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IT innovation adoption by enterprises: Knowledge discovery through text analytics

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ABSTRACT

Enterprise adoption of information technology (IT) innovations has been a topic of tremendous interest to both practitioners and researchers. The study of technological, managerial, strategic, and economic factors as well as adoption processes and contexts has led the field to become a rich tapestry of many theoretical and conceptual foundations. This paper provides a comprehensive multi-disciplinary classification and analysis of the scholarly development of the enterprise-level IT innovation adoption literature by examining articles over the past three decades (1977–2008). We identify 472 articles and classify them by functional discipline, publication, research methodology, and IT type. The paper applies text analytic methods to this document repository to (1) identify salient adoption determinants and their relationships, (2) discover research trends and patterns across disciplines, and (3) suggest potential areas for future research in IT innovation adoption at the enterprise level.

1. Introduction

Adoption of information technology (IT) innovations has been a topic of significant interest to researchers and practitioners over the past three decades (e.g. [18,53,56]). Broadly, there are two complementary perspectives on IT innovation adoption: the first and more frequently examined perspective includes the adoption of IT innovations by the individual user. Often referred to as the bottom–up view, individual IT innovation adoption research has focused on user characteristics, behavioral motivation, and contextual elements. Enterprise IT innovation adoption on the other hand focuses on the firm and firm-level characteristics.[1] This perspective has gained particular interest due to enterprises' increasing dependence on IT as well as some highly publicized successes and failures over the past two decades. Consequently enterprise-level IT innovation adoption studies have focused on why, how, and under what conditions enterprises have succeeded or failed in adopting and implementing IT innovations. These issues have been examined for a wide range of different IT innovations, including enterprise information systems, electronic commerce, database management systems, network and telecommunications infrastructure, computer hardware, enterprise architecture components, and business productivity applications, among many others. As a result, previous studies have identified drivers and inhibitors, explored the influence of important technological, individual, organizational, strategic, economic, and managerial, and environmental factors, and examined key processes and stages associated with the adoption of IT innovations.

Because IT touches upon virtually all aspects of an enterprise's value chain, researchers have drawn on theories, frameworks and models from a variety of complementary academic reference disciplines such as information systems, computer science, economics, organizational sciences, marketing, and strategic management. In doing so, enterprise adoption research has thus become a rich tapestry of a plethora of theoretical and conceptual foundations.

Despite arguments that research within this domain is exhausted, enterprise adoption of IT continues to be a topic of interest to decision makers, managers, vendors, and users alike. Practitioners have argued that within corporate IT, the pace of technology change has increased so significantly that executives who do not embrace IT innovations at some level risk ending up behind the competition. Indeed, in today's global and competitive environment, IT innovations can provide enterprises with the ability to streamline and transform their organization, create new forms of organization, provide enhanced collaboration capabilities, generate new competitive advantages, and potentially enable them access to new industries and markets [7,15,58].

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[1] Unquestionably, there is a strong relation between individual and enterprise adoption of IT innovations. Many IT innovations are often first adopted by individuals and later assimilated into the organization. As a result it is not surprising that there is large body of research examining individual IT innovation adoption. Interested readers are referred to [27] W. R. King and J. He, "A meta-analysis of the technology acceptance model," *Information and Management*, vol. 43, pp. 74–755, 2006, [32] P. Legris, J. Ingham, and P. Collerette, "Why do people use information technology? A critical review of the technology acceptance model," *Information & Management*, vol. 40, pp. 191–204, 2003, [57] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: toward a unified view," *MIS Quarterly*, vol. 27, pp. 425–478, 2003. for extensive reviews.

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However, IT innovation adoption strategies must be carefully evaluated and balanced as IT budgets are tightening. Consequently, with the continuous emergence of IT innovations, there will be not only a need but also an opportunity to understand and study how and why enterprise adoption occurs, what contextual factors have changed, what fundamental value IT innovations can deliver, and in what ways they align or transform corporate strategy. As a result, we anticipate that IT innovation adoption research will continue to proliferate.

