Developing a business analytics methodology: a case study in the foodbank sector

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ABSTRACT

The current research seeks to address the following question: how can organizations align their business analytics development projects with their business goals? To pursue this research agenda we adopt an action research framework to develop and apply a business analytics methodology (BAM). The four-stage BAM (problem situation structuring, business model mapping, analytics leverage analysis, and analytics implementation) is not a prescription. Rather, it provides a logical structure and logical precedence of activities that can be used to guide the practice of analytics (i.e., a mental model). The client for the action research project is The Trussell Trust, which is a UK charity with the mission of empowering local communities to combat poverty and exclusion. As part of the action research project the research team created the UK's first dynamic visualisation tool for crises related to food poverty. The prototype uses foodbank data to map geographical demand and aligns findings to 2011 Census data to predict where additional foodbanks may be needed. Research findings are that: (1) the analytics methodology provides an umbrella for, and applies equally to, data science and Operational Research (OR); (2) that the practice of business analytics is an entangled and emergent mix of top-down analysis and bottom-up action; and, (3) that, for the third sector in particular, analytics can be usefully approached as a collective and community endeavour.

KEYWORDS: analytics, OR for community development, data mining, problem structuring methods, business modelling, soft systems methodology, business analytics methodology

1. INTRODUCTION

There is much excitement around business analytics and data science as commercial organizations explore how they can use their large volumes of data to create value in their business, and governments and communities seek to create value of a broader nature through exploitation of their data resources (Davenport and Harris, 2007; McKinsey, 2011; Yui, 2012; Davenport, 2013). A number of researchers have argued that the growing attention and prominence afforded to analytics presents an important challenge and opportunity for the OR (Operational Research) community (Liberatore and Luo, 2010; Mortenson et al., 2015; Ranyard et al., 2015). Many in the OR community have sought to align themselves with analytics; for instance, INFORMS in the USA and The OR Society in the UK now offer analytics related events, training, certification and publications. However, the number of analytics-orientated studies in journals associated with OR is still comparatively low (Mortenson et al., 2015).

A popular view of analytics is encapsulated by Davenport and Harris' (2007) succinct and widely adopted definition: "By *analytics* we mean the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions." (p. 7, emphasis in the original). Business analytics can also be viewed as sitting at the intersection of OR, artificial intelligence (machine learning) and information systems (Mortenson et al., 2015). It can be further characterized by descriptive (e.g., customer segmentation), predictive (e.g., customer churn modelling), and prescriptive (e.g., offer this loyal customer a discount) model building using data sources that may be heterogeneous (e.g., text, video) and 'big'. These models enable organizations to make quicker, better, and more intelligent decisions to create business value in the broadest sense – potentially the difference between survival and extinction in an increasingly competitive world. Thus, business analytics is concerned primarily with the context in which techniques from OR and data science are deployed.

Organizations are keen to jump on the analytics bandwagon but, as with previous phenomena, such as the growth of information technology in the 1990s and the dotcom bubble at the turn of the century, many are likely to waste money, resources and attention in their quest to become data-driven and to adopt evidence-based decision making. Consequently, how the application of analytics might unfold within organizations is a fertile area for research. George et al. (2014), in a message from the editors of the Academy of Management Journal argue that "… management scholars will need to unpack how ubiquitous data can generate new sources of value, as well as the routes through which such value is manifest (mechanisms of value creation) and how this value is apportioned among the parties and data contributors …" (p. 324).

Thus, the current research seeks to address the following question: how can organizations align their business analytics development projects with their business goals and strategy? To pursue this research agenda we adopt an action research framework to develop and apply a business analytics methodology (BAM). Because the creation of business value is dependent upon an understanding of the nature of the 'business' in which analytics will be deployed, BAM adopts an approach based upon the emerging field of business modelling (Zott et al., 2011; Baden-Fuller and Haefliger, 2013). Specifically, we draw on the business model canvas of Osterwalder and Peigneur (2010) in combination with problem structuring and modelling tools from the soft systems methodology (SSM) (Checkland, 1981; Checkland and Scholes, 1990; Wilson 1984). BAM seeks to expose, define, and potentially innovate or reinvent an organization's business model and then use this analysis to systematically identify key leverage points for the deployment of analytics. Thus, our aim is to develop a BAM that will connect analytics with an organization's ongoing thinking regarding purpose, strategy and core activities and thus ultimately to help an organization to create business value.

The structure of the paper is as follows: in the next section we review the literature and develop the BAM framework. In the third section the research methodology and the action research setting are described. The results of the case intervention are described in section four and the contribution and implications of the work discussed in section five. A summary of the paper is given in the final section.

2. THEORETICAL DEVELOPMENT AND APPROACH

2.1 Business analytics methodologies

While methodologies are commonplace in information systems development, ranging from the software-focused (e.g., agile software development (Highsmith and Cockburn, 2001)) to the organizational (e.g., Multiview (Avison and Wood-Harper, 1990)) they appear to be less prevalent in business analytics and data science. Searching the literature resulted in remarkably little on business analytics methodologies and data science methodologies that addressed the organizational context. However, one exception is the area of data mining. A poll of 200 users of the KDNuggets Web site in 2014 (Piatetsky, 2014) asked "What main methodology are you using for your analytics, data mining, or data science projects" and reported that 43% (42%) use CRISP-DM, 27.5% (19%) use their own methodology, 8.5% (13%) use SAS's SEMMA (Sample, Explore, Modify, Model, Assess) and 7.5% (7.3%) use KDD (Knowledge Discovery in Databases). The equivalent 2007 percentages are shown in parentheses. The remaining responses (covering 13.5% of respondents) include categories such as in-house methodology, non-domain specific approaches, and no methodology.

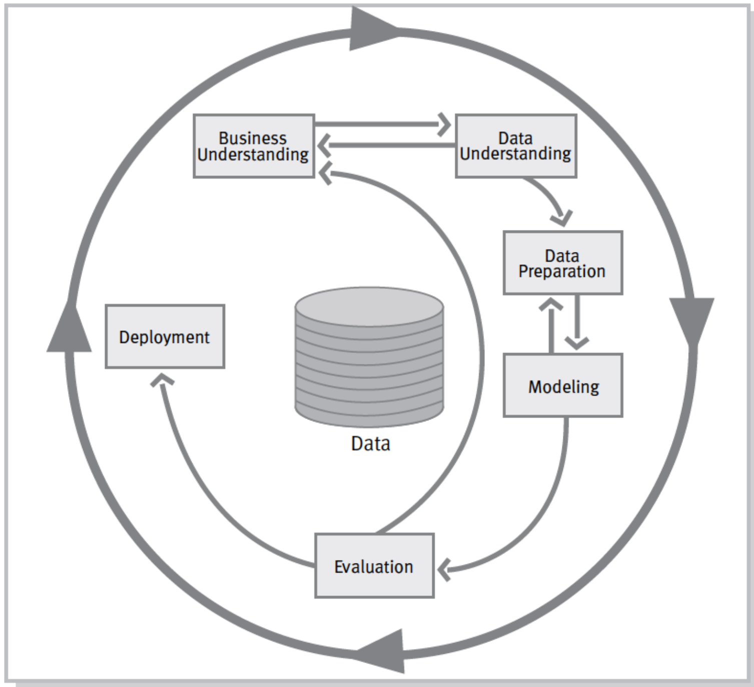


Figure 1: Phases of the CRISP-DM reference model (Chapman et al., 2000)

The CRoss-Industry Standard Process for Data Mining (CRISP-DM) (Chapman et al., 2000) reference model (Figure 1) consists of six phases. The arrows show the most important dependencies between stages (although this sequence is not fixed) and the outer cycle reflects the ongoing nature of data mining work. The business understanding phase is concerned with the project objectives and business requirements, which are then converted into a data mining problem definition and project plan. The data understanding phase is concerned with becoming familiar with the data, identifying data quality problems, discovering initial insights and finding interesting areas for making hypotheses. These two phases are reciprocally linked.

The SEMMA process (Azevedo and Santos 2008) was developed by the SAS Institute. The acronym SEMMA (Sample, Explore, Modify, Model, Assess) covers the steps involved in a data mining project. Similarly, the KDD (Knowledge Discovery in Databases) process, as presented in Fayyad et al. (1996), consists of five stages: Selection; Pre-processing; Transformation; Data Mining; Interpretation/Evaluation. The input to the KDD process is data and the output is knowledge.

The KDD and SEMMA approaches are primarily data-driven and neither gives substantial attention to business context and business objectives. The CRISP-DM process takes greater account of the business context, breaking the business understanding phase into four tasks: determine business objectives, assess situation, determine data mining goals, and produce project plan. The CRISP-DM process model suggests that business objectives are couched in terms of business goals (e.g., to retain customers) that can be couched as business questions (e.g., will lower transaction fees reduce the number of customers who leave?). CRISP-DM advises that the outcomes from a data mining project should be assessed in business terms, ranging from the relatively objective (e.g., reduction in customer churn) to the more subjective (e.g., to give rich insight into customer relationships).

It is clear from the CRISP-DM process that identifying business goals is viewed as an essential aspect of projects that might be labelled ‘data mining’. This view is further supported by Khabaza (2010), who proposes nine laws of data mining. Rule 1 (Business Goals Law) argues:

> “… data mining is concerned with solving business problems and achieving business goals. Data mining is not primarily a technology; it is a process, which has one or more business objectives at its heart. Without a business objective (whether or not this is articulated), there is no data mining.”

However, despite the high reported level of use of the CRISP-DM methodology, it appears it is no longer supported or in active development and has therefore not been developed to take account of more recent developments in big data and data science. Similarly, neither the SEMMA nor the KDD methodology appears to be actively supported or developed in recent years. Further, while these earlier approaches are referred to as methodologies they are perhaps better characterized as process models. It is, therefore, time to reconsider the role of methodology in business analytics development and how the use of a methodology can contribute to the achievement of business goals. We contend that the business goals can be understood in systemic terms in the context of the *business model* of the organization.

