Designing IS Service Strategy: An Information Acceleration Approach

Abstract

Information technology-based innovation involves considerable risk requiring foresight; yet our understanding of the way in which managers develop the insight to support new breakthrough applications is limited and remains obscured by high levels of technical and market uncertainty. This paper applies discrete choice analysis to support improved empirical explanation of how and why decisions are made in information systems. A new experimental method based on information acceleration is also applied to improve prediction of future IS service strategies. Both explanation and prediction are important to IS research and these two behaviourally sound methods complement each other. Specifically, the combination of information acceleration and discrete choice analysis removes misspecification artefacts from response variability and generates more accurate parameter estimates that better explain IS decision making.

Keywords: experimental research, IS service strategy, decision-making, discrete choice analysis, information acceleration

While good hockey players skate to where the puck is,
a great hockey player skates to where the puck is going to be.

(Wayne Gretzky)

Introduction

The development of an information systems (IS) service strategy is a challenging combinatorial problem requiring the allocation of appropriate resources to connect information technologies, coordinate suppliers, and respond to the needs of internal units and end-clients. In common with Gretzky, those managers with the insight to manage this complexity and the foresight to identify where the next business opportunities *are going to be* are likely to garner the greatest returns from investments in IS. The decision to invest in an IS service strategy is of this type and requires a series of choices about the future service attributes that will meet organisational and competitive needs. Although the demand for executives with insight and foresight is great, recent industry reports reveal that these skills are in short supply (Dubie, 2007).

To improve this situation, we need rigorous quantitative research methods that support both empirical explanation and prediction. According to Gregor (2006) both are needed to test theory and guide action effectively. Academics are rightly interested in (1) explaining how, why and when decisions are made, and (2) predicting needs and anticipating technological diffusion in future time periods. Practitioners are also interested in both explanation and prediction; because IS investment decisions based on idiosyncratic criteria and simple heuristics have been shown to deliver inconsistent results (Lyytinen & Robey, 1999).

A discrete choice experiment (DCE) is a choice-based conjoint technique that tests the explanatory power of underlying decision models by systematically varying the characteristics (attributes) of interest according to statistical design theory. The choice-based DCE method is particularly powerful because it models preference heterogeneity in ways that are behaviourally sound (Louviere & Woodworth, 1983). For clarity, it is hard to go past the remarks by Lenk and Bacon (2008, p.1):

> *Discrete choice elicitation is often preferred to other measurement methods because it better aligns with actual choice behaviour and avoids some of the well documented biases inherent to alternative methods, such as ratings.*

The measurement method is theoretically grounded and takes as a given that while one individual may make choices by carefully trading off the pros and cons of alternatives (a compensatory rule), another may make the same decision by choosing that which is best on one or more favoured attributes (a non compensatory rule). Like other choice-based approaches, DCE supports greater predictive accuracy relative to advanced ratings-based conjoint approaches (Ding *et al*., 2005; Karniouchina *et al*., 2009). The method does not force subjects to place answers on scales that are inconsistent with the "natural" decision processes used by managers, and offers greater control over alternate explanations and stronger evidence of causality.

First pioneered in manufactured products (Urban *et al*., 1996, 1997) and recently extended to space tourism (Crouch *et al.*, 2010) and technology choices (Devinney *et al*., 2004), information acceleration (IA) supports more accurate prediction of technology acceptance and diffusion. The technique begins with the construction of scenarios that allow respondents to better understand the future choice situations they may face. In particular, multimedia technology is used to 'accelerate' respondent learning and experience, enabling the researcher to develop and implement DCE surveys that include a wide array of information, features, risks/benefits and contexts. Information acceleration is particularly useful to IS researchers that are frequently required to work in innovative situations where precedents may not exist on which people can base their decisions. Moreover, IA's ability to combine and model alternative configurations of resources and capabilities is valuable within IS because the success of new information technology is frequently dependent upon resource complementarities (Piccoli & Ives, 2005; Coltman *et al.,* 2010).

The essence of preference measurement involves an analysis of both the systematic and stochastic (random) components of decision making. Until recently, scholars have presumed, often tacitly, that "systematic differences in behavioural outcomes are driven primarily by (differences in) what is predictable and deterministic, not what is unobserved and stochastic" (Salisbury & Feinberg, 2010, p.1). This assumption has recently been identified as a major limitation (Louviere & Swait, 2010). However, the combination of DCE and IA allows scholars to control for conditions that can result in differences in response variability based on high unobserved or stochastic error. In other words, combining DCE and IA allows the scholar to better control for within-subject variance to address heterogeneous preferences, and between-subject variance to address heterogeneous errors arising from differing levels of uncertainty. Thus, the combination of DCE and IA proposed in this paper provides greater realism in quantitative modelling by minimising the impact of uncertainty.

The remaining sections of the paper are organised as follows. In the next section the proposed methodology is described. This is followed by an illustrative empirical application of IA to the delivery of IS services. The IS service function is central to most contemporary businesses and we argue that it represents a singularly good example of the way IA can be applied to address uncertainty in an organisational setting. The substantive findings suggest that IA can be used to provide a more rigorous model for understanding the contingent nature of tangible and intangible IS resources in a service environment.