The objective of this paper is not to suggest new theories or propositions concerning enterprise adoption of IT innovations, as there is no lack of these. Given the vast nature and diversity of the enterprise adoption literature, there is also no attempt made to offer a comprehensive recitation of research findings or methodologies. The purpose is, rather, to provide a sufficient assessment of the current state of enterprise adoption research by providing a comprehensive classification and analysis of the scholarly development of the literature. Our work differs from previous literature review and meta-analytic studies in several ways [25,27,59]. While IT innovation adoption is predominantly a phenomenon studied by information systems researchers, it is a complex topic that touches upon a plethora of issues central to other disciplines, including operations management, strategy, marketing, and organizational behavior. Consequently, examination of solely IS publications would not provide an accurate and holistic reflection of IT innovation adoption research [59]. In contrast to earlier review studies, this paper therefore does not focus only on IS studies or research in a single discipline, but examines all relevant academic disciplines.

A second key difference of this study is the application of text analytic methods to identify, explore, and evaluate the rich literature on enterprise adoption of IT innovations. Traditionally, literature reviews required manual identification, evaluation, and coding of relevant text sources. The resulting process is extraordinarily resource-intensive; consequently, researchers often limit the scope and scale of their analysis. Often times, review studies focused their assessments on title, abstracts, and keywords of research articles only, which has been identified as a clear limitation for comprehensive analysis of a topic domain [59]. More recently, it has been argued that text mining techniques could significantly improve literature assessments as they enable researchers to examine both structured and unstructured full-text data more rapidly and accurately [16]. In this paper, we harvest this power by using a full-text mining approach to extract key phrases and information, identify central themes, and apply concept linking.

Lastly, a key difference of this paper is the examination of over three decades of IT innovation adoption research. In contrast to most previous review studies, which limited their analysis to five to ten-year time spans, we provide a comprehensive picture of the scholarly development and trajectory of research and are thus able to identify important longitudinal trends in enterprise-level IT innovation adoption topics, methods, drivers, inhibitors, and contexts.

The remainder of this paper is structured as follows. Section 2 describes the research methodology and text mining technique used to conduct the multi-disciplinary literature classification and analysis. Section 3 presents the results of the study. Research implications are discussed in Section 4. The paper concludes in Section 5.

2. Method

The study of enterprise adoption of IT innovations is not confined to a single discipline. As such, the identification of relevant studies becomes quite cumbersome and requires an integrative literature analysis approach. We combine manual identification, extraction, and coding of articles with full-text analytics to automatically extract key terms and discover research patterns. An overview of our research approach is shown in Fig. 1.

2.1. Data sources

A preliminary scan of the literature reveals several complementary research streams that examine enterprise adoption of IT innovations. In order to simplify the classification of the relevant literature, we used a combination of previously identified supporting discipline subject areas to consolidate and group the various publication outlets into five broad research streams (see Table 1) [34,35].

Given the increasingly growing base of studies across these five categories, we conducted an extensive search of the literature by searching several comprehensive online databases. These included ABI/INFORM, Academic Search Elite, ACM Digital Library, Emerald Fulltext, IEEE Xplore, Science Direct, and the Social Science Citation Index (SSCI). In those cases where online access was not available, a hardcopy of the article was obtained through the university library and interlibrary loan systems.

It should be noted that our study focused on highly ranked journals as identified in previous studies and ABS rankings [1,20,34,39,45]. We decided not to include conference proceedings, books, book chapters, theses, dissertations, and articles from the popular and trade press due to the commonly accepted belief that scholarly, peer-reviewed journals tend to be the best outlets for disseminating new knowledge [17,39]. A complete list of journals included in our literature analysis, categorized by research stream, is shown in Table 2.

