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ORIGINAL RESEARCH

Business analytics capability, organisational value and competitive advantage

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ABSTRACT

Business Analytics makes the assumption that given a sufficient set of analytics capabilities exist within an organisation, the existence of these capabilities will result in the generation of organisational value and/or competitive advantage. Taken further, do enhanced capability levels lead to enhanced impact for organisations? Capability in this study is grounded in the four pillars of Governance, Culture, Technology and People from the Cosic, Shanks and Maynard capability framework. We set out to undertake the first empirical investigation to measure if there is a positive relationship between Business Analytics capability levels as defined by Cosic, Shanks and Maynard, and the generation of value and competitive advantage for organisations, and do enhanced capability levels lead to enhanced impact. Data gathered from a survey of 64 senior analytics professionals from 17 sectors provides evidence to support that a strong and statistically significant correlation exists between higher capability levels and the ability to generate enhanced organisational value and competitive advantage. Additionally, a revised definition of Business Analytics is proposed, given that Business Analytics should give rise to organisational value and/or competitive advantage and that for this to occur the necessary capabilities must be in place.

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Business analytics; capability; maturity; organisational value; competitive advantage

1. Introduction

An important question for Business Analytics is *Can organisations yield organisational value and competitive advantage from investments in Business Analytics?* Thankfully, there are many examples of case studies where specific organisations demonstrate that they can leverage data for impact (e.g., (T. Davenport, 2014b; T. H. Davenport & Harris, 2007; T. H. Davenport, Harris, & Morison, 2010; Sharma, Mithas, & Kankanhalli, 2014; Wixom, Yen, & Relich, 2013)).

Reasonable questions that follow include *What capabilities need to exist to generate impact?* And *Where should investments in Business Analytics be made in an organisation to enhance impact?* The Information Systems (IS) literature provides evidence to support a strong relationship between IS capability and achieving organisational value and competitive advantage (e.g., (Bhatt & Grover, 2005; Johnston & Carrico, 1988; Saraf, Langdon, & Gosain, 2007)). As Business Analytics can be considered a component of an IS capability it follows that if a sufficient set of Business Analytics (BA) capabilities can be clearly identified, and further, if enhanced capability levels are demonstrated to lead to enhanced organisational value and competitive advantage it makes it easier for organisations to make the informed and targeted investments in BA capabilities with the reasonable expectation that their investments will yield impact. Taken further again, and in the spirit of BA, we should set out to conduct experiments to gather data to answer these questions to provide the evidence to support organisations in making these investment decisions.

Recently a theoretically grounded capability framework has been proposed for Business Analytics (Cosic, Shanks, & Maynard, 2015), which provides us with a foundation upon which to investigate if these capabilities can translate into organisational value and competitive advantage. Figure 1 outlines the Cosic et al. (2015) capability framework for Business Analytics. However, this framework has not been tested in an empirical study to measure levels of capability, and further to test whether increasing levels of capability translate into increased levels of organisational value and competitive advantage. As such a gap in the literature exists in the form of empirical investigations which set out to measure these capabilities and the resulting levels of value and competitive advantage.

In this study, we adopt the survey research method for explanation purposes pinsonneault:1993 to test, for the first time, if we can measure correlation between the Cosic, Maynard and Shanks BA capability levels, and levels of organisational value and competitive advantage. Adopting this approach we wish to test for empirical evidence to support the assumption that investment in Business Analytics capabilities translates into impact. The following sections outline the background literature, the theoretical model under investigation, the experimental design, results and discussion before drawing conclusions and suggesting further avenues for research.

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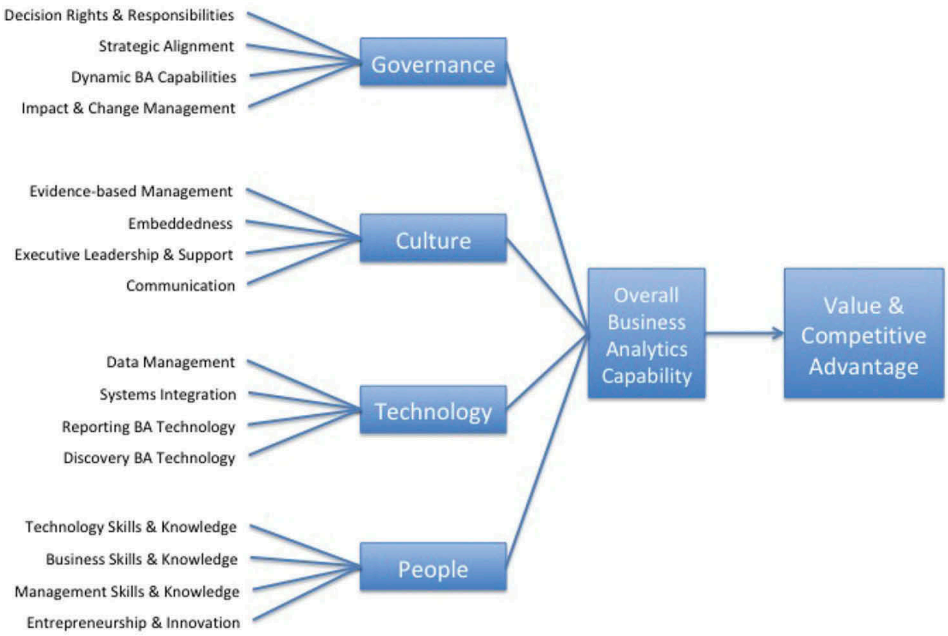

Figure 1. Cosic et al. (2015) capability framework, which has been adopted in this study.

2. Background literature

Generating organisational value and/or competitive advantage is the *raison d'être* of Business Analytics. In the first issue of this journal, Delen and Ram (2018) set out some of the challenges of Business Analytics, with justifying the return on investment in analytics being recognised as a significant challenge for organisations, and a recent survey showed organisations are using analytics as a competitive differentiator (EY, 2017). In other words for Business Analytics to exist, organisations must move beyond insights to support decision-making with impact, thus justifying the return on investment.

Once we recognise that generating organisational value and/or competitive advantage is the reason for the existence of Business Analytics, *What capabilities need to exist to generate this impact?* And *Where should investments in Business Analytics be made in an organisation to enhance impact?* Putting this latter question in another way, *Do enhanced levels of capabilities result in enhanced impact?*

In order to address this question we first need to identify the salient capabilities and what is meant by value and competitive advantage before we can attempt to measure their levels within organisations. Within the Business Analytics literature capabilities and their impacts on value and competitive advantage are often interwoven in discussions around analytics maturity. T. H. Davenport et al. (2010) introduced DELTA and variants (see (T. Davenport, 2014a, 2014b)) with a corresponding five-point scale of maturity representing levels of impact ranging from the bottom level of *Analytically Impaired* to the top being *Analytical Competitors*. Implicitly improving capabilities are linked to moving towards competitiveness of an organisation relative to others. Important from a modern perspective on Business Analytics, the additional T for Technology in the DELTTA variant takes into consideration the advent of Big Data (T. Davenport, 2014b) such that this model captures salient capabilities under the themes of Data, Enterprise, Leadership, Targets, Technology and Analysts. More recently Davenport has proposed the addition of, for example, a P for Product to capture the development of new products arising from analytics insights (T. Davenport, 2014a). Similarly, Schmarzo writes about higher levels of maturity resulting in the ability to Monetise insights and to leverage insights for Metamorphosis or business model transformation (Schmarzo, 2015). Schmarzo's level range from Monitoring, Insights, and Optimisation to Monetisation and Metamorphosis. In terms of value for an organisation, Davenport and Schmarzo, both capture the idea of monetisation of analytics, which can have an impact on an organisations development of new products, services and even lead to business model transformation. McAfee and Brynjolfsson. (2012) ask if *"using Big data intelligently will improve business performance?"* and undertook a study to address this using a set of questions captured in (Brynjolfsson & Andy, 2013). In their assessment, they considered Leadership, Talent Management, Technology, Decision Making and Culture. INFORMS (2014) have also proposed and adopted an Analytics Maturity Model across a ten-level scale, although this translates into three maturity levels of Beginning, Developing and Advanced (Howard, 2014).

