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An empirical investigation of the key determinants of data warehouse adoption

K. (Ram) Ramamurthy [a,*,1], Arun Sen [b,1], Atish P. Sinha [a,1]

[a] Lubar School of Business, University of Wisconsin-Milwaukee, P.O. Box 742, Milwaukee, WI 53201, USA
[b] Mays Business School, Texas A&M University, College Station, TX 77845, USA

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Abstract

Data warehousing (DW) has emerged as one of the most powerful decision support technologies during the last decade. However, despite the fact that it has been around for some time, DW has experienced limited spread/use and relatively high failure rates. Treating DW as a major IT infrastructural innovation, we propose a comprehensive research model – grounded in IT adoption and organizational theories – that examines the impact of various organizational and technological (innovation) factors on DW adoption. Seven factors – five organizational and two technological – are tested in the model. The study employed rigorous measurement scales of the research variables to develop a survey instrument and targeted 2500 organizations in both manufacturing and services segments within two major states in the United States. A total of 196 firms (276 executives), of which nearly 55% were adopters, responded to the survey. The results from a logistic regression model, initially conceptualizing a direct effect of each of the seven variables on adoption, indicate that five of the seven variables (three organizational factors – commitment, size, and absorptive capacity – and two innovation characteristics — relative advantage and low complexity) are key determinants of DW adoption. Although scope for DW and preexisting data environment within the organization were favorable for adopter firms, they did not emerge as key determinants. However, the study provided an opportunity to explore a more complex set of relationships. This alternative structural model (using LISREL) provides a much richer explanation of the relationships among the antecedent variables and with adoption, the dependent variable. The study, especially the revised conceptualization, contributes to existing research by proposing and empirically testing a fairly comprehensive model of organizational adoption of an information technology (IT) innovation, more specifically a DSS technology. The findings of the study have interesting implications with respect to IT/DW adoption, both for researchers and practitioners.

Keywords: Absorptive capacity; Adoption; Data warehousing; Decision-support technology; Innovation factors; Organizational factors

1. Introduction

One of the most powerful decision-support tools to have emerged in the last decade is data warehousing [4,67,80,87]. Firms develop data warehouses to support managers answer important business questions that require analytics such as data slicing and dicing, pivoting, drill-downs, roll-ups, and aggregations. The data warehousing (DW) market is growing rapidly with the Gartner

* Corresponding author.
E-mail addresses: ramurthy@uwm.edu (K. (Ram) Ramamurthy), asen@cgsb.tamu.edu (A. Sen), sinha@uwm.edu (A.P. Sinha).
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group forecasting that it would reach $29 billion by 2006. A report [43] suggests that nearly 70% of the companies responding from all over the world are currently developing some type of DW and business intelligence (BI) applications.

Although a majority of the large U.S. firms appear to have adopted DW, the road to DW success has been littered with failures [43,63,80]. The average first-year cost of a DW project is about $1.26 million, the average project effort is about 4.46 person-years, and nearly half of all DW initiatives end up as failures [38]. According to a February 2005 press release by Gartner, "through 2007, more than 50 percent of data warehouse projects will have limited acceptance, or will be outright failures." While the goal of DW has been to facilitate a comprehensive customer view – the ability to access, integrate, and analyze pertinent data across all of their most important channels – less than 20% of large companies claim success [43]. Further, small and midsize firms may have been slow at adopting DW.

A variety of factors in addition to cost and resource requirements may be responsible for the high failure rates of DW projects and the relatively low DW adoption rates among smaller firms. Rather than being a specific application, a DW project belongs to the category of an IT infrastructure type project that provides a foundation for IS application development, adding value to the firm [30,98]. While DW enables organizations to exploit decision making, business intelligence, customer relationship management (CRM), and supplier relationship management (SRM) opportunities, it requires significant up-front expenses with benefits realizable over the long term. Also, because DW provides future "options value" [[5]: pp. 276–278], its adoption requires the cooperation and commitment of a number of stakeholders. Further, DW adoption might need to be treated as a strategic decision accompanied by a clear plan, an understanding of the need for process and data integration, and a potential transformation of the existing ways of conducting business. A recent study [22] found that strategic and transformational orientation focusing on DW resulted in a significant performance improvement for the First American Corporation bank.

In light of the foregoing, the objective of our study is to identify and examine the key factors associated with DW adoption. As explained in the next section, DW is a major, infrastructure type innovation. Our study makes the following contributions:

- Drawing from the existing IT innovation models [32,90], it is among the few, early studies to develop a fairly comprehensive model (incorporating a coherent set of technological and organizational determinants) of adoption of DW, a major, infrastructure type innovation that is empirically validated using logistic regression. In addition, it presents an empirically derived alternative LISREL structural model that portrays a richer and more complex set of relationships among the study variables.
- It targets a large number of manufacturing and service firms and successfully obtains multiple responses (from both senior IT and Line Managers) to empirically validate the research model, unlike most prior research on IT infrastructure innovations, which has either used very small sample sizes (1 or 2 firms) or examined a small set of research variables.
- It brings to the forefront the importance of organizational commitment and absorptive capacity in the adoption of an IT innovation like DW.
- It offers a number of interesting implications for IT/DW practice and research.

The paper is organized as follows. In the next section, we describe what data warehousing is and briefly discuss why it should be treated as a major, infrastructure type innovation. In Section 3, we propose our research model and lay down the research propositions. The research methodology, data collection, and evaluation of psychometric properties are discussed in Section 4. In the following two sections, we present the results of the study's original and alternative models and their implications. We conclude by identifying the limitations of the study and the possible directions for future research.

2. Data warehousing — Infrastructure and innovation

2.1. Data warehouse and data warehousing

A data warehouse is "a subject-oriented, integrated, non-volatile, and time-variant collection of data in support of management's decisions" [[52]: p. 31]. Unlike on-line transaction processing (OLTP) database systems, which are detailed, application-oriented, and used to run the day-to-day operations of a firm, data warehouses are organized around subjects (e.g., customer, product, order, supplier, etc.) and store historical and summarized data for facilitating business decision making.

One of the most important aspects of a data warehouse is data integration [67]. Data is extracted from multiple heterogeneous source systems and placed in a staging area where it is cleaned, transformed, pruned, reformatted, standardized, combined, and summarized before loading into the warehouse [10]. This process is known as ETL (extraction, transformation, and loading). Data warehouses are non-volatile in the sense that end-users cannot update the data directly. Because old data is not overwritten, a data warehouse is able to maintain a history of the data (a series of snapshots) unlike OLTP databases that only store current-valued data. The source systems are operational systems that record business transactions; the source data could be production data (e.g., DB2, Oracle, or Sybase databases), external data (e.g., from ACNielsen or Wall Street Journal), internal data (e.g., company's spreadsheets, flat files, other documents), or archived data. The need to handle such diverse, heterogeneous sources of data leads to considerable complexity [38].

DW architectures can be broadly classified into two types: enterprise-wide DW and conformed data marts. The former, espoused by Inmon [52], provides an enterprise view of corporate data with a single, central storage of data. Kimball [61] is a proponent of the latter architecture, in which the DW is a logical collection of individual data marts, which are built one at a time. A data mart is narrower in scope than an enterprise DW catering to the needs of a department or a functional group of users.

Data warehouses are designed to answer business questions that require analytics such as drill-downs, roll-ups, pivoting, slicing and dicing, and aggregation of data, which are best supported by on-line analytical processing (OLAP) tools. At the front end, multi-dimensional databases (MDDB) or cubes allow users to perform advanced OLAP, data mining, and advanced reporting functions. Organizations can gain competitive advantage by leveraging DW technology for business intelligence initiatives.

Data warehousing is a still relatively new technology that "brings the vision of an entirely new (customer-centric) way of conducting business to reality" [61]. It can provide "environments promising a revolution in organizational creativity and innovation" [63]. While the various benefits attributed to a data warehouse are attractive, failure rates have been high with a 2005 Gartner report stating this number to be about 50%. A survey by the Cutter Consortium found that 41% of companies had failed data warehouse projects and only 15% rated their DW efforts as a major success [43]. DW systems also require a great deal of maintenance, which many organizations cannot or may not be able to support [38]. Further, the costs involved in the ETL process on a continuing basis can become prohibitive. It is therefore likely that in general larger organizations, by virtue of their greater resource mobilizing capabilities, will be better able to address these demands.

Therefore, a data warehouse, with its emphasis on data integration [60] and architecture integration policies [54], newness of technology [61,63], and a strong focus on organizational decision support [72] – including customer relationship [60] and e-commerce [53] – is an organizational-level technology innovation, not a tool to be adopted only by an individual, a small group of users, or the IT department.

2.2. Data warehouse as an infrastructure

IT infrastructure has been generally defined as a set of shared, tangible IT resources that provide a foundation for supporting current and enabling future business applications [5,30,84]. Managing IT infrastructure entails making decisions on hardware and software platforms, data and network architectures, corporate standards for acquisition and deployment of resources, etc. [97]. The capabilities of IT infrastructure are expected to influence business value by effectively supporting business processes [83]. IT infrastructure capabilities include the services it provides, its reach (enterprise-wide and inter-organizational vs. local), and its range (i.e., the functionality that can be shared), with an emphasis on organizational flexibility afforded for the future [[7]: p. 6]. DW falls very much into the category of an IT infrastructure technology (focused on data architecture) because it provides a foundation for integrating a diverse set of internal and external data sources, enabling enterprise-wide (and even inter-organizational) data access and sharing, enforcing data quality standards, providing answers to business questions, and promoting strategic thinking through CRM, data mining, and other front-end BI applications [98].

2.3. Previous IT innovation models and data warehouse as a major innovation

The popular dual (*technical* and *administrative*) core model of organizational innovation [23] was extended by [90] as a tri-core model exclusively for the IT innovation context. It categorizes IT innovations as — Type 1: technological process innovation restricted to IT function with a focus on IT administration (1a) or IT technical tasks (1b); Type 2: IT products applied to the host organization's administrative processes; and Type 3: focused on integrating IT products and services with the host organization's core business work processes (3a), business work products and services (3b) or suppliers, customers and other business partners (3c). Swanson presents arguments for a need to identify the type of IT innovation being examined since the antecedents could be different for each type. This model focuses primarily on size/slack resources, structure of the IT unit and/or the host organization, diversity of the IT portfolio, and orientation of IT (to its profession vs. to business and its strategy) as the antecedents.

Fichman [32] proposed a typology of IT innovations based on the types of technology (Type I vs. II) and locus of adoption (individual vs. organizational). Type 1 innovations impose relatively low knowledge burden and fewer user interdependencies while Type 2 innovations impose high knowledge burden and high user interdependencies. The key determinant for Type 1 innovations is a "willingness to adopt" and for Type 2 is the "ability to adopt." High knowledge burden can be mitigated by absorptive capacity.