2.2. Inclusion criteria

The literature search was based on a number of different descriptors adapted from the Barki keyword classification scheme, which is commonly used to classify studies in the management information systems (MIS) and technology management literature [5,6]. These descriptors included: “Information Technology Adoption (EL05)”, “IS Implementation (FD)”, “Diffusion of Innovation (DD0502)”, “IS Planning (EF)” and “Strategic Planning (AF0406).” While additional descriptors could have been used, the authors believe that these descriptors sufficiently describe and capture the breadth of potential topics associated with the study of enterprise adoption of IT innovations.

The timeframe of our analysis is 1977 to 2008. The starting date of 1977 was chosen based on the first occurrence of an article [62], to the best of the authors' knowledge, specifically addressing the issue of enterprise adoption of IT innovations. Our time period is more comprehensive than any other study on integrating findings on IT innovation adoption. Most studies have used a short, 1, 5 or 10-year span. We argue that a broader time horizon enables a much richer longitudinal comparison of studies and a more accurate evaluation of the scholarly development and evolution of the field.

The full text of each article was reviewed by the authors to eliminate those articles that did not meet the selection criteria. The selection criteria for article inclusion were as follows:

- *Articles focused solely on the adoption of IT innovations*. This eliminated those studies that considered organizational innovations, such as processes, methodologies, managerial philosophies and strategies; non-IT innovations, such as manufacturing technologies; and administrative innovations in general
- *Articles with the enterprise, organization, or firm as the focal unit of analysis*. This eliminated a substantial body of research that focused primarily on individual (e.g. end-user, consumer, customer, etc.) and group (e.g. team, community, etc.) adoption of IT.
- *Studies published in one of the six functional categories and associated leading journals*, as these were considered the most likely outlets for relevant and rigorous enterprise adoption research.
- *Studies based on rigorous research methods*. Each of the included studies had to be based on rigorous research methods to ensure validity, consistency, and quality. This eliminated editorial notes, research notes, and executive overviews.

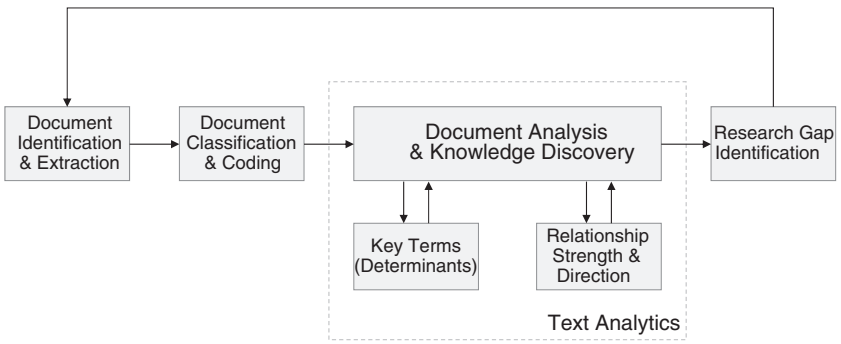

Fig. 1. Research approach.

Based on these selection criteria, our comprehensive search yielded 472 articles from 66 journals.

2.3. Classification

The full-text of each of the 472 articles was reviewed by the authors and classified according to categories suggested by previous studies [38,60]. The articles were classified and coded as follows.

- *Year of publication*. The dataset was divided into four time periods, namely 1977–79, 1980–89, 1990–99, and 2000–08.
- *Functional discipline*. See Table 1.
- *Publication*. See Table 2.
- *Research methodology*. The classification scheme for research methodologies used in this study is based on several existing taxonomies [2,19,42] and is shown in Table 3.
- *IT innovation*. The starting points for this type of classification were IDC's taxonomies of software, hardware, and network infrastructure and Northern Light's information technology term catalog [14,22,50]. However, since both of these taxonomies provide a significant level of detail not necessary for the purpose of this study, the authors integrated the two taxonomies and used a simplified two-level hierarchy. The classification scheme for IT innovation type is shown in Table 4.