2.2 Business modelling

The notion of 'business model' has received increasing attention from both academic and practitioner communities dating from around 1995 (Zott et al., 2011). It is emerging as a new unit of analysis, but unfortunately its systemic and organization-level nature has led to the literature being fragmented within disciplinary silos. For example, relevant research has been undertaken in areas such as economics, finance, strategic management, firm performance, e-business, information systems, systems engineering and innovation management (Zott et al., 2011; Osterwalder and Pigneur, 2013; Markides 2015). Furthermore, Zott et al. (2011) argue researchers often adopt idiosyncratic definitions of business models "to suit the purpose of their studies" (p.1020).

Despite this fragmentation several useful definitions have been presented in the literature. Rappa (2001) provides a succinct definition:

> "In the most basic sense, a business model is the method of doing business by which a company can sustain itself – that is, generate revenue. The business model spells out how a company makes money by specifying where it is positioned in the value chain."

Zott and Amit (2010) give a more systemic conceptualization of a firm's business model as "a system of interdependent activities that transcends the focal firm and spans its boundaries." Perhaps the most comprehensive definition is given by Al-Debei et al. (2008):

> "The business model is an abstract representation of an organization, be it conceptual, textual, and/or graphical, of all core interrelated architectural, co-operational, and financial arrangements designed and developed by an organization presently and in the future, as well as all core products and/or services the organization offers, or will offer, based on these arrangements that are needed to achieve its strategic goals and objectives".

Through a systematic examination of the literature on business models, Zott et al. (2011) identified four major themes: First, a business model is based on a focal firm, but its boundaries extend wider than the firm. Second, definitions emphasize a "system-level, holistic approach" (p.1020) to how a firm does business. Third, conceptualizations of business models focus on the activities of firms and their partners. Fourth, business models explain both value creation and value capture.

For the purposes of the current research, it was necessary to both define the business model concept and to develop an approach which would enable a business model to be made explicit among researchers and stakeholders; i.e., practical analytical tools would be needed. A popular technique for achieving this is to use the business model canvas (BMC) developed by Osterwalder and Pigneur (2010). The BMC is formed from nine inter-locking building blocks: a value proposition; customer segments, customer relationships, and channels; key partners, key activities, and key resources; and, cost structure and revenue streams. This highly visual mapping method is a powerful way of mapping the current business model and for thinking about how the model might be redesigned.

We also recognized that OR and systems researchers have developed a range of frameworks and methods relevant to business model development and strategy making. Dyson

(2000) argues for the utility of OR in handling strategic issues and points out that an early definition of OR involves developing a "scientific model of the system…with which to predict and compare the outcomes of alternative decisions, strategies and controls" (p.5). He likens this definition to the idea of micro-worlds introduced by Senge (1992), where managers can experiment and predict the impact of changes to a business system. In a similar vein, Kunc and Morecroft (2007), Gary et al. (2008) and Morecroft (2015) explore the role of system dynamics modelling and simulation in corporate strategic development. O'Brien and Dyson (2007) take these ideas further and present a strategic development framework in which OR models of organizations are used to explore future performance and to evaluate alternative future options.

From a soft OR tradition, a range of problem structuring methods (PSMs) have been developed to support business innovation and strategic thinking (Rosenhead and Mingers, 2001; Mingers and Rosenhead, 2004). In particular, Eden and Akermann (2000) and Akermann and Eden (2011) use causal mapping models to explore business models and support the facilitation of strategy making processes. However, none of these OR researchers employ an epistemology which uses conceptual representations as comprehensive as the holistic business model concepts identified by Zott et al. (2011).

The development of comprehensive holistic conceptual tools relevant to organizational referents (and therefore business models) has been a focus of the applied systems thinking community (Jackson 2003). Beer developed the viable system model in an attempt to develop a generic scientific model of system viability (Beer 1979, 1985; Espejo and Harnden 1989). Checkland (1981) employs a 'human activity system' concept within SSM, which is directly relevant to business model mapping when used in primary task mode. Wilson (2001) uses ‘enterprise model building’ within SSM to make assumptions explicit concerning what an organization is required to do (i.e., unpacking its fundamental nature and identity).

In a similar vein, Hindle and Franco (2009, 2010) combine causal mapping and SSM to support the innovation of “Fitness to Drive” arrangements within the UK Department for Transport. Like Checkland (1981) and Wilson (2001), they argue that creating explicit conceptualizations of real-world enterprise referents (such as business processes or business units) adds value within the innovation process and can be done effectively using the systemic epistemology of SSM. Gondal (2004) combines SSM with traditional strategic analysis tools such as PESTEL in the design of a new Internet venture.

In a literature review and critical analysis, Halecker and Hartmann (2013) propose a systemic view of business model innovation arguing the practical definition and understanding of the business model concept “is close to that of systems thinking” (p. 257). They conclude that systems thinking can contribute to business model innovation by: providing a common starting point for different views of the business; a holistic view of the business; exposing previously hidden connections; and, recognizing complex root cause-effect relationships.

Following from Halecker and Hartmann (2013) we propose using the combination of a soft OR method, SSM, together with the business model canvas (BMC). SSM provides a framework for dealing with unstructured problems and complex situations involving multiple stakeholders, multiple perspectives, conflicting interests, and uncertainty (Hindle, 2011). SSM helps participants clarify their understanding of a problem situation, to converge on potentially actionable ways of intervening in that situation, and to gain commitment to change in the problem situation. Also, SSM contains a systemic epistemology and associated modelling language, which is well suited to conceptualizing organizational referents at the level of the business model. The systematic and intuitive appeal of the BMC make it an excellent tool for working with managers and other stakeholders to get an explicit definition of the business model.

The systemic epistemology of SSM supports a detailed specification of the business model using the 'purposeful activity system' concept (Checkland and Poulter 2006). Following Hindle and Franco (2009, 2010) and Hindle (2011), the use of the epistemology enables analytical steps such as creating a 'baseline' or descriptive systems model, and more creative steps such as innovating the baseline model and the creation of alternative system designs (employing alterative *Weltanschauungen* or worldviews).

Hence, although we assume a primary requirement of an organization's business analytics development is that it is *aligned* with the organization's business model, we recognize this relationship may not be static. Chesborough (2010) argues "a mediocre technology pursued within a great business model may be more valuable than a great technology exploited via a mediocre business model" (p. 354). Analogously, mediocre analytics that support an effective business model may be of more use than high-performing analytics that support a weak business model. Thus, BAM encourages an organization to *innovate* its business model rather than simply taking the business model as given.

2.3 The BAM approach

The purpose of the BAM approach is to support an organization in gaining value from business analytics; from initial thoughts right through to completed analytics. The application of BAM involves two streams of work that are fundamentally interlinked (Figure 2). First, there is a top-down *analysis* process that focusses on the business model of the organization and seeks to develop a business analytics development portfolio. Second, there is the bottom-up doing of *analytics* that is grounded in data, tactical work, model building and technology. We argue the top-down analysis is logically prime but, in practice, the analytics work and the analysis process are inseparable and entangled.

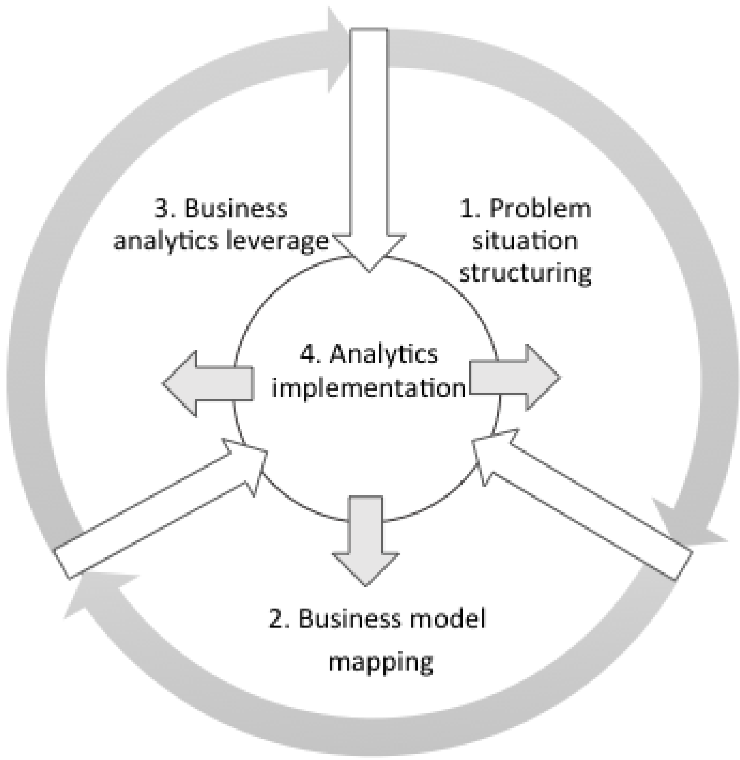


Figure 2: The Business Analytics Methodology (BAM)

Within the top-down *analysis* process, SSM and the BMC are used in conjunction to structure, map and innovate the business model. The formal representation of the business model is then used to identify leverage points for business analytics, i.e. those applications that are most likely to lead to the creation of value for the organization and the best use of scarce resources. These leverage points, in principle, become the basis of an organization's business analytics strategy and its portfolio of analytics development projects. The application of BAM thus involves the following four activities:

- *Problem situation structuring:* the context in which analytics will be deployed is expressed through the medium of a 'rich picture'. The business model is viewed within a complex situation, which is centered on the focal business unit, but with boundaries extending into the environment (environmental constraints, industry dynamics, supply chains, competitors, partners, customers, etc.). We attempt to express the situation "as is" in all its messiness; i.e. taking a holistic view, capturing alternative viewpoints, identifying key issues and features. At this stage we begin to see how the business model functions as a whole and the interests and worldviews of the various stakeholders become apparent (Hindle, 2011).
- *Business model mapping:* using the business model canvas (BMC), supported by the systemic epistemology of SSM, the organization's business model is formally mapped and (possibly) innovated. The techniques of CATWOE (Checkland and Scholes, 1990), a mnemonic that describes root definition and activity modeling from SSM are employed to conceptualize the business unit as a "purposeful activity system". The root definition requires a concise textual definition of the identity of the business unit and can open up opportunities for business model innovation. The activity model enables a more detailed analysis of the key activities highlighted in the BMC and also the generation of system-level performance measures.
- *Business analytics leverage:* analytics opportunities are matched to the systems-informed business model mapping and a leverage matrix of analytics project opportunities is produced (categorized according to value/difficulty). The formal representation of the business model generated by the preceding stage is used to identify leverage points for

business analytics; i.e. the applications that are most likely to lead to the creation of value and the best use of scarce resources.