Cosic et al. (2015) provided the first theoretically grounded synthesis of capability and maturity models existing in the Business Analytics literature to develop a capability framework comprised the four pillars of Governance, Technology, People and Culture (see Figure 1). Up until that study, and as noted by Cosic et al. (2015) there was an " *absence of an explicit definition for the term BA capability within the extant literature*". Moreover, Cosic et al. (2015) state at the outset of their study that BA capabilities "*can potentially provide value and lead to organisational performance*", however they did not go so far as to test if they can measure if in fact that *potential* is realised in practice.

Given that Cosic et al. (2015) provide the only definition of Business Analytics capability in the extant literature, and we adopt this definition in the current study it is worth exposing this definition here. As illustrated in Figure 1 there are four pillars to the definition of Business Analytics capability, namely, Governance, Culture, Technology and People with four main strands to each pillar.

The Governance capability pillar captures the importance of the need for assignment of decision rights and responsibilities, such that there are identifiable individuals within an organisation who are accountable for outcomes and actions arising from Business Analytics activity (Weill & Ross, 2004). That there is an alignment of an organisations business strategy and its Business Analytics activities and a commitment to this from leadership and management within the organisation (Williams & Williams, 2006). That changes to the business environment can be handled through leveraging and potentially reconfiguring an organisations Business Analytics resources (Sharma & Shanks, 2011), and that an organisation can successfully effect change management which may be required as a result of the insights arising from Business Analytics activities (Negash, 2004).

The capability of Culture is comprised of evidence-based management where decisions and actions are grounded in facts arising from data with less emphasis on intuition (Pfeffer & Sutton, 2006), the degree of embeddedness of Business Analytics within an organisation (Shanks, Bekmamedova, Adam, & Daly, 2012), executive leadership and support in advocating the use of Business Analytics and evidence-based management (Laursen & Thorlund, 2010), and the requirement for a culture of open communication between analytics teams and business users (T. H. Davenport & Harris, 2007).

Technology is defined in terms of data management, systems integration, reporting and visualisation, and discovery technology. Data management encompasses all aspects of being able to source relevant data, ensure the quality of an organisations data including master and metadata management, and the ability to integrate new with existing data (Watson & Wixom, 2007). Systems integration captures the requirement for the seamless integration of operational systems with Business Analytics systems (Sharma & Shanks, 2011). Reporting and visualisation include the idea of self-service, and the ability to develop and use relevant technology to facilitate the manipulation and exploration of an organisations data (Watson & Wixom, 2007). Discovery technology covers an organisations ability to tackle less structured problems in order to discover new insights (Negash, 2004).

Finally, People capability includes the requirement for the existence of individuals with skills around Business Analytics technologies, individuals with business domain expertise, and that individuals in management level roles have the necessary skills to prioritise and manage Business Analytics projects, effect change managements as required, to effectively communicate the value of Business Analytics activities (T. H. Davenport & Harris, 2007), and having individuals who are open to and capable of innovation within the organisation (Sharma & Shanks, 2011).

In the following section, we outline the theoretical model tested in this study.

3. Theoretical model & hypothesis

As the capability framework identified by Cosic et al. (2015) is the first and only theoretically grounded synthesis of capability and maturity models existing in the Business Analytics literature it provides us with a foundation upon which to measure if these capabilities can translate into organisational value and competitive advantage, and further, if enhanced capability levels result in enhanced value and/or competitive advantage. As such we adopt the Cosic et al. (2015) capability framework in this study. Stating the model more formally

$$VCA = CS \tag{1}$$

where

$$CS = \mu(w_g G + w_c C + w_t T + w_p P) \tag{2}$$

where VCA corresponds to a Value and Competitive Advantage score, corresponds to the Capability Score which is comprised of the mean (μ) of an organisations Governance capability score (G), its Culture capability score (C), Technology capability score (T), and People capability score (P). For simplicity adopting the principle of Occam's razor, and following the recommendation of T. Davenport (2014b), we assume there is a linear correspondence with equal weighting between the four capabilities and any resulting value and competitive advantage (i.e., $w_g = w_c = w_t = w_p = 1.0$). That is, the capability framework as developed by Cosic et al. (2015) implies that there is a correspondence between capability and value and competitive advantage scores realised by an organisation. Such that, increased levels of capability should give rise to increasing levels of value and competitive advantage.

We operate under the null hypothesis that there is no correlation between capability score (CS) and the organisational value and/or competitive advantage score (VCA). More formally,

H_0: There is no correlation between CS and VCA scores, such that the effect size (r) measured by Pearson's Product-Moment Correlation is $r < 0.5$ at significance level $= 0.05$.

In this study, for the first time, we set out to test this model using the survey research method. As such we take the existing theoretical model from the literature as stated above in equations (1) and (2), and develop a new survey instrument in an attempt to measure the level of each capability and the corresponding level of organisational value and competitive advantage. For each of the five components of the model (G, C, T, P, and VCA) we identify a set of questions from the literature. The following section exposes the design of the survey instrument.

4. Survey instrument design

The key contribution of this study is to start to address the question *Do enhanced levels of Business Analytics capability result in enhanced organisational value and competitive advantage for organisations?* To this end, we set out to test the null hypothesis that there is no correlation between capability and organisational value and/or competitive advantage scores as measured in this study using the survey research method. In developing the survey instrument we have adopted best practice for survey research (straub, 1989; pinsonneault, 1993; groves et al, 2009), and we detail the key survey design issues below.