As noted, DW is not one specific innovation but an infrastructure that spans multiple cores of Swanson's model and forms the base for additional IT innovations. Within this model's [[90]: p. 1076] scheme, it could qualify for Type 1b (e.g., as a large data source for IT staff in project implementation), Type 2 (e.g., providing current and historical data for management evaluation, coordination and control), Type 3a (e.g., operational processes and members of the host organization accessing and sharing the data stored in the DW), and as Type 3c innovation (e.g., integrate the host adopting organization with its customers/suppliers through data sharing and facilitate coordination). In view of the fact that DW can qualify for multiple classifications in the tri-core model, it is important to consider variables belonging to many categories noted earlier rather than a narrow set usually associated with one type of innovation. Using Fichman's typology, DW would qualify to be a Type 2 innovation in view of the high knowledge burden (and thus, a need for absorptive capacity) for both IT developers and users of DW, and enterprise-wide (and, often, inter-organizational) dependence. For these and other reasons discussed later, we consider orientation (business/strategic benefits), resource (size), organizational (scope), and strategic (vision and commitment) factors, and absorptive capacity.

A data warehouse can have profound influences on organizations because it can shift data ownership, alter access and usage patterns, change how jobs are performed, and modify business processes, thereby triggering major organizational changes [98]. DW projects often fail due to design and technology factors, and socio-technical factors [27,38,63]. In terms of technology, DW introduces a large number of components, often separately purchased, imposing a high integration burden on the adopting unit. DW projects could have political ramifications because they transcend internal functional boundaries/barriers and external inter-organizational links, lead to changes in data ownership and access, expose lapses in extant data management practices, and drastically influence and transform organizational work practices [27]. Adopting organizations need to be aware of political landmines relating to turf protection and control, user resistance and power struggles, and lack of cooperation from stakeholders. Political issues could assume even greater proportions because DW projects tend to be time-consuming and expensive.

In view of DW's potential for providing significant benefits, and for triggering large-scale changes to business processes, an understanding of the key factors that influence DW adoption would be useful in developing guidelines for evaluating DW and in formulating strategies to overcome the constraints to its adoption. A few empirical studies have examined the adoption of infrastructure type innovations such as open systems [16], CASE tools [33], and ERP systems [75]. Most research on IT infrastructure has either used small samples or examined a set of research variables without any specific framework and with only IT managers. Our study seeks to build on past studies on IT innovation adoption and organization theory by empirically testing a fairly comprehensive model of key determinants of DW adoption. Specifically, it examines a number of organizational (orientation, resource, scope, strategic) and technological factors that could influence the adoption of DW using multiple responses from a wide variety of firms. A key reason for choosing many organizational/management factors for investigation is that it is often argued that these factors, rather than just technology, are responsible for failed DW projects [80].

3. The research model and theory

We draw upon two primary research streams, organizational theory/behavior research and diffusion of innovation, to develop the study's research model (Fig. 1) and associated propositions.

3.1. Organizational factors and adoption of innovation

3.1.1. Organizational commitment

Organizational commitment is a key element for an innovation to be adopted and subsequently used. Such commitment encompasses at least two aspects: senior management's support and buy-in (participation, involvement, and support) of the key stakeholders for the innovation. Management support has generally emerged as a key variable in past research in innovation [31,101] and IT implementation literatures [50,65,66,85,92]. Active senior management involvement and support enables the development of a strategic vision and direction, besides sending appropriate signals to various parts of the organization of the importance of the

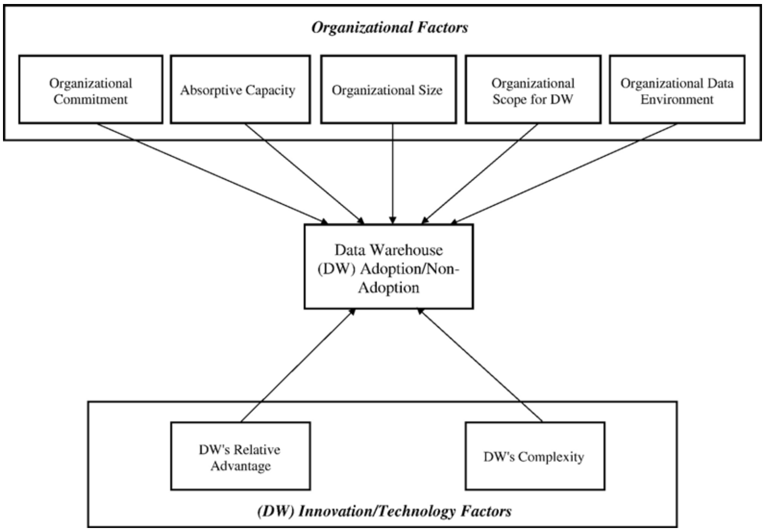

Fig. 1. Research model of direct effects.

innovation initiative to sustain a favorable attitude [69]. It is also necessary to have the buy-in and support of key stakeholders by making them aware of the innovation's capabilities/consequences, and involving them in the decision-making process. Stakeholder/user participation and involvement have been argued to be a key in generating their buy-in [47].

DW, as illustrated, is a major innovation that can have profound influences on organizations because it can trigger significant politically charged issues. These are further exacerbated due to high multiyear investments in the order of millions of dollars. All of these demand the highest level of attention, support, engagement, and commitment from senior management and key stakeholders. Further, given the potential for DW to influence a firm's competitive position, as well as its business relationships, the need for senior management to get involved and mobilize commitment of key organizational stakeholders is crucial. The tri-core model of IT innovation [90] emphasizes orientation to business and strategy as a key variable for Type 2 and 3 innovations. This is often reflected in commitment. Therefore, we propose that:

H1. Organizational commitment is positively related to adoption of DW.

3.1.2. Organizational absorptive capacity

Absorptive capacity is the ability of key organizational members to utilize available or preexisting knowledge [39]. It facilitates a sort of recreation process of the knowledge within their minds [3]. An organization's absorptive capacity also indicates its ability to recognize the value of new (external or internal) information, assimilate and apply it effectively to realize economic benefits [20]. It has been suggested to be critical to an organization's innovativeness [84]. Applied to the IT domain, an organization's absorptive capacity reflects its capability to absorb information relating to suitable IT innovations through its employees' individual knowledge repositories, cognitive structures and processes for supporting operational or strategic activities and enhancing organizational performance [13]. Research on new product development and management is supportive of the notion that absorptive capacity is a prerequisite for rapid innovation and flexible organizational response to changing market conditions [73].

A major IT innovation like DW requires an awareness of what it can provide or enable, and an understanding of "how-to" exploit its potential within an organizational context or need [82], referred to also as the embedded context [93]. Adoption of DW is unlikely unless key stakeholders/users can creatively identify unique ways through which new knowledge can be extracted by integrating data from multiple functional areas within the firm [71]. However, such creative thinking may be unlikely unless adequate knowledge exists within the firm. The study [32] notes that the "ability to adopt" is critical with respect to Type II innovations; such ability has been found to be a key in adoption of open systems [16]. Kotler [63] underscores this point:

> "… the organization as a whole must understand that the potential innovation, evolution and constant flexibility wrought by the data warehouse technology is what will make the difference in the end. …

Fully leveraging the capabilities of the data warehouse requires not only the necessary IT resources, but also the human insights for identifying growth opportunities and acting on new insight."

In light of the above arguments, we propose that:

H2. Organizational absorptive capacity is positively related to adoption of DW.

3.1.3. Organizational size

A number of previous studies identify size as having an important influence on the adoption of innovations [24,25,62]. The findings have, however, been inconsistent. It has been suggested that smaller firms may be more efficient at generating and adopting innovations than larger firms [99]. However, large firms are more capable of mobilizing resources (slack) required for innovations as well as offering the economies of scale/scope required to effectively utilize them after adoption. Slack has been recognized as a factor that often explains an organization's innovative behavior [12,25,88]. It provides a cushion of spare resources that prevents the firm from fatal hazards in the face of a rapidly changing environment, and stimulates creativity and experimentation [28,64]. Additional resources provide funds for the adoption of innovation and for supporting projects that would not necessarily be approved on a tight budget. Recent studies have found organizational size to be positively related with adoption of innovation in commercial banks and insurance industry [e.g., [37]].

Data warehouses are expensive, multiyear investments. To understand their value prior to adoption and later during implementation requires a diverse set of skills and expertise. The requisite financial resources and skills are more readily available in larger organizations. Also, larger organizations can benefit more from adoption of DW than smaller firms because they may be able to use DW more efficiently and effectively by exploiting the economies of scale and scope. Larger firms may also be able to more easily provide a cost justification for DW adoption. Further, the tri-core model of IT innovation [90] emphasizes size as a key variable for Types 1 to 3 innovations. Therefore, we propose that:

H3. Organizational size is positively related to adoption of DW.

3.1.4. Organizational scope for DW in the task environment

While attractiveness of an IT innovation is often a strong motivator behind its adoption, mere attraction to an innovation's superiority can often blind and bind organizational units to hasty and non-retractable investment decisions [70]. Research in strategic IT systems found that in the absence of adequate scope, benefits are not sustainable [59]. It is therefore imperative that evaluation of the innovation's suitability is conducted within the specific task environment of the adopting unit. That is, there should be adequate *scope in the task environment* to exploit the innovation and derive significant benefits [77,81,101]. The extent to which an organization's task environment provides opportunities for using the innovation significantly influences its adoption and future use/diffusion [90,101].

The portfolio and base of IT applications – both existing and being planned for the future – that can make use of the data from the data warehouse, the robustness of the existing IT infrastructure to accommodate and leverage the new DW innovation, and the complexity of the data itself are some of the factors that influence the scope for DW use within the task environment and, therefore, its adoption [43,46,89]. For instance, a firm that has a large portfolio of IT applications relating to CRM and SCM, product design, and pricing, and a fairly robust infrastructure is likely to provide greater scope for DW in its operations. A larger base of IT applications affords greater economies of scale and scope for DW as well. Therefore, we propose that:

H4. Organizational scope (for exploiting DW) is positively related to adoption of DW.

3.1.5. Organizational data environment

An organization's data environment is significantly dependent on how well the data resource management (DRM) is performed. Typically, DRM is responsible for a number of data planning and DRM policy functions, such as developing and enforcing data naming conventions, data dictionary standards, and data integrity and security policies in large organizations. DRM is also responsible for technical functions such as managing the operation of databases, data modeling and design, database security, documentation, and education and support. Poorly organized DRM functions are often reflected in important corporate information being locked in a variety of systems, making it difficult to compile, integrate and consolidate information, and to interpret and share data across IT applications. An effectively organized DRM function, on the other hand, offers a number of benefits such as reducing errors and increasing the ability to access previously unavailable information [35,36,55].

