Decision Support Systems 97 (2017) 58–68

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Patterns of business intelligence systems use in organizations

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ARTICLE INFO

Article history:
Received 9 June 2016
Received in revised form 12 March 2017
Accepted 12 March 2017
Available online 21 March 2017

Keywords:
Business intelligence
Decision support
Use patterns
Behavioral economics
Case study
Secondary analysis

ABSTRACT

Business intelligence (BI) is often used as the umbrella term for large-scale decision support systems (DSS) in organizations. BI is currently the largest area of IT investment in organizations and has been rated as the top technology priority by CIOs worldwide for many years. The most important use patterns in decision support are concerned with the type of decision to be supported and the type of manager that makes the decision. The seminal Gorry and Scott Morton MIS/DSS framework remains the most popular framework to describe these use patterns. It is widely believed that DSS theory like this framework can be transferred to BI. This paper investigates BI systems use patterns using the Gorry and Scott Morton framework and contemporary decision-making theory from behavioral economics. The paper presents secondary case study research that analyzes eight BI systems and 86 decisions supported by these systems. Based on the results of the case studies a framework to describe BI use patterns is developed. The framework provides both a theoretical and empirically based foundation for the development of high quality BI theory. It also provides a guide for developing organizational strategy for BI provision. The framework shows that enterprise and smaller functional BI systems exist together in an organization to support different decisions and different decision makers. The framework shows that personal DSS theory cannot be applied to BI systems without specific empirical support.

1. Introduction

Business intelligence (BI) is often used as the umbrella term for large-scale decision support systems (DSS) in organizations. Surveys by industry analysts and vendors consistently find that BI development and deployment is one of the highest priorities for CIOs and will remain so at least until 2017 [26,30,33,54]. Kappelman et al. [38] in the annual *SIM IT Issues and Trends Study* reported that BI was the largest organizational IT investment in 2015, and has been the largest since 2009. Put simply, BI is one of the most important IT applications in an organization and is expected to remain so for some time.

It is important to distinguish between the general IS movement of BI/Analytics/Big Data and the IT artifacts that are used in organizations. This project focuses on the IT artifacts that are BI systems. Davenport's definition is used to guide the research: a BI system is “a wide array of process and software used to collect, analyze, and disseminate data, all in the interests of better decision making” ([17], p. 106). BI systems can be defined by their organizational scope. The most complex systems that support management decision-making, enterprise BI systems, are usually developed by the central IT department to support as many managers in an organization as possible. At a minimum, they have users from more than one division. The data available to an enterprise BI system is organization-wide in scope and interest and often comes from a data warehouse (DW) or a federation of data marts. A second type of BI system, functional BI, is where development is restricted to one division, department, or function and the governance of the system is the responsibility of that business unit rather than the IT department. Most commonly functional BI systems have their data provided by a specialized data mart. When vendors, consultants, and researchers talk about BI, they usually mean enterprise BI systems.

Use patterns in decision support are normally concerned with the type of decision to be supported and the type of manager that makes the decision. The reason for this focus is that the type of task and type of user in DSS are fundamentally different from the users and tasks supported by enterprise transaction-based, web-based, mobile, social systems, and other IS. The decision/manager focus is unique to DSS and is central to understanding BI systems. A review of BI case study research in all journals and the four major AIS conferences (ICIS, ECIS, PACIS, AMCIS) from 2000 to 2016 found 68 papers. Of these, 13 addressed BI systems use in some way. None addressed decision maker and decision type use patterns. This means that BI use patterns is a gap in the BI research literature.

In terms of BI systems use by managerial level, Negash [57] related that “BI assists in strategic and operational decision making” (p. 179) and that “Business intelligence is used by decision makers throughout

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http://dx.doi.org/10.1016/j.dss.2017.03.005
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the firm. At senior managerial levels, it is the input to strategic and tactical decisions. At lower managerial levels, it helps individuals to do their day-to-day job." (p. 189). Audzeyeva and Hudson [8] argued in their study of BI benefits that "Key organizational benefits of BI … include better management decisions at both middle management and strategic levels and support for the accomplishment of strategic business objectives." Arnott and Pervan [7] as part of a critical analysis of 25 years of general DSS research examined the level of decision tasks addressed in BI research. They found that 22.5% of BI research concerned strategic decision tasks. Isik et al. [35] reported "many companies currently utilize BI primarily for structured decision making based on internal data" (p. 14). Collectively this means that, to some extent, BI aims to address many types of decision making in organizations.

Based on this discussion, the phenomenon of interest of this project is the pattern of use of BI systems in organizations. The unit of analysis is a BI system, a large-scale IT artifact that supports decision making in organizations. The formal research question that guided this project is "What are the patterns of BI systems use in organizations?" The paper is organized as follows: first, the theory background and the design of the secondary case study research is described. Case study research involving eight BI systems is then described and analyzed. From the cross-case analysis a framework for the pattern of BI systems use in organizations is developed. After considering the limitations of the research, the paper concludes with a discussion of the academic and professional implications of the research.

2. Theory background

To explore the patterns of BI systems use, two groups of theory were used. The first is the seminal framework of Gorry and Scott Morton. The framework led to the development of the DSS field and is still influential in DSS and BI research. The second theory background is the dominant contemporary approach to understanding human decision-making from behavioral economics. This is followed by a note about the transfer of theory between DSS types and the nature of frameworks in IS theory.

2.1. The Gorry and Scott Morton framework for decision support systems

Defining management processes and decision-making tasks in three level typologies has been a persistent theme in business research since the 1960s. These typologies have attained paradigm status and are often used without citation (for example, [1,2,63]). The most popular management process typology is Anthony's strategic planning/management control/operational control continuum [3]. According to Anthony and Dearden [4] strategic planning is the process of deciding on the goals of the organization, the resources needed to attain these goals, and the policies for acquisition and use of these resources; management control is the process by which managers assure that resources are obtained and used effectively and efficiently in the accomplishment of the organization's goals; and operational control is the process of assuring that specific tasks are carried out effectively and efficiently. The process typology is not isomorphic with management tiers but is in a sense related. For example, an executive who is at the highest level of an organization can tackle strategic and tactical tasks and use a range of operational and management control processes. However, the general argument is that the higher that a manager is in an organization the more likely they will be to use strategic planning processes and make strategic decisions. Anthony's typology is widely accepted in business research and critiques are rare. An exception is Langfield-Smith [47] who argued that in terms of management accounting "the artificial boundaries between, operational, managerial and strategic control, as initially described by Anthony [3], may no longer hold." (p. 209). Most IS researchers view Anthony's typology as a continuum rather than discrete categories.

