THE AFFORDANCES OF BUSINESS ANALYTICS FOR STRATEGIC DECISION-MAKING AND THEIR IMPACT ON ORGANISATIONAL PERFORMANCE

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Abstract

Increasingly, business analytics is seen to provide the possibilities for businesses to effectively support strategic decision-making, thereby to become a source of strategic business value. However, little research exists regarding the mechanism through which business analytics supports strategic decision-making and ultimately organisational performance. This paper draws upon literature on IT affordances and strategic decision-making to (1) understand the decision-making affordances provided by business analytics, and (2) develop a research model linking business analytics, data-driven culture, decision-making affordances, strategic decision-making, and organisational performance. The model is empirically tested using structural equation modelling based on 296 survey responses collected from UK businesses. The study produces four main findings: (1) business analytics has a positive effect on decision-making affordances both directly and indirectly through the mediation of a data-driven culture; (2) decision-making affordances significantly influence strategic decision comprehensiveness positively and intuitive decision-making negatively; (3) data-driven culture has a significant and positive effect on strategic decision comprehensiveness; and (4) strategic decision comprehensiveness has a positive effect on organisational performance but a negative effect on intuitive decision-making.

Keywords: Business analytics, Affordance, Data-driven culture, Strategic decision comprehensiveness, Intuitive decision-making, Organisational performance, Questionnaire survey.

1 INTRODUCTION

While business analytics (BA) refers to the processes and techniques of data analysis for the generation of knowledge and intelligence (Davenport and Harris 2007; Goes 2014), strategic decision-making (SDM) is the process of creating organisational mission and objectives and choosing the courses of action to achieve those goals (Eisenhardt and Zbaracki 1992). Based on sophisticated information technologies (IT) (Davenport 2013), BA offers the possibilities for organisations to use data-driven insights to improve their SDM and performance (e.g., Kiron and Shockley 2011; Bernhut 2012; Gillon *et al.* 2014). While there is indication that companies use BA perform better than those that do not (Kiron and Shockley 2011; Lavalle *et al.* 2011; Kiron *et al.* 2012, 2014), "many companies are still struggling to figure out how, where and when to use analytics" (Kiron *et al.* 2012, p.17), or "unsure how to proceed" (Barton and Court 2012, p.79), or "struggling to achieve a worthwhile return" (Marchand and Peppard 2013, p.105). Thus, a fundamental research question yet to be answered is how BA can be sued to affect SDM and organisational performance.

As an emerging body of research, extant BA studies are predominantly practice driven (George *et al.* 2014); there is little empirical analysis based on hypothetico-deductive method. Thus, little is known about the mechanisms through which BA improves SDM and organisational performance. The literature on SDM, instead, has accumulated a vast amount of knowledge of SDM processes and outcomes. While prior SDM literature suggests that rational decision processes are preferred over intuitive processes when data is available and reliable (e.g., Khatri and Ng 2000; Dhami and Thomson 2012), the effects of both processes on performance are mixed (e.g., Rajagopalan *et al.* 1993; Miller and Ireland 2005). Besides, SDM research has yet to examine how BA might affect SDM characteristics and ultimately organisational performance. The absence of such an understanding inevitably constrains the abilities of organisations to fully realise the benefits from their investments in BA.

This paper therefore seeks to reduce the above research gap by focusing on the following: what are the possibilities for SDM that BA can provide to an organisation and how such possibilities can be realised? How does BA influence SDM thereby to improve organisational performance? In order to advance the discussion we first draw on the IT affordance literature (e.g., Robey *et al.* 2013; Strong *et al.* 2014). As affordance is "the possibilities for goal-oriented action afforded to specified user groups by technical objects" (Markus and Silver 2008, p. 662), we aim to develop an understanding of the basic and decision-making affordances that BA affords to assist an organisation in SDM, and how these affordances can be realised by the organisation to improve its SDM and finally its performance. We then draw on SDM literature to investigate how decision-making affordances are associated with key decision process characteristics such as SDM comprehensiveness (Rajagopalan *et al.* 1993; Hough and White 2003; Miller 2008) and intuitive SDM (Simon 1987; Khatri and Ng 2000). The key variables in this research include BA, data-driven culture, decision-making affordances, and strategic decision comprehensiveness, intuitive decision-making and organisational performance as an outcome variable. A research model is developed to specify the paths from BA to decision-making affordances to SDM process characteristics and ultimately to organisational performance. Although the concept of affordances has been used in IT related studies and BA has been suggested to improve SDM and ultimately organisational performance, however, no published research has investigated the relationship between BA and SDM and organisational performance from the affordances perspective yet. Thus, this research contributes to the existing literatures conceptually and empirically. The next section of the paper presents the literature review, the research model and hypotheses. The subsequent sections describe the instrument development and the data collection processes, and reports on the findings. The final section discusses the results and implications.

2 LITERATURE REVIEW AND RESEARCH MODEL

We begin with reviewing the existing literature on IT affordances, based on which we understand BA as basic affordances and develop the concept of decision-making affordances. Subsequently, we draw upon relevant literature to develop hypotheses regarding the effect of decision-making affordances on SDM. We conclude by developing our research model to summarise the paths linking BA to SDM and to organisational performance.