- *Analytics implementation:* in this activity data is collected, and models built and deployed. First, existing data is collected and reviewed, and its quality assessed. Insights are gained from the data using *descriptive* analytics and further data needs are identified. Second, the internal data is enhanced and combined with external and open data sources as part of an exercise in *data improvement*. Third, *predictive* models are built and the models used to support improved decision-making. Fourth, analytics models are integrated into the operational activities of the organization and analytics applied *prescriptively* as appropriate.

3. RESEARCH METHOD

In order to develop the Business Analytics Methodology, an action research framework was employed (Eden and Huxham, 1996; Baskerville and Wood-Harper, 1996; Checkland and Holwell, 1998) involving a real world intervention. The primary purpose of the intervention was to perform business analytics, but it's important to note that business model and technology innovation were also viewed as a desirable outcomes. According to Checkland and Poulter (2006), the key criterion of action research is to achieve recoverability, "that is to say, make the whole activity of the researcher absolutely explicit (including the thinking as well as the activity)" (p.177). In order to achieve this, they argue, the researcher must state in advance "the framework of language (the epistemology) in terms of which what counts as knowledge from the work will be expressed" (p.177). The definition of an epistemology also helps differentiate action research from consultancy (Baskerville and Wood-Harper, 1996). For the purposes of this research the epistemology is based upon the concept of a Purposeful Activity System from SSM in conjunction with the elements of the BMC, as presented in Figure 2.

The intervention constituted applied research into the innovation of foodbank operations in the UK (Hindle et al., 2016; Vidgen et al., 2016). The research was a pilot study of the NEMODE Network+ Research Call 2014 and the aim of the project was to investigate the use of technology in changing foodbank operations in the UK. The research was led by a team of three business analysts, one of whom is a consultant with experience in organizational development in the third sector, and two of whom are academics with extensive practical experience in the application of problem structuring methods, business model mapping, and business analytics. Two data scientists joined the business analysts for the implementation phase of the project (Activity 4).

The pilot study involved the development of an analytics strategy for the Trussell Trust, our client organization (Susman and Evered, 1978). The Trussell Trust operates the largest foodbank network in the UK (Defra 2014). The trust is a charity with the mission of empowering local communities to combat poverty and exclusion, and operates across the whole of the UK. 1,109,309 people were given emergency food and support in 2015-16 by Trussell Trust foodbanks, although these were not all unique users (http://www.trusselltrust.org). The number of Trust foodbanks has risen from 80 in January 2011 to 424 in 2016.

Each Trussell Trust foodbank is a franchise business unit that provides three days' emergency food supplies and advice to individuals and families in urgent need. The client journey is initiated through a range of external agencies, such as the citizen advice bureau and local authority services, who offer foodbank vouchers to clients in need. Clients are generally limited to three vouchers per six-month period and many clients will only use the foodbank once.

The foodbank staff are trained to support effective dialogue with clients and try to ‘signpost’ clients to relevant services and potential support depending on perceived need. The application of BAM presented in this paper relates to the Trussell Trust organization as a whole, although BAM was also used at individual foodbank level.

4. RESULTS – APPLICATION OF BAM

To illustrate the application of the BAM we present the intervention using the four activities presented in Figure 2:

4.1 ACTIVITY 1: Problem Situation Structuring

We start by expressing the problem situation using the SSM technique of rich picture diagramming (Checkland and Poulter 2006). The rich picture is a way of representing our mental models of a problem situation, helping us to surface and record our assumptions about the relationships and interconnections between the elements we perceive as being pertinent in the problem situation. The rich picture diagram is not a formal technique; people will develop their own style. Rich pictures can be created using graphics software, such as Photoshop or Microsoft PowerPoint, but there is a danger the result will be rather stiff and formal and the use of standard clip-art can make it clichéd.

Rich pictures develop over time as the intervention unfolds. This means the original diagram can be elaborated - or re-drawn entirely - as the project develops. The rich picture is not an objective representation of an external reality; it says as much about the person(s) creating the diagram as it does about the problem situation. Rich pictures can be created collaboratively with the client or used as an internal thinking device by the project team. What is appropriate depends on the situation and on the characteristics of the would-be improvers of the situation. It is often useful to develop rich pictures collaboratively in a workshop with members drawn from different areas of the organization.

Expression of the Trussell Trust's strategic situation was based upon stakeholder workshops, site visits and interviews with Trussell Trust staff. The final rich picture was developed on a whiteboard jointly with stakeholders and then transcribed into a graphics package to allow it to be used for communication (Figure 3). A key feature of the rich picture is the "more than food" initiative. The mission of the Trust is to raise users out of poverty – not simply to feed them in times of crisis. Note the cross on the side of the Trust cube in the centre of the diagram – this represents the Christian values of the Trust. Some foodbank organizations focus on distributing food to those in need. In doing so they address the immediate need of the user (hunger) but do little to tackle the underlying cause of food poverty. In contrast, the Trust engages in 'signposting' to help direct foodbank users toward advice groups such as debt, mental health, and alcohol and drug advice.

In changing lives the Trust also seeks to influence Government policy and to do this must engage with the media and gather research data to make its case. Parts of the media are antagonistic toward foodbanks, feeling that foodbank usage is rising because food from a foodbank is in effect a free good rather than foodbank usage representing an underlying issue of poverty and deprivation. This potential antagonism is depicted by the crossed swords symbol. Through the problem structuring process a number of strategic issues and priorities were identified for the Trussell Trust network.

The first of these is the issue of being able to cope with the rapid growth of the foodbank network over the last five years. The second is developing central IT services to support foodbank managers and foodbank network operations. The third is developing their data resource and gaining leverage through data analytics. This included recognition of the value of the data to their strategic objectives. The fourth is developing the concept of "more than food" to improve the impact of the network in terms of changing lives. For example, the Trust has experimented with co-locating debt services with foodbanks following donations from Martin Lewis of MoneySavingExpert.com (Jones, 2016). The fifth is managing ongoing relationships with a wide range of stakeholders (corporate/ media/ policy/ research). The last is reassessing the goals and strategic direction of the organization.

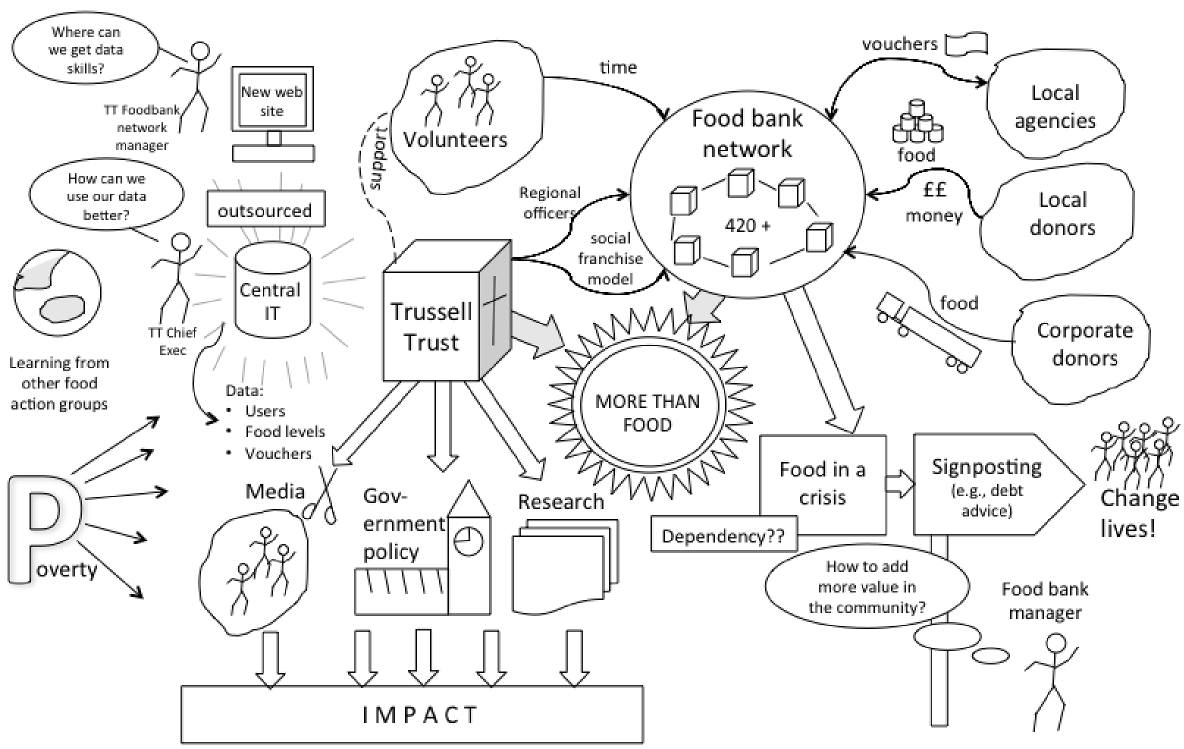


Figure 3: Rich Picture of the Trussell Trust's current strategic situation

4.2 ACTIVITY 2: Business Model Mapping

In developing a formal representation of the business model we use the BMC in conjunction with SSM, by viewing the focal business unit as a purposeful activity system (PAS)

(Checkland and Poulter 2006). The finished business model canvas should be plausible and intuitive. It should tell a compelling and convincing story and – in hindsight – may well appear obvious. Getting to this stage is not so simple, however. Each element of the canvas needs to be considered carefully, the fit of the elements needs to be reviewed, and the overall purpose of the business model (plus any boundaries and constraints) needs to be reflected on and articulated. Business model mapping is a learning process among stakeholders and therefore unlikely to be linear.