The three-level typology of decision tasks that has reached paradigm status is Nobel Prize winner Herbert Simon's phase model of decision-making [67,68]. The phase model views decision making as taking place in three staged, iterative and recursive processes of intelligence (gathering data), design (arriving at alternative solutions), and choice (choosing the best alternative). An important part of the phase model is the concept of decision structuredness. A totally structured decision is one where all decision phases can be specified; a totally unstructured decision is one where no aspect of the decision phases can be articulated. Lying on a continuum between structured and unstructured decisions are semi-structured decision tasks that exhibit varying degrees of structure or clarity of definition and understanding.

The seminal article of the general DSS discipline is the 1971 paper *A Framework for Management Information Systems* by Anthony Gorry and Michael Scott Morton. Their framework was based on a combination of Anthony's management process and Simon's decision structuredness typologies and is shown in Fig. 1 ([28], p. 62). The tasks below the dotted line in Fig. 1 have decreasing levels of structure and Gorry and Scott Morton termed the IS that can support these tasks "decision support systems". Above the line they typified IT support as structured operational IS; today many of these would be regarded as DSS. The important implication is DSS can support most of the cells in the framework. Further, they argued that over time, with increasing research and practice, the line would move down the figure as semi-structured tasks become structured. In Fig. 1, structured operational control tasks are the easiest for an IT professional to conceptualize and then develop systems to support. Keen and Scott Morton [41] suggested that unstructured tasks, especially the bottom right hand of Fig. 1, are mainly supported by human intuition. Kirs et al. [44] provided an experimental validation of the Gorry and Scott Morton framework that, at the time, justified the framework's seminal position.

Gorry and Scott Morton's framework is one of the most important contributions to DSS research and with 2233 citations[1] it is one of the most cited papers in all IS research. Fig. 2 shows citations of the framework over time and the most interesting aspect of the figure is that the 1971 framework is more popular with researchers today than when it was published. The DSS framework has attained paradigm status and is often used uncritically as the basis of recent research. For example, Isik et al. [35] in developing their project's hypotheses relate: "Gorry and Scott Morton's [28] framework of management information systems is a well-established, theoretically grounded representation of the decision environment." (p. 16).

The main issue with the Gorry and Scott Morton framework is the validity of Simon's phase model of decision making – the source of the vertical axis of the framework. Simon's phase model was developed in the 1940s and Simon's is a different kind of scholarship to current business research; most of Simon's publications would now be classified as conceptual studies. The nature of business and behavioral science research is radically different today and the standards of rigor and validity, and the statistical techniques that are currently used, did not exist when Simon developed his theory of decision-making. The problem is as Lipschitz and Bar-Ilan [49] relate "Considering the variety and ubiquity of phase models, it is surprising to find that the empirical evidence for their descriptive and prescriptive validity is very slim." (p. 48). Lipschitz and Bar-Ilan conducted experimental research that found disconfirming evidence for the phase model's prescriptive validity and only weak support for its descriptive validity. The conclusion from the empirical testing of the phase model is that it lacks the necessary scientific validity to be part of an important and influential framework like Gorry and Scott Morton's. Another issue with the Gorry and Scott Morton framework is that, like Simon's research on decision making, it is a conceptual study and the assignment of decision tasks and systems in the framework was based on opinion, rather than on empirical research.

[1] Google Scholar, February 2017.

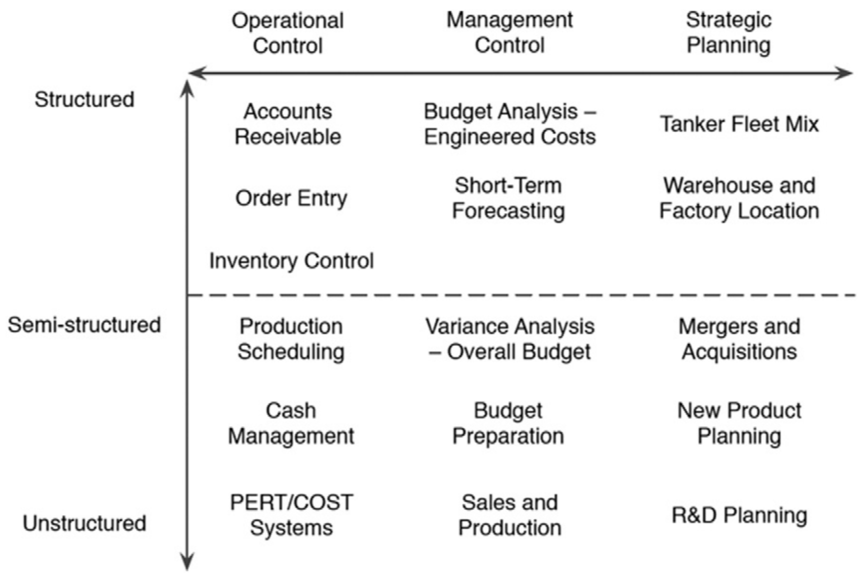

Fig. 1. Gorry and Scott Morton's MIS/DSS framework.

2.2. The dual process theory of decision cognition

The dual process theory of decision cognition is the successor to Simon's phase model of decision making in behavioral economics. The dual process theory holds that decision-making occurs within and between two cognitive systems. Kahneman and Frederick [37] typified these systems as two families of cognitive operations; they are not a continuum like the concept of decision structuredness. In an influential paper, Stanovich and West [71] termed these systems System 1 and System 2 in order to avoid descriptive labeling and terms have become standard. Table 1 is partly based on Thaler and Sunstein ([73], Table 1.1), Evans ([25], Table 2), and Stanovich and West ([71], Table 3) and shows the properties and nature of the two cognitive systems.

System 1 is fast, automatic, effortless, and intuitive. When facing a decision, System 1 is the first in action. It operates through innate, instinctive behavior. In an evolutionary sense, System 1 is the oldest form of decision-making ([71], p. 660; [36], p. 301). It is difficult to explain or document how System 1 arrives at a decision, we only know it has when the decision enters our consciousness. System 2 is slow, deliberate, and requires significant cognitive effort. The complex System 2 evolved uniquely in humans. System 2's abilities are not innate and must be formed through education, both formally in schools and universities, and less formally in families, the work place, and social interaction. The essence of System 2 is the application of a set of rules or algorithms to a decision task.

While described as discrete systems, System 1 and 2 can operate at the same time and can interact. Evans [24] described the situation as being like two minds in the same body. Kahneman and Frederick [37] related: “System 1 quickly proposes intuitive answers to judgment problems as they arise, and System 2 monitors the quality of these proposals, which it may endorse, correct, or override.” (p. 51). Control can also pass from System 2 to 1. System 1 is associated with expertise and expert judgment while System 2 is the realm of the calm rational advisor, but also the learner and novice. Over time System 2 tasks can be converted to System 1 through exposure and experience.