As noted, heterogeneous data from very diverse set of sources with differing formats and semantics are extracted from different source systems and then cleaned/scrubbed, transformed, combined, and formatted before being loaded into the warehouse [10,52,61,98]. A data environment that is not properly managed is likely to suffer from problems relating to quality, reliability, security, availability, integrity, and standards. Such an environment would pose greater challenges for introducing DW, setting up roadblocks to its adoption. The challenges are further exacerbated in distributed and inter-organizational environments where few guidelines for effective organization of DRM exist [36,55]. Therefore, we propose that:

H5. Quality of existing organizational data environment is positively related to adoption of DW.

3.2. Innovation characteristics and adoption of innovation

Studies using the diffusion of innovation (DOI) research stream [82] to examine the influence of innovation characteristics on adoption of innovation have been very popular. A meta-analysis of research in this area [94] found that out of as many as 25 innovation attributes studied by researchers, three are usually consistently related to adoption. They are: *relative advantage*, *compatibility*, and *complexity*. The IT literature has tended to favor the use of Technology Acceptance Model (TAM) [26] that makes use of parallel concepts of DOI research: perceived usefulness (analogous to relative advantage), and perceived ease of use (reverse of complexity). The thrust of both classical DOI and TAM research streams has been on individuals' willingness and voluntary adoption of innovations [32,82]. While there is an extensive body of research using innovation attributes over the past three to four decades, most studies have examined the impact of innovation attributes on individual-level adoption [2,14]. Barring a few studies in the context of inter-organizational systems (IOS) and electronic data interchange (EDI) [40,51,78], the influence of innovation attributes on organizational-level adoption has not been extensively studied. The results have also been somewhat inconsistent and no clear patterns have emerged [32].

3.2.1. DW's relative advantage

As noted above, one variable that has consistently emerged as a facilitator of adoption is *relative advantage*, which is the degree to which an innovation is perceived to be better than the one it replaces [82,101]. In an organizational adoption decision, perceptions of favorable benefits from an innovation provide economic and political legitimacy to the adoption decision [18]. Perceived advantage of an innovation over existing or alternative products/processes has been found to be positively associated with adoption [82,94,93]. This variable was found it to be important in explaining adoption of transportation-related innovations [31] and for Web adoption [2].

Initial research indicates that DW can offer several benefits to an organization [96,98] that include: enabling effective decision support and business intelligence solutions; facilitating OLAP; ensuring data integrity, accuracy, security, and availability; easing the setting and enforcing of standards, facilitating data sharing, and improving customer service [35,36,55,86]. Therefore, we propose that:

H6. DW's relative advantage is positively related to adoption of DW.

3.2.2. DW's complexity

Complexity, which is determined by the degree to which an innovation is perceived to be difficult to understand and use, has been noted to be another important determinant of innovation adoption [82]. Previous studies have found this to be an important variable for various types of innovations [24,94], in the context of transportation innovations [31], and in MRP systems [21].

As noted, DW has the potential to create radical changes to existing business processes and is often viewed within the context of business process re-engineering [98]. IT literature is replete with horror stories of failed implementations due to overt/covert resistance to adopt IT innovations that are complex and have a potential for major organizational changes [58,68]. Large-scale anticipated changes that can result from DW would be expected to be negatively associated with its adoption. Hence, we propose that:

H7. DW's complexity is *negatively* related to its adoption.

4. Research methodology

4.1. Data collection approach, sample characteristics and response bias

A field questionnaire-based survey was considered appropriate for data collection to ensure greater external validity and generalizability of the results. Elaborate precautions were taken at each stage in the construction and administration of the survey [29]. An initial prototype of the survey for measuring the study's constructs was developed. Multiple indicator items were used to measure the constructs and, wherever available, scales used in prior empirical studies were adapted to suit the research context.

The initial version of the questionnaire instrument was pre-tested with four faculty members having expertise in management, innovation, databases, data warehouses, and general IT domains. The improved version was pilot-tested with senior IT managers and functional area managers in each of eight different companies to assess clarity, readability, understandability, and to gain an initial idea of time commitment. Response to the pilot-test survey was followed up with interviews lasting 45 to 60 min with each respondent to gain a better insight into the comprehensiveness of coverage of the instrument in capturing important concepts. Minor revisions to the phrasing of some of the statements emerged from these pilot-tests. These pre- and pilot-tests suggested a fair degree of initial content validity to the survey instrument.

The actual study targeted soliciting responses from two senior executives within each company, one in Information Systems/Services (CIO, VP, or DW/DBA manager) and the other in a functional area (VP Marketing, Operations, Finance, or Human Resources). Because of resource constraints, we decided to focus on two major states in the U.S. — one in the Midwest and the other in the South. Both these states are well developed and are likely to invest in major technology innovations such as DW. The source data for this mailing list was the Harris InfoSource Directory [45]. Since DW technology is expensive, we decided to sample firms that employed at least 200 (full-time equivalent) employees, hoping that these firms would be able to find the resources and afford the investment.

Since the survey was unsolicited, quite long, fairly complex, and involved a large proportion of small-to-medium sized businesses, we expected a low response rate. Computations indicated that a minimum sample size of 106 would be required to realize an adequate *statistical power of the test* β of at least .80 [19]. We mailed the surveys to 2498 companies in these two states. All responses were received within 12 weeks with about 60% of these obtained within 4 weeks of mailing. We received responses from 254 companies; however, we could not make use of 56 of these responses because they could not be delivered by the Post Office and, thus, returned back to us; in some cases, blank surveys were returned back due to turnover of executives, mergers/acquisitions, etc. This resulted in a net sample size of 198 companies, yielding a net response rate of 8%. Two data points were dropped due to missing values thereby yielding a usable sample size of 196 firms. The demographic characteristics of the sample are shown in Table 1.

About 55% of the respondents (107 firms) have already adopted and are using data warehouses, while

Table 1
Profile of responding firms (n=196)

Characteristics	Percent of total
1. Use of data warehousing technology	
Adopters of DW (n=107)	54.6
Non-Adopters of DW (n=89)	45.4
2. Geographic regions represented	
Upper Midwestern U.S. (n=106)	54.1
Southern U.S (n=90)	45.9
3. Industry representation	
Manufacturing (n=95)	48.7
Service (n=100)	51.3
Missing data (n=1)	
4. Firm's SIZE — number of employees	
201–400 (n=68)	35.8
401–800 (n=48)	25.3
801–1500 (n=25)	13.1
1501–3000 (n=26)	13.7
3001–6000 (n=6)	3.2
6001–15,000 (n=7)	3.6
More than 15,000 (n=10)	5.3
Missing data (n=6)	
5. Age of the responding firms (years)	
1–10 (n=10)	6.6
11–20 (n=19)	12.6
21–50 (n=56)	36.8
51–80 (n=31)	20.4
81–120 (n=28)	18.4
Over 120 years (n=8)	5.3
Missing data (n=44)	
6. Job title of the respondents	
CEO/COO/CIO/CFO (n=28)	14.4
V.P., General Manager, etc. (n=42)	21.6
Director, Controller, etc. (n=54)	27.8
Manager, Senior Analyst, etc. (n=70)	36.1
Missing data (n=2)	
7. Respondents' tenure	
Less than or equal to 2 years	12.4
2.01–5 years	25.7
5.01–10 years	15.0
10.01–15 years	13.4
15.01–20 years	12.4
20.01–25 years	11.8
25.01–30 years	6.2
Greater than 30 years	3.1
Missing data (n=2)	

Table 2A
Test for response bias

Variables	Early Respondents	Late Respondents	Test Statistic	Value (significance)
DW adoption:				
A=Adopters	A=63	A=44	Chi-square	χ^2=0.17 (p=.77)
B=Non-adopters	B=55	B=34		
Firm size: # of employees (mean and standard deviation) [a]	6.727 (1.374)	6.744 (1.417)	T-value	t=0.076 (p=.94)
Age of the firm in years (mean and standard deviation)	55.40 (38.53)	55.14 (38.45)	T-value	t=−0.041 (p=.967)
Distribution of responses by geographical regions:				
C=U.S. Midwest	C=60	C=46	Chi-square	χ^2=1.249 (p=.31)
D=U.S. South	D=47	D=33		
Industry segments:				
E=Manufacturing	E=55	E=40	Chi-square	χ^2=0.671 (p=.46)
F=Service	F=63	F=37		
Average tenure (years) of respondents within the firm	11.28 (9.08)	12.84 (9.87)	T-value	t=1.168 (p=.24)

[a] Natural log transformed (employee size) used due to high degree of skewness in the responses.

nearly 45% (89 firms) are still non-adopters. There was an almost equal split of the sample in terms of manufacturing vs. service representation; about 49% (95 firms) were from the manufacturing sector and the remaining about 51% (100) belonged to the service sector. Both geographic regions of the U.S. (54% from the Midwest — 106; 46% from the South — 90) were almost equally represented. We obtained two responses from each of 80 of these 196 firms, and one response from each of the remaining 116 firms (either from the functional or IT executive).

As shown in Table 1, the responding firms are widely dispersed in terms of size (full-time employee count), age, job title, and experience of the responding executives. Over 61% of the responding firms are small to medium sized enterprises (up to 800 employees). Most of the firms are quite mature in terms of age with about 39% of them having been in existence for over 50 years. Practically all the responding executives were at least functional area or IT managers; about 36% of them were at least VPs. Finally, about 47% of the responding executives had an experience of over 10 years with the firm.

Before proceeding with further data analyses it was necessary to test for any non-response bias. This was assessed via two approaches. First, in line with prevailing practice [17,100], the data was analyzed for any differences on key demographics between the early and late respondents (as noted earlier, about 60% of responses were received within 4 weeks). The rationale was that late respondents are more akin to non-respondents; if there are no differences, the data could be combined. The second was a comparison between the respondents and non-respondents from the target population (as noted, the net response rate was about 8%). Fortunately, we could obtain some demographic data from [45] for the non-respondents that allowed us to perform this test as well. The results of these tests are presented in Tables 2A and 2B.

Table 2A displays the results of the comparison on key demographics (adoption/non-adoption; size; age; geographical distribution; industry segment representation; etc.) between early respondents (118 firms that returned the surveys within 4 weeks) and late respondents (82 firms that returned the surveys after 4 weeks). The comparison revealed no statistically significant

Table 2B
Test for response bias and generalizability to population frames

Variables	Respondents	Non-respondents	Test statistics	Value (significance)
Distribution of responses by geographical regions:				
C=U.S. Midwest	C=106	C=1276	Chi-square	χ^2=0.090 (p=.76)
D=U.S. South	D=90	D=1034		
Industry segments:				
E=Manufacturing	E=95	E=1250	Chi-square	χ^2=1.904 (p=.17)
F=Service	F=100	F=1060		
Firm size: # of employees (mean and standard deviation) [a]	6.378 (0.851)	6.118 (0.716)	T-value	t=11.52 (p=.001)
Firm size: sales revenue (mean and standard deviation) [a]	22.121 (2.096)	21.745 (2.083)	T-value	t=0.006 (p=.938)
Age of the firm in years (mean and standard deviation)	55.59 (38.41)	46.31 (34.43)	T-value	t=4.776 (p=.029)

[a] Natural log transformed (employee size) used due to high degree of skewness in the responses.

differences for either the adoption rate or any of the other variables (size, age, industry, geography, etc.), thus providing no evidence of non-response bias [17].