In testing instrument validity we are attempting to provide confidence that we are effectively measuring each of the five components of the theoretical model outlined in Section 3. For each component of the model (Governance, Culture, Technology, People and Value and Competitive Advantage) we associate a series of survey questions, which have been sourced from the literature. The subsequent statistical analysis underpinning instrument validity seeks to explore the relationship between each question and the model component it is supposed to partly capture, and if the set of questions sufficiently captures each component. The greater the confidence we have that the questions capture each component of the model, the greater the confidence we can then have in the subsequent analysis of the relationship between the model components corresponding to capability and

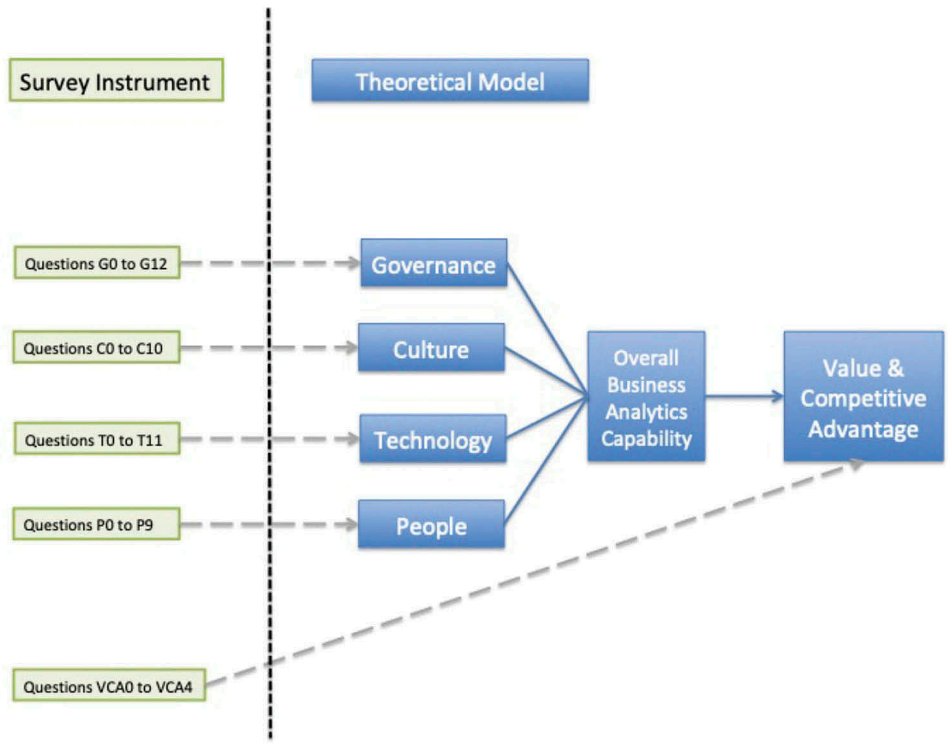

Figure 2. A high-level overview of the relationship between the survey instrument and the theoretical model under investigation.

organisational value and competitive advantage. Figure 2 presents a high-level overview of the relationship between the theoretical model and the survey instrument.

4.1. Content and face validity

The survey questions are designed to test the theoretical model outlined in Section 3 with a series of questions for each of the four capabilities (G, C, T and P) from which individual capability scores can be calculated. The individual capability scores are then combined to generate a mean Capability Score (CS). A further series of questions is used to measure Value and Competitive Advantage (VCA). Responses to questions on each feature of the model are measured on a five-point Likert scale. For the majority of questions this involves using the level labels of Disagree Strongly(1), Disagree Somewhat(2), Neither Agree or Disagree(3), Agree Somewhat(4), Agree Strongly(5).

To ensure content validity we ground the survey questions in the literature by drawing heavily upon Davenport's DELTTA maturity model (T. Davenport, 2014a, 2014b; T. H. Davenport et al., 2010) adopting existing questions from the Appendix of (T. Davenport, 2014b), which in turn stands on the shoulders of Brynjolfsson and Andy (2013) and correspond with the features of each capability as detailed by (Cosic et al., 2015). We also take inspiration for the VCA questions employed taking into consideration the more recent perspectives of Schmarzo (2015)'s maturity index by capturing, for example, monetisation of insights and business model transformation, and EY's 2017 survey of Data & Advanced Analytics (EY, 2017). More explicitly, for VCA we introduce questions which attempt to capture; an organisations ability to leverage data and analytics, the relative competitiveness of an organisation, and its ability to monetise insights from analytics activities.

To ensure face validity and reliability the survey was tested by a small group of four senior analytics professionals drawn from the banking sector, one of the big four professional services organisations, an analytics industry professional support body, and a telecommunications organisation. The resulting survey questions are provided in Appendix A with each question labelled to aid easy identification with the constructs under investigation (i.e., G for governance capability, C for culture, T for technology, P for people and VCA for value and competitive advantage).

4.2. Construct validity

There are two aspects to construct validity in this study. The first relates to the correspondence between the survey questions adopted and their relationship to the features of the theoretical model, and secondly the validity of the theoretical model itself. There is a catch-22, or chicken and egg predicament here. Survey questions for each feature of the model are drawn from existing questions from the literature corresponding to each model feature, which inspired the generation of the model itself. As such, to the survey respondents, we present the complete set of questions corresponding to the complete set of features identified by Cosic et al. (2015) and use the survey instrument to undertake a post-hoc analysis of construct validity. This analysis can be used to guide further refinement of the model and provide guidance for instrument design in follow up studies.

4.3. Sampling

The analysis undertaken in this study is based upon a survey of 64 senior Business Analytics professionals, drawn from 17 sectors (see Figure 3). These professionals were sampled from the Top 100 organisations in Ireland with many of these representing the EMEA region headquarters of globally leading multinational technology and service corporations, and also includes Government departments and Semi-state agencies with advanced analytics capabilities. We can get a sense of the size of the organisations the respondents come from in a chart of the revenue in the surveyed organisations in the most recent fiscal year (Figure 4). Potential respondents were contacted by email and asked to complete an anonymous online survey using the Qualtrics platform. The 64 respondents have 50 unique job titles, which are provided in Table 1 where we can see the predominantly senior management levels held by these individuals. It should be highlighted that a potential limitation of any survey is the target population and its potential to introduce bias into survey outcome and in judging the generality of the findings beyond the sample population to the true population. In this study we deliberately targeted senior individuals who had an organisational perspective on any impact that might arise from investments and activities in and around Business Analytics, as the key research question is to test the correlation between arising levels of organisational value and/or competitive advantage and the levels of Business Analytics capability that exist in that organisation.

5. Survey results

We now present the results of the survey to examine the central research question of this study which is to ascertain if there is a positive relationship between Business Analytics capability levels (*CS*) and the generation of value and/or competitive advantage (*VCA*), and if enhanced capability levels lead to enhanced impact. More formally, using the model outlined in

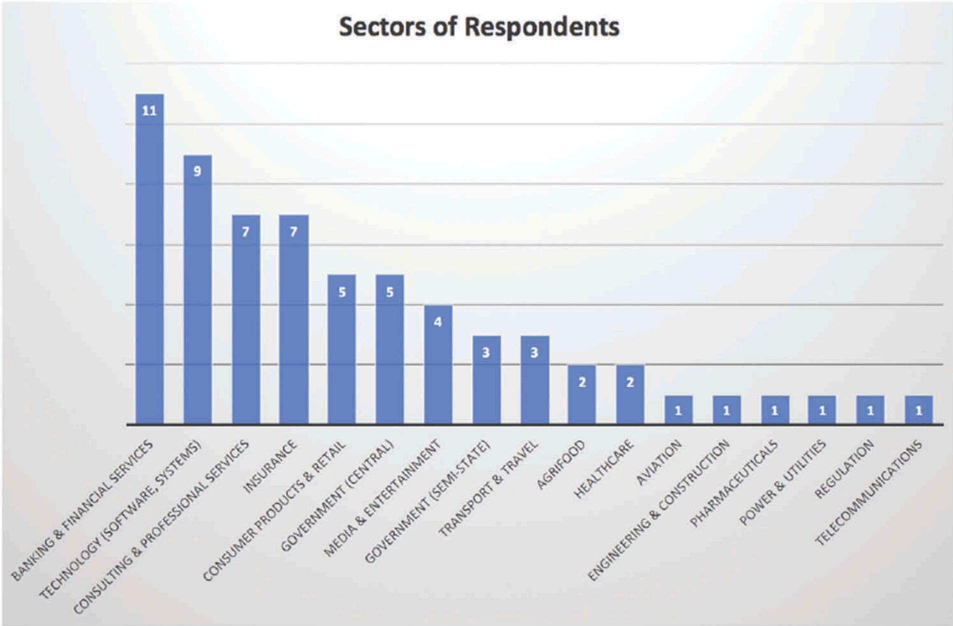

Figure 3. Sixty-four senior Business Analytics professionals drawn from 17 sectors were surveyed.