Far from being ineffective or second rate, in management decision-making the fast, intuitive processes of System 1 can lead to superior outcomes compared to System 2 rule-based processes [20,45,59]. Both difficult and strategic management tasks will likely be System 1 dominant and a decision maker's conception of such tasks is likely to be volatile [16]. System 2 managerial tasks are likely to be more stable in their internal representation. Knowing when to replace System 1 intuitions with System 2 rules and algorithms is a difficult decision for both managers and analysts. It is also a decision that depends on context, particularly the skills and experience of the decision maker. Bazerman and Moore [9] argued that “a complete System 2 process is not required for every managerial decision, a key goal for managers should be to identify situations in which they should move from the intuitively compelling System 1 thinking.” (p. 4). It may also be preferable to move away from Systems 2 processes in some situations.

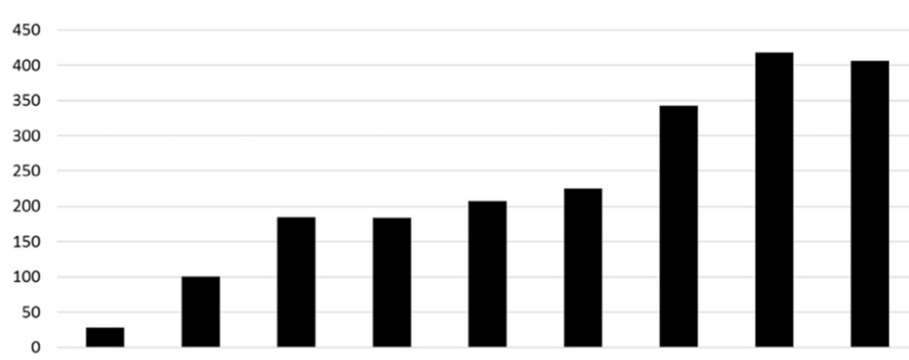

Fig. 2. Citations to the Gorry and Scott Morton framework.

Table 1
The two cognitive systems of decision making.

System 1	System 2
Unconscious	Conscious
High capacity	Low capacity
Automatic	Controlled
Holistic	Analytic
Associative	Rule based
Effortless – undemanding of cognitive capacity	Effortful – demanding of cognitive capacity
Fast	Slow
Skilled	Rule following
Highly contextualized	Decontextualized
Personalized	Depersonalized
Acquisition by biology, exposure, and experience	Acquisition by cultural and formal tuition

2.3. A note on DSS theory transfer and frameworks

Clark et al. [15] identified a broad class of applications that support management decision-making that they established were separate from operational enterprise IS. Through their meta-analysis they found that DSS need separate theory to explain and predict the outcomes of DSS development and use. Further, they argued that theory developed in one form of DSS should apply to others, both to current and future management support approaches ([15], p. 603). However, their work was undertaken before BI became the norm in industry and it could be that DSS theory transferability does not always apply to BI. In addition, Hong et al. [32] and Davison and Martinsons [18] argue that context is critical to a theorizing process in the IS discipline. Table 2 shows an analysis of the context of enterprise BI systems compared to other IS.

The table was developed with structured input from BI academics and practitioners using a two round Delphi-like approach. It shows the degree of similarity of enterprise BI to the other system types; the average score is below medium similarity. Importantly, it shows that in terms of system scope and scale, enterprise BI systems are very close to operational enterprise IS compared to traditional personal DSS. The context differences in the table mean that theory from traditional personal DSS cannot be uncritically applied to BI. BI systems are not just data-driven DSS, they are a complex mix of data and analytics. Any theory transfer needs to be based on BI specific empirical testing of the theory.

Frameworks are important to IS research. A framework is defined as a "set of assumptions, concepts, values, and practices that constitutes a way of understanding the research within a body of knowledge" ([62], p. 41). Weber [76] argued that research frameworks can "provide guidance in relation to the development of new, high-quality theory". Weick [77] expressed this guidance situation as an "interim struggle". Weick argued that academic artifacts, like empirically and theoretically grounded frameworks, represent an important stage in the theorizing process and are therefore important for an academic discipline. Some scholars propose that a framework can also be regarded as a theory. Gregor [29] argued that a framework is a Type I theory or a theory for analyzing. Gregor [29] related "Analytic theories analyze "what is" as opposed to explaining causality or attempting predictive generalizations." (p. 622). Frameworks are common outcomes of IS research. Influential examples include Al-Mudimigh et al. [2], Lee et al. [48], Shang and Seddon [65], and Weill [78]. The theory background in this project also involves research frameworks, although factor models underlie one of these frameworks. Further, the major outcome of this research project is a framework in the sense of Gregor's Type I theory. As Sutton and Staw [72] relate "Data describe *which* empirical patterns were observed and theory explains *why* empirical patterns were observed or are expected to be observed." (p. 372). In this sense, the framework developed later in this paper can be characterized as a kind of theory.

Table 2
A comparison of different types of business IS.

System attribute	Degree of similarity with enterprise BI systems	
	Traditional personal DSS	Transaction processing systems/ERP/ecommerce
Scope	Low	High
System scale	Low	High
Task	Medium	Low
Users	Medium	Low
User discretion	Medium	Medium
Technology	Low	Low
Development methods	Medium	Medium
Governance	Low	Medium
Overall	Low/medium	Low/medium

3. Research design

In order to investigate the patterns of use of BI systems a case study approach was adopted. A case study allowed the detailed study of both the decisions being supported by BI systems and the nature of the systems use by a variety of users. The authors had previously investigated BI development and use in case studies involving eight BI systems. It was decided to pool the case data from these projects to investigate the research question of this project.

3.1. Secondary qualitative analysis

The style of case study and theory-building research in this paper can be called case study using secondary analysis. Secondary analysis "allows researchers to put to new or additional uses data that were originally collected for other research purposes" ([31], p. 8). There is a long history of the secondary analysis of data from quantitative studies in social science [74]. Meta-analysis is perhaps the best-known form of secondary analysis. It is "a quantitative combination of the statistical information from multiple studies of a given phenomenon" ([14], p. 33). Examples of quantitative secondary analysis in IS research include Dennis et al. [19], Kohli and Devaraj [46], and King and He [43].

Qualitative secondary analysis is much less common in social science research and there is often a fuzzy dividing line between what constitutes the use and re-use of case study data [27]. For interpretive researchers, data is socially constructed and the re-use of data is simply a different construction. In this sense, there is no conceptual difference between primary and secondary data. Case data can be reused in different publications without any reference to reuse, reanalysis, or reinterpretation. For other qualitative researchers, the division between use and reuse is clearer. Using data that was collected to address a specific research question to answer a new question is secondary analysis. The main issue with qualitative secondary analysis is the potential for a lack of fit between the available data and the requirements of a secondary analysis ([27], p. V3–110). This fit can be assured and data from different cases can be combined if the primary cases studied similar phenomena, had similar units of analysis, and used similar data collection techniques. They do not need to have had similar research questions. For example, in the case studies below each participant was asked to think about a decision they had made that was supported by a BI system. For this interview question, the data collection in the case studies can be considered "similar".