Table 2B presents the results of the comparison on key demographics for respondents to this study (196 firms) and non-respondents (2310 firms) on four of the seven variables (used in Table 2A) for which data was available. While there are no differences between the two groups on geographic representation or industry, the responding firms are somewhat older and larger (on employee size but not on sales revenue) than non-responding firms, suggesting a slight bias. Therefore, care must be exercised in generalizing the results to the entire population of firms (see discussion later).

4.2. Operationalization of constructs

All the measurement scales used to operationalize the study constructs are grounded in previous research and theory.[2] Except for the dependent variable, *adoption* (a binary measure), all indicators representing the research constructs (except size) were measured using a seven-point Likert-type scale ranging from strongly disagree (1) to strongly agree (7). A number of these were also negatively phrased (later recoded) and interspersed to minimize problems of thoughtless, mechanistic responses.

Seven indicators represented organizational *commitment* capturing aspects of resource commitment for DW, risk-taking posture, sponsorship, support, recognition and acceptance of consequential changes, etc. [25,44,85,98]. *Absorptive capacity* was adapted from the scale developed in [91] and measured with three indicators capturing the aspects of the extent of understanding the nuances of DW, existing level of technical savvy, and extensiveness of training required. *Scope* (for DW) within the organization's task environment was measured with three indicators tapping into the extensiveness of portfolio of applications capable of using DW, robustness of IT infrastructure, and complexity of existing data [59,70,90]. The *data environment* prevailing within the organization was represented by three indicators capturing aspects such as reliability, standards, and quality [35,36,55]. Organization *size* was represented as a logarithmic transformation (to natural base) of the number of employees. Such a transformation is a standard practice and was used to minimize the variance within the sample since there was a wide range of values for employee size and skewness in the distribution [62].

Innovation attributes, relative advantage, and complexity were measured adapting the scales used in previous (IT) innovation research [2,40,78,82]. *Relative advantage* was measured by six indicators capturing benefits such as effective decision support; improved on-line analytical processing; availability of high quality/accurate/secure data; high payback; low cost access; and data mining/improved customer service [36,55,96,98]. Three indicators were used to measure *complexity*, tapping into aspects of difficulty of understanding, effort needed, and ease of use [26,78].

4.3. Test of psychometric properties

The measurement scales were tested for various validity and reliability properties [17]. Validity measures the degree to which a scale accurately measures the constructs under investigation, and reliability measures the stability of the scale. Construct validity is normally evaluated using three forms of validity: *content*, *convergent*, and *discriminant validity*. Content validity assesses if *all* the aspects of the construct are being measured. The extant theory bases that we used to identify the various indicator items and the detailed process that we employed during pre- and pilot-tests for refining the items provide adequate confidence in the content validity of the measurements.

Convergent validity assesses the extent to which indicator items measuring a construct converge together and measure a single construct; it is also referred to as unidimensionality [34]. Discriminant validity is the degree to which the indicators of theoretically distinct concepts are unique from each other [17] and is normally established through exploratory factor analysis (EFA) and/or confirmatory factor analysis (CFA) [74]. We performed both EFA and CFA. A joint principal component EFA (of 25 indicators representing six constructs, excluding organizational size) with varimax factor rotation was used to test both convergent and discriminant validity. It tests if the theorized indicators converge together on appropriate constructs and discriminate across multiple constructs with minimal cross loading among factors. The standard criteria of Eigen values greater than 1.0, factor loading greater than 0.4, and a well explained/simple factor structure were used [42,100]. The results are shown in Table 3.

The results reveal that all the constructs exhibit satisfactory levels of convergent and discriminant validity. A six-factor structure emerged, matching the

[2] Appendix A provides the indicators used to represent the constructs and the extant research support.

Table 3
Joint exploratory factor analysis to assess discriminant validity

No.	Variables [a]	Factor loading	Eigen value and variance explained [b]	Reliability: Cronbach alpha	Criterion validity [a]
F1.	DW's relative advantage		4.814–19.26%	0.907	0.786 ($p<.001$)
	R_ADV1	0.521			
	R_ADV2	0.868			
	R_ADV3	0.808			
	R_ADV4	0.547			
	R_ADV5	0.830			
	R_ADV6	0.855			
F2.	Organizational commitment		3.459–13.83%	0. 929	0.772 ($p<.001$)
	O_COMT1	0.681			
	O_COMT2	0.814			
	O_COMT3	0.837			
	O_COMT4	0.611			
	O_COMT5	0.657			
	O_COMT6	0.576			
	O_COMT7	0.623			
F3.	Organization's absorptive capacity		3.376–13.51%	0.702	0.442 ($p<.001$)
	ABS_CAP1	0.714			
	ABS_CAP2	0.585			
	ABS_CAP3	0.757			
F4.	Organization's data environment		2.388–9.55%	0.797	0.287 ($p<.001$)
	DAT_ENV1	0.910			
	DAT_ENV2	0.884			
	DAT_ENV3	0.668			
F5.	DW's complexity		2.382–9.53%	0.786	−0.313 ($p<.001$)
	COMPLEX1	0.860			
	COMPLEX2	0.767			
	COMPLEX3	0.793			
F6.	Organizational scope		1.582–6.33%	0.627	0.431 ($p<.001$)
	O_SCOPE1	0.624			
	O_SCOPE2	0.544			
	O_SCOPE3	0.848			
7.	Organization size (natural log transform of # of employees)	N/A	N/A	N/A	0.240 ($p<.001$)

[a] Test of *criterion validity* assessed using correlation analysis for each construct with other independent measures of the same/respective constructs.

[b] Joint factor analysis of the 25 indicators: Cumulative variance explained by 6 factors (F1–F6)=72.0%.

study's six multi-indicator constructs with all pre-defined indicators loading onto their respective constructs. The factor loadings were quite high with a minimum of 0.52 to a maximum of 0.91. The six factors explained 72% of the total variance. The results also exhibited adequate discriminant validity with no significant cross loading of indicators across factors.

In addition to the above forms of validity, *criterion validity* was also evaluated in this study. Each scale of the study constructs was correlated with another independent measure of the same construct (see Appendix A for details). Significant correlation among the two measurements of each construct would attest to criterion validity [74,100]. The last column of Table 3 provides the results of this correlation analysis; all seven correlation-values are significant ($p<.001$), attesting to satisfactory criterion validity.

Reliability of the measurement scales was assessed through Cronbach's Alpha that tests the internal consistency of the scales. A minimum threshold of 0.6 is normally considered as adequate for exploratory empirical studies [74]. The fifth column of Table 3 provides results of the Cronbach Alpha test. All six constructs have alpha greater than the minimum threshold of 0.6, attesting to satisfactory reliability.

A CFA using LISREL 8 [57] was also performed to evaluate construct validity (unidimensionality/convergent validity and discriminant validity). We developed measurement models to assess the *unidimensionality*[3] of each multi-indicator construct. Unidimensionality, which evaluates if the indicator items load on to the latent construct, is assessed by the significance of the factor loadings of the items. *Discriminant validity*, which evaluates if the indicator items load on to the theorized latent construct and not to others, is usually assessed in CFA by evaluating the significance of chi-square change between a constrained model where the correlation between the two latent constructs is set to 1 and an unconstrained model where the correlation is set free. CFA tests if the indicator items load on to a single construct or two separate constructs. Pairwise comparisons of all constructs were performed; since there are six study constructs, fifteen nested models were developed and the significance of the change in chi-square ($df=1$) was assessed for each model. This approach has been used extensively in recent research [e.g. [11,15,56]]. As with EFA Criterion validity was also examined. The results of validity tests are presented in Tables 3A and 3B.

As can be noted from Table 3A, all indicators loaded onto the corresponding pre-defined constructs and all

[3] The fitted model is $x_i=\lambda_i\xi+\varepsilon_i$, where x_i is the ith indicator in the pool of indicators for the construct; λ_i is the loading of indicator x_i on the unobserved trait, ξ; and ε_i is the random error in indicator x_i.

Table 3A
Measurement model — Confirmatory factor analysis

No.	Variables and their indicators	Loading	Composite reliability: r^c	Criterion Validity[a]	Mean (standard deviation)		*T*-value (significance level)
					Adopters	Non-adopters	
1.	Organization size (Natural Log transform of # of employees)[b]	N/A	N/A	0.240 ($p<.001$)	7.074 (1.570)	6.299 (0.946)	4.014 ($p<.001$)
2.	Organization's absorptive capacity		0.745[c]	0.442 ($p<.001$)	4.006 (1.097)	3.051 (1.051)	6.189 ($p<.001$)
	ABS_CAP1	0.913[d]					
	ABS_CAP2	0.455					
	ABS_CAP3	0.702					
3.	Organizational scope		0.753	0.431 ($p<.001$)	5.184 (0.922)	4.665 (1.060)	3.666 ($p<.001$)
	O_SCOPE1	0.680					
	O_SCOPE2	0.525					
	O_SCOPE3	0.899					
4.	Organization's data environment		0.743	0.287 ($p<.001$)	4.706 (1.071)	4.549 (1.066)	1.017 ($p<.311$)
	DAT_ENV1	0.833					
	DAT_ENV2	0.785					
	DAT_ENV3	0.518					
5.	DW's relative advantage		0.906	0.786 ($p<.001$)	5.332 (0.849)	4.260 (1.013)	8.055 ($p<.001$)
	R_ADV1	0.620					
	R_ADV2	0.880					
	R_ADV3	0.729					
	R_ADV4	0.692					
	R_ADV5	0.801					
	R_ADV6	0.957					
6.	DW's complexity		0.794	−0.313 ($p<.001$)	3.896 (1.136)	4.074 (0.787)	1.246 ($p<.214$)
	COMPLEX1	0.772					
	COMPLEX2	0.623					
	COMPLEX3	0.845					
7.	Organizational commitment		0. 926	0.772 ($p<.001$)	5.069 (0.933)	3.638 (1.015)	10.265 ($p<.001$)
	O_COMT1	0.834					
	O_COMT2	0.759					
	O_COMT3	0.793					
	O_COMT4	0.877					
	O_COMT5	0.821					
	O_COMT6	0.837					
	O_COMT7	0.667					

[a] Test of criterion validity assessed using correlation analysis for each construct with other independent measures of the same/respective constructs.
[b] Not applicable since the marked construct is a single-item or computed measure.
[c] The formula for Composite Reliability $\rho_{c}=(\Sigma\lambda_i)^2/[(\Sigma\lambda_i)^2+(\Sigma 1-\lambda_i^2)]$.
[d] All loadings λ_i with *T*-statistics significant at better than $p\leq.001$.

loadings (λ_i) are significant ($p<.001$). The various fit indices (with the associated acceptable thresholds) indicated at the bottom of Table 3B are all satisfactory [8,9]. The results from Table 3A attest tounidimensionality of the constructs. Table 3B results provide strong evidence for convergent validity as well as discriminant validity, with all of $\Delta\chi^2$ significant at $p<0.001$.

