finding further interactions between rational, experience-based, and emotional processing modes. This further strengthens the theoretical contribution of our study: While recent behavioral purchasing research examined the use of intuition and rationality in sourcing *teams* following the *dual* systems tradition (Kaufmann et al., 2014), our study implies that *multiple* decision systems might interact when *individual* purchasing managers make decisions (Evans, 2014).

Contributing to the still embryonic literature on BSM, we also compared the financial and non-financial supplier performance between the identified decision-making patterns. Linking the five derived clusters with financial and non-financial performance, we found lower values for decisions made through a predominantly intuitive style. This finding might strengthen the assumption that rationality helps to mitigate potential negative effects that can result from the quick intuitive processing mode; in fact, rationality might thus be a necessary counterpart to intuition within the context of supplier selection (Epstein, 2010; Salas et al., 2010).

Further, the performance differences among the clusters were higher for financial than non-financial performance, which might underscore that in the case of non-financial performance—which can be more difficult to evaluate because of the higher dependence on soft instead of hard facts—the use of intuition can be more effective than it is in cost-focused decisions. Nevertheless, the highest financial performance values were found for clusters that included high values of rational processing (with and without using significant levels of intuition). This finding again underscores the importance of maintaining a high level of rationality in making supplier selection decisions and thus adds further evidence to information processing theories (Kaufmann et al., 2014; Miller, 2008). The highest non-financial performance values were found for balanced processing clusters, again strengthening the assumption that rationality and intuition can complement each other effectively (Sloman, 1996).

5.1. Managerial implications

Our study indicates that several processing modes are used in purchasing contexts—namely, rational, experience-based, and emotional processing. Increasing volatility, supplier disruption risk (Ro et al., 2016), uncertainty (Flynn et al., 2016), and time pressure (Thomas et al., 2011) in purchasing contexts also increases the difficulty of relying on extensive rational analyses only; nevertheless, the results of our research from the supplier selection context show

that high values of rational processing provide the key to high performance. The highest performance values could be found for decision-makers who successfully combined high degrees of rational processing with medium degrees of experience-based and emotional processing. For example, consider the following scenario: A purchasing manager has to deal with a complex supplier selection decision for which he first shortens the supplier list to five possible suppliers based on formal criteria such as price and delivery time (rational processing). He decides to conduct a more thorough analysis of the five suppliers, keeping in mind that a decision needs to be made soon. The purchasing manager relies on his experience and gut feeling to focus on further aspects of the five potential suppliers, thereby speeding up the decision process. For instance, the purchasing manager sees parallels to a previous decision he has made or experiences a positive or negative gut-feeling regarding a supplier. Through further, guided rational analyses, a final decision for one or against the other suppliers is then made. Thus, managers might increase their performance by using a holistic approach, combining both rationality and intuitive processes instead of maintaining an either/or preference for one instead of the other. A predominantly intuitive approach requires particular caution because, in the pattern-matching process, patterns might be connected and analogies drawn that do not actually provide an appropriate fit to the new situation. Practitioners would achieve greater success by at least using post-hoc rational analyses for verification or overriding (Evans, 2010; Pareto, 1935).

Toward that end, guidelines, formalizations, and routines/standard operating procedures should be seen as safety nets that can ensure higher levels of rationality, rather than as rigid rule books that stifle the use of the upside of intuition. However, it is also important to remember that a flood of information can lead to "losing sight of the forest for the trees." Too much information and too many criteria make analytic procedures less effective or possible because decision-makers might willingly or unintentionally focus on the wrong or less relevant data (Dobelli, 2013; Gigerenzer and Goldstein, 2011; Goldstein and Gigerenzer, 2011). Sometimes less actually is more. In addition, rational analyses might be seen as inerrant and thus bear the risk of not being critically checked, while intuition is known to be prone to biases and therefore might be investigated more thoroughly.

Thus, intuition and big/smart data can both be faulty, so that one might raise the question of whether practitioners need to critically examine both, recognizing their limits and biases (Gigerenzer, 2007). Further, intuition depends on experiences and on faith or trust that their intuition is on target; the more decision-makers trust their intuition, the less stressful the decision situation is to them (Gigerenzer, 2007). Methods to develop trust in one's intuition include diaries (e.g., "which intuitive decisions did I make today and how effective, positive, or negative were they? ") and attentiveness training.