A major advantage of secondary qualitative analysis is a significant increase in empirical quantum. This increase in the amount of data leads to greater generalizability of qualitative research. Most BI case study research examines one BI system (for example, [8,11,75]). The secondary analysis in this paper examines eight BI systems and involved 38-person months of work in data collection and analysis. This represents a significant increase in research scale over other published BI case study research. The nuances and meaning of case study data is best understood when the primary researcher is deeply immersed in data gathering, analysis, and interpretation. For this reason, secondary qualitative analysis is likely to be of higher quality if it is conducted by the primary researchers.

3.2. General case research design

This paper involves theory-building case study research as suggested by Cavaye [12], Eisenhardt [23], and Woodside and Wilson [80]. Each case study in this paper used a “common” single-case design ([82], p. 52) with a BI system as the unit of analysis. Cases were sourced opportunistically through business and professional networks. The selection criteria for the cases were similar. The mandatory case selection criteria were that the BI system had been in operation for at least two years and that the researchers have access to all relevant BI developers and users for interviews. The BI users included both direct and indirect users. The desirable but not mandatory selection criteria were that the researchers could observe BI governance committees and have access to relevant project documentation.

Each case's primary data collection involved semi-structured interviews of between 40 and 70 min. Where possible, the interviews were audio recorded. Only one organization declined approval for the audio recording of their staff during interviews while senior executives generally declined audio recording. For interviews without audio recording notes were taken during the interview. Transcripts of the audio recordings of the interviews and interview notes were entered into the qualitative data analysis software NVivo. In each case, documents about the BI systems were collected. These documents varied by case and included governance committee agendas and minutes, business cases, and the technical architecture of BI systems. The studies were contemporaneous. For the secondary data analysis, all coding and matrix construction from the primary analyses was abandoned. Using the primary NVivo databases each case interview transcript was reexamined using codes derived from and the theory background in Section 2; this is termed hypothesis coding ([61], p. 147). The analysis tactics that were employed included clustering, noting patterns and themes, and partitioning variables ([56], ch. 11).

4. An intensive exploration of eight BI systems

This section presents the case studies of eight BI systems. First, the nature of the case organizations and the BI systems is described. This is followed by the cross-case analysis.

4.1. BI case overviews

LGA (Large Government Authority) is a semi-autonomous Australian federal government authority. Headquartered in Melbourne, Australia, its annual operating revenue is A$1.5 billion and it has 11,500 staff. It is widely regarded as a highly effective public enterprise. Business IT services are relatively centralized at LGA following a transfer of most IT professionals to the central IT Division. Despite this centralization, executives and managers have considerable discretion in how they personally source IT services for decision support. Three BI systems were studied at LGA: BIS (the Business Intelligence Service), PAS (the Planning and Analytics System) and Prospector (analysis and management of prospective customers). All developers of all three systems were interviewed, as were 32 BI users. These users included executives, middle managers, senior analysts, and business analysts. Some participants agreed to multiple interviews. In addition, 18 meetings of the BI Steering Committee over four years were observed.

BIC (Big Insurance Company) is an Australian insurance provider headquartered in Melbourne, Australia with branches in all Australian states and territories. BIC works as an intermediary between providers, agencies, and brokers. It employs over 4000 employees and its operational revenue is A$11 billion. Its organization structure is functional for finance and legal, and divisional for marketing, sales and operations. BIC is part of an insurance conglomerate that is pursuing a strategy based on cost savings through the coordination of its component companies. BI systems in BIC have evolved from a decentralized approach in which BI systems were implemented by each department to a centralized enterprise BI system. The BI project is part of the CFO's office rather than being driven by IT. The main profile of the BIC participants was senior management. Twenty-two users were interviewed; seven direct users and seven indirect users matched with their eight intermediaries. These intermediaries were senior analysts or managers that used the BI system on behalf of more senior users. The 22 participants came from four business areas and five functional areas. In addition, three BI developers including the BI Director were interviewed.

CIC (Chinese Insurance Company) is a large insurance company offering life insurance products and services to the Chinese domestic market. Headquartered in Northern China its annual operating revenue is ￥2.6 billion and it has around 5000 staff. The company was founded in 2002 as a joint venture by Chinese and Canadian firms; it transferred to total Chinese control in 2010. IT services are centralized at CIC's headquarters, but business departments employ their own business analysts. CIC has a centralized BI system with enterprise wide scope called CMS (Core Management System). Twenty participants who were either users or developers of CMS were interviewed including a general manager, deputy manager, project managers, business analysts, operation manager, finance planner, and marketer.

AG (Alibaba Group) is a very large Chinese ecommerce company that offers a complex mix of products and services, both domestically and internationally. Headquartered in Hangzhou its annual operating revenue is ￥76.2 billion and it has around 22,000 staff. The company was founded in 1999 and was floated on the NYSE in 2014 in the world's largest ever IPO (US$25 billion). AG is the world's second largest retailer by value. AG has 25 business units, the most prominent of which are Alibaba, 1688, AliExpress, Taobao Marketplace, Juhuasuan, Alipay, Tmall, eTao, Alibaba Cloud Computing (ACC), and Laiwang. It also has two cross-group or cooperative departments: Alibaba Research and ICBU. Unlike the other case organizations, IT services are decentralized in AG and each business unit has their own BI team. Three major BI systems were studied at AG: Business Advisor (sales analysis platform), Taobao Indicator (consumer behavior analysis platform), and EDP (web-based ecommerce analytics platform). AG is typical of emerging entrepreneurial companies in China. Twenty-eight AG participants were interviewed. They included an executive, deputy directors, operation director, product managers, operation managers, technical experts, development engineers, and business analysts.

The combined case studies involved 142 in-depth interviews of BI users and developers, the analysis of 86 decisions supported by BI systems, and the four-year longitudinal observation of a BI Steering Committee. Table 3 summarizes the BI systems that were studied. All organizations except AG wished to remain anonymous and their identity has been disguised as a condition of university ethics committee approval.

4.2. Cross case analysis

4.2.1. General patterns of BI systems use

Table 4 shows the perceived user and decision profiles from the eight BI systems. The user profile data are reasonably accurate as they were based on system logs. The decision profile data were estimates provided by senior participants and represented their perception of the nature of the decisions that are supported by the BI systems. These perceptions turned out to be biased.

The finding that stands out in Table 4 is that the majority of BI users are professionals, not managers or executives. The enterprise BI systems (BIS, Actor, CMS) are the closest to the large-scale DSS stereotype and in these systems 81% of users are professionals. Interestingly in the

Table 3
The BI systems.