The factor loadings were used to measure *composite reliability alpha*, ρ_c [15].[4] As can be noted from Table 3A, all composite reliability, ρ_c, coefficients had satisfactory values — greater than the typical

[4] The formula for composite reliability is $\rho_c=(\Sigma\lambda_i)^2/[(\Sigma\lambda_i)^2+(\Sigma 1-\lambda_i^2)]$.

Table 3B
Measurement model — Test for convergent and discriminant validity

Variable group/constructs involved	Measurement model fit and test of convergent validity	Nested models with	Discriminant validity test: $\Delta\chi^2(1)$ and level of significance
1. Absorptive capacity	$\chi^2_{df=255}=511.2$, $p<.01$	# of Models = 15	
2. Organizational scope	χ^2/df (Normed-χ^2) = 2.01	Cov(1,2) = 1.0	$\Delta\chi^2(1)=38.9$; $p<.001$ [a]
3. Organizational data environment	GFI = 0.82	Cov(1,3) = 1.0	$\Delta\chi^2(1)=111.2$; $p<.001$
4. DW's relative advantage	CFI = 0.90	Cov(1,4) = 1.0	$\Delta\chi^2(1)=88.9$; $p<.001$
5. DW's complexity	NNFI = 0.88	Cov(1,5) = 1.0	$\Delta\chi^2(1)=195.3$; $p<.001$
6. Organizational commitment	RMSR = 0.083	Cov(1,6) = 1.0	$\Delta\chi^2(1)=43.9$; $p<.001$
	RMSEA = 0.081	Cov(2,3) = 1.0	$\Delta\chi^2(1)=44.45$; $p<.001$
		Cov(2,4) = 1.0	$\Delta\chi^2(1)=24.5$; $p<.001$
		Cov(2,5) = 1.0	$\Delta\chi^2(1)=118.1$; $p<.001$
		Cov(2,6) = 1.0	$\Delta\chi^2(1)=35.8$; $p<.001$
		Cov(3,4) = 1.0	$\Delta\chi^2(1)=195.5$; $p<.001$
		Cov(3,5) = 1.0	$\Delta\chi^2(1)=153.9$; $p<.001$
		Cov(3,6) = 1.0	$\Delta\chi^2(1)=196.3$; $p<.001$
		Cov(4,5) = 1.0	$\Delta\chi^2(1)=125.1$; $p<.001$
		Cov(4,6) = 1.0	$\Delta\chi^2(1)=162.7$; $p<.001$
		Cov(5,6) = 1.0	$\Delta\chi^2(1)=124.8$; $p<.001$

Assessment of measurement model fit.
Normed-χ^2; Desired/acceptable threshold ≤ 3.
GFI = Goodness of Fit Index; Desired/acceptable threshold ≥ 0.8 — [8,52].
CFI = Comparative Fit Index; Desired/acceptable threshold ≥ 0.9 — [9].
NNFI = Non-Normed Fit Index; Desired/acceptable threshold ≥ 0.9 — [47].
RMSR = Root mean Square Residual; Desired/acceptable threshold ≤ 0.1 — [52].
RMSEA = Root Mean Square Error of Approximation; Desired/acceptable threshold ≤ 0.08 — [52].
[a] *Discriminant validity* among the study constructs is strongly supported in all instances.

0.6 threshold set in previous research [17]. Based on the findings of these tests we conclude that the research variables in this study exhibit satisfactory psychometric properties.

5. Study results

The descriptive statistics (mean and standard deviation) of the seven constructs examined in this study and the simple bivariate relations among them are presented in Table 4.

In general, the responding firms in this study on average appear to be medium sized companies (mean = 830 employees), have a moderate level of organizational commitment, and a less than average level of absorptive capacity. They provide a fairly large scope for DW and moderately good data environments. They perceive DW as being able to offer significant benefits and perceive it to be about average in terms of complexity. Note that *t*-tests of the study constructs across the adopter/non-adopter groups are provided in Table 3A. All study variables displayed significantly higher values for the adoption group except on data environment and DW complexity (even here the values are in favor of the adoption group).

Bivariate findings in Table 4 show that the contextual factors correlate significantly among themselves, except between size and data environment. The two innovation attributes are also significantly correlated. Generally, the results suggest that larger firms seem to have greater commitment and greater scope for DW, and that commitment may be associated with higher absorptive capacity, greater scope, and better data environment. Quite naturally, with higher relative advantage, commitment is more evident; likewise, commitment is difficult when the (DW) innovation is perceived to be more complex.

5.1. Choice of logistic regression analysis

Since the research model of this study makes use of seven metric independent variables and one binary dependent variable, *adoption*, logistic regression was deemed to be a suitable statistical technique [42]. Logistic regression analysis is similar to traditional regression but uses a binary dependent variable and is less stringent in terms of normality assumptions. We

Table 4
Correlation among and descriptive statistics of study variables ($n = 196$)

Study variables	V1	V2	V3	V4	V5	V6	V7
Organizational size [a]	6.723 (1.376) [b]						
Organization's absorptive capacity	.227**	3.572 (1.175)					
Organizational scope	.360**	.173*	4.948 (1.018)				
Organizational data environment	.092 n.s.	.204**	.281**	4.635 (1.069)			
DW's relative advantage	.286**	.398**	.452**	.115 n.s.	4.845 (1.068)		
DW's complexity	−.145*	−.336**	−.094 n.s.	−.214**	−.205**	3.977 (0.994)	
Organizational commitment	.238**	.620**	.326**	.228**	.708**	−.273**	4.419 (1.203)

** — $p < 0.01$; * — $p < 0.05$; n.s. — not significant.
[a] Except organization *size* (a natural logarithmic transformation of actual employee count) all variables are measured on a 1–7 range Likert-type scale (1 = strongly disagree; 7 = strongly agree).
[b] Descriptive statistics (mean and standard deviation) of each construct displayed in the major diagonal.

used logistic regression to test this study's seven propositions; the results are shown in Table 5.[5]

As in traditional regression analysis, a base model is first created to set a standard for comparison. However, rather than using mean to calculate the sum of squares (as in multiple regression), the mean is used to set the log likelihood (−2LL) value. We used the greatest reduction of −2LL as the criterion for selection of variables in the stepwise model (forward) selection procedure [42]. There are two statistical tests: 1) a chi-square test for the change in −2LL value from the base model (comparable to overall F test in regression), and 2) Hosmer and Lemeshow measure of overall fit, which is another chi-square test of significant difference between the observed and predicted classifications (of the cases to the groups). In addition, Wald statistic is used to test the level of significance of individual coefficients (similar to regression coefficients). Finally, analogous to the R^2 in multiple regression analysis, three measures — *pseudo* R^2, Cox and Snell R^2, and Nagelkerke R^2 are used to assess the explanatory power of the model.[6]

The results from Table 5 indicate that five of the seven study variables – *organizational commitment*, *absorptive capacity*, *size*, *relative advantage*, and *complexity* – emerge as significant determinants of DW adoption. Neither "respondent type" nor "industry type" has any effect. The −2LL value of the base/null was 257.69 and that of the final model was 158.53, reflecting an improvement, Δ (−2LL), of 99.16; the chi-square (χ^2) for the improvement (comparable to overall R^2) is significant ($p < .001$). Hosmer and Lemeshow measure of overall fit, $\chi^2 = 10.08$, was not significant, indicating no significant differences between the observed and predicted classifications. All three R^2 values vary from .39 to .55 (Pseudo, Cox and Snell, and Nagelkerke) suggesting a satisfactory explanation capability of the logistic regression model.

One final test in logistic regression analysis is to examine the classification ability of the model, i.e., the ability to classify the cases using the logit function into the correct groups. The classification results are also provided in Table 5. While the overall classificatory accuracy is quite high (81.3%), note that the values could be slightly inflated due to classifying the same sample (no hold-out sample) on which the logistic function was developed. It is, thus, necessary to compare the classification ability of this model with a chance model. As advised, we chose the proportional chance criterion when the *a priori* groups (of adopters vs. non-adopters −0.557 vs. 0.443 in our case) are not identical. As shown in the bottom of Table 5, the proportional chance accuracy, π, is determined by the formula $[k^2 + (1-k)^2]$ where "k" is the proportion of the sample in the first group (i.e., 0.545). On this basis, the proportional chance criterion, π, is 50.41%, which is much less accurate than our logistic regression model (81.3%). A t-test (see bottom of Table 5) of the level of significance of the classification accuracy ($t = 8.45$,

[5] Note that we received responses from IT as well as functional area managers to the survey, and manufacturing as well as service firms. To control for any distinctive knowledge differences among different types of executives responding to the study and for any unique industry conditions, we included "Respondent Type" (IT vs. Line Manager) and "Industry Type" (Manufacturing vs. Service) as categorical covariates to examine their influences. We also developed separate models excluding 'Respondent Type' with only the 121 Line manager and 155 IT manager responses (vs. the total sample size of 196). There were no qualitative differences in the results. However, wherever we had two responses from a firm, we averaged the values across the two responses as per research practice, since the unit of analysis is at the firm and not individual level.

[6] Pseudo R^2 is calculated as $\frac{-2L_{\text{null}} - (-2\text{LL}_{\text{model}})}{-2\text{LL}_{\text{null}}}$ or $\frac{\Delta(-2\text{LL})}{-2\text{LL}_{\text{null}}} = \frac{99.16}{257.69} = 0.385$.