Section 3 we test the null hypothesis that there is no correlation between *CS* and *VCA* scores.

For each practitioner response, for each capability pillar, we calculate the mean capability score across all the questions associated with that capability. An overall BA capability score is then calculated for each response by calculating the mean of the four pillar capability scores. Similarly, we calculate the mean score across the Value & Competitive Advantage questions. As each question is scored on a 5-point Likert scale, the mean will range from 0 to 5 in each case. From these scores, we generate a scatter plot (Figure 5) of the mean Capability Score versus Value & Competitive Advantage Score where each respondent/organisation is represented as a point on the plot.

In Figure 5 we observe that as total capability score increases, the value & competitive advantage score also increases. This implies that there is a positive relationship between increasing capability and increasing the resulting value and competitive advantage scores.

Table 2 details the Pearson Correlation scores between Value & Competitive Advantage compared to the Capability Score in addition to the individual components of the score (namely Governance, Culture, Technology and People). A correlation score of 0.81 suggests a strong relationship between the Capability score level and a corresponding level of Value & Competitive advantage. Interestingly, examining the component scores, technology capability has the weakest (but still strong) correlation (0.65),

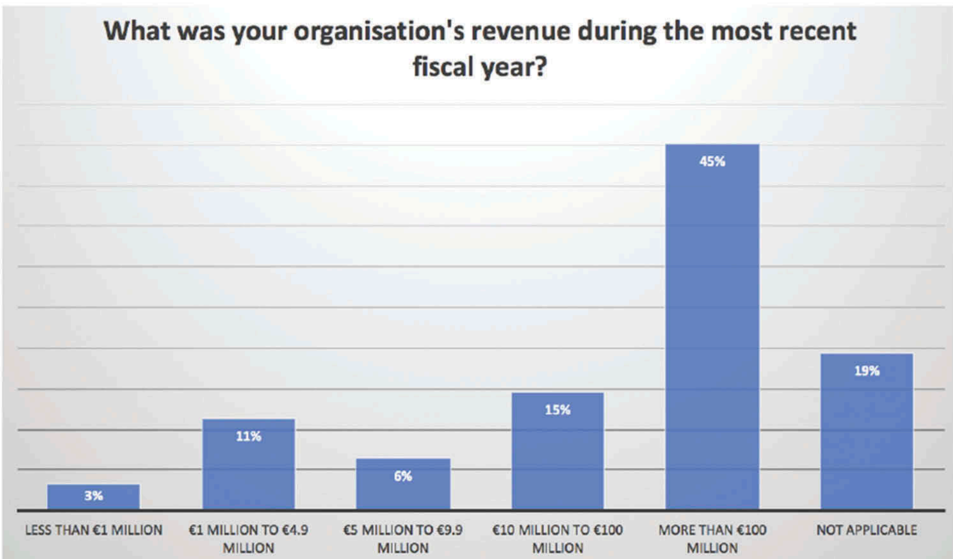

Figure 4. A chart of the revenue (€) of organisations surveyed during the most recent fiscal year.

Table 1. Job titles of respondents with the top six most common appearing first in the left column, with the remaining titles presented in alphabetical order.

CEO/President (x5)	Head of Big Data
Chief Analytics Officer (x4)	Head of Business Applications & Data
Chief Data Officer (x3)	Head of Customer Data & Predictive Modelling
Chief Digital Officer (x2)	Head of Customer Operations
Director of Analytics (x2)	Head of Data & Insights
Analytics Manager (x2)	Head of Data Analytics
BI Software Dev Mgr	Head of Data Science
Business Development Director	Head of HR Analytics
Business Information Manager	Head of Insights
Business Integration Manager	Head of Private Sector
CFO/Treasurer/Comptroller/ Controller	Head of Ticketing Systems
Chief Actuary	Insight and Analytics
Chief Marketing Officer	Lead Data Architect
Chief Technology Officer	Manager Analytics
Consultant Director	Manager, Analytics/Data Science
Data Analyst	MD Data
Digital Research & Analytics	Performance Reporting
Digital Team Lead	Quantitative Analytics Manager
Director Data Analytics	Sales Manager
Director of Innovation	Senior Business Analyst Team Lead
Director Transformation	Senior Data Analyst
Director, Data & Analytics	Senior Director Data Science
General Manager	Senior Manager Data Analytics
Group Data Infrastructure Lead	Solutions Architect
Head of Analytics	VP Data & Analytics

with people capability having the strongest individual component correlation (0.76) to value and competitive advantage.

Given a sample size of 64, and a significance level of 0.05 (i.e., the Type I error rate of rejecting a true null hypothesis), and assuming a correlation value of 0.5 (i.e., the effect size of 0.5 for correlation is considered strong for social sciences according to Cohen s(1988)) and above which all of the correlation

Table 2. Correlation analysis of value & competitive advantage with the total capability score and individually with the four component capability pillars.

	Pearson correlation				
	Capability	Governance	Culture	Technology	People
Value & competitive advantage	0.81	0.73	0.70	0.65	0.76

coefficients occur in our observations, the power of our test (i.e., the Type II error rate of failing to reject a false null hypothesis) is 0.99 (Cohen, 1988).[1]

As further validation, a randomised response control, which selects a random response for each question was run the same number of times as the number of respondents (i.e., 64 times). The Pearson Correlation scores for the equivalent random response survey were approximately 0.0 in each case, indicating that no correlation exists between capability score and value & competitive advantage score in the hypothetical control scenario where respondents replied randomly to the survey questions.

Calculating the significance of the correlation between the Capability score and the Value & Competitive Advantage score using Pearson's product-moment correlation results in a p-value of 9.918e-16. Coupled with the power analysis, the observation of correlation is statistically significant. With an effect size of 0.81 (which is greater than 0.5) and a p-value of 9.918e-16, we therefore reject the null hypothesis that there is no correlation between capability levels and levels of organisational value and/or competitive advantage at a significance level of 0.05.