The coding of articles was conducted in two phases. Phase 1 included the coding of all articles by the authors and three doctoral students, who have had prior experience with research methodologies and are conducting doctoral research in innovation management and technology strategy. Since articles could employ multiple research methodologies, coders were allowed to identify up to two per article. Similarly, coders were allowed to identify up to two IT innovation types studied per article, if applicable. If an IT innovation type could not be identified in the classification scheme, coders were instructed to determine the most appropriate term and category and assign it to the article. In phase 2, the authors and doctoral students resolved any disagreements on article classification by discussion and consensus.

2.4. Intercoder reliability

Intercoder reliability, defined as "agreement among coders about the categorization of content," was assessed using Krippendorf's alpha [21,28]. This method was preferred over percentage agreement, as it corrects for chance agreement among coders. Krippendorf's alpha is a chance-corrected measure of intercoder reliability that assumes multiple coders (m), n cases, and k mutually exclusive and exhaustive nominal categories [28]. Statistics were calculated in SPSS 14.0 using a macro developed by [21]. The resulting intercoder reliabilities for research method and IT innovation type studied were $\alpha_{rm} = 0.8613$ and $\alpha_{it} = 0.9072$, respectively. These results are well above the recommended level of $\alpha = 0.800$, thus indicating a sufficiently high intercoder agreement for article classification.

Table 1
Functional discipline categories.

Category	Functional discipline (sub-disciplines)
I	Information Systems and Computer Science
II	Decision Sciences (Decision Theory, Operations Management, Production Management, Operations Research)
III	Management and Organization Sciences (Business, Strategy, Marketing, Finance, Org. Behavior)
IV	Economics
V	Innovation

2.5. Text analytics

Recent research has suggested the tremendous potential for enriching traditional literature analyses with text data mining methods [10,16,43,54]. In contrast to traditional literature analyses, in which a small set of articles within a specific discipline is examined, the use of text mining enables researchers to identify topical relationships and discover research trends in a large set of documents across multiple scholarly domains. Traditional literature analyses are often time and resource intensive. Text analytics overcomes these challenges by applying automated means to extract and discover knowledge in unstructured data sources.[2] Unquestionably, text mining is of significant value to researchers [16].

Surprisingly, however, text mining has not been used extensively for analyzing and classifying literature. Notable exceptions exist in the system biology, biomedical, and bioinformatics domains, where researchers have mined various data repositories (e.g. MedLine) for identifying gene functionalities, molecular interactions, and disease progression, for example [12,24,37]. Given the very large and highly cross-disciplinary corpus of IT innovation studies, we argue that text mining is particularly valuable in this context.

We used Northern Light's MI Analyst engine for analyzing and classifying articles [49]. MI analyst is a powerful web-based software tool that provides researchers with the ability to identify key relationships and automate "meaning extraction" from a large corpus of documents. Meaning extraction is an emerging technology that identifies elements of information and concepts contained within documents and document repositories, and surfaces combinations of these informative elements and concepts that imply meaning in the […] purpose of the search process. Meaning extraction applied to search applications dramatically improves and accelerates a searcher's ability to gain insight into a topic and answer specific research questions [49].

Most text mining systems identify key phrases (or "themes") that recur often in the documents in the repository and provide faceted navigation of the themes. While potentially interesting as a discovery exercise and sometimes impressive at first viewing, the usefulness of this

[2] Common data mining approaches are applied to structured data sources, in which key fields and terms are indexed and stored in a database. The key advantage of text mining is its ability to analyze massive amounts of unstructured data.

Table 2
Journals included in study.