Articulation of the system concept is achieved with a CATWOE analysis, a system definition (called a 'root definition' in SSM), and an activity model. The CATWOE analysis (Checkland and Scholes, 1990, presented in Table 1) is a similar type of analysis to the BMC, but is entirely focused on the PAS concept. It defines six key elements of the business model: customers, actors, transformation process (referred to in Table 1 as "T"), *Weltanschauung* (or worldview), owners and environmental constraints.

CATWOE	**Application to Trussell Trust**
Customer (who benefits/disbenefits?)	Those in society needing help (e.g., people in poverty, foodbank clients, people needing benefits)
Actor (who performs the T?)	Trussell Trust, foodbanks, social enterprises
Transformation (what is the T?)	To change lives
Weltanschauung (what makes the T meaningful?)	Christian values mean that we should bring communities together to end hunger and poverty in the UK by providing compassionate, practical help whilst challenging injustice
Owners (who can stop the T?)	Trussell Trust, foodbanks, referral agencies
Environmental Constraints (what aspects affect the business unit)	National and regional economy, short to medium term Government policies, benefit system, Christian values, national and local culture, employment practices, housing provision, research relevant to changing lives, media

Table 1: CATWOE analysis of the Trussell Trust

The root definition is derived from the CATWOE and captures the value proposition (or operational purpose), the means of delivery and the strategic objective(s) (or the owner's long-term objectives). This exposes the level of clarity and agreement within the team regarding the fundamental nature, branding and strategic direction of the organization. The root definition constructed for the Trussell Trust network is:

The Trussell Trust changes the lives of people in poverty **by** directing a coordinated set of operations [including a large franchised network of foodbanks, a growing number of social enterprises, national media campaigns and the generation of a national data resource] **in order to** actualise Christian values and address the underlying causes of food poverty and social injustice.

The root definition is then developed into an activity model. The objective is to identify the main activities undertaken within the business unit and arrange these into a logical model. It's worth noting we are still trying to describe the business model 'as is' rather than create an ideal model of the business unit. In this sense the modeling process is distinct from the otherwise similar process of 'enterprise model building' described by Wilson (2001). Also, the activity model operates as an extension of the 'key activities' element of the BMC. Figure 4 shows the activity model developed for the Trussell Trust.

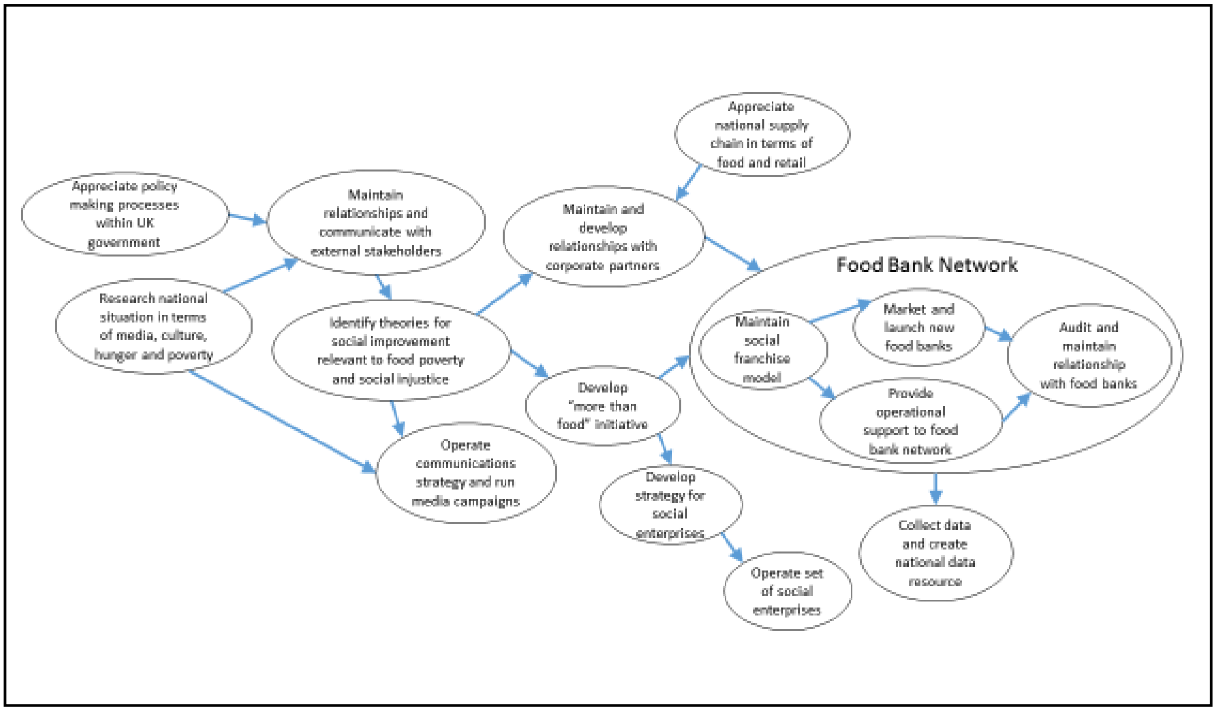


Figure 4: Activity Model – Trussell Trust Foodbank Network

The BMC is constituted of nine basic building blocks that show the logic of how an organization sustains itself in its niche. The needs of different customer segments (1) are satisfied through an organization's value propositions (2), which are delivered through channels (3). The organization maintains customer relationships (4) and receives revenue streams (5) through the successful delivery of the value propositions. Key resources (6) are the assets and competencies needed to deliver value through key activities (7) in collaboration with key partners (8) outside of the enterprise. Finally, these business model elements result in a cost structure (9). Figure 5 shows the identification of the key elements of the Trussell Trust business model using the BMC, which should be understood in the context of the wider PAS analysis.

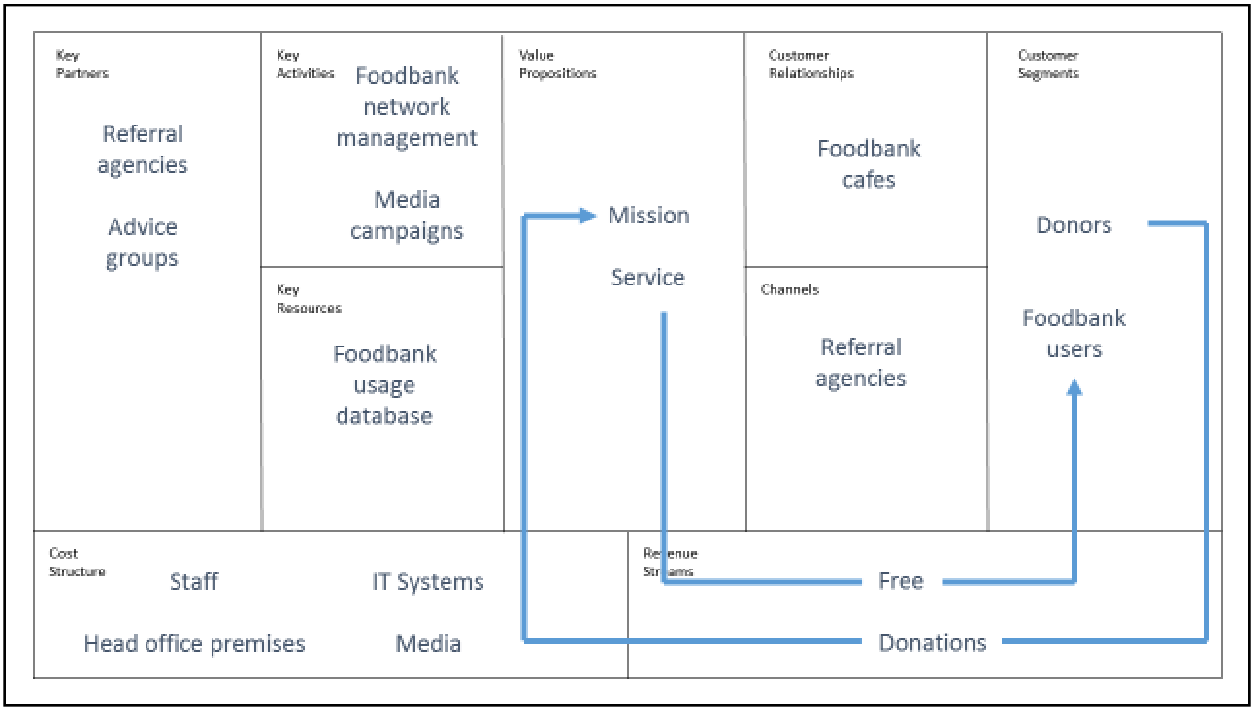


Figure 5: Business Model Canvas – Trussell Trust Foodbank Network

Even though the Trussell Trust is a not-for-profit organization the business model canvas is still relevant. In this context we needed to represent two distinct and rather different customer segments. The first segment contains the service users – those people in food poverty and in need of emergency food provision. There is no revenue stream associated with the provision of this service. The second segment is the donors, who provide resources of different types (principally food and money) to support the mission of the Trust. The channel through which users access the foodbank service is via referral agencies, who distribute foodbank vouchers. Relationships with service users are managed through interaction at foodbanks when food is collected in exchange for a voucher (e.g., signposting sessions conducted in the foodbank café).

Key activities for the Trust are managing the foodbank network and media campaigns (see Figure 4 for a comprehensive model of activities) – the first is essential to helping individual foodbank users and the second is needed if the underlying causes of food poverty are to be addressed. A key resource is the database of foodbank usage, which provides the data needed to produce reports and communicate effectively to stakeholders such as donors, the media, and Government. Key partners are referral agencies (they issue the vouchers to users), and advice groups (they are where users are signposted to). The structure of the Trust leads to a cost structure of head office and regional staff, head office premises, IT systems, and media campaigns.

4.3 ACTIVITY 3: Business Analytics Leverage

The BMC and systems modelling generated in the preceding stage are now used to identify leverage points and opportunities for business analytics, i.e., to identify the data, tools and analyses that are most likely to address the goals of the business and make best use of scarce resources.