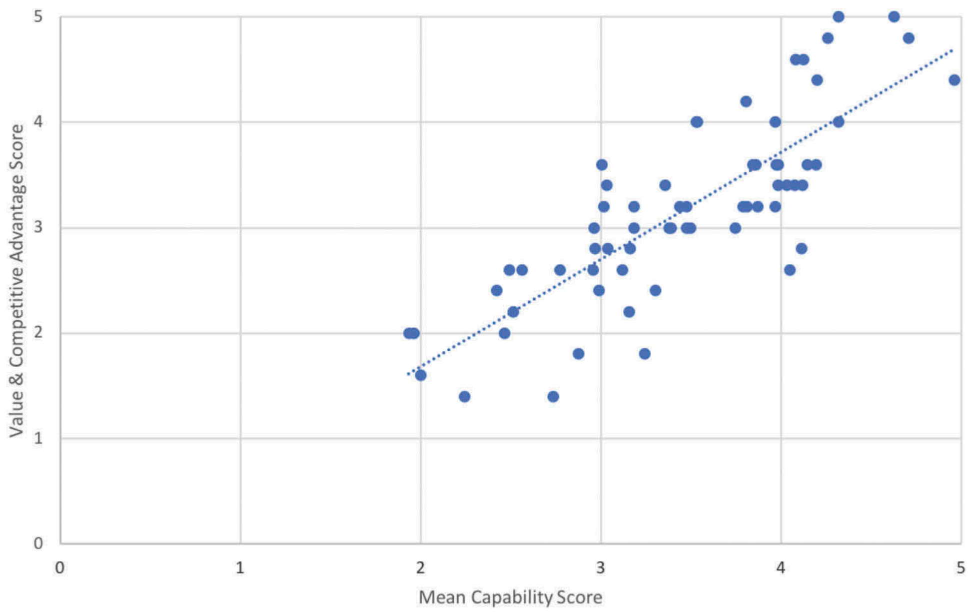

Figure 5. Scatter plot of the mean capability score versus the value & competitive advantage score, which shows a positive relationship between increasing values of total capability score and an organisations value & competitive advantage score. In other words, higher levels of business analytics capability correspond with higher levels of realised value and competitive advantage.

6. Model analysis & construct validity

As we reject the null hypothesis that there is no correlation between capability score and value and/or competitive advantage score, we explore the alternative hypothesis that the model outlined in Section 3 is valid, and that the instrument has some utility to allow organisations to measure their capability level, and inform organisations on their potential to realise value and competitive advantage. Moreover, if the model could also be used to suggest where investments in Business Analytics capabilities could be targeted.

First, we explore the inter-item correlation for each component of the instrument, to give an indication of the uni-dimensionality of each question and therefore its potential to provide a unique contribution to the component score. Correlation scores which are too high suggest the question does not provide a unique contribution, so moderate to high values are typically desired (e.g., around .5 to .7). However, we should consider the theoretical foundation for each question before we consider recommending its exclusion. Figure 6 details the correlation analysis of each question for each model component. It can be observed that the questions relating to People (*P*) exhibit the strongest inter-item correlation. For the majority of questions across the instrument components values are .6 or below.

Following inter-item correlation analysis, we now determine if we can proceed with Factor Analysis to further test construct validity by calculating Kaiser-Meyer-Olkin correlation (KMO) and Bartlett's test of sphericity (BS). This test if we can reject the null hypothesis that the questions are independent, and so can expect to see dependencies between them. Questions associated with each component of the model (i.e., *G*, *C*, *T*, *P* and *VCA*) should have functional dependencies between themselves and the

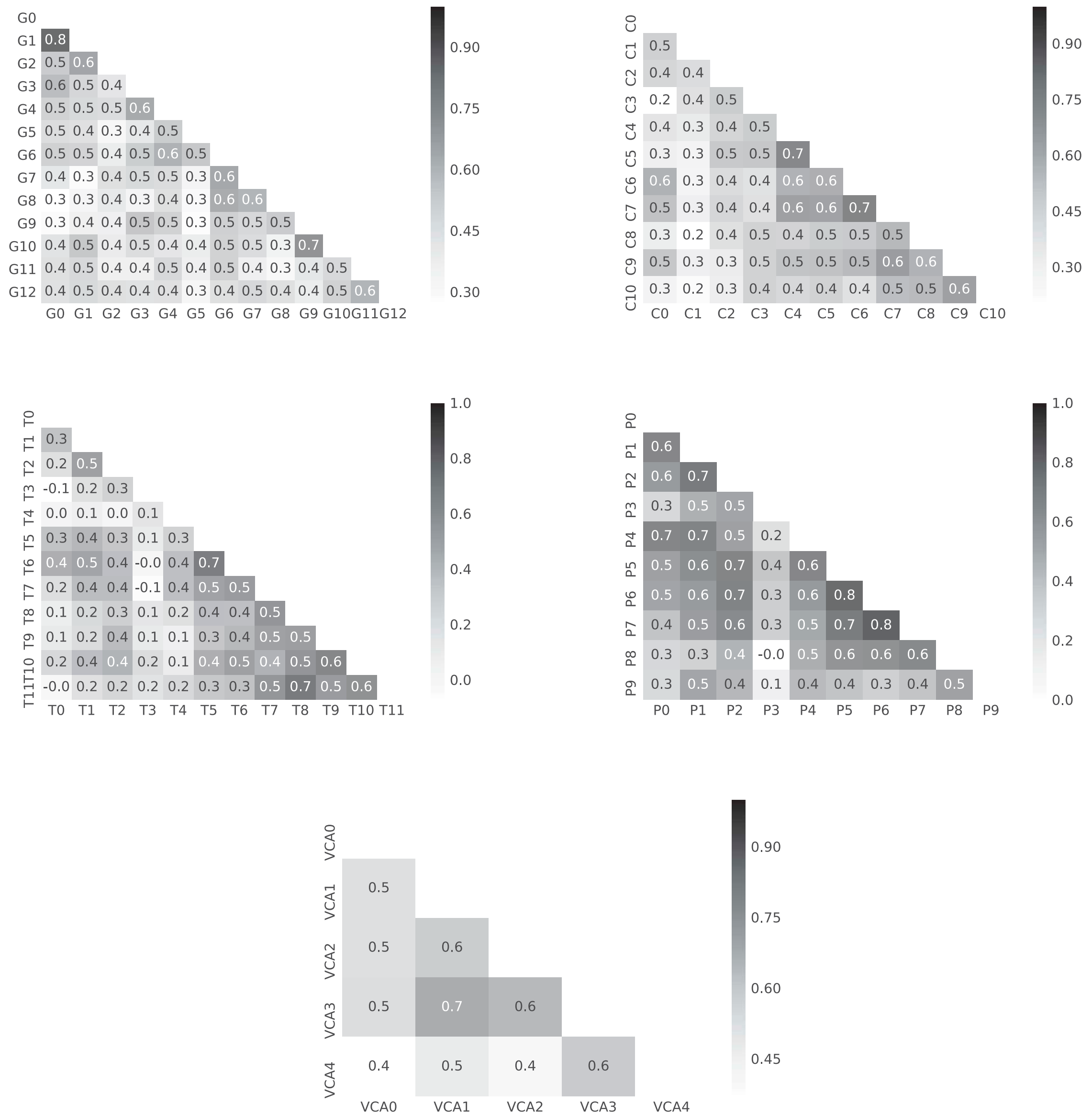

Figure 6. Inter-item correlation of survey questions associated with each component (**g**overnance, **c**ulture, **t**echnology, **p**eople, and **v**alue & **c**ompetitive **a**dvantage) of the model.

feature. As observed in Table 3 KMO scores of 0.6–0.7 and above, coupled with a BS p-value of less than 0.05 suggests it is possible to adopt Factor Analysis on each component of the model.