BI system	BIS	PAS	Prospector	Actor	CMS	Business advisor	Taobao indicator	EDP
System scope								
- Users	Enterprise	Enterprise	Functional	Enterprise	Enterprise	Functional	Functional	Enterprise
- Developers	Enterprise	Functional	Functional	Enterprise	Enterprise	Functional	Functional	Functional
General governance archetype	Federal	Feudal	Feudal	Business monarchy	IT monarchy	Feudal	Feudal	Feudal
No of users								
- Internal	450	250	50	100	100	100	250	400
- External	0	0	0	0	10	Millions	0	0
Level of delegation	High	Low	None	High	High	Low	Low	Low
User profile								
- Professionals	75%	68%	0%	90%	78%	73%	35%	70%
- Managers	20%	30%	70%	8%	20%	25%	60%	28%
- Executives	5%	2%	30%	2%	2%	2%	5%	2%
Decision profile								
- Operational	20%	30%	30%	20%	60%	50%	20%	55%
- Tactical	78%	40%	30%	70%	38%	42%	70%	40%
- Strategic	2%	30%	40%	10%	2%	8%	10%	5%
No of developers								
- Internal	7	1	1	47	5	1	1	1
- Consultants	>10	4	>10	4	>20	>10	>10	>10
Budget								
- Initial	A$8m	Confidential	Confidential	Confidential	¥5m	Confidential	Confidential	Confidential
- Annual	A$1.2m	A$200K	A$300k	Confidential	Confidential	Confidential	Confidential	Confidential
Main software	Business objects, oracle	Cognos, oracle	Salesforce	Futrix, business objects	Business objects	Proprietary AG software	Proprietary AG software	Proprietary AG software
Organization		LGA		BIC	CIC		AG	
Employees		11,500		4000	5000		22,000	
Annual revenue		A$1.5b		A$11b	¥2.6b		¥76.2b	

enterprise BI systems it was reported that only 33% of decision tasks were operational (the likely decision focus of professionals). The extreme case is BIC's Actor where 90% of users are professionals but only 20% of the supported decision tasks are operational. The use of intermediaries to access BI data may confound this data but, generally across the cases, the decision type profile is at odds with the user profile data. The reasons for this mismatch lie first in the difficulty of understanding Anthony's typology (confusing management process for levels in an organization), and second in the desire of BI developers and IT departments to be relevant and important to the organization.

Participants wanted to be important to their organization and they had a tendency to exaggerate the importance of their work even when participants were shown a card with Anthony's definitions during interviews. Users tended to inflate the level of their decision tasks and developers inflated the importance of the tasks that their system supports. This inflation was least for senior executive users and highest for technical BI developers. When participants in LGA were asked if the decision task distribution is likely to change in the next five years they unanimously reported that a greater percentage of strategic tasks will be supported by their system. The BIC BI Director believed that operational decisions were not the province of BI and related "*It's not a BI thing … operational reporting would be your day-to-day line management type of report*". Further, he wanted to completely shift effort from operational to strategic support. It is difficult to imagine that the sole use of a BI system would be to set or change the organization's goals or set an organization's policies in a strategic planning process. This participant probably equates "strategic" with "important" and in this sense his goal is understandable. The desire for BI system relevance and importance was evident in all the cases.

Table 4
Perceived user and decision profiles in the cases.

	Enterprise	Functional	All
User profile			
- Professionals	81%	49%	61%
- Managers	16%	43%	33%
- Executives	3%	8%	6%
Decision profile			
- Operational	33%	37%	36%
- Tactical	62%	44%	51%
- Strategic	5%	19%	13%

Although decision-makers can directly use BI systems to support their decision tasks, there are many scenarios where they delegate the use of the BI system to subordinates. The enterprise BI systems exhibited higher levels of indirect use than the functional BI systems (Prospector, PAS, Business Advisor, Taobao Indicator, EDP). Most BIC decision makers indicated that they preferred to delegate their access to an intermediary. BIC's National Personal Insurance Manager described the work pattern of a business analyst who uses Actor to support senior management: "(*BA's name*) *is part of our team, we discuss and talk about the reports… He sits in the same room with us and reviews them* (the BI reports), *so he hears us and contributes to the discussion… so he's not just the person who produces them, but he has a say in the interpretation…. I would probably feel uncomfortable if all he did was produce them….*" This is a radically different work pattern to that of operational IS analysts. A row in Table 3 identifies the general level of delegation of use in each system.

One of the key concepts in DSS development theory and practice is that the decision makers who are the potential users of a DSS can freely choose whether or not they actually use the system. They are regarded as discretionary users [6,41]. Building interest and commitment from these demanding users is crucial for ongoing DSS use [15]. On the other hand, the users of operational IS do not have a choice about their system use. The discretionary use characteristic of small-scale personal DSS (PDSS) is thought to transfer to other larger types of DSS [51, 69,81]. The case study analysis found that true discretionary use was rare in the eight BI systems. There was not one example of discretionary use in the AG or CIC systems. In CIC, the use of CMS (the enterprise BI system) is part of professional staff performance assessment. In all cases, intermediaries that were using a BI system on behalf of a more senior manager had no discretion in their system use. Once information was provided by intermediaries, the decision makers did have some discretion in how they used the BI system output.

A common pattern in the cases is exporting data from the BI system to another application for the actual decision support processes. Spreadsheets were the most popular final tool in the decision support chain but analytics software like SPSS and SAS also featured in the cases. A senior business analyst at AG related: "*I have to export data and calculate myself… the current BI system is operationalized and most suitable for checking up daily sales, but I am looking for yearly*". A decision can have many data inputs other than an enterprise BI system. For example, at BIC the CFO related: "*If you're going to do a pricing decision you would use the business intelligence …to get that data. The financial data may show you've got an issue. You'd then get the pricing actuaries to delve into their data, and they've got data that goes back 20 years, to do pricing*".

Another pattern in the cases was for senior personnel to not use BI systems, functional or enterprise. For example, the CEO at LGA said: "*BI is absolutely strategic to LGA*" but when asked what IT support he used for strategic decision-making he replied: "*My spreadsheets*". The Deputy CIO at CIC when considering senior use said: "*No executive will use it*". Supporting this view a senior user at CIC related: "*The CMS system is neither convenient nor easy to use. My colleagues and I all believe so*." These attitudes and practices of senior personnel make it difficult to provide meaningful support with a BI system. Five executives in the cases related that they had looked for data in their BI systems to help with a specific significant decision, but found none. Both LGA functional BI systems were developed because the IT Division had repeatedly refused to provide the applications. This is because the requests for development did not score highly enough in the IT Division's annual assessment of requested projects. These functional BI systems were developed because the divisions had financial discretion. When data is not available in an enterprise BI system, decision makers will seek other sources of information including PDSS and functional BI systems.