The Science of Preference Methods

Although methods such as case studies (Benbasat *et al.*, 1987; Lee, 1989), action research (Kaiser & Bostrom, 1982; Wood-Harper, 1985), and survey techniques (Cheon *et al.*, 1993; Im & Grover, 2003) are well suited to the multi-layered, exploratory nature of work in IS, these methods only support limited decision-making inferences. For example, measures obtained by survey methods are not suited to capturing trade-offs made by managers. Consider the decision process a managers goes through in the search for a new ERP system. Under utility maximization theory (von Neumann & Morgenstern, 1947) a manager would adopt a compensatory strategy by first holistically evaluating every system in the market, and then form a weighted linear equation based on all the pertinent variables before selecting the system with the highest overall utility score. Alternatively, under a satisficing theory (Simon, 1957), managers only evaluate systems with particular features (i.e., decision attributes) that meet certain conditions (e.g., below a given price threshold), stopping when they find one good enough.

Even where the use of structural equation (Marcoulides & Saunders, 2006; Lewis *et al*., 2003) and latent class modelling (Coltman *et al*., 2007) can provide evidence of relationships between variables, they cannot capture the trade-offs involved in compensatory strategies directly. Another key limitation of these methods is that they downplay the context of IS decision-making. Diverse contexts make it difficult to design surveys that capture all relevant variables and alternative configurations (Bowen & Wiersema, 1999). Clearly, an appreciation for how managers actually make decisions when faced with current and future uncertainty is a critical step in improving the prospects of IS investments.

To overcome these limitations, a small number of IS researchers have begun using stated preference methods to elicit individual preferences for goods, services and strategies. For example, Raghu *et al*. (2009) used a binary discrete choice technique known as contingent validation to assess 'willingness to pay' for open source software. Additionally, there has been limited application of the more common ratings-based conjoint in IS. For example, Tiwana and Bush (2007) used a ratings-based approach to evaluate the relative importance of transaction cost and knowledge-based features in IS outsourcing, while Bajaj (2000) adopted a similar approach in examining IS manager decision models. In summary, while DCE and related methods such as conjoint are not entirely new to IS scholars, there has been no such application of IA in the discipline.

Modelling Discrete Choices

Pioneered by McFadden (1986), the choice-based DCE approach is based on information integration theory in psychology (Anderson, 1981) and random utility theory in economics (Ben-Akiva & Lerman, 1985; Hensher & Johnson, 1980). Random utility theory describes the behaviour of humans and is therefore distinctly different to ratings-based conjoint analysis which is based on a theory of numbers. It posits the existence of a latent construct similar to traditional utility theory whereby a decision-maker is able to discriminate, rationally, between the alternatives in a choice task. Random utility theory proposes that these latent utilities can be decomposed into a systematic or explained component, and a random or unexplained component. The relationship can be expressed as:

$$U_{in} = V_{in} + \varepsilon_{in}$$

where U_{in} is the latent utility that individual n associates with choice option i, V_{in} is the systematic or explained component of utility that individual n associates with option i, and ε_{in} is the random component associated with individual n and option i.

In DCE a respondent's response to systematic manipulations of attributes is used to derive their underlying utility preferences (McFadden *et al.*, 2005). The approach draws on Thurstone's (1927) law of comparative judgment to place attributes on a common scale that can be modelled in the form of a multinomial logistic regression (Luce & Suppes, 1965; McFadden, 2001). The bounded rationality of decision-makers is directly accounted for in the experimental design, which explicitly considers the notion of value (utility) to establish reference points. Importantly, DCE produces preference structures that proportionally match those in real markets, as well as the decision strategies used to resolve such choices (Adamowicz *et al.*, 1994; Louviere *et al.*, 2000; Morikawa, 1989). Stated and revealed preference models differ by a constant of proportionality, often termed a 'scale parameter' (Swait & Louviere, 1993). Although the presence of a scale parameter makes it necessary to scale stated preferences in order to apply them in real markets, it does not alter the significance, relative importance or direction of effects (Swait & Louviere, 1993).

Design theory can be used to ensure that the experimental attributes in a DCE are orthogonal and allow the researcher to plan the experiment in ways that ensure a desired level of accuracy (Burgess & Street, 2005; Street *et al.*, 2005). The need for probability sampling is also less acute in this experimental method because randomisation is used to control for pre-existing informational states that can influence perceptions and create confounding effects.