Eigenvalues for each model component and their corresponding scree plots are provided in Table 4 and Figure 7. We use these to determine the number of factors from which we can examine factor loadings and establish the relationship of each question to the model component. The number of factors employed is determined from the elbow of the scree plot and the number of factors with eigenvalues above 1.0.

Factor loadings are provided in Table 5–9. In the majority of cases the factor loadings of $> = 0.5$ provide evidence to suggest a relationship between each Question and the model component of interest, and, therefore, support retaining each survey question. That is, we observe that each question is included in at least one latent factor at or above the threshold loading. A small number of exceptions occur, namely questions G5 (*Our process for prioritising and deploying our data assets (data, people, software, hardware) is directed and reviewed by senior management*) and C1 (*Non-executive level managers in our organisation utilise data and analytics to guide their decisions*) fall

Table 3. Kaiser-Meyer-Olkin correlation (KMO) and Bartlett's test of sphericity (BS) question independence tests for each model component.

	VCA	Governance	Culture	Technology	People
KMO	0.84	0.82	0.88	0.80	0.87
BS	7.8e-24	7.9e-60	7.6e-44	3.4e-31	5.2e-60

Table 4. Eigenvalues for component factors, with the number of factors with values above 1.0 being adopted for factor loading analysis.

	F0	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
VCA	3.14	0.67	0.50	0.41	0.29								
Governance	6.45	1.26	0.90	0.84	0.78	0.61	0.51	0.47	0.41	0.29	0.24	0.16	0.10
Culture	5.51	1.12	0.96	0.81	0.60	0.46	0.43	0.35	0.29	0.27	0.21		
Technology	4.61	1.54	1.26	1.10	0.73	0.57	0.53	0.46	0.39	0.30	0.28	0.23	
People	5.54	1.22	0.90	0.76	0.38	0.32	0.27	0.25	0.19	0.15			

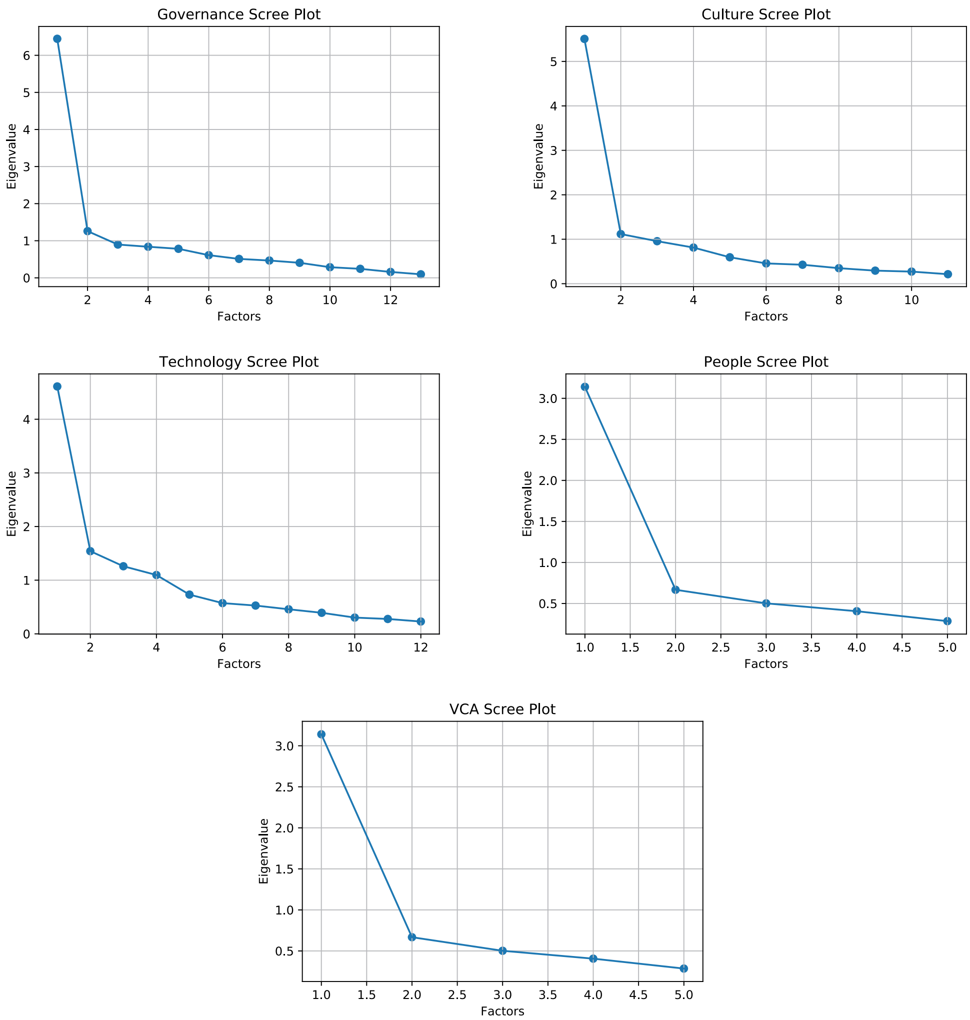

Figure 7. Eigen value scree plots of factors for (**g**overnance, **c**ulture, **te**chnology, **p**eople, and **v**alue & **c**ompetitive **a**dvantage) of the model.

Table 5. Value & competitive advantage questions factor loading analysis with all questions showing association with the VCA model component.

	VCA0	VCA1	VCA2	VCA3	VCA4
F0	0.60	0.62	0.71	0.60	0.28
F1	0.30	0.47	0.33	0.67	0.64

just below our chosen factor loading threshold. The loading threshold is somewhat subjective, and the theoretical underpinning for the question should also be taken into consideration before its exclusion. If an organisation is truly exploiting Business Analytics it is not unreasonable to expect that all decision-makers, including non-executive managers will use analytics, or that senior management would have an interest in data asset strategy. Coupled to the earlier inter-item correlation analysis for these two questions, they both have good uni-dimensionality, and as such we consider the evidence to support their exclusion to be weak.

In summary, the statistical analysis of the model components and related questions in the instrument provides evidence to support construct validity when coupled with the fact that the questions have been sourced from the literature underpinning each theoretical construct.

7. Discussion

From the results observed in this study, we see a very strong signal to suggest that there is a strong positive correlation between enhanced Business Analytics Capability and increasing Organisational Value and/or Competitive Advantage. This provides additional evidence to support the many examples of case studies where individual organisations have demonstrated the successful leveraging of investments in Business Analytics for impact (e.g., (T. Davenport, 2014b; T. H. Davenport & Harris, 2007; T. H. Davenport et al., 2010; Sharma et al., 2014; Wixom et al., 2013)).

In this study, we define Business Analytics Capability in terms of the capability framework of Cosic et al. (2015) along the four dimensions of Governance, Technology, People and Culture. Based on survey responses we observe that the People dimension plays the largest contribution to the overall impact of Business Analytics followed closely by Governance and Culture, with Technology at the bottom of the list (but still demonstrating a strong correlation with organisational value and/or competitive advantage). Given rapid advances in technology and the need to stay on top of technology trends we can sometimes overlook the significant role Governance, Culture and People play in realising value from Business Analytics, and the results observed in this study remind us of this.