2.1 Related Literature on IT Affordances

The concept of affordances is initially developed in ecological psychology by Gibson (1986) to study the behaviour of animals in their environments, which refers to what is offered to someone or something by an object. Recently in the IT literature, a number of papers have used the concept of affordances to specify the possibilities for action that different features of IT as a material object offer to organisational users, thereby to help understand the relationship between IT and organisational practices. Consequently, several common themes are emerging. First, consistent with the concept of affordance developed by Gibson (1986) but used in the context of organisations, IT affordances are neither properties of IT artefacts nor the organisational users alone; they are relational (e.g., Leonardi 2011; Volkoff and Strong 2013). Second, an IT artefact can be used differently by a specific user/group, even when using the same IT artefact (Leonardi 2013). Third, there is a need to differentiate between perceived and actualised IT affordances. IT affordances have to be perceived before they can be actualised; but perceived IT affordances may not necessarily be actualised by organisational users (Zammuto *et al.* 2007; Robey *et al.* 2013). In order to actualise an IT affordance, organisational users need to have the “necessary capability” and “an intention or goal that is served by actualizing the affordance”(Volkoff and Strong 2013, p. 822). Further, IT affordances can be actualised differently by various users (Leonardi 2013; Volkoff and Strong 2013). Fourth, a few authors recognised that the ideas of IT affordances need to be extended for use at the organisational level, in addition to the individual and team levels (Robey *et al.* 2013; Volkoff and Strong 2013; Strong *et al.* 2014).

Additionally, several methodological issues can be identified. To start with, many studies discussed the concept of IT affordances at an abstract and conceptual level (e.g., Markus and Silver 2008; Robey *et al.* 2013), while empirical studies examine one single case only. Regardless, many discuss IT affordances at individual or group level (e.g., Goh *et al.* 2011; Leonardi 2011, 2013). Although IT affordances are seen to be a salient and useful concept (e.g., Goel *et al.* 2013; Leonardi 2013), the mechanisms and processes of transforming lower-level IT affordances to higher-level affordances are largely missing so far (Strong *et al.* 2014).

Therefore, IT affordance has emerged as an important area of study while further conceptual development is clearly needed for understanding for example various other types of affordances (e.g., Zammuto *et al.* 2007) at the organisational level (e.g., Robey *et al.* 2013), and how lower-level affordances can be developed into higher-level organisational affordances. Based on the above, we next develop our understanding of the affordances that BA provides to organisational decision-making.

2.2 BA Affordances and Decision-making Affordances

BA was developed to provide data-driven insights to support decision-making. BA can be categorised into descriptive, predictive, and prescriptive (Kiron and Shockley 2011; Kiron *et al.* 2012; Delen and Demirkan 2013; Watson 2014). From the affordance perspective, BA features offer the possibilities for data analysis and decision support at a basic level to an organisation; by itself, BA is unable to explain its uses and impact. When it is applied by an organisation, its users must have perceived at least the possibilities it affords to the organisation. Thus when an organisation implements BA, this can be interpreted as the organisation’s effort to actualise the perceived opportunities afforded by BA. In this sense, BA implemented in an organisation is already a relational concept bringing together the statistical features of BA and how the users perceive and use BA; it is the actualised *affordances* to the organisation for data processing and providing support for decision-making at the organisational level.

However, pertaining to decision-making, BA provides only *basic affordances* that are the enabling conditions for exercising other higher-level decision-making affordances.

Building upon the basic affordances provided by BA, decision-making affordances are higher-level affordances that can be defined as the possibilities for data-driven decision-making, adapting the affordance definition (Markus and Silver 2008; Strong *et al.* 2014). Decision-making affordances include identifying problems and opportunities, defining strategic objectives and criteria for success, developing and evaluating alternatives, and prioritising and selecting one or more alternatives, drawing on Simon (1947). These decision-making activities are not new: they have been an essential part of any businesses and academic research since the inception of business practice. However, in the context of BA, data-driven decision-making has created unprecedented opportunities for businesses to make fast and comprehensive decisions based on unparalleled data-driven insights into customers and operations. In addition, businesses are much more likely to be able to use BA effectively when they have a data-driven culture, which is "a pattern of behaviours and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organisation" (Kiron *et al.* 2012). When big data, advances in IT, BA and decision-making come together, decision-making has been brought to a completely new level that is ever so data-driven. As a result, true data-driven decision-making comes into being, allowing managers to see what was previously invisible (Barton and Court 2012) and to conduct systematic and rational analysis. This represents "*a qualitative change in opportunities to generate value and competitive advantage*" (Gillon *et al.* 2014, p. 288). In line with this, we understand the concept of decision-making affordances.

Having highlighted that decision-making affordances are the relations between BA (basic affordances) and a data-driven culture, the question remains to be answered is how they are related? Based on prior literature on contingency theory regarding the relationship between technology and organisational form and function, we take the view that a data-driven culture mediates the relationship between BA and decision-making affordances. For example, Woodward's (1958, 1965) influential research on manufacturing technology and organisational structure suggested that technology can be an important determinant of organisational forms and functions. Thompson and Bates (1957) and Perrow (1967) suggested similar views based on different studies. Likewise, the notion of technology can result in changes in organisational form and function is also supported by Galbraith (1974) and Jelinek (1977), and by Zammuto *et al.* (2007) and Leonardi (2011) from the perspective of recent IT affordances. Thus, we propose the following hypotheses:

H1: *BA is positively and directly associated with decision-making affordances*.