However, DCE has some limitations that need to be acknowledged. First, it is assumed that researchers can identify all (or at least as many as possible) drivers of choice and express these factors in terms understood by decision-makers (Swait & Ben-Akiva, 1987). This requirement is challenging when decision-makers are required to make choices from amongst alternatives that are not well understood (e.g., choices regarding innovative technology or service applications). As noted by Krieger *et al*. (2003), the need exists in such cases for ‘information bridges’ that connect current understanding to future states. The IA methodology proposed in this paper provides a means of creating an information bridge where managers are expected to make choices without access to full information. Such information bridges are particularly important where subjects might be expected to differ in their levels of understanding. Recent research on has shown that variation in errors due to differing levels of uncertainty can bias substantive findings (Salisbury & Feinberg, 2010). Experimental control through IA is a tractable approach that allows uncertainty to be modelled more directly to evaluate its impact on part-worth utilities.

Accelerating Understanding to Reduce Uncertainty

Information acceleration aims to provide an information bridge that gives the decision-maker (customer or IS manager) the same experience and information today that he or she will have in the future when actually considering new products or services (Urban *et al*., 1997). This allows accurate data regarding information conditions, preferences, and intentions to be collected and modelled. In an IA, information technologies are used to create a virtual environment that reflects future decision contexts, including new technologies and the evolutionary paths that they may take. The virtual environment usually includes richly coded information—diagrams, multimedia, and feedback loops—that allow the researcher to simulate the decision-making context (Reber & Millward, 1968).

One of the first IA projects evaluated demand for a radically new electric car (Urban *et al.,* 1996, 1997). Respondents read a series of newspaper/magazine articles from the ‘future’ and then assessed vehicle details by interacting with a full array of verbal, pictorial, video, and text material. In an IS context, the Future Choice Initiative used IA to measure the demand structures for a new personal digital assistant with full voice recognition and computer simulated communication, and new web-based IS services for financial institutions (Coltman *et al*., 2006). The central idea is to ‘accelerate’ the process by which decision-makers acquire information and experience new technologies and environments. By guiding participants through this learning process, researchers can reduce uncertainty over the future context and then more accurately model choices and decisions.

The combined DCE/IA approach offers important methodological benefits. For example, in isolation DCE measures heterogeneity by repeated measures to capture within-subject variance. Meanwhile, between-subject sources of variation have traditionally been relegated to covariate modelling and at worst assumed away as random error. In contrast, the dual DCE/IA approach uses experimental control over between-subject variance to better measure sources of uncertainty directly. This is important because recent evidence indicates that uncertainty impacts not only the mean but also the variance of error distributions, making the treatment of heterogeneity through covariates or homoscedastic assumptions dangerous (Salisbury & Feinberg, 2010).

Information acceleration might be considered an important "missing piece" in quantitative choice response measurement because it (1) supports prediction by accelerating learning and providing more accurate insight into alternative scenarios, and (2) can experimentally control for the uncertainty that leads to response variability (i.e., heterogeneous errors). The salience of IA is highlighted by recent research suggesting that as much as 40-80% of variance in estimates is due to response variability rather than preference heterogeneity (Islam *et al*., 2009). Information acceleration provides an experimental alternative to parameterise heteroscedasticity and capture between and within subject variance—an issue that is at the cutting-edge of stated preference research (Fiebig *et al*., 2010; Magdison & Vermunt, 2007).

Illustrative Empirical Application

To illustrate the advantages of the combined DCE/IA method, we turn our attention to a common IS problem: namely, assisting managers to better understand how tangible and intangible IS resources influence the development of customised IS service strategies. The role of complementary human resources is well accepted in the IS literature (Powell & Dent-Micallef, 1997; Piccoli & Ives, 2005) and this contingent relationship necessitates the use of relative measures based on choice measurement that can accurately capture compensatory strategies.

Our methodological approach represents an important alternative to empirical methods that rely on post-hoc statistical analysis to ameliorate the effect of context. These alternatives provide no means of accurately capturing decision strategies in future choice situations where uncertainty makes simple, rational choice models inappropriate (Gigerenzer, 1996). This is where an IA is essential. By accelerating understanding of new decision states, we can observe decision-making around the introduction of new technologies and the evolutionary paths that such technologies may take. The behaviourally grounded method provides stronger explanation of the observed decisions, and allows better prediction of the development of IS service strategies.

Substantive Hypotheses

In order to make the empirical illustration as realistic as possible, we proffer the following two hypotheses to provide a context for the ensuing analysis.

H1: *Tangible IS resources, intangible IS resources, and IS customisation will be strategically important to managers in the selection of IS service strategy*.

H2: *Receipt of the IA will reduce uncertainty as observed in an increase in systematic variance explained and a reduction in the attenuation of the strategic importance of the research attributes (i.e., tangible IS resources, intangible IS resources, and IS customisation).*

Support for the first hypothesis (H1) is drawn from the extant IS literature that identifies IS resources and IS customisation as important attributes impacting firm performance (Brynjolfsson & Hitt, 2000). Information systems resources take both tangible and intangible forms (Melville *et al.,* 2004). Tangible resources include IS infrastructure such as technology and software applications that utilise the infrastructure (Broadbent &

Weill, 1997). Intangible resources, on the other hand, include human and organisational factors in the successful implementation of IS services (Tippins & Sohi, 2003; Hatch & Dyer, 2004). The resource-based view of the firm suggests that both types of resources will be important to future IS service strategy and positional advantage.