Before delving into the specifics of the analytics practice for the Trust, we can use the BMC to provide a generic road map for analytics applications (Figure 6). Here, the key areas of customer, delivery, financial, and value are shown as grouped entities. Note that the contribution to strategic aims is incorporated within the value proposition, thus linking the BMC firmly to the business strategy.

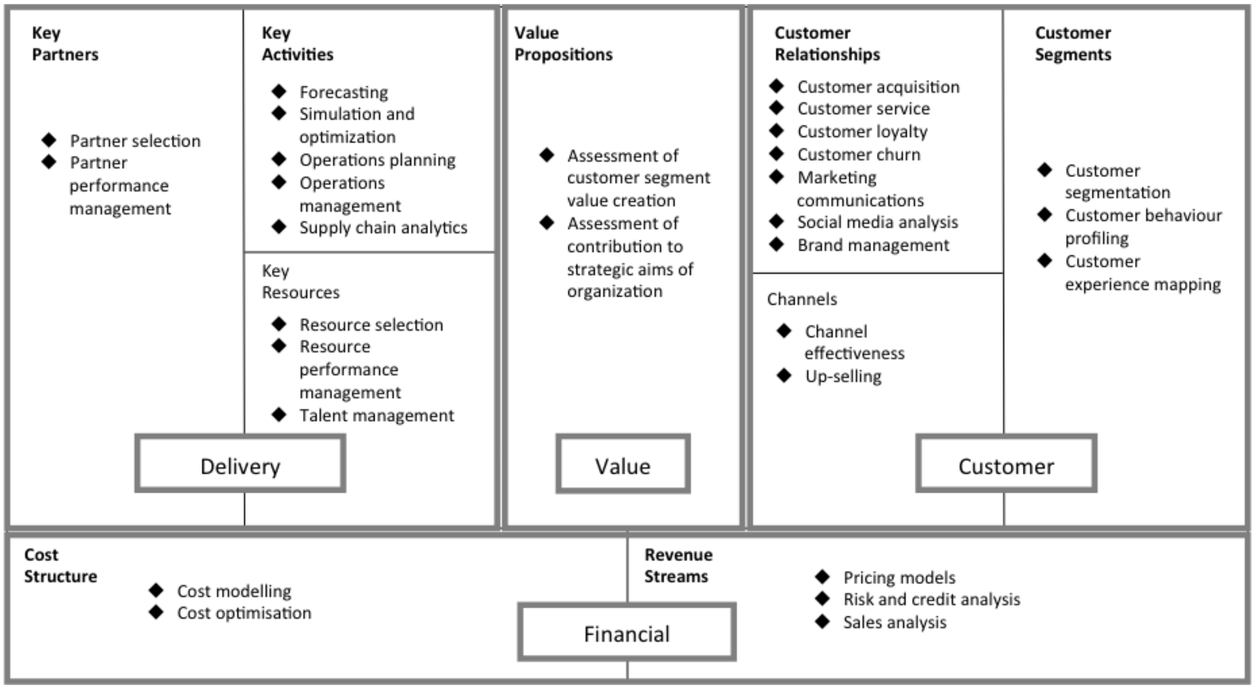


Figure 6: The BMC with a generic analytics overlay

Analytics applications may be local to a BMC element, span several elements (e.g., financial modelling will likely incorporate revenue streams and cost structure), or relate to the business model as a whole (e.g., strategic objectives). While the areas of analytics shown in Figure 6 will apply to a greater or lesser extent to any organization, without the specific context of the business model and the systems modelling it would be difficult to know where to start with the application of analytics and which areas to focus on.

Canvas element	Business questions/issues	Potential applications of analytics
Customer segments: service users and donors	Where are service users currently located in relation to individual foodbanks? What reasons do individuals give for their use of foodbanks? What segmentations of service user and donors might be possible? What need for foodbanks would we expect within geographical areas? Where are foodbanks located in relation to geodemographic features and need? What motivates individuals and corporates to donate?	Geospatial analysis and visualization of service users and foodbanks Predictive/explanatory models of foodbank use Geospatial analysis and visualization of expected need for foodbanks Service user and donor segmentation models Individual service user and donor behavioural models
Value propositions: mission and service	Are the lives of service users being changed? What are the underlying causes of food poverty and social injustice? Are donors' philanthropic needs being satisfied? Are the wider aims of influencing policy being achieved?	Experimental design with control groups to test efficacy of interventions (e.g., co-locating financial advice services in foodbanks) Sign-posting models to provide effective advice to service users Donor satisfaction modelling Predictive/explanatory models of food poverty to expose underlying causes Modelling of Trust's impact on policy and society
Revenue streams	Which donation strategies work best?	Donor prediction modelling and assessment of different fund-raising strategies
Channels	Are referral agencies the best way to access people in poverty? How can donors be reached?	Modelling and assessment of different channels, e.g., online support, apps, and call centre advice lines Donor platforms effectiveness modelling
Customer relationships	How can service interaction be personalized? Is face-to-face interaction in foodbanks the best way of building relationships with service users? How can stronger relationships be built with donors?	Assignment of unique service user id would allow tracking of individual service users and building of personal relationships (requires changes to enterprise systems) Experimentation and modelling of relationship building, e.g., social media platforms Donor loyalty modelling

Table 2: Front office business analytics opportunities matrix for foodbanks

The components of the BMC are now systematically mapped in matrix form against potential analytics applications (Tables 2 and 3). For each element of the BMC business issues are framed as questions and then potential analytics approaches are identified. The questions arise from the problem structuring work in Activity 2 and represent the things the business needs to understand if it is to make effective and better decisions.

Canvas element	Business questions/issues	Potential applications of analytics
Key activities: foodbank network management, media campaigns	Where should foodbanks be located? What reach do foodbanks have? How well are individual foodbanks performing? Do foodbanks have the right foodstuffs and products at the right time and right place? What makes an effective media campaign? Which ones work best?	Geospatial mapping of foodbanks to visualize coverage, location of service users, travel times, referral agencies, advice groups Geospatial analysis to predict where foodbanks are needed (incorporating open data sets on deprivation) Predictive models of future foodbank demand (e.g., time series analysis) Predictive modelling of individual foodbank performance Short-term predictive modelling of foodstuff demand Simulation of foodbank network operations to enable optimization Modelling of media strategies to identify which campaigns work
Key resources: foodbank usage database	How should the foodbank database be developed?	Development of the data resource and sharing data with agencies to create a joined-up service. Inclusion of non-Trust foodbanks to build a more complete picture of food poverty. Modelling of data quality (e.g., completeness, accuracy, credibility).
Key partners: referral agencies, advice groups	How well are referral agencies performing? How well are advice groups doing in tackling causes of food poverty?	Analysis of performance of foodbanks, referral agencies, advice groups
Cost structure	Can costs be reduced?	Modelling of cost structure

Table 3: Back office (operational) business analytics opportunities matrix for foodbanks

Tables 2 and 3 present a considerable array of analytics opportunities and for any business it will not be possible to pursue all of the options highlighted in the problem structuring activity. We apply a straightforward and visual approach to analytics project selection using the dimensions of perceived difficulty and potential for value creation. ‘Difficulty’ is a multi-dimensional construct that could relate, for example, to data availability, data science skills, political issues, funding, leadership, and so on. Every organization is faced with its own set of challenges that will make some projects easier to execute than others. The second dimension considers potential for value creation, which is also multi-dimensional being comprised of tangible and intangible benefits. Together the two categories give four quadrants (Figure 7):

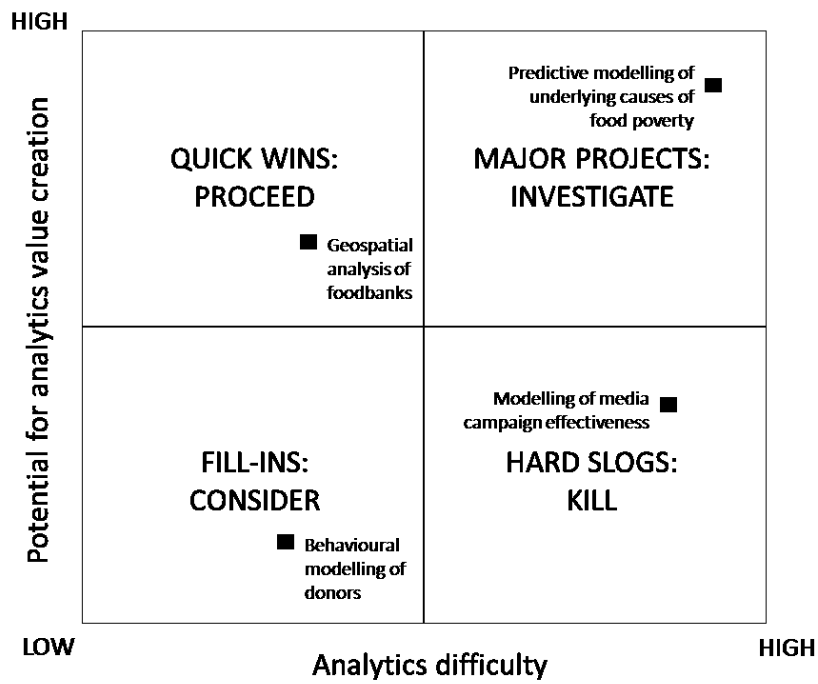


Figure 7: Analytics leverage matrix with illustrative analytics applications

- **Quick wins:** these are high value areas where analytics can be applied to create value with relative ease (e.g., using technologies and techniques that are tried and tested). For example, the Trust has achieved considerable value from geospatial analysis and visualization as they had never before seen their data presented in this way and were able to use the geospatial analysis, combined with open data on poverty, to predict where foodbank need would be greatest.

- **Major projects:** these are also high value areas but are more difficult to achieve. For example, understanding the underlying causes of food poverty is a difficult modelling challenge and might require partnering with research institutions to build a convincing and useful model. This work is vital and is under way but will not be a quick win.
- **Fill-ins:** these are lower value projects but as they are not considered to be difficult to implement they may still merit inclusion. For example, behavioural modelling of donors would be useful to the Trust but is not currently a business priority.
- **Hard slogs:** as these analytics projects are likely to be low in value and difficult to achieve they are best avoided. For example, modelling the effectiveness of media campaigns will likely be difficult to do and is not expected to add much by way of actionable insight.