As with any experimental design, there are limitations and assumptions, and in this study, the most important areas include the choice of capability framework and the survey design. Reliability was investigated early on during Face validity using a small population, further testing of the reliability of the instrument in

Table 6. Governance questions factor loading analysis showing question G5 has weakest association with the governance model component.

	G0	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12
F0	0.23	0.20	0.36	0.51	0.58	**0.38**	0.71	0.71	0.69	0.70	0.56	0.45	0.51
F1	0.85	0.92	0.54	0.47	0.45	**0.43**	0.37	0.22	0.15	0.21	0.40	0.43	0.41

Table 7. Culture questions factor loading analysis showing question C1 has weakest association with the culture model component.

	C0	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
F0	0.14	**0.27**	0.46	0.62	0.70	0.75	0.57	0.69	0.65	0.66	0.64
F1	0.99	**0.41**	0.37	0.16	0.29	0.22	0.49	0.44	0.21	0.36	0.16

Table 8. Technology questions factor loading analysis with all questions showing association with the technology model component.

	T0	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
F0	−0.01	0.17	0.32	0.08	0.10	0.31	0.32	0.58	0.76	0.68	0.67	0.82
F1	0.56	0.64	0.48	0.02	0.06	0.59	0.72	0.36	0.11	0.24	0.38	0.00
F2	−0.10	0.16	0.24	0.99	0.07	0.03	−0.09	−0.12	0.05	0.05	0.14	0.06
F3	0.01	−0.01	−0.11	0.08	0.73	0.30	0.38	0.33	0.15	−0.05	−0.03	0.21

Table 9. People questions factor loading analysis with all questions showing association with the people model component.

	P0	P1	P2	P3	P4	P5	P6	P7	P8	P9
F0	0.64	0.82	0.70	0.56	0.58	0.58	0.52	0.44	−0.01	0.28
F1	0.28	0.31	0.44	0.03	0.46	0.62	0.65	0.67	0.98	0.46

a larger population is desirable. In terms of construct validity, we assume the Cosic et al. (2015) framework sufficiently captures the necessary set of Business Analytics capabilities for successful generation of organisational value and competitive advantage. This framework has been adopted here as it is the first and only Business Analytics capability framework which exists arising from a theoretically grounded synthesis of the literature and perspectives of practitioners, and as such provides us with the strongest foundation at present to undertake this study. On the survey design, additional key factors that can translate into limitations include the respondent sampling strategy, the sample size, question and response design, etc. A standard and well-studied Likert-scale is adopted for responses using a set of questions relating to capabilities, which are predominantly drawn from the Business Analytics literature. Future work will no doubt look to refine both the Cosic et al. (2015) framework and the related question set which can be adopted. On sampling strategy, we wish to target the most informed respondents possible, drawn from as wide a set of different kinds of organisations as possible, and in particular from respondents who have insights into the existing capability levels within an organisation and the subsequent organisational value and/or competitive advantage that can arise. To this end, we focused on senior professionals within the organisations surveyed. On sample size and observed effects, we undertook a rigorous statistical analysis including power and a randomised response control, which gives us confidence to reject the null hypothesis that no correlation exists between capability levels and levels of organisational value and/or competitive advantage given the sample size adopted in this case. We welcome further studies which seek to test and refine the instrument and further test the relationship between capability levels and levels of impact in a larger population.

With our current focus on Business Analytics Capability levels and the importance of these in realising the organisational value and/or competitive advantage, it is interesting to consider how we define Business Analytics. In the first issue of this journal, Business Analytics has recently been defined by Power, Heavin, McDermott, and Daly (2018) as follows:

> Business Analytics is a systematic thinking process that applies qualitative, quantitative, and statistical computational tools and methods to analyse data, gain insights, inform, and support decision-making.

Both the theoretical framework of Cosic et al. (2015) and the results observed from the data gathered in this study suggest that we should reconsider this definition to take on board that to be successful in Business Analytics we need to embrace all of the dimensions of capability (People, Governance, Culture in addition to Technology), and how in organisations Business Analytics should result in organisational value and/or competitive advantage in order to justify investment in this area. In other words for Business Analytics to exist, organisations must move beyond insights to support decision-making with impact, thus justifying the return on investment. From the results of the survey undertaken in this study, there is a clear correlation observed between organisational value and/or competitive advantage and enhanced levels of Business Analytics capabilities, which leads to confidence that targeted investments across the four pillars of Business Analytics capabilities should lead to improved impact for the organisation.

While there is nothing incorrect about the earlier definition of Business Analytics, in terms of Business Analytics in practice, we feel it is necessary to demonstrate the impact that investments in Business Analytics can have on an organisation, whether that is through organisational value and/or competitive advantage. We also feel it is important to reflect the four capability dimensions. To this end we propose modifying the earlier definition towards an alternative definition of Business Analytics to explicitly recognise the need for Business Analytics to result in organisational value and/or competitive advantage, therefore demonstrating return on investment, and the four capability pillars which drive the impact of Business Analytics as follows:

> Business Analytics leverages governance, culture, people and technology capabilities and a systematic thinking process that applies qualitative, quantitative, and statistical computational tools and methods to analyse data, gain insights, inform, and support impactful decision-making giving rise to organisational value and/or competitive advantage.

We propose that this could be simplified further to:

> Business Analytics leverages governance, culture, people and technology capabilities to support impactful decision-making giving rise to organisational value and/or competitive advantage.

8. Conclusions & future work

A model of Business Analytics Capability and its relationship to Organisational Value and/or Competitive Advantage is proposed, which is grounded in the existing framework of Cosic et al. (2015). We set out to test the null hypothesis that there is no correlation between a Capability score and an Organisational Value and/or Competitive Advantage score using the survey research method. Analysing responses from 64 senior Business Analytics professionals drawn from 17 sectors, this study provides empirical evidence to support a strong and statistically significant correlation between Business Analytics Capability and a corresponding return in organisational value and competitive advantage. In turn, these findings support the adoption of the Cosic, Shanks and Maynard capability framework, which is comprised of four pillars of Governance, Technology, People and Culture, and as such provides a list of ingredients that organisations should focus on in order to effectively leverage Business Analytics into organisational value and competitive advantage. Of particular note is the importance attributed to the People, Governance and Culture capability pillars over and above Technology, which speaks to the interdisciplinary nature of Business Analytics and the need to blend quantitative (computational, mathematical and statistical) and more qualitative social and decision sciences. From a practical perspective, these observations suggest investment be directed primarily towards People, Governance and Culture over and above Technology assets as these may have a larger impact for an organisation. Or, at the very least these pillars of Business Analytics capability should not be neglected in favour of technology investments. Given the fact that investments in Business Analytics require the demonstration of organisational value and/or competitive advantage and that in this study we provide strong evidence to support that increasing capability levels correlate with increased levels of such impact, we propose a new definition of Business Analytics to capture the salient capabilities and the need for impact generation.

Future work will involve gathering additional data over time to monitor whether we continue to observe the correlation between increasing levels of capability, value and competitive advantage, and to widen the sectoral coverage to potentially allow segmentation of the analysis to uncover any differences that may exist between sectors. There is also scope to refine the question set employed to more precisely define and measure individual capabilities, organisational value and competitive advantage.