Category	Journal title	Acronym
I	ACM Transactions on Information Systems	ACM TIS
I	Behavior and IT	BIT
I	Communications of the ACM	CACM
I	Communications of the AIS	CAIS
I	Decision Support Systems	DSS
I	Electronic Markets	EM
I	European Journal of Information Systems	EJIS
I	IEEE Computer	COMP
I	Information and Management	IM
I	Information and Organization	IO
I	Information Systems Frontiers	ISF
I	Information Systems Journal	ISJ
I	Information Systems Management	ISM
I	Information Systems Research	ISR
I	International Journal of E-Commerce	IJEC
I	Journal of Computer Information Systems	JCIS
I	Journal of E-Commerce Research	JECR
I	Journal of Global Information Management	JGIM
I	Journal of Information Systems	JIS
I	Journal of Information Technology	JIT
I	Journal of IT Theory and Application	JITTA
I	Journal of Management Information Systems	JMIS
I	Journal of Organizational Computing & E-Commerce	JOCEC
I	Journal of Strategic Information Systems	JSIS
I	Journal of the AIS	JAIS
I	MIS Quarterly	MISQ
I	SIGMIS Database	DB
II	Decision Sciences	DS
II	European Journal of Operational Research	EJOR
II	IEEE Transactions on Engineering Management	TEM
II	International Journal of Production Research	IJPR
II	Interfaces	IF
II	Management Science	MS
II	OMEGA	OM
II	Production & Operations Management	POM
III	Academy of Management Journal	AMJ
III	Academy of Management Review	AMR
III	Administrative Science Quarterly	ASQ
III	European Journal of Marketing	EJM
III	Harvard Business Review	HBR
III	Industrial Marketing Management	IMM
III	Journal of the Academy of Marketing Science	JAMS
III	Journal of Business Research	JBR
III	Journal of General Management	JGM
III	Journal of Management	JMGT
III	Journal of Marketing	JMKT
III	Journal of Marketing Research	JMR
III	Organization Science	OS
III	Sloan Management Review	SMR
III	Strategic Management Journal	SMJ
IV	American Economic Review	AER
IV	Applied Economics	AE
IV	International Journal of Economics of Business	IJEB
IV	Journal of Economic Dynamics & Control	JEDC
IV	Journal of Economics	JE
IV	Journal of Industrial Economics	JIE
IV	RAND Journal of Economics	RAND
IV	Review of Industrial Organization	RIO
IV	Structural Change & Economic Dynamics	SCED
IV	World Economy	WE
V	Economics of Innovation & New Technology	EINT
V	Industry and Innovation	I&I
V	International Journal of Innovation Management	IJIM
V	Journal of Product Innovation Management	JPIM
V	R&D Management	RD
V	Technovation	TECH

Table 3
Classification scheme of research methodologies.
Adapted from [42].

Methodology	Definition
Case study	Study of a single phenomenon (e.g., an application, a technology, a decision) in an organization over a logical time frame
Content analysis	A method of analysis in which text (notes) are systematically examined by identifying and grouping themes and coding, classifying and developing categories
Field experiment	Research in Org. setting that manipulates and controls the various experimental variables and subjects
Field study	Study of single or multiple and related processes/phenomena in single or multiple organizations
Frameworks and conceptual model	Research that intends to develop a framework or a conceptual model
Interview	Research in which information is obtained by asking respondents questions directly. The questions may be loosely defined, and the responses may be open-ended
Laboratory experiment	Research in a simulated laboratory environment that manipulates and controls the various experimental variables and subjects
Literature analysis	Research that critiques, analyzes, and extends existing literature and attempts to build new groundwork, e.g., it includes meta-analysis
Mathematical model	An analytical (e.g., formulaic, econometric or optimization model) or a descriptive (e.g., simulation) model is developed for the phenomenon under study
Qualitative research	Qualitative research methods are designed to help understand people and the social and cultural contexts within which they live. These methods include ethnography, action research and interpretive studies.
Secondary data	A study that utilizes existing Org. and business data, e.g., financial and accounting reports, archival data, and published statistics.
Speculation/ commentary	Research that derives from thinly supported arguments or opinions with little or no empirical evidence
Survey	Research that uses predefined and structured questionnaires to capture data from individuals. Normally, the questionnaires are mailed (now, fax and electronic means are also used)