As with any form of analysis, priorities change over time as the environment changes and the business strategy evolves. Thus, hard slogs might become major projects in response to business model changes and major projects might become quick wins as new technologies become available. Lastly, bear in mind that value and difficulty are perceptions and are therefore specific to the situation and the people conducting the analysis. What is difficult for one organization might be relatively easy for another; a model that is initially considered difficult to build might turn out to be straightforward in practice (and vice versa).

4.4 ACTIVITY 4: Analytics Implementation

For the final stage of the application of BAM – Activity 4 Analytics Practice – two data scientists with strong and extensive backgrounds in statistics, machine learning, and visualisation joined the core project team. The data scientists started contributing by securing internal and open data and conducting a preliminary exploration of the data. The aim of the exploration was to understand what data was available, the quality of that data (missing values, miscoded data, etc.), and to identify what extra data might be needed. The data scientists then went on to find patterns in the data and these were presented to the Trust and the project team in two workshops. The findings were discussed to explore possible reasons for the patterns and to identify future avenues for analytics development. The domain experts (managers from the Trust and foodbank personnel) made sense of the patterns, proposed hypotheses as to why the patterns might be observed and the data scientists developed models to test these hypotheses. This exploration and speculation initially emanated from the data, but subsequently provided an input to the activities 1 to 3 of the BAM (Figure 2).

In the light of activities 1 to 3, and following discussion between the project team and stakeholders from the Trust, the following activities were agreed:

- to conduct exploratory analysis of open data and data from the foodbank network;
- to create a prototype mapping app using free-to-use open source software that enables both Trust HQ and local foodbank stakeholders to perform geospatial analysis and visualization;
- to explore the value of explanatory/predictive models where relevant;
- to support the development of enhanced data collection, visualisation and analytics capabilities within the Trust.

Regarding open data, 2011 Census data was taken from the Office for National Statistics (ONS). A Python program was used to scrape the various census data, resulting in 75 tables of data. Census data were taken at the lowest level of granularity available, i.e., ward level (for example, within the Cheltenham local authority the College Ward is coded as E36002906). Regarding the Trust's data, primary foodbank data were taken from the Trust's database as a SQL extract. The foodbank data relates to the details captured when a voucher is entered into the system to record a client receiving a food package. The individual visit data are then aggregated in various ways, e.g., to ward level, for the purpose of foodbank modelling using the statistical programming language, R. A file of postcode data is used to convert six-digit postcodes to latitude and longitude format for geospatial modelling of service users.

The analytics started with exploratory analysis of the Trust's data. The data provides details of each foodbank visit and captures basic details of the client, such as reason for referral by agency (e.g., benefit delays, homelessness), age, ethnicity, and number of children in the household. The first task was to visualise the data and to provide descriptive insights for the Trust's management. These insights were discussed in a workshop and where the team identified a pattern then the Trust's managers would seek to provide an explanation for that pattern. Initial predictive modelling was conducted to get beneath the trend and to predict the foodbank maturity cycle. For example, Figure 8 shows foodbank usage categorised by region and crisis type, in which it can be seen, for example, that low income is an issue in the North East, and benefit delays in the North West.

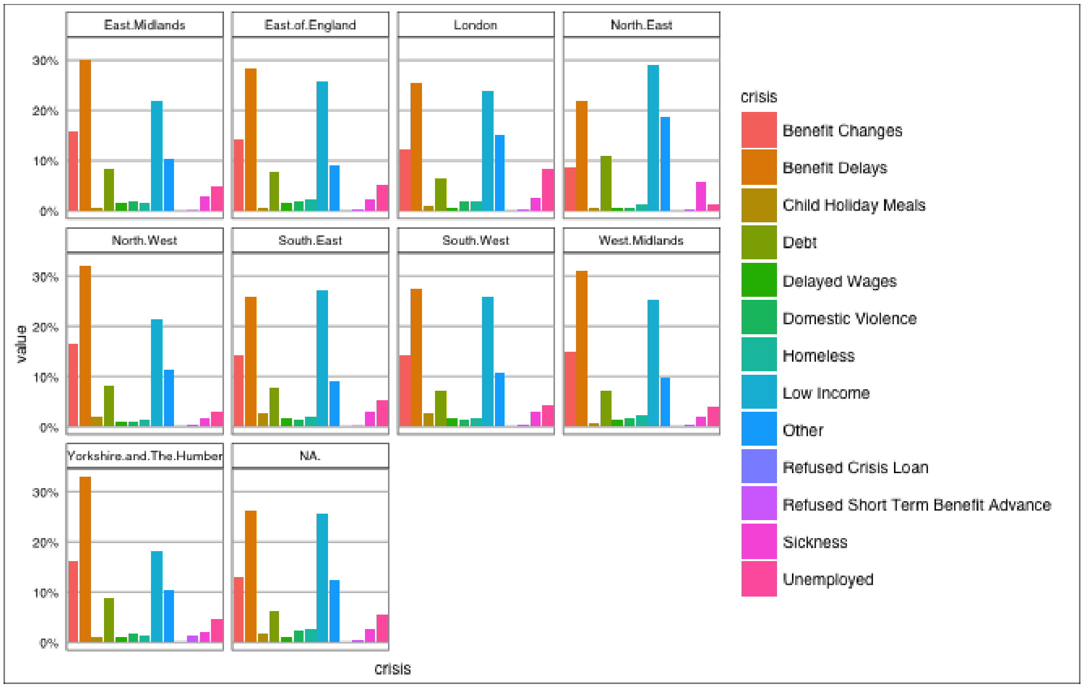
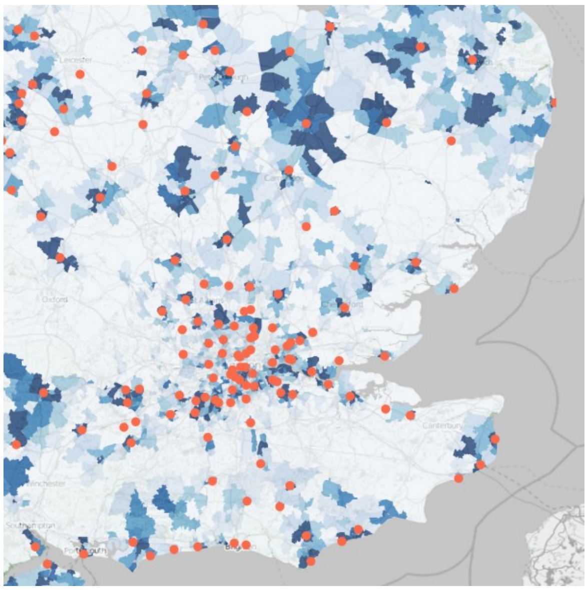


Figure 8: Descriptive analytics - foodbank usage by region categorized by crisis type

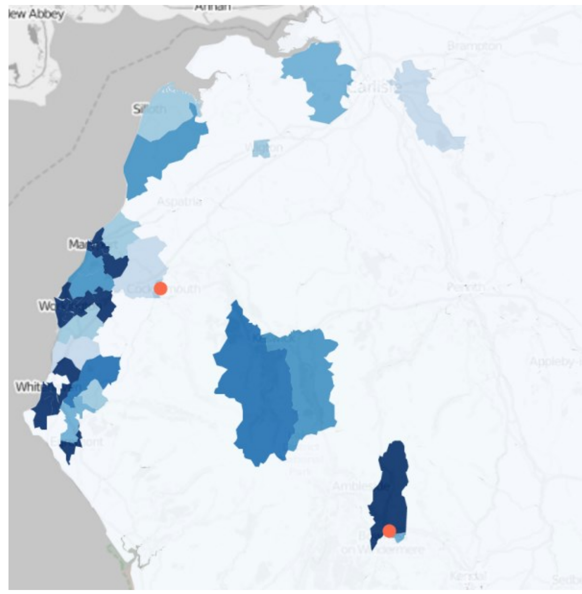
While Figure 8 illustrates foodbank demand more sophisticated models are needed, e.g., drawing on Bayesian models and richer data (e.g., weather data, changes in Government policy) to understand the underlying causes of foodbank demand. However, although predictive models are needed in the medium term, the immediate need was to allow the Trust and individual foodbanks to explore and understand their data better.

In order to explore catchment area characteristics, the Google Maps distance matrix API is used to access travel times. Google provides estimates of travel time for driving using the road network, walking via pedestrian paths and pavements, bicycling via cycle paths and preferred streets, and via public transit routes. The OpenStreetMap resource is used to provide base maps with GDAL (Geospatial Data Abstraction Library) and TopoJSON is used to format the foodbank map geo shapes. To enable the Trust and individual foodbanks to examine and interact with their data and the analytics a Web-based foodbank app was developed using D3, a

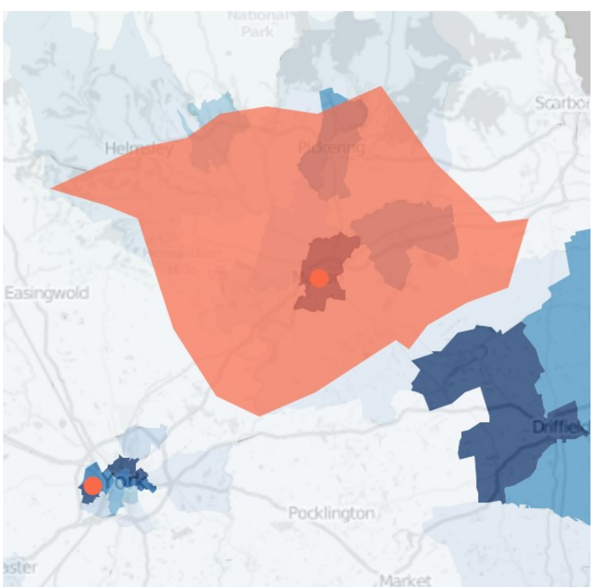
JavaScript library for manipulating documents based on data using HTML (hyper text markup language), SVG (scalable vector graphics), and CSS (cascading style sheets) (see d3js.org).