H2: *BA is positively and indirectly associated with decision-making affordances through the mediation of a data-driven culture*.

2.3 Strategic Decision-Making in the Context of Business Analytics

Following Mintzberg *et al.* (1976), strategic decision in an organisation is "*important, in terms of the actions taken, the resources committed, or the precedents set*" (p. 246), which has a critical effect on the organisation's prosperity and survival (Eisenhardt and Zbaracki 1992; Miller 2008). While a number of different perspectives on SDM can be differentiated (Hutzschenreuter and Kleindienst 2006), rational and intuitive processes are frequently contrasted by prior studies (e.g., Khatri and Ng 2000; Dhami and Thomson 2012). Rational processes are characterised by decision-makers gathering appropriate information, developing possible alternatives, evaluating the alternatives and selecting the best possible alternative (e.g., Eisenhardt and Zbaracki 1992; Rahman and de Feis 2009). In line with this view, *strategic decision comprehensiveness* refers to the extent to which an organisation attempts to be exhaustive and inclusive in making and integrating strategic decisions (Fredrickson and Mitchell 1984; Atuahene-Gima and Haiyang 2004).

However, for decision situations where problems are ill-structured and complete, accurate, and timely information is not available, intuitive SDM offers a valuable alternative (Simon 1987; Khatri and Ng 2000; Kutschera and Ryan 2009). Intuitive SDM depends on "holistic hunch and automated expertise" (Miller and Ireland 2005). While seen as an effective approach to SDM, a number of studies have warned that intuitive processes need to be used cautiously (e.g., Khatri and Ng 2000; Miller and Ireland 2005) because it can be dangerously unreliable in complicated decision situations (Bonabeau 2003).

The importance of these features in SDM and the recent development in BA have stimulated us to ask how the intuitive and rational SDM might be shaped by implementing BA alongside developing a data-driven culture in organisations. First, we argue that a data-driven culture developed in an organisation would facilitate its SDM comprehensiveness, drawing on BA studies. Davenport (2006) argued that a data-driven culture would inspire a companywide respect for measuring, testing, and evaluating quantitative evidence, while Kiron and Shockley (2011) suggested that companies with a data-oriented culture are characterised by data-driven leadership, analytics used as a strategic asset, and strategy and operations guided by analytical insights. Similarly, Ross *et al.* (2013) stated that organisations with a data-driven culture follow practices such as establishing one undisputed source of performance data, giving decision makers at all levels timely feedback, and consciously articulating business rules based on data. Thus, it is conceivable that a data-driven culture encourages organisations to conduct systematic analysis of available data to make strategic decisions. Thus:

H3: *Data-driven culture has a positive effect on strategic decision comprehensiveness*.

Second, an organisation is expected to be able to significantly improve its SDM comprehensiveness when it has realised its decision-making affordances. As discussed previously, BA enables organisations to effectively capture, integrate and analyse data. This means that the accuracy, sophistication, and completeness of rational analysis will be significantly improved (Molloy and Schwenk 1995). BA does not make decisions but input from BA can help make better decisions (Bell 2013). Using the data-based insights to provide input to decision-making, decision-making affordances enable organisations to use rational decision processes to systematically identify business problems and opportunities, define strategic objectives and criteria for success, develop and evaluate alternatives, and select the best alternative. SDM literature suggested that in business a successful decision is most likely when sufficient information is available (Rodrigues and Hickson 1995) and viable organisational strategies can be generated based on complete and accurate information about the likely relationship between choices and outcomes (Dean Jr and Sharfman 1996). Therefore, we propose:

H4: *Decision-making affordances have a positive effect on strategic-decision comprehensiveness*.

Third, SDM literature suggested that rational processes are preferred when data is available and reliable; otherwise, intuitive processes should be a better choice. A few prior studies demonstrated that there is a statistically significant negative correlation between rational and intuitive processes (Sadler-Smith 2004; Elbanna *et al.* 2013). However, this does not mean that rational and intuitive processes are mutually exclusive; actually, a number of studies suggested that rational and intuitive processes should be used to complement each other at the same time (Robey and Taggart 1982; Sadler-Smith 2004; Coget and Keller 2010). In line with the above, we argue that, in the context of BA, the need for intuitive SDM, while it remains important, will be reduced since data availability has been significantly improved, and data-driven insights so gained can be used to provide input for more comprehensive SDM. Therefore, we hypothesise:

H5: *Decision-making affordances are negatively associated with intuitive decision-making*.

H6: *Strategic decision comprehensiveness is negatively associated with intuitive decision-making*.

Finally, prior empirical SDM studies suggested that there is a complex relationship between SDM and organisational performance. While some studies suggested comprehensive process leads to better organisational performance (e.g., Eisenhardt and Zbaracki 1992; Miller 2008), others demonstrated that with an unstable environment there is a consistently negative relationship between comprehensiveness and organisational performance (e.g., Mintzberg 1973; Fredrickson and Mitchell 1984). Regarding the performance impact of intuitive SDM, prior empirical SDM studies showed mixed results as well in various research contexts (e.g., Khatri and Ng 2000; Elbanna and Child 2007; Dayan and Elbanna 2011). Drawing upon the literature on SDM and BA, we tend to take the view that organisational performance can be improved since BA can provide unprecedented data-driven insights that in turn will significantly improve SDM. Thus,

H7: *Strategic decision comprehensiveness has a positive effect on organisational performance*.