The customisation of IS processes has been shown to facilitate the provision of specialised IS services, in turn allowing differentiated product and service offerings. IS customisation is important in making technology work successfully in a specific business (Feeny & Willcocks, 1998). Research into IS service strategy has identified a number of contextual features, such as organisational culture and task characteristics, with which IS should be aligned. Alignment requires the customisation of an IS service strategy to the specific features present. Greater customisation of IS allows firms to produce more strongly differentiated products and services (Kathuria *et al.*, 1999). Information systems customisation also impacts performance outcomes by allowing firms to pursue distinctive IS service strategies (Richard & Devinney, 2005).

The second hypothesis (H2) tests arguments already discussed about the influence of uncertainty on the decision-making process. In particular, uncertainty has been shown to increase response variability and place cognitive pressure on subjects to adopt simplified decision strategies (heuristics) (Schwenk, 1986). These strategies can produce a range of systematic errors including the framing effect, overconfidence and cognitive biases (Tversky & Kahneman, 1974).

Uncertainty increases response variability, giving the stochastic (random) component a larger influence relative to the systematic component of decision making. As shown by Salisbury and Feinberg (2010, p. 3) this uncertainty alone can account for changes in observed outcomes. Generally, the presence of uncertainty will attenuate the role of the hypothesised research attributes. The IA aims to provide a reduction in uncertainty that shifts the balance between systematic and random variance back towards the systematic component. The reduction in uncertainty will lead to improved model fit for participants in the IA condition and increase the observed effect-sizes associated with the research attributes outlined in H1.

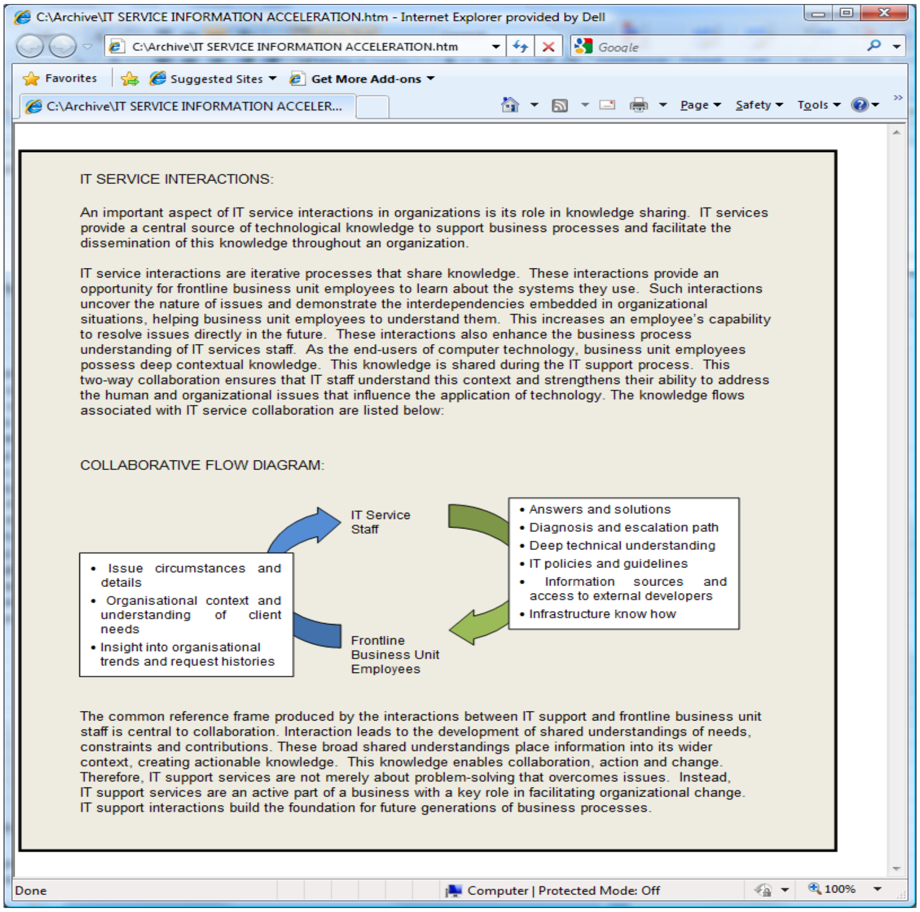
To ensure that the observed effects were indeed attributable to the IA manipulation, a range of variables shown to influence the selection of an IS service strategy were also included as controls. The most important of these were cost advantages, competitive intensity, and governance mode. Each control was measured directly and their influences separated from the research variables.

Information Acceleration Manipulation

The experiment started with a close description of the IS service process. This was followed by the IA for a randomly assigned group of participants. An IS support scenario was used in order to provide a broad illustration. The visual and textual description of the IS service process was developed through extensive qualitative research that included semi-structured interviews with five IS managers responsible for IS service strategy decisions. The scenario sought to address all variables identified in Larsen's (2003) taxonomy of IS success factors. The scenario information allowed us to better control for random effects associated with individual-level differences and was common to participants who received the IA and those who did not.