Table 5
Logistic regression (MODIFIED) model results ($n=196$)

Research model relationships	Logistic coefficient (standard error)	Wald statistic (significance level)	Score statistic	Support for model
Variables in the model:				
Organizational commitment	1.253 (.299)	17.615***	N/A	H_1: Yes
Organization's absorptive capacity	0.305 (.194)	2.014*	N/A	H_2: Yes
Organizational size	0.378 (.179)	4.431**	N/A	H_3: Yes
DW's relative advantage	0.543 (.275)	3.895**	N/A	H_6: Yes
DW's complexity	−0.590 (.254)	5.377**	N/A	H_7: Yes
Variables not in the model:				
Organizational scope for DW	–	–	.062$^{\text{n.s.}}$	H_4: No
Organizational data environment	–	–	.827$^{\text{n.s.}}$	H_5: No
Respondent type: IT vs. Line Manager	–	–	.612$^{\text{n.s.}}$	–
Industry type: Manufacturing vs. Service	–	–	.236$^{\text{n.s.}}$	–
Model fit properties:				
Final: −2 log likelihood (−2LL)=158.53				
Δ (−2LL)=99.16; χ^2 (Δ, $df=5$) $p\leq.001$				
Hosmer and Lemeshow test $\chi^2=10.08$ ($df=8$, $p=.26$)				
Pseudo $R^2=.385$				
Cox and Snell $R^2=.412$				
Nagelkerke $R^2=.550$				

Classification results[a]		Adopter	Non-adopter	Correctly predicted %
	Adopter	83	19	81.4
	Non-adopter	16	69	81.2

Stepwise procedure with reduction in −2 log likelihood as the criterion used in developing the logistic regression model.
*** — $p<0.01$; ** — $p<0.05$; * — $p<0.10$; n.s. — not significant.
[a]The overall classification accuracy of the logistic regression model (p) at 81.3% relative to *proportional chance criterion* π at 50.41% calculated as $[k^2+(1-k)^2]$ on original proportion of adopters (k) of 54.5% is significant ($t=8.449$, $p\leq.001$), where $t=\frac{(p-\pi)}{\sqrt{\frac{\pi(1-\pi)}{n}}}$.

$p<0.001$) confirms the superiority of the logistic model developed in this study vis-à-vis a chance model [[42]: 268–270]. Overall, these results provide support for five of the seven propositions laid down in our research model.

The somewhat unexpected insignificant findings from the logistic regression model for organizational scope and data environment suggest that the relationships of the study's six antecedents with adoption are probably much more complex than the direct links that we had proposed. We took this as an opportunity to explore alternative models of relationships. We developed one such model as a LISREL structural model, where organizational commitment serves as a mediator between adoption and the innovation attributes (relative advantage and complexity), which in turn serve as mediators between commitment and contextual variables (absorptive capacity, scope, and data environment). These contextual variables are conceptualized to be dependent on the size of the firm. Fig. 2 displays the structural model results.

The overall statistical support for the model is significant ($\chi^2_{(df=14)}=18.72$, $p>0.18$; GFI=0.98; AGFI=0.94; NFI=0.96; NNFI=0.96; CFI=0.99; RMSR=0.058; RMSEA=0.042). The χ^2 value for our model is insignificant ($p>0.18$) as desired and the Normed $-\chi^2$ (χ^2/df) is 1.34, much less than the cutoff value of 3.0. Given the criticism leveled against the χ^2 statistic as being insensitive to sample size, it was complemented with fit indices. All the above-noted *fit* statistics are much better than the desirable thresholds for these fit statistics indicated at the bottom of Table 3B [48].

Fig. 2 also provides the estimates of the structural coefficients for each path and their significance levels. The results indicate that *organizational commitment* has a significant positive effect on *DW adoption* ($\beta_{76}=.48$, $p<.001$). DW's *relative advantage* has a significant positive ($\beta_{64}=.54$, $p<.001$) and DW's *complexity* a significant negative ($\beta_{65}=-.93$, $p<.01$) influence on commitment. *Absorptive capacity* has a significant positive ($\beta_{41}=.31$, $p<.001$) and a significant negative

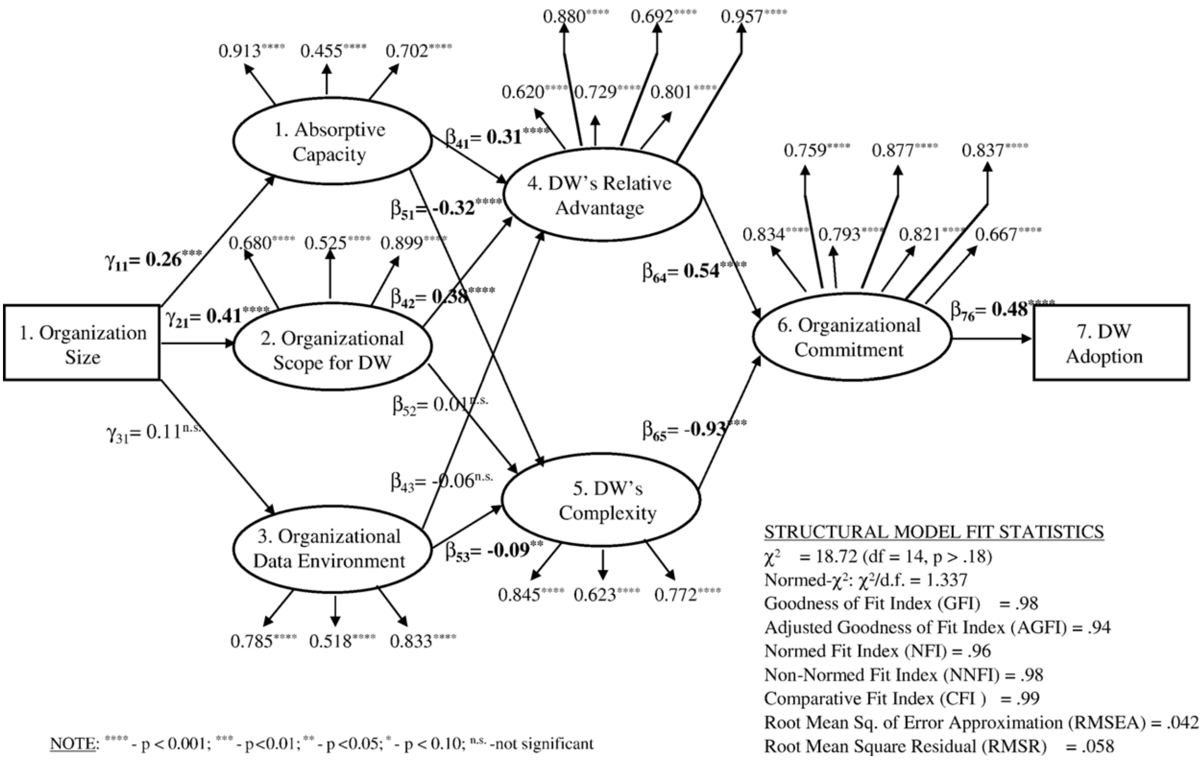

Fig. 2. Alternative LISREL model results of the confirmatory factor analyses and structural model.

($\beta_{51}=-.32$, $p<.001$) influence, respectively, on relative advantage and complexity. Organizational *scope* has a significant positive influence ($\beta_{42}=.38$, $p<.001$) on relative advantage but no influence on complexity. On the other hand, organization's *data environment* has a significant negative influence ($\beta_{53}=-.09$, $p<.05$) on complexity but no influence on relative advantage. Finally, *firm size* has a significant positive influence on absorptive capacity ($\gamma_{11}=.26$, $p<.01$) and scope ($\gamma_{21}=.41, p<.001$) but no influence on data environment.

6. Discussions and implication of the results

We discuss the findings of the study under two separate categories: direct and structural model results.

6.1. Direct effects model results

Five of the seven antecedents – *organization size*, *absorptive capacity*, *relative advantage*, *complexity* and *commitment* – in the *direct effects model* emerged to be important determinants of a firm's DW adoption decision. Notwithstanding the conflicting findings in previous literature, the emergence of *size* as a key factor underscores the fact that not only are larger firms more able to afford the resources (including tools and expertise) required to introduce DW but can also expect to capitalize on the economies of scale/scope within its environment after its implementation. Such firms are in a better position to cost-justify the massive investments required for DW and are also able to take on more risk in terms of financial exposure [37]. A larger firm is more likely to deal with a larger customer and supplier base, providing greater opportunities for leveraging the initial investment in the DW infrastructure innovation. It is also likely that larger firms would be required to be better externally focused in terms of customer orientation and service, given that greater stakes would be involved in terms of market share erosion. It also confirms the suggestions laid down in Swanson's tri-core model of the importance of size. However, with the growing popularity of relatively affordable DW technologies like Microsoft's SQL Server, we expect more and more small/midsize companies to invest in data warehousing.

The result on *commitment* is generally in line with previous research on organizational adoption of IT innovations [65,94] and DW [50]. However, [41] found only partial support (support for EDI but not for CAD/CAM) for this strategic motivator in their study. Also, unlike much of the past research that has examined top management or user support separately, this study considered not only support, but also sustained commitment of all the stakeholders. Senior management in different firms respond to environmental forces in different ways. Some firms seize the opportunity promised by a new innovation and seek to leverage it for their competitive benefits; others languish and are surpassed by their competitors. Top management's futuristic vision/support, accompanied by its ability to convince key stakeholders to see merit in new innovations and win over their support, plays a critical role in determining a firm's response. The DW adoption decision is a strategic decision for many companies [22] since it requires careful consideration at the highest levels. If organizational commitment were lacking, it would be difficult to obtain resources to even consider adopting DW technology.

A key finding of this study is the significant influence of *absorptive capacity*, a variable that has often been cited as important [20,32] and yet received little empirical attention, except in one major study [13]. Clearly, the adoption of a technology innovation is more than investing the financial resources to acquire or build it. The ability to create and nurture an environment to absorb and transfer the skill base to exploit the nuances of an innovation is a key to its adoption. This is especially critical in the context of an IT infrastructure type innovation such as DW [30,98].

Both innovation attributes – *relative advantage* and *complexity* of DW – were found to be important determinants of adoption. The positive effect of relative advantage and negative effect of complexity on adoption are in line with previous findings in the general innovation literature as well as in the IT innovation/TAM literature [1,2,14,26,31,40,79,78,93]. A few studies, however, found different results for complexity. Research studies [2,79] did not find any effect for complexity on acceptance of web and EDI adoption, respectively, and [16] found a positive relationship between complexity (of IT infrastructure) and adoption of open systems. The significance of *relative advantage* reiterates that organizations do expect and need confirmation that substantive benefits from the innovation are feasible before its adoption can be considered. This is especially true in the context of major multi-million dollar investments required for DW. The negative relationship between *complexity* and DW adoption seems quite natural. High complexity of DW sets up significant challenges in understanding not only the basic technology, but how it fits into the existing architecture and aligns with other technology components. Such complex new innovations may demand development of significantly new skill sets and additional competency within the firm.