5.2. Limitations and future research

We examine the use of *three* different processing dimensions on the level of the individual decision maker: rational, experience-based, and emotional processing. Our results show that all three dimensions are distinct but seem to interact in multiple ways. Therefore, the question arises as to whether *dual*-process theories need to be extended; the focus on only two dimensions might not fit the complexity of real decision-making. The latest psychology research also has pointed to the fact that the term "dual-processing" might be misleading because findings lend support to the assumption of *multiple* interacting systems (Brocas and Carrillo, 2014; Evans, 2014). In this vein, because we have not differentiated rationality further, prospective research might examine whether additional rationality and/or intuition dimensions need to be included to allow for more holistic examination of human decision modes.

The HJDM and BOM/BSM streams which are rooted in cognitive psychology mainly focus on the decision-making processes of indivi-

duals (Bendoly et al., 2010). Although recent supplier selection research jumped directly to the sourcing team level (Kaufmann et al., 2014) before investigating the interplay of decision modes on the individual level, there is still discordance about the underlying intuition dimensions that need to be considered in decision-making research (Akinci and Sadler-Smith, 2012; Sinclair, 2011; Tazelaar and Snijders, 2013). To start with a clarification of such underlying decision-making dimensions and their interplay and configurations, we chose the purchasing manager's supplier selection decision-making process as the unit of analysis. Nevertheless, future research might focus on the more complex setting of cross-functional sourcing teams (Driedonks et al., 2010) and further investigate the interplay of the sourcing team members' mixes of rational and intuitive approaches. For instance, in such a scenario, one might expect purchasing managers to follow another, possibly more rational decision-making approach (e.g., meticulous data analysis) than representatives of other departments as for example users of a service (e.g., the IT department or the marketing department), who might be positively biased towards specific service providers. Such investigations would then of course also require changes to our developed scales/items to be able to measure not only the individual manager's *independent* choice of decision mode – as assumed for simplification purposes in our research design – but also if and how team members chose their decision modes *interdependently*.

For this study, we made another simplifying assumption and treated the supplier selection as a singular event. Future studies could take a more differentiated view as a supplier selection is typically a multi-stage process that starts with identifying sourcing requirements and potential supply sources and ends with reaching an agreement with a supplier. It may well be that our respondents used for example more rationality in identifying the initial long-list of potential suppliers and more intuition when evaluating individual suppliers' innovation capabilities or cultural fit. We also suggest that future research revisit the wording of some questions which might be perceived as leading the respondents into a negative direction (i.e., the item "I was not completely sure about how to decide, so I decided based on my gut feeling." from the emotional processing scale, or the item "I did not have time to decide analytically, so I relied on my experience." from the experience-based processing scale) and consider developing additional scale items.

Further, we did not use multiple sources to measure supplier performance as an outcome variable. While we reduced recall bias (Podsakoff et al., 2003) by asking respondents to think of a supplier selection which took place within the past three months, we were not able to collect objective data to measure the selected suppliers' performance and compare it to subjective data. Future research should additionally include objective criteria such as on-time delivery and quality issues of the delivered material.

As contingencies may affect supplier selection, we put forth stringent requirements for purchasing managers participating in this study and controlled for factors such as the type of purchase item (product vs. service, item complexity, item dynamism), the type of purchasing situation (re-buys only, size of supply base, purchase item-related experience of the purchasing manager), and the type of supplier relationship (limited to new suppliers only). However, future research may want to account for a broader set of factors, including for example market conditions, user preferences, corporate objectives, urgency, or value of purchase.

It further appears fruitful to generally extend the focus of this study and investigate the usefulness of different types of intuition in different supply management situations. Promising research questions could therefore be: Does experience-based intuition lead to more entrepreneurial outcomes in collaborative product development projects? Is emotional processing positively related to efficiency, and which purchasing processes would therefore benefit from it? What happens if contradictory intuitions occur in buying teams? Do purchasing managers have to rationalize their intuitive decisions to obtain buy-in at the

group-level? How can chief purchasing officers create intuition-conducive environments? Answering questions like these, by demonstrating empirically the existence of links between intuitive decision-making and performance, will allow the SCM discipline to provide managers with research-based tools to improve their decision-making.

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