feature is limited as the terms that are automatically identified in this way often contain little substantive content. For example, during earnings announcement season many documents will surface "quarterly results" as a common theme. By itself, this is of little value as a text mining event because the text string contains nothing of significance. Some text mining systems measure the degree to which themes are related using statistical measures, and users are given the ability to automatically expand the search terms to "related" terms. For example, the term "quarterly results" might be found to be related to the term "quarterly earnings". This is sometimes referred to as "semantic" search.

From an analysis perspective, the ability to detect and measure relationships between text strings can be very useful if used to extract meaning rather than to expand search terms. A classic example comes from the pharmaceutical domain. Imagine that Treatment A for Disease X is found on a literature search to be related to Gene H, and that Disease Z is found to also be related to Gene H. A text mining engine might surface the overlapping relationship to the researcher, in effect suggesting that Treatment A be considered for use on Disease Z.

Northern Light MI Analyst features such "meaning extraction". A key feature of MI Analyst is that the researcher can specify term lists that represent interesting concepts and combinations of concepts in proximity that imply meaning. The system is flexible in that any text string can be deemed an entity of interest and any relationship between the entities that can be expressed in Boolean and proximity operators can be used to extract meaning. For example, if a company name, "quarterly results", and "falling profits" are found near "higher energy costs" one can infer the "meaning" that the subject company reported a profit squeeze because oil prices jumped. Because of its flexibility in entity and relationship specification, MI Analyst can be used to research any question using any corpus of material available to the researcher.

The basic technical architecture of MI Analyst includes Data Preparation (text extraction, entity extraction, and relationship identification), a Meaning Taxonomy that specifies text strings for entity extraction and rules sets for identifying relationships, a Document Records Database, an Indexing Engine, an Index, a Query Server, and the Analyst Portal (i.e., user interface) (Fig. 2).

Table 4
Classification scheme of IT innovation type.

Type	Select examples
Applications	Administrative, Authoring and Publishing Software, Browser, Business Intelligence & Analytics, Collaboration & Communications, Content Management, Customer Relationship Management (CRM), Decision Support Systems (DSS), Electronic Data Interchange (EDI), Engineering, Enterprise Resource Planning (ERP), Executive Information Systems (EIS), Geographic Information Systems (GIS), Healthcare, Human Resources (HR), Manufacturing and Supply Chain, Office Applications, Open Source, Sales Force Automation (SFA), Search, Strategic Information Systems
Application development	CASE, Programming Languages, Web Site Design/ Development Tools
Data and knowledge management	Data integration, Data mining, Data warehouse, Database design, Database management system (DBMS), Distributed databases, Information processing, information search and retrieval, Knowledge management, Object oriented databases, Relational database, XML
Electronic commerce and electronic business	B2C/B2B E-Commerce, Electronic Payment Systems, Electronic Billing, Electronic Marketplace, Electronic Trading, E-Hub, Internet/ World Wide Web, Website
Enterprise architecture	Distributed computing, Distributed systems, Enterprise Application Integration, Grid computing, Grid networking, Middleware, Service oriented architecture, Web services
Hardware	Components, Core Technologies, High Performance Computing, Laptops, Mainframes Memory, Peripherals, Personal Computers, Servers
Mobile/wireless	Smartphones, Handheld devices, Personal Digital Assistants, Text Messaging, Mobile Computing, Cellular Phones, Ubiquitous Computing, iPhone, Blackberry
Networking and communications	Telephony, ISDN, Broadband Access (e.g. Cable, DSL), Local Area Networks, Wide Area Networks, Client/Server Architecture, Peer-to-Peer Architecture, Service Oriented Architecture and Web Services, Network Standards and Protocols, System and Network Management Software, IP Convergence, Routers, Virtual Private Networks, Voice over IP
Platforms	Operating Systems, Windows, Unix, Linux, Mac, Windows NT, OS/2, Windows XP
Security	Adware, Spyware, Authentication, Identity Management, Antivirus, Firewall, biometric IT, Digital signatures, Inter net monitoring, Encryption,
Storage	Backup software, optical storage, storage area networks, storage media, tape drives, magnetic storage
Virtualization	Network Virtualization, Storage Virtualization, Desktop Virtualization, Server Virtualization, Autonomic Computing, Utility Computing