H8: *Intuitive decision-making has a positive effect on organisational performance*.

As a result, our research model can be summarised in Figure 1

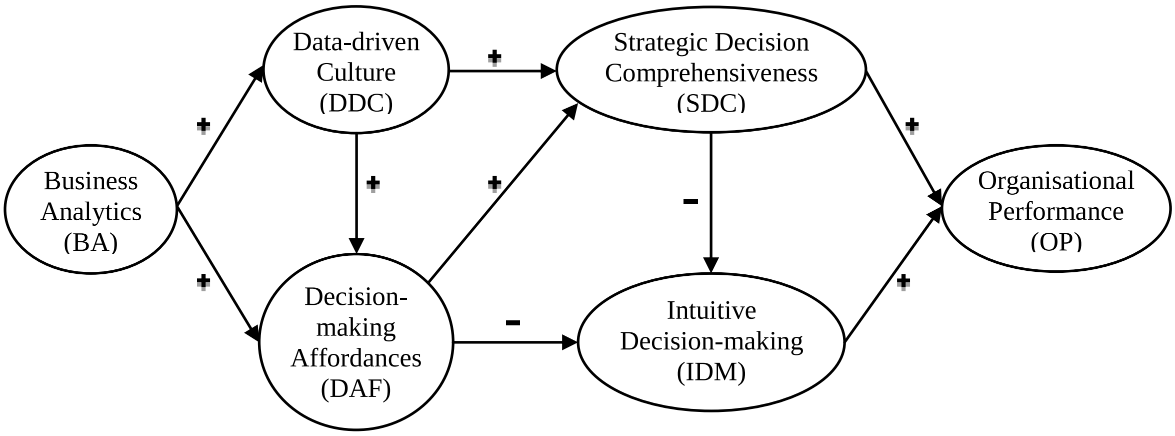

Figure 1. Research Model

3 RESEARCH METHODOLOGY

The hypotheses were tested empirically using partial least squares structural equation modelling (PLS-SEM) that is recommended to be well-suited for research situations where theory is less developed and formative constructs are part of the structural model (Wetzels *et al.* 2009; Gefen *et al.* 2011; Hair *et al.* 2013). Although SDM has been widely discussed and relevant constructs have been developed, IT affordance and BA are new and few relevant constructs have been defined so far. In the following section, we outline the instrument development, validation, and dissemination processes.

3.1 Research Model Constructs and Measures

In order to empirically test the proposed research model, both formative and reflective constructs and their indictors were defined, which are summarised in Table 1. As BA and IT affordances are still emerging as new research areas and there are few previously empirically validated measurement items, we have developed new constructs together with their indicators. To develop constructs properly is challenging because the scale development procedures suggested in the literature are limited (MacKenzie *et al.* 2011; Hair *et al.* 2014). Failing to properly define constructs may cause serious problems such as damaging the validity of the constructs (MacKenzie *et al.* 2011). In order to develop our constructs properly, we evaluated the measurement models based on four decision rules: the direction of causality between construct and indicators, interchangeability of the indicators, covariation among the indicators, and the nomological net for the indicators (Petter *et al.* 2007). As a result, we have formatively defined BA, data-driven culture, and decision-making affordances as composite concepts. The rest of the constructs together with their measurements, already empirically validated by prior studies, are adapted from SDM studies to the current research context.

Constructs	Indicators	References
Business Analytics (BA) (Formative)	The extent to which your company uses the following types of Business Analytics • BADESC: Descriptive Analytics provides the context of and trending information on past or current events • BAPRED: Predictive analytics provides an accurate projection of the future happenings and the reasoning as to why • BAPRES: Prescriptive analytics recommends one or more courses of action and show the likely outcome of each decision	(Kiron and Shockley 2011; Kiron *et al.* 2012; Delen and Demirkan 2013)
Decision-making Affordance (DAF) (Formative)	Rate your company's capability to perform the following activities • DAFIPO: Identifying problems and opportunities • DAFDSO: Defining strategic objectives and criteria for success • DAFDEA: Developing and evaluating alternatives • DAFPSA: Prioritizing and selecting one or more alternatives	(Simon 1947; Armstrong 1982)
Data-Driven Culture (DDC) (Formative)	The extent to which you agree or disagree with the following statements about you company's culture • DDCBELI: We believe that having, understanding and using data and information plays a critical role • DDCOPEN: We are open to new ideas and approaches that challenge current practices on the basis of new information • DDCDEP: We depend on data-based insights to support decision making • DDCUSE: We use data-based insights for the creation of new products • DDCNEED: Individuals have data need for decisions	(Davenport *et al.* 2001; Kiron and Shockley 2011; Lavalle *et al.* 2011; Kiron *et al.* 2012)
Strategic Decision Comprehensiveness (SDC) (Reflective)	Faced with an immediate, important, non-routine threat or opportunity, we: • SDCCRIT: Consider many different criteria and issues when deciding the course of action to take • SDCMULT: Thoroughly examine multiple explanations for the problem or opportunity • SDCSUGG: Conduct multiple examinations for the suggested course of action • SDCRESP: Search extensively for possible responses • SDCALTE: Develop many alternative responses	(Dean Jr and Sharfman 1996; Goll and Rasheed 1997; Atuahene-Gima and Haiyang 2004)
Intuitive Decision Making (IDM) (Reflective)	Faced with an immediate, important, non-routine threat or opportunity, we: • IDMGUTF: make decisions based on 'gut-feeling' • IDMEXPE: make decisions relying on past experience • IDMJUDG: make decisions relying basically on personal judgment	(Khatri and Ng 2000; Elbanna and Child 2007)
Organisational performance (OP) (Reflective)	The extent to which you agree or disagree with the following statements about your company's performance, on average, in the past five years • OPPRO: We are more profitable than our key competitors • OPSAL: Our sales increased faster than our key competitors • OPMAR: Our market share increased faster than our key competitors • OPROI: We had better return on investment than our key competitors	(Fredrickson and Mitchell 1984; Eisenhardt and Bourgeois III 1988)