4.2.2. Management decision making and BI systems use

It is axiomatic that if a BI system exists to support decision-making in an organization then the BI developers need to have a good understanding of the organization's decision tasks and work with decision makers to improve the effectiveness of their decision making. This is a difficult and challenging environment for IT developers. It is an environment where functional BI systems seem to outperform enterprise BI systems.

In LGA the Deputy CIO who commissioned the enterprise BI system related that she didn't know the nature of decisions being supported by BIS while the BI Director said, "*We don't have a lot of visibility about the end result*". The result of these attitudes was a strong focus on getting the data structures and data sourcing "right" rather than understanding decision tasks. The assumption in this techno-focus is that once the data provision is in place then decision makers will make better decisions with the information from the BI system. This common belief that a greater volume and variety of high quality data presented by a BI system will inevitably lead to improved decision making has no empirical support and represents a strong assumption by developers.

Enterprise BI developers have more problematic relationships with their users than functional BI system developers. Personal DSS, where a relatively small system is developed for an individual manager, or a small group of managers, for a decision task, is the original form of DSS. PDSS developers work very closely with their manager to build an understanding of the decision task. A fundamental issue that enterprise BI developers face was articulated by an LGA analyst: "*You can't satisfy all the users you know… the users are different*". The question for developers becomes whose conception of the decision task is embodied in the BI system. The most problematic user/developer relationship occurs when a developer believes that they have considerable power in the development process and developers believe that they can decide what is developed. This is another example of an operational IS attitude. One of BIC's state managers described his perception of developer attitudes as: "*It's more, "well I don't understand why you'd need that so I'm not going to do* (develop) *it*"*.… At the moment we've got really black and white BI people*". Unfortunately, the BI cases show that a focus on decision-making is difficult in enterprise BI. In the functional BI systems at AG the developers did understand that decision-making should drive BI development. One said "*We need to unearth their system requirements, understand difficulties in their management…*". A similar attitude existed in the LGA functional BI systems. The Prospector analyst said, "*Because I've been embedded in Customer Relations for so long I understand their business very well now*." These functional BI developers had a personal DSS-like approach and attitude.

A popular goal is for the data in the enterprise BI system to represent a single-version-of-the-truth. This idea has been aggressively sold by vendors and consultants and has been adopted by researchers (for example, [5,79]). The CFO of BIC provided a clear statement of this ideal "*Imagine our CEO… at the top, having a pyramid of people doing their own things with data. If everyone produces data differently, he's effectively got this many different versions of the truth*." Both users and developers in the cases mentioned the single-version-of-the-truth. A manager in LGA said: "*…the BI is the source of truth. That is where I go to get the information for my analysis and reporting*." On the other hand, the most senior technical developer at BIC held a contrary view: "*… it's always been talking about one source of truth; everyone just wants one set of numbers but that's a utopia you're never going to reach*."

5. A framework for the use of BI in organizations

This section begins with the update of the Gorry and Scott Morton in light of the cross-case analysis of the eight BI systems. The section then analyses 86 decisions made with BI support in the case studies and fits them to the new structure. This analysis is then generalized to yield the new framework for BI systems use in organizations.

5.1. Use patterns from the BI system case studies

What emerges from the cross-case analysis is insight into decision support using BI systems in large organizations. These organizations are able to deploy expensive BI reporting and analytics software and their attendant data infrastructure, and they are able to afford a number of functional BI systems. Fig. 3 shows the BI framework that updates the Gorry and Scott Morton framework for BI systems. The major change to the Gorry and Scott Morton framework is to replace Simon's structuredness typology with the dual process theory of decision cognition. Replacing the vertical axis of the Gorry and Scott Morton framework is far from a simple renaming of rows. This axis in Fig. 3 is not a continuum as was the case with Simon's model but represents three distinct types of decision situation. The first row in the framework involves System 2 tasks that are rule-based, analytic, and effortful. They are associated with decisions with clear contexts and processes. The bottom row involves System 1 decisions that are associative, fast, unconscious, and skilled. The middle row of the figure identifies tasks that involve a strong interaction between System 1 and System 2 processes. As mentioned in Section 2.2, System 2 here acts in two main ways; first to modify and mediate the intuitive System 1 responses and second to train the decision maker's System 1. It is important to note that this interaction is particularly strong and is not like adding a short or brief process from one system onto another. In Simon's structuredness conception, and consequently the Gorry and Scott Morton framework, the goal of DSS (and BI) was to add structure to decisions [52]. Increasing the structure in semi-structured decisions was accordingly the explicit goal of system development of early DSS [40, 70]. This philosophy has remained central to all forms of DSS. In the Fig. 3 framework there is no value proposition attached to the two cognitive systems or the three rows. They are simply different, one is not superior to the other. As discussed in Section 2, the goal of many senior executives is acquiring greater System 1 abilities while the goal for many operational decisions is greater System 2 involvement.

Fig. 3 shows the result of the analysis of 86 decision tasks that were supported by BI systems in the case studies. Each decision was mapped to one of the nine cells in the updated framework. The descriptions provided for Anthony's managerial activities and information characteristics by Lucas et al. [50] were employed to assign each decision to one

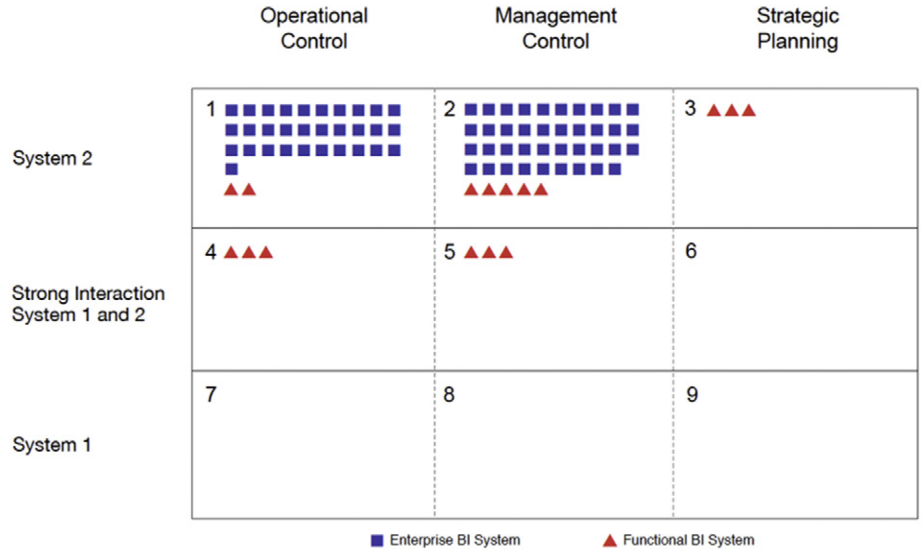

Fig. 3. Decision tasks supported in the case studies.