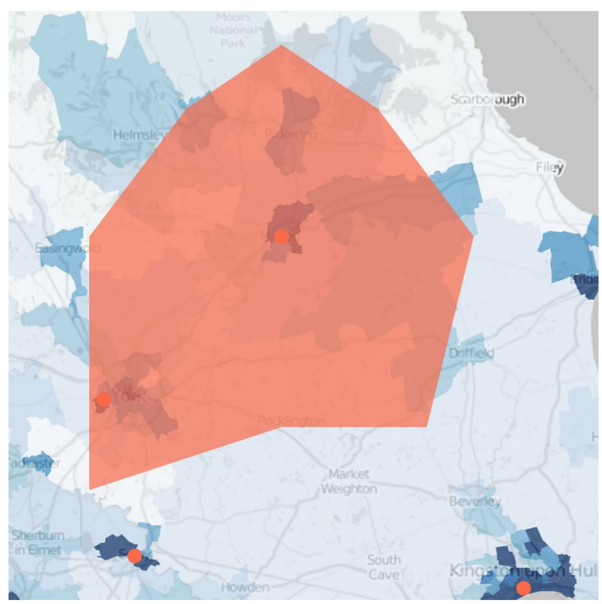
(a) national usage



(b) usage by crisis - homeless



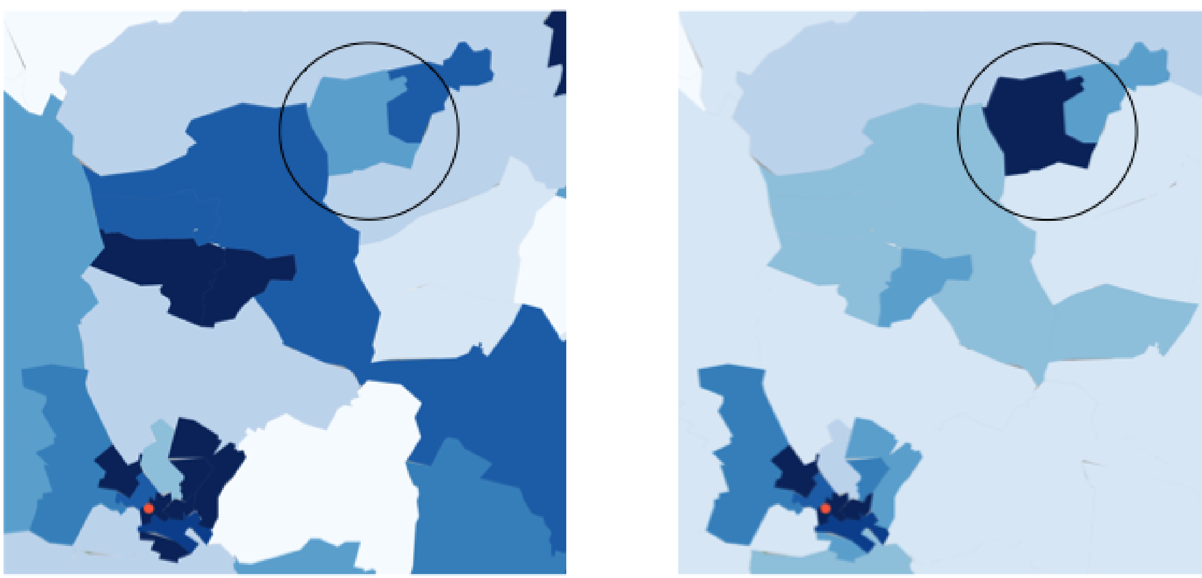
(c) foodbank reach



(d) travel time to foodbank (car)

Figure 9: Data visualization – the foodbank mapping app

On opening the app the user sees a map of the UK with individual Trussell Trust foodbanks shown as dots (Figure 9a). The user is able to zoom in on any particular area of interest, for example a region or a foodbank catchment area. Heat maps showing demand – the darker the colour, the greater the demand – visualise regional patterns of need. Usage can also be shown via the crisis type (e.g. homelessness, child holiday meals, etc.) reported at the time of referral (Figure 9b). To explore individual foodbanks the app user clicks on a foodbank to see the actual reach of the selected foodbank (Figure 9c). Each foodbank can also see their reach in terms of travel time based on 30 minutes travel by car, on foot, or by public transport (Figure 9d).



(a) actual foodbank usage (b) predicted foodbank usage

Figure 10: Predictive analytics – predicted foodbank usage based on 2011 Census deprivation indices

The app can further be used to explore the location of foodbanks. Figure 10a shows the actual usage of the Trust's foodbanks, while Figure 10b shows the predicted need (calculated using the deprivation indices from the 2011 Census). The circled area shows low levels of actual foodbank usage while the predicted usage is high. On the basis of this particular visualization the Trust explored why this might be the case (e.g., a non-Trust foodbank may be operating in this area) as a result of which it identified a gap in foodbank provision and is now planning to open a foodbank to serve the circled area.

5. DISCUSSION

5.1 Finding 1: business modelling drives analytics, data science and OR methods

The original aim of the action research project was to investigate the use of technology in changing foodbank operations in the UK. Hence, the research team's initial focus was on foodbank operations and the nature of the overall foodbank network. However, as the case study progressed, we were able to explore the Trust's business model and their operational and strategic purposes were defined as 'changing the lives of people in poverty' and 'actualizing Christian values and addressing the underlying causes of food poverty and social injustice', respectively. It thus became clear the Trust had a broader and richer notion of its identity and purpose than simply operating a network of foodbanks. We noted their sophisticated media operation and how they had developed 'more than food' initiatives such as co-locating welfare advice services within foodbanks to provide clients with support for the crisis type (e.g., debt) that had led to referral. To have viewed the Trust as simply a system for feeding people in emergencies would have missed their true identity and ambition and led to technology and analytics focused on low level operational goals (feeding people) rather than strategic ones.

In this sense, appreciation of the business model enabled us to appreciate what efficaciousness, efficiency and effectiveness might mean for the Trust. To draw on an old adage: it is better to do the right thing wrong than to do the wrong thing right. And, to paraphrase another old adage, attributed to Kant: business modelling without analytics is empty while analytics without business modelling is blind.

In this sense, the top-down analysis process represented by the outer cycle and the inward arrows in Figure 2 provides the sort of business context implied by the notion of 'business knowledge' in the discipline of data mining. Khabaza's (2010) rule 2 of data mining (Business Knowledge Law) argues:

> "A naive reading of CRISP-DM would see business knowledge used at the start of the process in defining goals, and at the end of the process in guiding deployment of results. This would be to miss a key property of the data mining process, that business knowledge has a central role in every step … whatever is found in the data has significance only when interpreted using business knowledge"

The BAM thus places analytics within an ever-present analysis framework focusing on the business model. Also, it's worth noting that in mapping and reimagining the business model the BAM may also lead to innovations in the business model. For example, the Trust's intention to become data-driven, use open data and share data with other charities addressing poverty constitute innovations in their business model under the umbrella mission of changing lives and working toward a fairer society.

In our action research, appreciation of the business model raised the question of how business modelling and analytics might work and live together. Our reflection on the way business modelling should drive analytics and provide an analytical framework led to the insight that analytics, data science and traditional OR approaches should all be guided in this way. This led to preliminary examination of literature within the quantitative, model-based OR tradition on foodbanks.

Wong and Meyer (1993), Johnson et al. (2005), Johnson and Smilowitz (2007), Thorsen and McGarvey (2017) and Wang et al. (2017) all provide examples of research in non-profit organizations or communities. But Lien et al (2014) provide an ideal example of traditional OR with their study of a sequential resource allocation problem motivated by distribution operations in foodbanks. They argue "the alternate objectives that arise in non-profit (as opposed to commercial) operations lead to new variations on traditional problems in operations research and inventory management" (p.301). The objective function they develop aims at equitable and effective service, as opposed to commercially oriented profit-based objectives (such as maximizing revenues or minimizing costs). In other words, the dynamic programming framework employed and the heuristic allocation policy recommended are driven and guided by the business model of their case organization, the Greater Chicago Food Depository.

More research is needed to explore how the BAM might incorporate and guide analytics, data science and traditional OR approaches in practice. There is a need to develop our understanding of the practice of business modelling and also to categorize the various tools and methods used within the overlapping areas of analytics, data science and traditional OR. The BAM is, therefore, a useful umbrella for bringing together techniques from data science and OR (Figure 6), leading to a both/and relationship rather than an either/or one.

5.2 Finding 2: business analytics development as a coevolving entanglement

While business modelling is logically viewed as a driver of analytics (Finding 1), in practice we realized there were two entangled dynamics at work. First, there is a top-down *analysis* process represented by the outer cycle and the inward arrows (see Figure 2), driven by problem situation structuring and analysis of the business model. Second, there is a bottom-up *analytics* process, which focuses on data and the practice of data science (data collection and assessment, model development, evaluation, and deployment), but which also informs and interacts with the outer business analysis process (the arrows radiating out from the analytics core in Figure 2). The top-down analysis is grounded in strategy, business model, business goals, and value creation. The bottom-up analytics is grounded in data, data science, tactical work, model building, and technology. Ultimately, we found these two dynamics to be entangled in practice. Further, it was not possible (or desirable) to separate out entirely the top-down from the bottom-up or the data science from the business analysis.

The data scientists focused on the bottom-up process of analytics development and implementation (i.e., activity 4 in Figure 2), which allowed internal and external data to be collected, assessed, and visualized. At the same time the business analysts in the team worked on understanding the Trust's strategic aims and business model. Both approaches provided valuable insight into the use and development of analytics. This situation indicates that data scientists and business analysts must be capable of working together and sharing their expertise and knowledge – the data scientists need to have a sufficient understanding of the business and the business analysts need sufficient technical skills to understand and evaluate the models. Communication between business analysts and data scientists was mediated in one direction through data visualizations and predictive models and in the other by business model mapping.