The *meaning taxonomy* includes the identification and organization of keywords and relevant terms. MI Analyst provides a comprehensive library of terms and related words. The researchers can specify a custom list of terms that is particularly applicable to the set of documents. Often times, these terms complement the existing library. In this study, we built a comprehensive list of IT innovation types (as outlined in Section 2.3) as well as IT innovation adoption determinants based on previous review studies (e.g. [25]) and our understanding of the domain. *Rule sets* are statements that specify what data the MI Analyst should identify and how it should process it. Rule sets organize the decision logic of identification and extraction of relevant data and data combinations. Examples include identification of two or more terms in a pre-defined word proximity of each other. For example, we are interested in understanding what factors would either increase or decrease the likelihood of IT innovation adoption and whether that relationship was significant. This scenario would require the identification of a *Factor* in one sentence proximity (~40 words) to the keyword *Adoption* (and/or its equivalents) as well as to the keyword *Significant* (and/or its equivalents). Rules are operationalized using a string of Boolean logic statements. A complete list of rules that we used in this paper is given in Table 5.

The user interacts with the set of documents through a highly interactive and user-friendly *analyst portal* (see Fig. 3). The portal provides users with various links and functionalities, including pre-defined search scenarios, shortcuts to sub-categories (e.g. functional disciplines and determinant categories) and document search capabilities. The portal has been designed to facilitate the analysis of research questions by allowing a full-text search to be combined with text analytics. The analyst can specify search terms or metadata (e.g., journal name, journal category, publication date, and author), thereby generating a traditional search result in the form of document lists responsive to the search query. Then in a few seconds MI Analyst analyzes the documents on the search result, extracting the entities, identifying the relationships, and surfacing the combinations that imply meaning. The alternative of manual inspection of the documents and manual tabulation of analytical data based on the manual inspection greatly inhibits the discovery process because it is too time consuming to iterate. Good first-cut analysis leads to better questions, which should lead to more insightful subsequent-cut analysis. Only an automated tool like MI Analyst can support powerful iterative discovery methods.

3. Results

3.1. Year of publication and functional discipline

The study of IT innovation adoption is a primary topic of interest to the information systems/computer science community [9]. This is not surprising as recent research has found that IT and organizations tend to be at the intellectual core of the IS discipline [52]. Correspondingly, a much larger proportion of studies should come from the IS/CS discipline. Our results confirm this expectation. Over two-thirds of all IT innovation adoption studies are published in Category I journals. Table 6 highlights the sharp increase in studies across all disciplines over the past three decades. Nearly two-thirds of all studies have been published in the past eight years, underlining the more recent focus on the topic. Our findings suggest that IT innovation adoption was a key research topic particularly during the late 90s, not only in the IS discipline (as shown by [52]) but also in complementary disciplines. Indeed, two other academic areas, namely the decision sciences and the organizational/management sciences, have emerged as prominent contributors to the IT innovation adoption field. This is not surprising given the natural fit of the topic to these two domains. IT innovation adoption is essentially a decision that organizations face; managerial and organizational issues play a critical role in enterprise adoption of IT innovation.