Among the seven antecedents, it is somewhat surprising that *scope* and *data environment* did not emerge as significant. Note, however, that *scope* was significantly higher for adopter vis-à-vis non-adopter firms (5.18 vs. 4.67, $t=3.67$, $p<.001$). Recall that operationalization of *scope* considered the existence of a robust IT infrastructure and the extent to which there existed a large portfolio of IT applications that could leverage DW. It is possible that many, especially smaller, firms may not already possess a robust infrastructure or a large base of applications to leverage the potential of DW. There may indeed be situations that such firms look to DW as a springboard, for example, to develop a number of beneficial applications in the future. Alternatively, it is also possible, as evidenced by some additional analyses (IT managers=5.12, Line=4.75, $t=2.91$, $p<.01$), that IT managers as compared to functional area managers may be in a better position to judge the organizational scope for leveraging DW's capability in view of their vantage position of being able to view the needs of the entire enterprise vis-à-vis line managers whose interest generally is restricted to their own functional area. Finally, it is also possible that key decision-makers, including IT managers, may have downplayed the importance of scope at the stage of making the adoption decision, hoping that they can "grow the need" for using DW once it is implemented — an evolutionary thinking that is not at all uncommon in data management efforts undertaken in industry [36].

It is also quite surprising that the quality of the existing data environment that may also suggest its maturity level [49,76] did not emerge as a determinant. Although the quality of *existing data environment* was higher for adopter via-a-vis non-adopter groups (4.71 vs. 4.55), it was not significantly different across the two groups ($t=1.02$, $p<.311$). There was also no difference in the responses of IT vs. line managers (IT managers=4.61, Line=4.59, $t=0.14$, $p<.89$). These suggest that both groups of firms have been able to realize more or less similar quality of data environment. Data quality is often cited as a core reason for building a data warehouse [98]. Maintaining data accuracy, availability, sharing and security ensures higher integrity of business decisions made, mined intelligence, etc. [22,35,36,55].

One final plausible reason for scope and data environment not turning out to be significant may be related to multicolinearity in the survey data. A common diagnostic used to assess the seriousness of multicolinearity problem is to examine if the 'squared correlation' among the antecedent variables approaches 0.80 [42]. From Table 4, the highest correlation is 0.708 between 'organizational commitment' and 'relative advantage'; thus, the highest 'squared correlation' is equal to 0.5013, which is much lower than the threshold of 0.80. Therefore, multicolinearity may not be the source for insignificance of these two variables. It is, however, possible that the influences of scope and data environment may have been suppressed/dominated by other variables such as commitment and size.

6.2. LISREL structural model results

Size was a key determinant in the *alternative research model* in influencing *absorptive capacity* and *scope*. However, it did not have significant influence on the *quality of data environment* which, in turn, did not influence *relative advantage* but negatively influenced *complexity*. The positive influence of size on absorptive capacity suggests that larger organizations possess more resources (multiple departments, areas of specialization, skill sets) and provide opportunities for learning within as well as across functional areas. More training resources are, and can be, devoted when embarking on adoption of technology innovations. Furthermore, it appears fairly obvious that larger firms are associated with greater scope both in terms of infrastructural capabilities and larger portfolio of applications to exploit the potential of standardized and integrated data available from DW. On the other hand, the insignificant influence of size on data environment suggests that one cannot take for granted that larger firms have necessarily enforced good data administration practices and nurtured a high quality data environment. Because of the large scale and scope of data it is in fact possible that such firms may face more challenges in maintaining a high quality data environment.

From the alternative model, it is seen that four of the six links between the three organizational variables and two DW innovation attributes are significant. Absorptive capacity had significant positive effect on relative advantage and negative effect on complexity; scope had a significant positive effect on relative advantage but no effect on complexity; and data environment had no effect on relative advantage but a significant negative effect on complexity. Greater absorptive capacity signals better appreciation of the potential benefits from adopting DW. The firm is better informed and more knowledgeable about DW, and therefore better prepared to understand and address the complexity that is associated with introduction of DW. The positive effect that scope has on relative advantage confirms the rationality displayed by the decision-makers in recognizing the higher payoffs that are associated with larger scope. The insignificant relationship between scope and complexity is somewhat contrary to normal expectations of a negative relationship. As we argued earlier, organizational decision-makers led by the IT executives may be downplaying the complexity of implementing DW spanning multiple areas and diverse suite of applications. Likewise, the insignificant relationship between data environment and relative advantage is also somewhat contrary to normal expectations of a positive relationship. It is plausible that if the quality of the data environment is already reasonable and there is a reduced need for data integration there could be doubts on the extent to which relative advantage would be garnered from DW. It is also likely that decision-makers think that one of the key outcomes of DW is to facilitate a high quality data environment, a situation of reversed directionality. However, a high quality data environment would reduce the complexity and associated challenges that are expected from adopting and implementing the DW.

The alternative model indicates very strong positive effects of relative advantage and strong negative effects of complexity on *organizational commitment*. Clearly, these effects do not really need lengthy explanation. Substantive benefits potential from DW and low complexity generate significant confidence and commitment on the part of decision-makers that pursuing DW is a right and good decision. Furthermore, when such a commitment has been generated, it leads to an actual decision of adopting DW, as indicated by the significant positive effect on *adoption*. The relative advantage of an innovation would reflect its perceived usefulness [26] or performance expectancies as labeled in UTAUT model [95]. Awareness of the benefits attributable to the DW innovation is often a prerequisite to obtaining senior management support and commitment. The ability of an organization to have appropriate mechanisms to continuously monitor technological developments in its environment, objectively evaluate the innovation's relevance to the firm, transfer the intelligence gathered, and, when convinced, spread the awareness to key stakeholders within the organization becomes an important issue. Emerging technology groups, R&D units, and championship of innovation are some of mechanisms that can scan, evaluate, interpret, and catalyze the change activity within the organization [5,71].

As observed above, complex new innovations demand development of significantly new skill sets and additional competency within the firm [16]. Development of such additional new expertise is not a short-term endeavor. Viewed in conjunction with the organization's absorptive capacity, adoption requires overcoming the knowledge barriers [6,13]. One obvious implication is that organizations contemplating adoption of complex technological innovations such as DW should first undertake an audit of their unit's knowledge level related to the domain of the innovation, and seek partnerships with DW vendors and consulting organizations whenever necessary. Such an audit process could be viewed as an evaluation of the organization's technology readiness.

7. Conclusions

The objective of this study was to examine the key determinants of adoption of DW, a technology that falls into the category of an infrastructure type innovation. Drawing upon extant body of research in organizational theory and IT innovation adoption, we proposed a research model that posited the direct impact of five organizational and two innovation factors on adoption of DW. The model was empirically validated using data from a large-scale field survey of nearly 200 firms in both manufacturing and service sectors located in two major states in the continental U.S. An analysis of the data indicated support for the proposed effects of five of the seven variables considered as being important in distinguishing adopters from non-adopters. Those five variables are: organizational commitment, absorptive capacity, organizational size, relative advantage, and complexity. An alternative model depicting a richer and more complex set of relationships was also derived and empirically validated as a LISREL structural model. A number of interesting findings from this model were discussed.

Implications: The findings of the study have important implications. It is important to pay attention to both organizational and technology factors when examining a major, infrastructure type innovation that has consequences for the entire enterprise. Recognition of the technology's potential benefits and associated complexity is capable of promoting the level of organizational commitment that is necessary for DW adoption. The results also highlight the vital role absorptive capacity can play in the adoption decision.

The results also imply that large organizations are more likely to have or afford greater degree of the needed DW expertise distributed throughout the enterprise and facilitate sharing such knowledge. Larger organizations provide greater opportunities for exploiting the potential of infrastructural innovations in view of bigger scope. Higher levels of absorptive capacity developed within firms and larger scope enables them to better evaluate the potential in DW as well as address the associated complexity and challenges. These, in turn, help generate organization-wide commitment. Given the importance of absorptive capacity, the implication for smaller firms may be that growing large is not the only pathway, but that they could explore other avenues to increase absorptive capacity (e.g., partnering with other small firms as consortiums, trade association membership, etc.). The importance of the various determinants and their implications should serve as starting points for decision-makers to make timely decisions and institute appropriate means to foster realization of these key determinants (e.g., absorptive capacity, commitment).

The study findings also provide insights for non-adopters from the point of view of IT management practice. In view of the fact that DW is an enabler of partner relationship management practices such as CRM and SCM, which could provide competitive advantage to a firm, non-adopters should seriously consider adopting DW. Those companies that have not adopted or are late adopters of DW may be at a competitive disadvantage. We believe that the findings of this study would be useful for non-adopters in enabling them to take into consideration the key determinants we identified and explore how well these firms could develop strategies and action plans. One of the most important determinants that we found is organizational commitment, which encompasses senior management's vision and support and stakeholder buy-in. While the latter dimension is less likely to be a hurdle in small firms, it is, however, possible that the senior management in small companies may not be well informed about new technologies and therefore risk becoming late adopters. Senior management needs to consciously try to allocate time to evaluate these new technologies and develop a vision for the use of IT innovations such as DW in order to remain competitive. Perhaps, industry associations such as the Data Warehousing Institute and groups that have a vested interest in the adoption of these technologies could play an active role in informing this target group of the strategic benefits that DW can offer.

7.1. Limitations

First, we restricted ourselves to sampling only two of the 50 states in the continental U.S. It is possible that a number of (macro-economic, political) factors such as competition, technology/resource suppliers, tax incentives, etc., could facilitate or hinder investment decisions. We are not sure of the extent to which the operating environments in other regions of the country are similar to the two regions examined in the study. Therefore, care must be exercised in generalizing the results to all the firms within the U.S.

Second, recall that the usable response rate was only about 8% of the population of firms targeted. Although we took extensive care in assessing "response bias," we do not know how many of the non-responding firms have or have not adopted DW. It is quite possible that many of the firms that did not have DW may have chosen not to respond to the study. Thus, there may be a "pro-technology bias" and the results should be interpreted carefully. Also, note that the study's data set included single respondents from 116 firms raising concerns about the extent to which a single respondent's view captures that of the entire firm.

Third, the study sample consisted of firms in both manufacturing and service sectors. The industry type did not have any effect on adoption decision. While the ability to examine both sectors is a positive aspect of the study, it is also somewhat of a weakness because the service sector is very broad, including firms from diverse specialties (insurance and investment to hospitality and restaurants). Such diverse firms are likely to have very different needs and expectations from DW innovation. The same rationale may be true of even manufacturing firms dealing in different product lines. The restricted sample size of 196 firms did not permit us to do any fine-grained data analyses based on different subspecialties.

Finally, we alluded that multicolinearity among the antecedent variables did not appear to be serious from examining the diagnostic, 'squared correlation.' However, it is possible that the influences of scope and data environment may have been dominated by other variables that emerged to be very significant in this study in the direct model. Also, there is the potential of inadequate evaluation of (at least) 'scope' by line managers. The operationalization of scope may need to be improved. For instance, many (especially small) firms may not already have a large base of applications that could work off DW but use DW as a springboard to develop suitable applications in the future.

7.2. Directions for future research

In addition to addressing the limitations noted above, future research could pursue a number of avenues. We alluded to key decision-makers downplaying the importance of "scope" at the stage of making the adoption decision, hoping that they can "grow the need" for using DW once it is implemented. We do not know whether this is evolutionary thinking in data management efforts [35] or political gamesmanship [58].