This view of practice leads us to propose that business analytics is appropriately viewed as a coevolutionary process (e.g., see Vidgen and Wang, 2006, 2009) within a business analytics ecosystem (Vidgen et al., 2017). According to Ehrlich and Raven (1964) coevolution is the result of interactions of unrelated species in which adaptive agents alter their structures or behaviours in response to interactions with other agents and with the environment. In this context, the actions of one type of entity (e.g., data scientists) alter the fitness landscape of other types of entity (e.g., business analysts) in reciprocal fashion. All the agents in an ecosystem (e.g., data scientists and business analysts) are striving for fitness and seeking to avoid extinction: "The actions of each agent changes the fitness landscapes of the other agents and thus the fitness landscapes are constantly changing and deforming." (Vidgen and Wang, 2006, p. 264). Kauffman (1993) identifies patterns of coevolution: high internal complexity and low levels of interactions between species leads to stasis while low internal complexity and high levels of interaction lead to chaotic behaviour and a system that never settles. Kauffman (1993) finds that performance of the system is best in an intermediate region, often known as the "edge of chaos" (see Padget et al., (2009) for the results of a simulation study of emergent behaviour in Kauffman's model of coevolution). The achievement of the edge of chaos is also "a requirement for the emergence of novelty" (Stacey 2003, p. 262).

Achieving the edge of chaos requires there to be an appropriate degree of structure (Brown and Eisenhardt 1998). Too little structure can lead to chaotic behaviours and too much structure can lead to a bureaucratic freezing in which innovation and creativity are squeezed out (stasis). At the edge of chaos "organizations never quite settle into a stable equilibrium but never quite fall apart, either" (Brown and Eisenhardt 1998, p. 12). The edge of chaos provides organizations "with sufficient stimulation and freedom to experiment and adapt but also with sufficient frameworks and structure to ensure they avoid complete disorderly disintegration" (McMillan 2004, p. 22).

Thus, if there is little or no interaction between the data scientists and the business analysts (i.e., they are not applying selection pressure to each other) then the likely result will be stasis: models are built blindly with little chance of creating business value and business models are mapped but not implemented in analytics. However, simple approaches to data science and business model mapping (i.e., each species has low internal complexity and can therefore move quickly) with high levels interaction between the species (i.e., between data scientists and business analysts) can lead to chaos as each applies pressure to the other to change and the changes reverberate back and forth leading to instability. A key challenge for management is therefore to manage the internal complexities of its business model mapping and data science activities (and the interactions between these species) in order to maintain its business analytics activities in a region of emergent complexity bounded by stasis and chaos, i.e., to be working at the edge of chaos. We propose that the BAM provides is a useful device for giving structure to an entangled analytics development process.

5.3 Finding 3: the value of business analytics within a community context

The OR community has a long-standing interest in practice within a community context, dating right back to the founding fathers of OR and the pioneering work of Russ Ackoff in the 1960s (Jackson, 2003; Midgely and Ochoa-Arias, 2004; Johnson et al. 2017). In the UK, the development of community-based OR has been associated with a critical evaluation of OR and the development of more participative and critical methods (Parry and Mingers 2004).

However, the value of business analytics within our project more closely reflects Johnson's (2015) findings in the USA. He develops a definition of non-profit "grassroots" and "safety net" community-based organizations (CBOs) and argues they have particular needs in terms of data analytics and information technology. He presents a preliminary survey of context-relevant analytics methods and software, which he splits into three areas of application (based upon CBOs in the USA): First, the exploration of data spatially through low cost or open-source web-based mapping applications (for example, PolicyMap and WorldMap). Second, 'database oriented technologies' which integrate data sources and provide descriptive analytics for practitioners 'at a variety of skill levels' (for example, the Boston Indicators Project and American FactFinder). Third, analytics methodologies aimed at 'prospective analysis' (also referred to by Johnson as prescriptive analytics) that are relevant to the allocation of resources or the design of new initiatives (for example, community-based operations research (Johnson 2012)).

Johnson (2015) goes on to provide a set of principles that might inform analytics practice within a community context. These include: First, it should be values-driven and reflect the mission of CBOs. Second, it should be collaborative among similarly situated CBOs. Third, it should utilize mixed methods in terms of quantitative and qualitative data and both computer-assisted and manual analysis. Fourth, it should require appropriate organizational resources and capabilities in terms of hardware, software and analytics training.

In terms of the case study with the Trussell Trust, we found similarities with these experiences in the USA. We undertook geo-spatial mapping using open-source software and found the use of open data to be important. We also explored the viability of prescriptive analytics. We used 2011 Census data to provide a mapping of poverty and deprivation in the UK and a Google Maps API to get travel times. Combining open data with foodbank data from the Trust provides a richer picture of food poverty in the UK than is possible using internal Trust data in isolation. Communication between analysts and managers was also an important element of the project. For data to be used in communication we found it needed to be visualized to allow users to interact with it. The interactive foodbank app allows the Trust and foodbank managers to explore their data further and ask questions such as: what reach do our foods bank have? What types of crisis are most prevalent?

We found that sharing data between similarly situated CBOs is likely to be important in terms of foodbanks. Future initiatives to incorporate data from non-Trust foodbanks will provide full coverage of UK emergency food provision for the first time. Sharing data with other charities involved in poverty alleviation, e.g., homelessness charities, will allow a fuller picture of the state of the nation to be created leading to better informed interventions with greater input to – and influence – on policy, thus supporting the mission to create a fairer society.

We also found the issue of appropriate organizational resources and capabilities to be relevant to the Trust. As mentioned above, we used open source software and freely available APIs to build models, access data, and make interactive visualizations. We chose not to buy proprietary software from commercial providers in these early stages of analytics adoption. However, using tools such as the statistical computation language R and the JavaScript-based interactive language D3 requires technical knowledge as well as statistical and modelling skills, which are not available at present within the Trust. There appears to be a shortfall of data scientists generally at present, although there are avenues for third sector organizations to get help on a pro bono basis in the UK; for example, from the OR Society and from DataKind.

As the project with the Trust unfolded it became evident there is a significant role for business analytics and data science within community research going forwards. We identified three major opportunities in our case study for the future: (1) non-Trust foodbanks could be added into the database to create a comprehensive map of UK food poverty; (2) other types of open data, such as data on health (e.g., obesity levels), crime, education, weather, etc. (for example see the London Data Store - http://data.london.gov.uk for publicly available datasets) could be added to the foodbank data to give richer context; (3) data could be pooled with other third sector organizations that are working to alleviate poverty to build a national data set.

5.4 Contribution to theory

Our literature search identified a gap in the research in the area of business analytics methodologies. While frameworks have been proposed (e.g., CRISP-DM, SEMA, KDD) these methods have not been maintained or developed further in recent years. Therefore, our research, through the development and implementation of the BAM, contributes to research by developing an analytics methodology (BAM). While the literature on business models is growing, the link to business analytics has not been made previously. It has also been argued that business model analysis would benefit from an injection of systems thinking (Halecker and Hartmann, 2013), although these calls to action do not appear to have been applied in practice. Our second contribution, therefore, is to theorize analytics through business models and systems thinking. A third contribution is in positioning the BAM as an umbrella framework for data science and OR, showing how both traditions can live together in an organizational setting. Fourthly, by theorizing business analytics as an entangled coevolutionary process (Kauffman, 1993) we propose a theoretical basis (coevolution) for thinking about the interplay of data/science and business/analysis in organizational development. In such a formulation the BAM, together with its various models, can be theorized as a boundary object (Franco, 2013) connecting the worlds of business and data science/OR.

5.5 Implications for practice

Business analytics and data science have been hyped relentlessly (redolent of dotcom bubble) leading to a severe danger that organizations lose sight of the value creation opportunities. Firstly, the BAM provides a way for organisations to articulate a business analytics development plan that can be checked for (i) alignment with the business goals and business strategy and (ii) communicated throughout the organization as part of the transformational journey to becoming data-driven. Managers should consider BAM as an interdisciplinary umbrella that helps different parts of the organization find a starting point to create their agenda for analytics. Secondly, the BAM provides managers with a practical set of tools for developing and analysing the organization's business model with an auditable link from business strategy to analytics implementation. We envisage the BAM being applied in different modes by different actors: for example, this could be external consultants using the BAM as a diagnosis tool, or it might be by an internal business analytics teams working within an organisation (and its constituent business units) to develop a business analytics implementation plan. Thirdly, the systemic business model mapping articulates assumptions that may be otherwise hidden, misunderstood, or have never been thought about in such fundamental terms. This approach encourages managers to develop their business models through analytics rather than taking the business model as fixed, given, or simply unarticulated. Fourthly, the coevolutionary view of business analytics as entanglement highlights the need to create an environment in which effective interactions between business analysts and data scientists are fostered. Lastly, our research highlights the potential for BAM in exploring third sector analytics as a community practice engaging multiple partners and stakeholders rather than one that is simply internal to a focal organization.

5.6 Limitations and future work

This is a single case study enacted through action research. Further cases studies are needed to develop the BAM further and to assess its performance, for example, in commercial enterprises and their constituent business units. We are also aware that the BAM lacks an ethical analysis dimension; given the rise of algorithms and their impact on individuals and society (O'Neill, 2016), and concerns about data use and privacy, then an ethical analysis stream in BAM may well be an essential avenue for further research. We also encourage empirical deductive studies that evaluate quantitatively the effectiveness of the BAM, e.g., in the form of cross-sectional surveys with analytics 'success' as an outcome variable, and field experiments.

6. SUMMARY

We have developed the BAM in response to the need for organizations to align their business analytics development projects with their business strategy. The four-stage BAM (problem situation structuring, business model mapping, analytics leverage analysis, and analytics implementation) is not a prescription. Indeed, it is unlikely to be seen in an organization as a step-by-step process with a clear beginning and end. Rather, it provides a logical structure and logical precedence of activities that can be used to guide the practice of analytics (i.e., a mental model). The action research allowed us to experience the analytics development process for real – and to produce real business benefits through the development of a prototype geo-spatial app.

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