The IA sought to closely explain the role of IS support in order to reduce uncertainty around its future role. The IA was delivered over a web-based interface to provide a visual representation of the IS service interactions. The use of carefully structured and sequential presentation of information kept the IA to a practical length, while still supporting step-by-step learning to accelerate awareness. A screenshot of the IA with all information shown is presented in Figure 1. Keeping the cognitive load to manageable levels is important for allowing learning to occur (Sweller, 1988). The diagrammatic representations of IS service were supported by a textual description in the IA and a set of ordered response questions that followed. These questions required participants to reflect on the information they had received. This type of reflection has been shown to be important in learning processes (Schön, 1983).

Figure 1. Screenshot of the Information Acceleration



IT SERVICE INTERACTIONS:

An important aspect of IT service interactions in organizations is its role in knowledge sharing. IT services provide a central source of technological knowledge to support business processes and facilitate the dissemination of this knowledge throughout an organization.

IT service interactions are iterative processes that share knowledge. These interactions provide an opportunity for frontline business unit employees to learn about the systems they use. Such interactions uncover the nature of issues and demonstrate the interdependencies embedded in organizational situations, helping business unit employees to understand them. This increases an employee's capability to resolve issues directly in the future. These interactions also enhance the business process understanding of IT services staff. As the end-users of computer technology, business unit employees possess deep contextual knowledge. This knowledge is shared during the IT support process. This two-way collaboration ensures that IT staff understand this context and strengthens their ability to address the human and organizational issues that influence the application of technology. The knowledge flows associated with IT service collaboration are listed below:

COLLABORATIVE FLOW DIAGRAM:

- Answers and solutions
- Diagnosis and escalation path
- Deep technical understanding
- IT policies and guidelines
- Information sources and access to external developers
- Infrastructure know how

- Issue circumstances and details
- Organisational context and understanding of client needs
- Insight into organisational trends and request histories

The common reference frame produced by the interactions between IT support and frontline business unit staff is central to collaboration. Interaction leads to the development of shared understandings of needs, constraints and contributions. These broad shared understandings place information into its wider context, creating actionable knowledge. This knowledge enables collaboration, action and change. Therefore, IT support services are not merely about problem-solving that overcomes issues. Instead, IT support services are an active part of a business with a key role in facilitating organizational change. IT support interactions build the foundation for future generations of business processes.

An initial pre-test was performed on 16 IT managers prior to final data collection to check that the diagrammatic representations of IS service and their textual description were appropriate.

Discrete Choice Experiment

The sample for the experiment was drawn from a database of managers linked to a leading business school through practitioner workshops and executive classes. Potential participants were screened on an index of three 5-point Likert-scale items relating to the importance of IS to 'firm performance', 'value creation', and their 'industry' to increase relevance and motivation (Dillman, 2000). Participants were selected if their combined score on these items was greater than or equal to 14, producing a sample of 75 participants. These participants had an average of 5.22 years of business experience. Comparison with those who had been screened out showed that the selected participants had more experience with IS support (p = 0.002) and development of business processes (p = 0.012), but were not significantly different in other demographics.

Having received the scenario information (for the 'non-accelerated' group) and also the IA (for the IA or 'accelerated' group) participants then completed a DCE measurement instrument. The research hypotheses isolated six variables for inclusion in the choice sets. The operationalisation of the variables as six two-level attributes in the discrete choice task was based on the review of measures used in past studies as outlined in Table 1. The modification of these measures to match the IS service scenario was based on the review of qualitative materials that was used in developing the experimental scenario and face validity input from the five IS managers who reviewed the scenario. The mapping of the variables to operational definitions that are familiar to managers added to the realism of the task, providing additional external validity.

Burgess and Street's (2003; 2005) design theory was used to develop a fractional factorial design. Observations were collected by delivering eight choice sets to each participant where each set contains three options. The design established the level of each attribute presented in each option. The second and third options were generated by applying a modulo arithmetic generator so that the levels appearing in the options were maximally different, with minimal overlap to maintain orthogonality (Huber & Zwerina, 1996). For a step-by-step guide through the design process see Street *et al.* (2005). The design allowed the estimation of the main effects of the six variables and a two-way interaction between two of them. This enabled the interaction between IS Customisation and governance mode to be assessed. While theory maintains that this interaction is relevant (see Williamson, 1996) no statistical support was identified in this sample and we therefore omit this interaction from the analysis.