Table 1. Constructs and Indicators of the Study

3.2 Data Collection

To test the hypotheses empirically, we collected data from UK enterprises. We generated a questionnaire survey using a seven-point Likert scale to provide responses to the model measurements of all constructs. The survey instruments were developed based on literature review and construct definitions discussed above and then were scrutinised by internal subject experts. After a few revisions, the survey was piloted to ensure that the respondents understood the questions and there were no problems with the wording or measurements. The survey instruments were then delivered electronically through

Qualtrics to managers, whose email addresses were identified from FAME database. Three rounds, one week apart, of emails including a cover letter with the questionnaire survey were sent. Of all sent emails, 771 surveys were opened; of these surveys started, we received 304 responses and 296 were usable responses, which represent a 38.4% response rate.

3.3 Respondents

We used a key informant approach (Bagozzi *et al.* 1991) to collect data. The reported positions of the respondents suggested that 20% of the respondents were in a senior managerial position and the rest of them were in a middle managerial position. Based on their position within the firm, the respondents were highly likely to participate in decision-making processes related to the topic of the survey (Phillips and Bagozzi 1986). The respondents were from a number of different industries, though 28% are from manufacturing sector, 15% from professional services, 9% from retail and wholesale, 8% from technology, and 6% from financial services. With regards to company size, 13% respondents were from small businesses with less than 50 employees; 53% were from medium businesses with employees between 50 and 249, and 34% respondents were from large companies with more than 250 employees. Overall, the sample seemed to be diverse, representing various industry, managerial position and experience.

3.4 Common Method and Non-respondent Bias

In order to control for method bias that compromises the validity of research conclusions (Podsakoff *et al.* 2003), we used both procedural and statistical remedies. We used procedural remedy to define scale items clearly, label every point on the response scale to help reduce item ambiguity (Krosnick 1999), and balance positively and negatively worded measures to control for acquiescence and disacquiescence biases (Podsakoff *et al.* 2012). Additionally, Harman's single-factor was conducted as a statistical remedy to assess common method bias (Podsakoff *et al.* 2003; Malhotra *et al.* 2007). The test was conducted to assess whether the common method variance associated with the data was high if a single factor explains most of the variance of all the indicators. Conversely, if more than one factor emerges to explain most of the variances, then the common method variance is low. The test result indicated that the first factor accounted for 35.90% of the total variance; thus, there is no evidence of a substantial respondent bias in this study.

Non-response bias was then assessed by comparing early (n=149) and late (n=147) respondents on all measures through a *t*-test. It is expected that early respondents accurately represent the average respondent while late respondents represent the average non-respondent (Armstrong and Overton 1977). The *t*-test results did not find significant differences between the two respondent groups, suggesting an absence of non-response bias.

3.5 Sample Size and Data Screening

In our structural model, the maximum number of arrows pointing at a construct is five. In order to detect a minimum R^2 value of 0.10 in any of the constructs for significant level of 1%, the minimum sample size required is 205 (Hair *et al.* 2014). Since we have 296 usable responses, the minimum sample size requirement is met. Data screening was performed using SPSS19. Missing data for an observation exceeding 10% had been removed. The remaining missing values were replaced by using the mean value replacement. In the sections that follow, we evaluate our measurement models based on the recommended processes and criteria (Petter *et al.* 2007; Hair *et al.* 2014).

3.6 Evaluation of the Measurement Model

The reflective measurement model was evaluated by considering the internal consistency (composite reliability), indictor reliability, convergent validity and discriminant validity (Hair *et al.* 2014). The results are summarised in Table 2 and 3, indicating the reflective measurement model is satisfactory.