We hope this study will inspire other researchers in our community to further test and refine the Cosic et al. (2015) framework, it is sufficiency and relevance to Business Analytics in practice, and to further test the relationship between capability levels and levels of organisational value and competitive advantage.

Note

1. Calculated in R using pwr.r.test (n = 64, r = 0.5, sig. level = 0.05).

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Appendix A. Survey Questions

Survey question responses are on a five-point scale. The majority of survey questions use the level labels of Strongly Disagree (1), Disagree(2), Neither Agree or Disagree(3), Agree(4), Strongly Agree(5), exceptions to this are explicitly listed below.

A.1. Governance

G0 There are clearly identified individuals in our organisation who are responsible for making decisions in relation to the planning, implementation and application of Business Analytics.
G1 There are clearly defined individuals who will provide input into decisions in relation to the planning, implementation and application of Business Analytics.
G2 Individuals responsible for making decisions in relation to the planning, implementation and application of Business Analytics are held accountable for the resulting actions and outcomes of these decisions.
G3 What best describes the role of data and analytics in the business strategy in your organisation?
  1 No analytics vision or strategy exists at this time.
  2 Some analytics strategy exists for functions or lines of business.
  3 Analytics strategy is established for the enterprise, but not fully aligned across the business.
  4 Analytics strategy is established and starting to be viewed as a key strategic priority.
  5 Analytics strategy is well established and central to the overall business strategy.
G4 We prioritise our analytics efforts to high-value opportunities to differentiate us from our competitors.
G5 Our process for prioritising and deploying our data assets (data, people, software, hardware) is directed and reviewed by senior management.
G6 Our senior executives regularly consider the opportunities that data and analytics might bring to our business.
G7 We consider new products and services based on data as an aspect of our innovation process.
G8 We regularly conduct data-driven experiments to gather data on what works and what does not in our business.
G9 We evaluate our existing decisions supported by analytics and data to assess whether new, unstructured data sources could provide better models.
G10 We identify internal opportunities for data and analytics by evaluating our processes, strategies and marketplace.
G11 We have the ability to reconfigure and leverage the organisations Business Analytics resources and capabilities in order to respond to changes in the business environment in a timely and efficient manner.
G12 We have the ability to manage human, technological and process impacts across the organisation arising from Business Analytics initiatives.

A.2. Culture

C0 Senior executives in our organisation utilise data and analytics to guide both strategic and tactical decisions.
C1 Non-executive level managers in our organisation utilise data and analytics to guide their decisions.
C2 Users, decision-makers, and product developers trust the quality of our data.
C3 Which best describes your organisation's current status regarding the organisation and governance of data analytics?
  1 No organisation exists for data analytics.
  2 Some informal data analytics groups exist in departments or lines of business.
  3 Data and analytics groups are well established in departments or lines of business.
  4 Enterprise-level data and analytics groups are emerging.
  5 Enterprise, department and lines-of-business data and analytics groups exist and are well-aligned
C4 Your organisation is effective at implementing test and learn processes that then impact analytics models and suggested actions?
C5 We use consistent methods/approaches for data and analytics initiative design (projects targeting a specific use case)?
C6 Our senior executives challenge business unit and functional leaders to incorporate data and analytics into their decision-making and business processes.
C7 Our organisation's management ensures that business units and functions collaborate to determine data and analytics priorities for the organisation.
C8 We structure our data scientists and analytical professionals to enable learning and capabilities sharing across the organisation.

C9 Our data and analytics initiatives and infrastructure receive adequate funding and other resources to build the capabilities we need.
C10 We collaborate with channel partners, customers and other members of our business ecosystem to share data content and applications.

A.3. Technology

T0 We have access to very large, unstructured, or fast-moving data for analysis.
T1 We integrate data from multiple internal sources into a data (or warehouse) lake for easy access.
T2 We integrate external data with internal to facilitate high-value analysis of our business environment.
T3 How does our organisation factor data privacy into a new initiative's design?
  1 Data privacy generally does not apply to us.
  2 We consider all legal, regulatory, and compliance considerations.
  3 We rely on corporate policies that often go above what is required.
  4 In addition to the above, we consider what we have brand permission from our customers to do with their data.
  5 In addition to the above, we create incentive mechanisms that allow us to share value (pricing, service levels, etc.) with our customers for use of their data.
T4 We maintain consistent definitions and standards across the data we use for analysis.
T5 We have explored or adopted parallel/distributed computing, and/or cloud-based services approaches to data management and processing.
T6 We employ a combination of big data and traditional analytics approaches to achieve our organisations' goals.
T7 We have seamless integration of Business Analytics systems with operational/transactional systems to exploit the capabilities of both.
T8 We are adept at using data visualisation to illuminate a business issue or decision.
T9 We have explored or adopted open-source software for analytics.
T10 We have explored or adopted tools to process unstructured data such as text, video or images.
T11 We have the ability to develop and utilise self-service analysis applications (e.g., reports, dashboards, scorecards, and data visualisation technology)

A.4. People

P0 We have a sufficient number of capable data scientists and analytics professionals to achieve our analytical objectives.
P1 Our data scientists and analytics professionals act as trusted consultants to our senior executives on key decisions and data-driven innovation.
P2 Our data scientists, quantitative analysts, and data management professionals operate effectively in teams to address data and analytics projects.
P3 Our data scientists and analytics professionals understand the business disciplines and processes to which data and analytics are being applied.
P4 We have programs (either internal or in partnership with external organisations) to develop data science analytical skills in our employees.
P5 Our Managers have the skills and knowledge to redesign business processes as a result of implementing Business Analytics projects.
P6 Our Managers have the skills and knowledge to prioritise and manage Business Analytics projects.
P7 Our Managers have the skills and knowledge to translate, communicate and sell the potential values and benefits of Business Analytics to Senior Executives.
P8 Our Managers have the skills and knowledge to manage new innovation as a separate activity to continuous improvement.
P9 Our organisation has an entrepreneurial mindset and vision, with the ability to rationally assess risk and benefits, and have a degree of freedom to pursue value-creating actions.

A.5. Value & Competitive Advantage

VCA0 Our organisation has the ability to apply and interpret data in a manner which meaningfully influences our business.
VCA1 How would you describe your current state of competitive ability in data and analytics?
  1 We are well behind our competitors.
  2 We are behind in some areas.
  3 We are generally at parity with competitors.
  4 We are ahead in most areas.
  5 We are market leading.
VCA2 Our organisation has monetised data as a result of our investment and activities in Business Analytics.
VCA3 We have transformed our organisations business model as a result of our investment and activities in Business Analytics.
VCA4 Which best describes how value is measured when demonstrating the impact of data analytics on your organisation?
  1 No visibility into the value created from analytics initiatives.
  2 Definition of business outcomes is typically established upfront, but measurement is often difficult.
  3 Performance of analytics is measured and managed, but inconsistent across functions and lines of business.
  4 Performance of analytics is managed consistently globally using a well-defined set of financial and non-financial measures.
  5 Analytics initiatives are managed as a portfolio with risk-weighted value assessments impacting resource allocation decisions.