Table 1. Experimental Variable Definition and Sources

Operational Definition	*Research Sources*
Tangible IS Resources: This is the scope of electronic IT service technologies. It is the proportion of IT service requests that can be handled through electronic technologies (such as remote access). Attribute levels: 25%, 75%.	Resources are assets such as plant, equipment and systems that enable a firm to perform activities (Barney, 1991). Tangible IS resources include computer systems. IS resources can be a source of competitive advantage (Powell & Dent-Micallef, 1997).
Intangible IS Resources: This is how strong an IS provider the firm is, as measured by the proportion of its 50 IT staff that possess tertiary or equivalent industry-standard accreditation. Attribute levels: 50%, 90%.	Implementation of IS requires human and organisational factors (Brynjolfsson & Hitt, 2000; Larsen, 2003). Powell & Dent-Micallef (1997) found that performance was largely attributable to intangible IS resources. Framing here drew on Poppo & Zenger (1998) who asked "does performing this function require personnel with extensive knowledge and skills?"
IS Customisation: This is the proportion of IT services that need to be specifically customised to the firm (as opposed to being standard processes that are used across the industry). Attribute levels: 25%, 75%.	The measure captured custom processes (Poppo & Zenger, 1998) based on the scale validated by Heide and John (1990). The related construct of standardisation was based on Pilling *et al.* (1994) that balanced "procurement of a customised component" against "purchase of a standardised component"
Cost Advantage: This is the cost efficiency of the offering as measured by how much more or less than the industry average is spent on a given level of service. The difference between these levels would translate into a $50,000 or 0.2% profit increase. Attribute levels: –0.25%, +0.25%.	Cost advantages provide a competitive advantage over rivals. Firms with lower costs are insulated from competition because they can make profit even when matching the prices of rivals (Porter, 1980).
Competitive Intensity: Frontline industry competition states how much rivalry the firm faces in its markets. It is the number of competitors that provide similar offerings. Attribute levels: 2 rivals, 10 rivals.	Entry barriers provide firms with market power allowing them to charge buyers higher prices (Bain, 1951; Porter, 1980). Market power exists when firms face few competitors (Bain, 1951).
Governance Mode: Whether IS is an in-house (i.e., internal) unit that is part of the same company, or an outside (i.e., external) provider to which the firm has outsourced end-user IT support services. Attribute levels: Internal, external.	Using a categorical governance mode variable is well established in the literature (Masten, 1984; Walker & Poppo, 1991). The experimental method allowed a strict distinction between market (outsourced) and hierarchical (in-house) governance avoiding hybrid forms (Rindfleisch & Heide, 1997).

Respondents were asked to indicate their most preferred and least preferred option in each choice set (i.e., which was 'best' and which was 'worst' of those presented). This draws on behavioural evidence that indicates participants are much better at making yes/no decisions (Thurstone, 1927). This decision question allowed a full ranking of the options to be constructed and produced an information matrix that was 100% efficient (El Helbawy & Bradley, 1978; Street *et al*., 2005). The required sample size was calculated by applying statistical theory to the asymptotic properties of the sample distribution (Louviere *et al*., 2000, p. 262). A sample size of 48 is required to achieve a relative accuracy of 10% at a probability of 0.95. The sample size of 75 surpassed this substantially. Finally, non-response bias was evaluated using ex-post statistical techniques. This testing indicated no significant differences between early and late respondents (Armstrong & Overton, 1977).

Empirical Results

Statistical analysis of the data was based on a conditional multinomial logistic (MNL) regression (McFadden, 2001). The MNL model makes certain assumptions about the distribution of errors that must be tested before progressing to an examination of the model parameters. Correlational analysis and the Hausman and McFadden (1984) specification test were applied to test the independence of irrelevant alternatives (IIA) assumption of the MNL model. These tests supported the IIA requirement that the presence or absence of alternatives has no impact on the utility of the selected option.

Table 2 summarises the performance of the MNL models for the non-accelerated and accelerated groups. The MNL models effectively described decision-making, producing likelihood ratio chi-squares of 640.055 and 687.121. Significant likelihood ratio tests strongly supported the ability of both the models to explain the data ($p < 0.001$). These very low p-values reject the null hypothesis that the modelled relationships could occur by chance. The models explained a reasonable proportion of the variance in observed choices with pseudo R^2 results of 0.137 and 0.189 for the non-accelerated and accelerated groups respectively.

Table 2. Model Fit Statistics

	Information Acceleration	
	No	*Yes*
Dependent Variable:	Choice	Choice
Number of cases	34	41
Log likelihood	-439.924	-495.817
Pseudo R^2	0.137	0.189
Likelihood Ratio χ^2	640.0548 ($p < 0.001$)	687.1209 ($p < 0.001$)

The parameter results of the DCE attributes presented in Table 3 strongly support H1. Main effects of the three research attributes (i.e., tangible IS resources, intangible IS resources and IS customisation) were all highly significant and their coefficients were in the hypothesised directions. Information systems resources had a very strong impact on decision making. Managers preferred higher levels of tangible IS resources. The influence of tangible IS resources was higher for the accelerated group ($\beta = 0.395$, $p < 0.001$), although it was still strongly positive in the non-accelerated group ($\beta = 0.243$, $p < 0.001$). Subjects in both groups weighed tangible IS resources as one of their main two influences. Choices also favoured higher levels of intangible IS resources in the non-accelerated ($\beta = 0.216$, $p < 0.001$) and accelerated ($\beta = 0.235$, $p < 0.001$) groups. The positive coefficient showed that subjects preferred IS service strategies that involved higher levels of intangible IS resources. Observed choices also showed that higher utility was associated with higher levels of IS customisation. The preference for a more customised offering was significantly positive in both the non-accelerated ($\beta = 0.189$, $p = 0.001$) and accelerated ($\beta = 0.390$, $p < 0.001$) groups. This supported H1 suggesting that managers sought customisation that could generate advantage through specialisation (Porter, 1980; Barney, 1991).