Construct	Indicators	Loading	Indicator Reliability	Composite Reliability	Cronbach's α	AVE
IDM	IDMEXPE	0.59	0.35	0.86	0.79	0.68
	IDMGUTF	0.94	0.88			
	IDMJUDG	0.91	0.83			
OP	OPMAR	0.91	0.83	0.92	0.89	0.76
	OPPRO	0.80	0.64			
	OPROI	0.87	0.76			
	OPSAL	0.94	0.88			
SDC	SDCALTE	0.73	0.53	0.92	0.90	0.71
	SDCCRIT	0.83	0.69			
	SDCMULT	0.91	0.83			
	SDCRESP	0.85	0.72			
	SDCSUGG	0.89	0.79			

Table 2. Convergent Validity and Internal Consistency Reliability

	BA	DAF	DDC	IDM	OP	SDC
BA	n/a					
DAF	0.54	n/a				
DDC	0.57	0.64	n/a			
IDM	-0.24	-0.27	-0.32	**0.83**		
SDC	0.21	0.30	0.26	-0.03	**0.87**	
SDS	0.44	0.54	0.61	-0.28	0.31	**0.84**

Square root of AVE on the diagonal; n/a -not applicable to formative constructs

Table 3. Inter-Construct Correlations

The formative measurement model was evaluated in terms of assessing multicollinearity, the indicator weights, significance of weights, and the indictor loadings (Hair *et al.* 2014). To assess the level of multicollinearity, the values of variance inflation factor (VIF) of all formative constructs were evaluated and there were no major collinearity issues based on the threshold value suggested for VIF (Petter *et al.* 2007; Hair *et al.* 2014). Based on bootstrapping process, all formative indictors' outer loadings, outer weights and the associated significance testing were assessed (Table 4). Based on the criteria suggested by Hair *et al.* (2014), the formative measurement model is valid and meaningful.

Formative Constructs	Indicators	Outer Weights	*p*-values	Outer Loadings
BA	BADESC	0.5434	0.0000^{***}	0.8959^{***}
	BAPRED	0.1957	0.0283^{*}	0.8487^{***}
	BAPRES	0.4041	0.0000^{***}	0.8588^{***}
DAF	DAFDEA	0.1277	0.2223^{ns}	0.9099^{***}
	DAFDSO	0.3864	0.0000^{***}	0.9364^{***}
	DAFIPO	0.2654	0.0013^{**}	0.8812^{***}
	DAFPSA	0.3113	0.0016^{**}	0.9252^{***}
DDC	DDCBELI	0.2094	0.0003^{***}	0.7901^{***}
	DDCDEP	0.4105	0.0000^{***}	0.9216^{***}
	DDCNEED	0.1076	0.0115^{*}	0.4902^{***}
	DDCOPEN	0.2359	0.0000^{***}	0.7217^{***}
	DDCUSE	0.2791	0.0000^{***}	0.8356^{***}

$^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$ ns=not significant

Table 4. Outer Weights & Significance Testing Results

3.7 Evaluation of the Structural Model

SmartPLS was used for testing the hypotheses and assessing the research model. A bootstrapping procedure (5,000 samples) was used to assess the significance of the hypothesised paths and the amount of variance in the dependent variables attributed to the explanatory variables (Hair *et al.* 2014). The results of the analysis are presented in Figure 2. The structural model was assessed in terms of collinearity and the significance and relevance of the structural model relationships (Hair *et al.* 2014). To assess collinearity issues, four sets of predictor constructs were evaluated and there is no collinearity issue found.

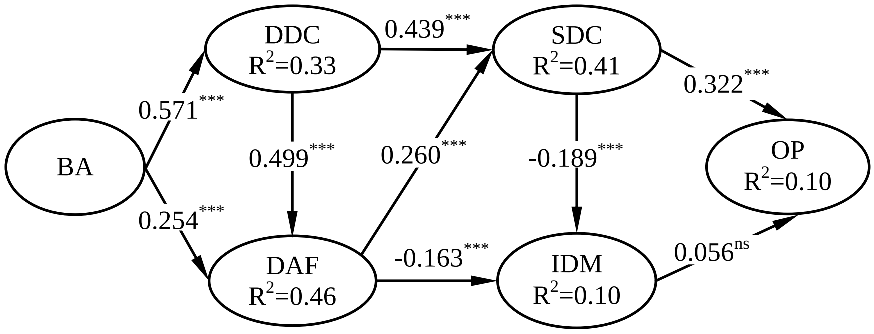

Figure 2. Empirical results

SDC was found to have the strongest total effect on OP (31%), followed by DDC (17%), BA (12%), and DAF (7%). BA was found to have the strongest total effect on DAF (54%), followed by DDC (50%). DDC had the strongest total effect on SDC (57%), followed by BA (39%) and DAF (26%). The predictive power of the model was assessed by the amount of variance attributed to the latent variables (i.e., R^2) and the value of the predictive relevance Q^2. All Q^2 were found to be above zero, thus providing support for the model's predictive relevance regarding the latent variables (Hair *et al.* 2014). The R^2 values indicate that the full model explains 46% of the variance in DAF, 41% in SDC, 33% in DDC, 10% in IDM and in OP. Based on Wetzels *et al.* (2009), the effect size suggested for R^2 is small=0.1, medium=0.25, and large=0.36. Thus, the effect sizes of DAF and SDC can be classified as large; the effect sizes of DDC is medium; and the effect sizes of IDM and OP are small.

3.8 Hypotheses Testing and Mediation Analysis

Table 5 shows the standardised path coefficient and p-value of each hypothesised path where it is applicable. Except for H8, the rest of the hypotheses were found to be significant.