of the three columns of the new framework. To distinguish between the three distinct types of decision processes, the researchers were guided by Table 1. Each researcher validated their coded decision tasks with another researcher. A third researcher acted as referee when the two other researchers did not agree on coding. Seventy decisions tasks were supported by enterprise BI systems and 16 were supported by functional BI systems. The decisions tasks supported by enterprise BI systems were located only in cells 1 and 2 where System 2 is the dominant cognitive style of decision making. In the case of strategic planning decision tasks that use System 2, enterprise BI systems are not evident. In this category decision makers employ functional BI systems. Functional BI systems are also used in cells 4 and 5 where decision tasks required a strong interaction between System 1 and 2. However, functional BI systems are not used in strategic planning decisions that required a strong interaction between System 1 and 2. No BI system in the case studies supported cells 6 through 9. Why cell 6 is empty is a topic for further research.

5.2. A general framework for BI-based decision support

Fig. 4 shows a generalization of the analysis of decisions from the BI system case studies. This updated framework shows the form of BI usage for each cell. The figure shows an ecology of decision support in organizations where different types of BI work collaboratively to support decision makers at all levels of the organization to make important decisions. The figure is not perfectly exhaustive in that there may be outliers that are not evident from the case studies. For example, there could be an example of successful enterprise BI decision support in cell 5 somewhere in an organization. However, the data in this study

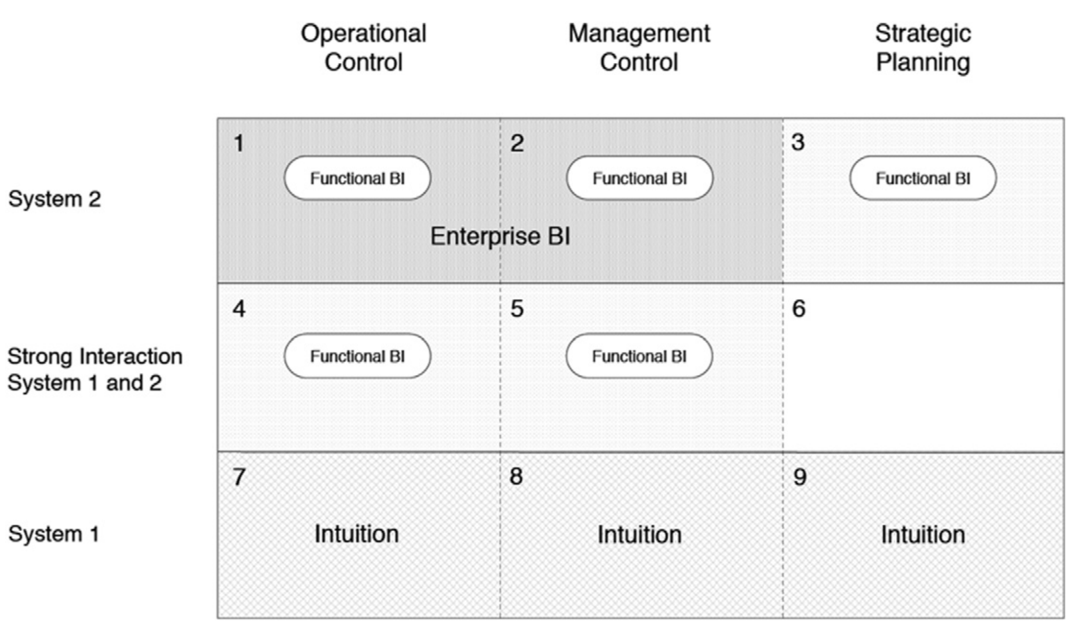

Fig. 4. A framework for BI-based decision support.

shows that this is not typical and probably should not be the basis of a general BI strategy.

If personal DSS theory could be transferred without modification to BI systems then enterprise BI systems would appear in cells 1 through 6 in the framework. Figs. 3 and 4 indicate that enterprise BI systems support the System 2 operational and management control decision (cells 1 and 2). Supporting System 2 processes means that they can be specified with some confidence using standard business analysis methods and techniques. There is unlikely to be any concerns about knowledge specificity in these cells [13] in that BI developers should be able to understand the rules behind the decisions. This means that there will be a minimal gap between the manager's mental model and the model embodied in the BI system – Gap 1 in Kayande et al.'s [39] three-gap framework of PDSS. This low Gap 1 implies that enterprise BI systems will perform well for decisions in cells 1 and 2. The decision tasks in these cells will also be relatively stable and this can justify expensive systems development. IT departments will be reasonably confident in their ability to develop and manage systems in cells 1 and 2. This pattern is also consistent with the newest large-scale DSS approaches of big data analysis and business analytics. Power [58] related “Analytic applications using the new data sources will most likely be focused at the day-to-day part of the organization hierarchy on operational control and operational performance decisions.” (p. 348).

The case study data shows that functional BI systems are an effective decision support approach for all System 2 tasks and for strongly interacting System 1 and 2 operational and management control tasks (cells 1 through 5 in Fig. 4). The case study data shows that functional BI systems have a greater tactical and strategic focus than enterprise BI systems. There were two motivations for developing functional BI systems in the cases. The first was the refusal of the central IT department to build functionality into the enterprise BI system that the business unit needed. The tasks supported by functional BI were important enough for the business unit to commit significant resources to their own BI development. The second reason for functional BI systems development was organization philosophy and structure; Alibaba is an example of this.

Functional BI systems can support some tasks that involve a strong interaction of System 1 and 2 processes. This is primarily because of their lower scale and development costs relative to enterprise BI. The tasks in cells 4 and 5 are more volatile than the System 2 tasks in cells 1 and 2. The systems that support interacting System 1 and 2 decisions will need frequent revision and reinvention in a similar fashion to personal DSS. Enterprise BI systems are simply too large to accommodate such change without incurring excessive costs. They also tend to have an internal scope that limits their usefulness for strategic decision tasks [55]. Functional BI systems are more like other DSS and are more agile and responsive to change in the understanding of decision tasks and the requests of users. They are not subject to the “heavy” governance and project management regimes that typify enterprise BI systems in IT departments. Unfortunately, their importance is commonly underestimated by IT departments and they are often dismissed or criticized as shadow IT [42,66].