Table 3. Model Parameters

	Information Acceleration							
	No				Yes			
	B	*SE*	*z*	*Sig.*	*B*	*SE*	*z*	*Sig.*
Research variables								
Tangible IS Resources	0.243	0.053	4.619	0.000	0.395	0.051	7.683	0.000
Intangible IS Resources	0.216	0.053	4.112	0.000	0.235	0.051	4.610	0.000
IS Customisation	0.189	0.055	3.430	0.001	0.390	0.056	6.956	0.000
Control variables								
Cost Advantage	0.265	0.053	5.027	0.000	0.378	0.051	7.366	0.000
Competitive Intensity	-0.218	0.053	-4.135	0.000	-0.140	0.051	-2.754	0.006
Governance Mode	0.117	0.051	2.295	0.022	0.055	0.047	1.160	0.250

The practical implications for the selection of IS service strategies was evident in the impact of the shift in attribute levels on the propensity to select a particular IS service strategy (i.e., a bundle of attributes in a given option). Table 4 shows how each shift in attribute level impacted aggregate decision-making. From this analysis, we see that tangible IS resources had a very strong impact on decision-making, with a shift in level increasing the odds of selection of that alternative by 27.48% ($p < 0.001$) for the non-accelerated participants and 48.36% ($p < 0.001$) for the acceleration group. Managers also preferred IS service strategies involving higher levels of intangible IS resources with both groups approximately 25% more likely to select a strategy involving the higher level of intangible IS resources ($p < 0.001$). The propensity to choose a more customised IS offering was also strongly positive in both the non-acceleration (20.78% increase in odds of choice, $p = 0.001$) and IA groups (47.64% increase in odds, $p < 0.001$).

Testing H2 required a comparison of the performance of the MNL models between the non-accelerated and accelerated groups. Comparing the pseudo R^2 results of 0.137 and 0.189 for the non-accelerated and accelerated groups demonstrated a 38% improvement in the systematic variance explained for the group receiving the IA. A likelihood ratio test of the improvement in the ability of the model to characterise the decision-making of accelerated participants produced a test statistic of 13.96 (7 df). This indicated a significantly improved ability to explain the preferences of the accelerated participants (p = 0.026). These results show that the IA improved the ability of the model to capture the choices made.

Table 4. Attribute Impact on Odds of Selection

		Information Acceleration	
		No	Yes
	Attribute Levels	*Impact on Odds of Choice*	
Research variables			
Tangible IS Resources	25% of requests online: 75% of requests online	27.48%***	48.36%***
Intangible IS Resources	50% of staff accredited: 90% of staff accredited	24.09%***	26.43%***
IS Customisation	25% processes customised: 75% processes customised.	20.78%***	47.64%***
Control variables			
Cost Advantage	0.25% cost disadvantage: +0.25% cost advantage	30.34%***	45.88%***
Competitive Intensity	2 BU competitors: 10 BU competitors	-19.62%***	-13.06%**
Governance Mode	Outsourced (external): In-house (internal)	12.39%*	5.65%

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

Table 5 presents Wald tests comparing the attribute coefficients across the two groups. Consistent with H2, all three relationships were strengthened in the expected direction for the IA group, and two of the three were statistically significant ($p < 0.05$). An increase in tangible IS resources associated with a level increase from 25% to 75% of requests handled online increased the coefficient from 0.243 for the non-accelerated group to 0.395 for the accelerated group, producing a significant Wald statistic of 4.263 ($p = 0.039$). The accelerated participants also placed greater positive weight on the possession of intangible IS resources. This finding was consistent with H2, though the coefficient was not statistically significant. Accelerated participants also chose significantly higher

IS customisation ($p = 0.011$). The coefficient increase of 0.201 for the IS customisation attribute for the accelerated group showed that the choices of accelerated participants were more strongly influenced by the level of IS customisation present. These results support H2 that the attenuation of the main effects of these attributes due to uncertainty was reduced by the provision of the IA.

Table 5. Difference Score Wald Test

	Diff.	*Wald*	*Df*	*Sig.*
Research variables				
Tangible IS Resources	0.152	4.263	1	0.039
Intangible IS Resources	0.019	0.065	1	0.798
IS Customisation	0.201	6.545	1	0.011

This application illustrates ways in which the combined DCE and IA approach can improve measurement. H1 was strongly supported showing that the DCE method is able to effectively explain decision-making structures. The results confirmed expected preferences suggested by IS theory (i.e., the decision models captured in the DCE were consistent with the hypothesised roles of tangible IS resources, intangible IS resources and IS customisation). Importantly, the IA was able to address response variability by experimentally addressing differences in uncertainty. As suggested in H2, the implementation of the IA improved the model fit and strengthened the observed systematic effects. The improvement in pseudo R^2 represented a shift between systematic and random variance that significantly reduced the role of error in the choices made.