Hypothesis	Hypothesised Path	Standard path coefficient	*p*-Values	Empirical evidence
H1	BA -> DAF	0.253	0.0000***	Yes
H2	BA->DDC->DAF	(partial mediation)		Yes
H3	DDC->SDC	0.438	0.0000***	Yes
H4	DAF->SDC	0.261	0.0001***	Yes
H5	DAF->IDM	-0.163	0.0001***	Yes
H6	SDC->IDM	-0.189	0.0000***	Yes
H7	SDC->OP	0.323	0.0000***	Yes
H8	IDM->OP	0.056	0.1381ns	No

***p<0.001, **p<0.01, *p<0.05, ns=not significant

Table 5. Summary Results of Hypotheses Testing

In particular, BA had positive effect on decision-making affordances (H1 supported). To verify H2, the mediating role of data-driven culture on the relationship between BA and decision-making affordance (DAF) was analysed, following the analysis processes recommended by Baron and Kenny (1986); however, our analysis was based on a bootstrapping procedure. The results are summarised in Table 6. The relative size of the mediating effect was decided by calculating the variance accounted for (VAF) based on Shrout and Bolger (2002). The VAF value suggested that DDC partially but strongly mediated the effect of BA on DAF. Thus, H2 was supported. We also found that DDC had a positive effect on strategic decision comprehensiveness (SDC) (H3 supported). DAF was positively associated with SDC (H4 supported) but was negatively related to intuitive decision-making (IDM) (H5 supported). As assumed, SDC had a negative effect on IDM (H6 supported) and a positive effect on organisational performance (OP) (H7 supported); but surprisingly, IDM was not statistically related to OP (H8 rejected).

Hypothesis	BA's direct effect on DAF	BA's direct effect on DAF with mediation	BA's indirect effect on DAF	VAF	Mediation type
H2	0.545^{***}	0.254^{***}	0.285^{***}	0.53	Partial

$^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$ VAF>0.80 full mediation, $0.20 \leq \text{VAF} \leq 0.80$ partial mediation, VAF < 0.20 no mediation

Table 6. The Mediating Role of DDC

4 DISCUSSION AND IMPLICATIONS

The major objective of this study was to develop an understanding of the mechanisms through which BA supports SDM, which in turn improves organisational performance. Our empirical findings are highly consistent with the research model proposed in this study. Overall, this research contributes to IT affordance research conceptually by developing an understanding of the decision-making affordances at organisational level, and empirically by providing strong evidence to support that BA as basic affordances can be transformed into higher-level organisational decision-making affordances. This study also contributes to BA and SDM research by conceptually developing and empirically testing a path model to understand the mechanisms through which BA supports SDM, which in turn improves organisational performance.

4.1 Theoretical Implications

IT affordance literature offers a rich approach to the study of the relationship between IT and organisational practices. As an emerging area of study, several authors have called for more research to understand for example various types of affordances (e.g., Zammuto *et al.* 2007) at the organisational level (e.g., Robey *et al.* 2013). To respond to this call, this paper has made several contributions to IT affordance literature. First, we have developed new affordances namely BA as basic affordances and decision-making affordances to understand the possibilities for organisational decision-making. Second, rather than discussing at the individual or team level, BA and decision-making affordances are organisational-level concepts that are appropriate for understanding how BA can be used to achieve organisational goals (Robey *et al.* 2013). Additionally, our findings demonstrate how BA affects decision-making affordances through the mediation of a data-driven culture, thereby to help elucidate the complex process of affordance actualisation in this specific research context (Volkoff and Strong 2013; Strong *et al.* 2014). Third, our findings provide one example of using quantitative methods to conduct affordance research, though the cognitive nature of the affordance concept tends to attract researchers using qualitative approaches.

Prior practice-driven BA research has highlighted two related points: BA offers the possibilities for organisations to be more effective at making strategic decisions and organisations are much more likely to be able to use BA effectively when they have a data-driven culture (e.g., Davenport and Harris 2007; Lavalle *et al.* 2011; Kiron *et al.* 2012). However, little research exists to clarify the mechanisms underlying such claims either conceptually or empirically. The absence of such an understanding unavoidably hinders an organisation's efforts at using BA for supporting SDM, which is evidenced by many businesses' struggling with BA implementations (Barton and Court 2012; Kiron *et al.* 2012; Marchand and Peppard 2013). We believe our research has reduced this research gap by providing insights into clarifying the mechanisms. Our study shows that implementing BA in an organisation contributes to forming its decision-making affordances; implementing BA results in the development of a data-driven culture; and a data-driven culture partially but strongly mediates the effect of BA on these affordances. As a result, decision-making affordances together with a data-driven culture positively influence SDM, which in turn improves organisational performance. In this sense, this study contributes to BA literature by conceptualising and empirically verifying the paths and mechanisms responsible for BA supporting SDM and finally improving organisational performance.