The case studies show that cell 6 does not exhibit any BI-based decision support. It may be that PDSS is the only IT-based support in this cell. It may also be that functional BI systems will be able to support decisions in this cell. As mentioned before, Cells 7, 8, and 9 in the framework represent System 1 decision tasks and the framework indicates that no IT-based decision support is possible in these cells. Developments in behavioral economics since the 1971 publication of the Gorry and Scott Morton framework show that the processes that underlie System 1 decisions are innate and unknowable. Only human intuition using System 1 processes is capable of this decision support. It is important for BI developers to recognize this situation. This row is retained in the framework to constantly remind developers and researchers of the difficulty of working on those decisions.

The general System 2 task orientation of enterprise BI developers limits their understanding of the lower rows of Fig. 4. BI vendors, consultants, researchers, and developers share a popular goal of making decision-making in organizations data driven and evidence based. They believe that by replacing human intuition with algorithms in BI systems, decision-making will be improved. As McAfee and Brynjolfsson [53] argue: “Data-driven decisions are better decisions—it's as simple as that.” This is a reasonable strategy for operational and management control decisions that are System 2 in nature (cells 1 and 2). Considerable care should be taken in applying the strategy to management control and strategic planning tasks that are strongly interacting System 1 and 2. Over time senior decision makers learn about and gain experience with their decision tasks. If they are effective with their decision tasks they are rewarded with promotion. What they have been doing during this iterative process of experience and learning is converting slow effortful System 2 processes into fast innate System 1 processes. This is the process of developing expertise for a difficult decision task. In this situation, an inexperienced business analyst or data scientist will not be able to specify or even understand the decision maker's processes. Due to knowledge specificity, they can only understand a non-expert System 2 rule-based approach to the decision [13]. They may not even be able to recognize useful information and relevant data, even that a specific decision situation exists. This situation is termed bounded awareness ([9], ch. 4). Converting a decision maker from an expert System 1 intuitive decision process to an algorithm and data centric System 2 process could significantly deskill the decision maker. This means that the action of strongly pursuing a data driven process in cells 3 through 6 in Fig. 4 could adversely affect the performance of an organization. In this case, an enterprise BI system is not appropriate for decision support.

6. Concluding comments

The understanding of BI use patterns is currently a gap in the BI research literature. Appropriately, the research question for this study was: What are the patterns of BI use in organizations? This paper has addressed the research question by updating the dominant DSS use patterns framework and conducting secondary analysis of a large set of case study data involve eight BI systems and 86 BI-supported decisions. The outcome of this research is a framework that explains the use patterns of BI systems in organizations. Frameworks are vital for the theory base of any discipline. As Weber [76] related it is important for a discipline to have high quality frameworks to guide the development of high quality theory. These frameworks should be based on rigorously tested theory and empirical evidence. The BI use framework meets these criteria and can be used to properly ground BI research in the types of decision and the types of management processes that BI systems can effectively support. It represents what Weick [77] called an interim struggle in theorizing.

This study found that enterprise BI systems are effective support for operational and management control decisions that are System 2 in nature. For these decisions, IT departments can confidently develop expensive systems in the knowledge that they will be effective for some time. This is because these decisions are not volatile or transitory and stable functional specifications can be developed. Although by definition a DSS, enterprise BI systems are best governed by similar processes and structures to operational enterprise IS. Rather than be restrictive in development opportunity, the use domain of operational and management control System 2 decisions provides, to all practical purposes, an infinite source of potential enterprise BI applications.

This project has clarified the role of functional BI systems in organizations. The smaller functional BI systems are important to organizations, particularly as they support decision types that enterprise BI systems cannot. Importantly, they have a greater ability to respond to changes in the nature and context of decisions. This feature is essential for decisions that involve strongly interacting System 2 and System 1 processes. Unfortunately, the importance of functional BI systems is commonly underestimated by IT departments and they are often dismissed as undesirable shadow IT systems.

This paper also illuminates the problem of transferring theory across DSS domains. This study has found that traditional personal DSS theory cannot be transferred to BI without empirical support as the differences between PDSS and BI are so great to invalidate a blanket transfer. Further, this paper shows that theory about operational enterprise IS can be useful for BI research. An example is the use of IT governance theory [78] to explain the federal governance of enterprise BI. Personal DSS theory would incorrectly prescribe a feudal or anarchy governance archetype. If personal DSS theory could be transferred without modification to BI systems then enterprise BI systems would appear in cells 1 through 6 of the BI framework.

A contribution of this paper to general IS research is the clarification of the nature of secondary qualitative analysis. This project demonstrated that qualitative case study data can be combined across studies if the phenomena of interest, units of analysis, and data collection techniques are similar. To date 68 BI case study papers have been published in journals and IS conferences of which 55 are single cases. It may be that many of these studies could meet the similarity criteria discussed in Section 3.1 and could be part of a secondary analysis of a significantly larger data quantum.

In practice, the new BI framework can be used by organizations to help understand and plan their BI environment. Importantly, it shows what kind of effective decision support can be expected from enterprise and functional BI systems. Using the framework practitioners can avoid making claims about decision types that they can't support. The fact that no DSS can support System 1 decisions is important for BI developers to understand. It is important that when developing a BI system, analysts determine the System 1 or 2 orientation of each decision that they are supporting. The cases show that delegation is an important pattern of use that should be considered in a BI strategy.

This paper is subject to a number of limitations. The first is the partly subjective nature of case data collection and analysis. The most rigorous data collection and analysis methods and techniques were used to minimize this limitation. Care was taken to remove biases in analysis like the situation where participants inflated the perceived importance of their decision tasks. A second limitation is the sample size with respect to generalizing the research results. On the other hand, this is one of the largest intensive analyses of BI practice to date. Another limitation is that the research only studied large and very large organizations; the findings may not generalize to small and medium enterprises who are increasingly using BI technology. The final limitation is the issue with secondary qualitative analysis concerning the level of fit between the available data and the requirements of a secondary analysis. Great care was taken to satisfy the appropriate fit requirements in this project.

Three areas of research follow this paper. The first will assess the relevance of the framework to BI practice. An applicability check in the style of Rosemann and Vessey [60] is planned using a focus group of senior BI professionals. Following this, the framework will be exposed to BI steering committees using a case study approach. These two studies will allow the assessment and evolution of the framework from both a governance and a senior user perspective. The second research area will expand the framework by examining the use patterns of personal DSS and functional BI systems in organizations using a multiple case study strategy. Hopefully this project will help to illuminate the empty cell in the BI decision support framework.

The framework developed in this study is descriptive in nature; it describes what is happening in organizations. It does not address what should happen in BI portfolio decisions especially in cells 4 through 6 that involve decisions with strong System 2 and 1 interaction. The issue for BI managers is which System 1 decisions to move to System 2 and vice versa. This problem is the third research area. Marsden and Pringy [52] provided an approach based on Simon's model to decide which unstructured decisions could be structured using a traditional personal DSS. Their approach could be modified to use dual process theory and heuristics and bias theory to determine optimum BI development in the cells of the BI framework.

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