The practical insights are also meaningful. Addressing uncertainty through the IA led to an altered picture of the preferences of the participants. In particular, IS customisation moved from being ranked the fourth most important influence on the IS service strategy in the non-accelerated group to being the second most important in the accelerated group. Without the IA a researcher would find that IS customisation was a lesser concern than cost advantage and intangible IS resources; however, after adjusting for uncertainty IS customisation was amongst the most important features in the decision models of these managers. This result is also important for academics as it suggests that unless uncertainty is controlled, one cannot be certain whether an observed result is due to systematic preferences or merely an artefact of model specification in the presence of response variability. Salisbury and Feinberg (2010) have recently reported on potential instances of this type of spurious effect in influential marketing studies.

Discussion

This paper aims to contribute to the diffusion of new quantitative methodology by demonstrating the tractability of a joint DCE/IA method in addressing: (1) conceptual issues around improving explanation and prediction, and (2) methodological issues caused by heterogeneous preferences and response variability. Brynjolfsson and Schrage (2009) argue that the future of organisational innovation will depend on experimentation that can be performed quickly and cheaply. Discrete choice measurement is a behaviourally grounded approach well suited to the explanation of complex, combinatorial decision-making processes used by IS managers. By combining DCE methods with IA, we have shown how multimedia tools can be used to provide managers with the insight and foresight required to develop more effective prediction of alternate IS configurations.

Our approach recognises that managers must, regularly, make choices among alternatives representing complex trade-offs between the perceived benefits and costs. Identifying methods that are aligned with such decision-making realities is a major challenge for IS researchers. Discrete choice experimentation is well suited conceptually, with the experimental design providing greater control over alternate explanations. This more clearly establishes the role of attributes and provides a better understanding of decision models. The conceptual usefulness of the results is also enhanced by the improved ability to predict beyond the current sample into the future. The linking of the combined DCE/IA method to broader behavioural theory provides a sound basis for out-of-sample prediction. From a methodological perspective, IA also provides a tool for addressing misspecification artefacts due to response variability. Response variability is a reality in preference measurement that needs closer attention (Swait & Louviere, 1993; Salisbury & Feinberg, 2010). DCE without IA is dangerous—as heteroscedastic error (i.e., variation in the random component) can lead to attenuation of underlying relationships as identified in our empirical illustration and even spurious substantive effects (Salisbury & Feinberg, 2010).

The combination of DCE and IA provides control over the composition of options and provision of information, directly addressing limited search processes and imperfect information filters (Simon, 1955; March & Simon, 1958). We believe that it is better to control for such assumptions in the experimental design phase, and to evaluate options experimentally designed to limit, and if desired exclude, unwanted artefacts. The IA applied here was able to control for such features, allowing significantly clearer observation of decision-making.

Improved specification of statistical models is also needed to fully account for response variability differences. Existing Hierarchical Bayes (HB) and Latent Class (LC) models need to be extended to allow specification of the scale parameter that can confound the estimation of coefficients (Magdison & Vermunt, 2007). We strongly believe that HB or another generalisable version of the MNL model, like the generalised multinomial logit model (see Fiebig *et al*., forthcoming), will eventually become widely accepted. In the interim, IA provides a tractable experimental method that IS researchers can apply using common statistical packages.

In addition to future research applying the IA approach in different business contexts, opportunities exist for combining the method with more traditional IS survey techniques. DCE/IA can be combined with both revealed data on performance implications or simulation modelling to allow evaluation of the performance implications of these decision models (see Louviere *et al*., 2000). The nature of DCE lends itself to the simultaneous collection of survey material that can supplement experimental results; for instance, individual-level covariates can be easily collected by a short follow-up survey after a DCE is completed. This would allow the evaluation of the performance of IS strategies and would represent an important contribution in linking IS strategy process and IS strategy content, strengthening the validity of IS research. The data can also be used to improve practical outcomes by embedding the model in a decision support system to provide an interactive tool for training decision-makers (Little, 1970). Recent advances in DCE also allow individual models to be estimated through the collection of full rank orders across options presented (Louviere *et al*., 2008). The designs needed to achieve this are not overly large, with the eight choice set, three option design used in this study suitable.

In sum, our empirical application shows how IA can contribute to an understanding of IS. Information acceleration might be considered a missing piece in quantitative modelling because it can address between-subject differences in uncertainty. Without this, within-subject DCE analysis provides only half the story and is subject to risks from decision biases around uncertainty. Information acceleration reduces the level of uncertainty and generates more accurate parameter estimates that better explain investment decisions in IS service strategies. The combined DCE/IA method gives researchers an essential foundation stone: confidence that substantive effects are true.

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