Next, this study contributes to SDM literature by conceptually assessing the impacts of BA, a data-driven culture, and decision-making affordances on SDM and organisational performance. While our findings provide additional empirical evidence to support IT's effect on SDM (Molloy and Schwenk 1995), they indicate new insights into SDM in the context of BA. One finding is that while strategic decision comprehensiveness has a positive effect on organisational performance (path coefficient 32.3%), the total effect of a data-driven culture on strategic decision comprehensiveness is 57%, followed by BA 39% and decision-making affordances 26%. This finding implies that while all these factors play important roles in positively influencing rational decision-making and organisational performance, developing a data-driven culture is a relatively important factor. Our findings also provide strong support to the view that there is a negative relationship between rational and intuitive decision-making (Sadler-Smith 2004; Elbanna *et al.* 2013). This finding suggests that the more data is available the less SDM depends on intuitive processes. This is mostly consistent with and to provide additional empirical evidence in support of the view that rational processes are preferred when data is available (Eisenhardt and Zbaracki 1992; Miller 2008) and intuitive processes otherwise (Khatri and Ng 2000; Kutschera and Ryan 2009). However, this finding does not rule out the views that rational and intuitive processes could be used to complement each other at the same time (Robey and Taggart 1982; Sadler-Smith 2004; Coget and Keller 2010). Moreover, although our finding seems to be interesting, caution should be exercised against any premature generalisation of this finding here because the amount of variance attributed to intuitive decision-making in our research model is only 10%.

In summary, although a number of previous studies have highlighted the possibilities for effective SDM that BA affords to organisations; little research exists regarding the mechanisms through which BA can be used to support SDM and finally improve organisational performance. At the same time, while an increasing number of IT affordance studies have explored the relationship between IT and organisational practices based on the concept of affordances, there is no research on BA related or enabled affordances yet. Thus, we have made an important step toward a better understanding of BA's impact on SDM and ultimately organisational performance. We hope that our findings will inspire others to conduct more research in the topic area to develop a coherent body of knowledge.

4.2 Empirical Implications

This study shows that implementing BA in an organisation contributes significantly to developing a data-driven culture, its decision-making affordances, and finally its organisational performance. One important implication of this finding for organisations is that they have incentives to invest in BA because this investment ultimately will improve their SDM and organisational performance. Another major implication of our findings to managers is that a clear understanding of the important intervening effect of a data-driven culture is a key to the effective use of BA. For example, our findings suggest that the formation of decision-making affordances depends on the development of a data-driven culture that encourages organisations to make data-driven decisions. Without a data-driven culture, the possibilities that BA affords to an organisation for decision-making are practically irrelevant. Thus, in order to use BA effectively for improving SDM, organisations should be aware of the importance of developing a data-driven culture, which intervenes the actualisation of the possibilities afforded by BA for effective SDM.

4.3 Limitations and Future Research

A potential problem of this study relates to the possibilities of ignoring salient factors in our consideration. For example, we do not incorporate environmental dynamism and consider its moderating effect on SDM (Goll and Rasheed 1997). The rationale for this omission is that the essence of such moderation largely reflects whether data are available and reliable (e.g., Fredrickson and Mitchell 1984; Khatri and Ng 2000). Since the confluence of big data, BA, and advances in IT has made data ever so available and reliable, we believe that any biases resulting from excluding environmental dynamism would be minimal in the context of this particular study. Nevertheless, our findings should be interpreted with this potential problem in mind.

A major theme of this study is that BA and decision-making affordances have a significant effect on SDM and organisational performance. Although essential, however, what we examined in this study is insufficient to offer a complete picture of how BA affects SDM. For example, prior research suggested that top management team, organisational structure, power distribution, and decision making quality (Rajagopalan *et al.* 1993; Shepherd and Rudd 2014) are vital variables affecting SDM and its outcomes. Thus, further research on the effect of BA on SDM need to consider other organisational variables.

One interesting finding from this study is that intuitive and rational SDM are negatively related, indicating that as data availability, data processing capability and data-driven decision-making increase, organisations become less dependent on intuitive decision-making. This is believable and is consistent with prior research in that rational processes are preferred when data is available (e.g., Eisenhardt 1989; Miller 2008). However, further research is certainly required for a better understanding of the roles that BA plays in influencing both rational and intuitive decision-making across various decision contexts. Further, although our findings show how BA affordances are actualised through the mediation of a data-driven culture, in-depth qualitative studies need to be conducted to elucidate the complex process of affordance actualisation.

Another limitation of this research is that we used perceived organisational performance as the dependent variable, while quantitative measures such as ROI and market share may provide more objective measures to complement the perceived measures.

Finally, we believe that this study will serve as a basis for qualitative studies examining the effect of decision-making affordances on SDM and for other IT affordance researches examining how basic affordances can be transformed into higher-level organisational affordances by using quantitative approaches.

4.4 Conclusions

This research seeks to develop an understanding of the mechanisms through which BA supports SDM and ultimately organisational performance, which has not been examined by others. Simultaneously, this research attempts to expand the scope of IT affordance research, which has been largely limited to understanding IT affordances at individual and group levels, by examining how basic affordances could be transformed into higher-level organisational affordances. Our findings indicate that actualising decision-making affordances provided by BA through a data-driven culture has a significant positive effect on SDM comprehensiveness and organisational performance. Undoubtedly, more research should be conducted to reveal the complex nature of BA related affordances and their impact on SDM and ultimately organisational performance. We hope that the conceptual and empirical analyses conducted in this study will lay a useful foundation for future work in this important area.

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