We assumed that DW, as an infrastructure innovation, would confer "flexibility" and "responsiveness" for both current and future IT applications. We did not directly measure flexibility, a key component of a responsive infrastructure, afforded by a data warehouse. Also, a DW is only one of four broad elements that constitute the IT infrastructure; inflexibility in any one of these could neutralize the potential benefits of the others. It is also possible that flexibility may not be the only or even the primary expectation from DW to all firms; it may be that data standardization, consistency, integration, and effective control are more important to some firms [22,55,89,98]. It is therefore necessary for future research to directly incorporate the many dimensions noted here and examine their influence on adoption (and subsequent use).

The study examined absorptive capacity, a key but less researched variable. Given the nature and objective of this study, we were interested in the "state" of absorptive capacity at a given time. Equally important may be the process of *how* absorptive capacity is nurtured and the ways in which its relationships with the other variables investigated in this study (formation of commitment via evaluation of relative advantage, and complexity of the innovation) is maintained over time to influence subsequent use within the organization. Also, the measurement of absorptive capacity may need improvement; we adapted Szulanski's scale but used only three of his seven indicators in the interest of size of the survey.

As with a recent study on DW implementation [98], despite being considered a very important variable, the quality of the data environment did not emerge to be a key determinant in the direct model and had only a moderate effect on complexity in the structural model. Perhaps, organizations have failed to maintain a high quality data resource management environment in light of the proliferation of heterogeneous data (e.g., with the onset of click-stream and call-center data) and, therefore, look to DW introduction as a way to develop a high quality data environment. It will be interesting to examine the underlying causes for this phenomenon.

This study made a fundamental assumption that organizational size and slack are interrelated; that is, larger firms possess more slack. It is possible that this may not always be true; larger organizations may be starved of resources or face competition for available resources from different parts of the enterprise. Future research could include slack as a separate variable. Importantly, it may be necessary to make a distinction between "absorbed slack" and "unabsorbed slack", and measure both these forms of slack comprehensively to identify their effects [12,25,88]. While absorbed slack corresponds to excess costs in organizations, unabsorbed slack refers to excess yet uncommitted liquid resources. Some research suggests that absorbed slack may be related to risk-taking and, therefore, to adoption of high-risk innovations such as DW.

While our use of logistic regression model in this study to examine adoption of DW as a binary decision is appropriate, it must be recognized that there is an underlying assumption of time invariance. Clearly, a non-adopter in this study may become an adopter at a later point in time. More sophisticated approaches such as survival analysis or hazard function (e.g., Cox regression models) could be considered in future research to model the adoption phenomenon. We presented an alternative structural model with a number of mediating variables between organizational size and adoption of DW innovation. It may be noted that there could be competing conceptualizations. For instance, organizational commitment could be grouped along with the two innovation attributes as mediating between the previous set of three organizational variables and adoption. Organizational commitment could also be conceptualized as a moderator of the relationship between the two innovation attributes and adoption. Obviously, there is a need for replication of the inductive model proposed here with new data sets as well as testing the alternative conceptualizations to determine which model could be optimal in explaining DW adoption.

Finally, we only examined the adoption decision. As DW becomes more prevalent, it would be necessary and interesting to examine what organizational benefits accrue from subsequent use/diffusion of the innovation within the organization [69]. It might be interesting to examine if there are any differences in DW use by firms that are proactive (those that adopt on their own initiative) vs. those that are reactive (e.g., those that adopt in response to partner firms' need for sharing data and intelligence or adopt because of other institutional pressures).

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Appendix A. Operationalization of study variables

A number of statements are given below seeking your best response. There is no right or wrong response to any of these. Please respond to ALL of the statements on a 1–7 scale (1 = strongly disagree; 4 = neutral; 7 = strongly agree). Do not omit any statements. We will use DW as an abbreviation for data warehouse/data warehousing. Wherever you may not know the exact response, please provide your best and most accurate judgment.

Study variables	Extant research support
1. Organizational commitment *(O_COMMIT)*	[25,44,85,98,101]
• Senior management in our company supports use of DW.	
• Senior management commits to provide all necessary resources for the development and operation of DW.	
• Senior management is willing to take all the risks (financial and organizational) involved in the adoption of DW (given that it is a major undertaking triggering enterprise-wide changes).	
• We have a vocal/visible business management sponsor for DW.	
• Key stakeholders (functions, departments, divisions, etc.) in our company understand the need for DW and consequent changes.	
• Key stakeholders (functions, departments, divisions, etc.) in our company are supportive of DW and consequent changes.	
• Key stakeholders (functions, departments, regions, etc.) in our company are aware of (un) favorable rewards for (not) using DW.	
• Overall, a strong business management sponsorship exists for DW within our company.[a]	
2. Organizational absorptive capacity *(ABS_CAP)*	[6,13,20,91]
• In general, our company's key (potential) users of DW are quite familiar with, have a vision for, and understand what DW can do for the company.	
• In general, at this time key users of DW need extensive training to develop the skills to understand and properly use DW.[b]	
• In general, at this time there are hardly any major knowledge barriers and our company's key users of DW can be described as being technically savvy to exploit DW capabilities.	
• Overall, there is inadequate level of understanding and technical sophistication on the part of our employees who will make use of DW.[a, b]	
3. Organizational Scope/Feasibility for DW *(O_SCOPE)*	[59,70,90]
• Our company has a robust IT infrastructure in place.	
• There are currently a large number of IS applications within our company that can make use of and benefit from DW.	
• The data currently available in our company is very complex.	
• Overall, DW addresses several critical business requirements of our company.[a]	
4. Organizational data environment *(DAT_ENV)*	[35,36,55]
• The data currently available in our company is of high quality.	
• The data that we currently use in our company is reliable.	

(continued on next page)

Appendix A (*continued*)

Study variables	Extant research support
• We *do not* have clear agreement on a common set of data definitions and business rules in our company at this time.[b]	
• Overall, information is shared openly throughout our organization. [a]	
5. Organization size *(SIZE)*	[24,25]
• Number of employees (natural log transformed in data analyses).	
• Overall, there is no difficulty in finding all necessary resources (funding, people, time) to implement DW within our company.[a]	
6. DW's relative advantage *(REL_ADV)*	[26,55,82,93,96,98]
• Using DW *does not* result in a high payback.[b]	
• DW improves decision-support operations within our company.	
• DW improves on-line analytical processing (OLAP)/data mining operations within our company.	
• All key stakeholders in our company (various departments/users) believe DW to be a high payback initiative.	
• DW readily provides quality data for management decision making.	
• Overall, implementing DW is beneficial to our company.	
• Overall, we believe the feasibility of implementation of DW within our company is high.[a]	
7. DW's complexity *(COMPLEX)*	[26,78,82,93]
• DW is (likely to be) difficult to understand, implement and use within our company.	
• Using DW requires a lot of (mental) effort in our company.	
• DW is (likely to be) cumbersome to implement and use within our company.	
• Overall, considerable resistance exists within our company toward implementation and use of DW.[a, b]	

[a]Alternative independent measures of the constructs to assess *criterion validity.*

[b]The marked indicator statements were reverse coded.

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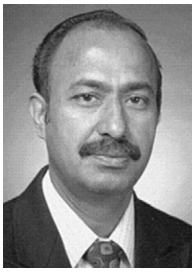

Dr. K. Ramamurthy is a Professor of Management Information Systems (MIS) at the University of Wisconsin-Milwaukee. He has a Bachelors degree in Mechanical Engineering and a graduate diploma in Statistical Quality Control and Operations Research in India, MBA from Canada, and Ph.D. degree in business, with a concentration in MIS from the University of Pittsburgh. He has nearly 20 years of industry experience and has held several technical and executive positions. His current research interests focus on electronic commerce including inter-organizational systems/EDI and the Internet; adoption, implementation and diffusion of modern information technologies; data resource management and data warehousing; decision and knowledge support systems for individuals and groups; IT business value; TQM including software quality; strategic IS planning; outsourcing and offshoring; and management of computer integrated manufacturing technologies. He has published extensively in major journals including *MIS Quarterly*; *Journal of Management Information Systems*; *IEEE Transactions on Software Engineering*; *Decision Sciences*; *Decision Support Systems*; *IEEE Transactions on Systems*, *Man and Cybernetics*; *European Journal of Information Systems*; *International Journal of Electronic Commerce*; *Journal of Organizational Computing and Electronic Commerce*; *International Journal of Human-Computer Studies*; *IEEE Transactions on Engineering Management*; *Journal of International Marketing*; *International Journal of Production Research*; *International Journal of Man-Machine Studies*; *OMEGA*; *Transportation Journal*; *INFOR*; and over 20 articles in a number of refereed *Conference Proceedings*. He is a charter member of AIS, and elected to Beta Gamma and Sigma honor society. He is an Associate Editor for *MIS Quarterly*.

Arun Sen received the M.Tech. degree in Electronics from the University of Calcutta, Calcutta, India, and the M.S. degree in Computer Science and the Ph.D. degree in Information Systems from Pennsylvania State University, State College, PA. He is a Professor in the Department of Information and Operations Management, Texas A&M University, College Station. His research interests include decision support systems, data base management, repository management and software reuse, case-based reasoning, technical and behavioral aspects of data warehousing, and E-Commerce. He has published over 45 research papers in journals such as *MIS Quarterly, Information Systems Research*, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, IEEE TRANSACTIONS ON SOFTWARE ENGINEERING, IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT, *Decision Sciences, Communications of the ACM, Information Systems, Computers and OR, Omega, European Journal of Operational Research, Decision Support Systems, Journal of MIS, Information and Management, and Omega*. He has served as an Associate Editor of *Journal of Database Management*. He has also been an Editor of special issues for *Decision Support Systems, Communications of the ACM, Database, and Expert Systems with Applications*. He was the Chair of INFORMS College on Information Systems, and a program chair for the Workshop on Information Technologies and Systems, 1996.

Atish P. Sinha received the Ph.D. in business, with a concentration in Artificial Intelligence, from the University of Pittsburgh, Pittsburgh, PA. He is an Associate Professor of MIS at the Sheldon B. Lubar School of Business, University of Wisconsin-Milwaukee. His current research interests are in the areas of data mining, data warehousing, and object-oriented software engineering. His research has been published in several journals, including *Communications of the ACM*, IEEE TRANSACTIONS ON SOFTWARE ENGINEERING, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, *Information Systems Research, International Journal of Human-Computer Studies, and Journal of Management Information Systems*. Dr. Sinha is a member of the Association for Computing Machinery, the Association for Information Systems, and the Institute for Operations Research and Management Sciences. He served as the Co-chair for the 16th Workshop on Information Technologies and Systems, 2006.