3.2. Publication

Given that the majority of studies come from the IS/CS domain it is not surprising that the top publication outlets for IT innovation adoption research are in the IS/CS discipline (see Table 7). Seven of the top 10 publications for IT innovation adoption research are Category I journals. The publication with the most articles (52 or 11.3%) on IT innovation adoption is *Information & Management*. The only three non-Category I publications represented in the top 10 are *IEEE Transactions on Engineering Management* (25 articles), *Technovation* (25 articles), and *Management Science* (15 articles). Among the top 25 publications there are five Category II and five Category III journals. One surprising observation is that despite being an innovation-centric topic, there is only one Category V journal in the top 25. This perhaps suggests that IT innovation adoption research has yet to become a core topic of interest in the innovation literature. Similarly, there are no Category IV journals present in the top 25.

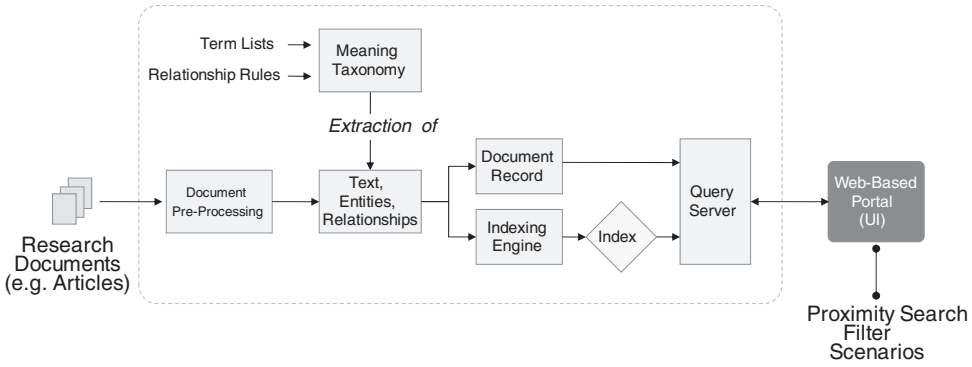

Fig. 2. Northern Light text analytics architecture.

3.3. Research method

Table 8 shows the frequency of research method used by functional discipline. The two dominant research methods for the study of IT innovation adoption by enterprises are frameworks and conceptual models and surveys, followed by mathematical modeling, interviews, and case studies. The least utilized research methods include laboratory and field experiments. This distribution of research methods is consistent across all functional disciplines.

3.4. IT type

Table 9 shows the frequency of IT innovation types by functional discipline. The most commonly studied IT type includes applications, such as electronic data interchange (EDI), enterprise resource planning (ERP), customer relationship management (CRM), and supply chain management (SCM). The second most commonly studied IT type includes electronic commerce and electronic business, which saw a particular surge in Category I journals during the late 1990s and early 2000s. This is followed by hardware, which is particularly prominent in Category II journals, and data and knowledge management. More recently, there has been a growth in studies examining mobile and wireless (in Categories I and III) as well as security (primarily Category I). Interestingly, there are no studies examining storage and platforms have only been examined in Category I and V journals.

3.5. Determinants

We categorized determinants of IT innovation adoption using the technology–organization–environment (TOE) framework [55]. The occurrence of the most frequent determinants in each category by time period is shown in Tables 10 through 12. The results show that in the beginning more emphasis was placed on firm characteristics than on IT and environmental characteristics. Organizational strategy, structure, and experience, in particular, have been the most frequently studied firm characteristics. More recently, top management support, trust, infrastructure, and integration have become more prominent firm-related determinants in enterprise adoption research. Interestingly, resources have been studied from numerous different perspectives, including human, financial, or more recently IT-specific. The most commonly used technology determinants include cost, complexity, compatibility, and relative advantage. These determinants were identified in a seminal meta-analysis [56] and have remained the most studied technology characteristics. Overall, cost and complexity are the two most frequently examined IT innovation determinants. Interestingly, factors concerned with IT innovation use, such as perceived benefits, perceived usefulness and ease of use, are less frequently studied at the enterprise-level. Environmental or external determinants of IT innovation adoption are shown in Table 12. The results show that early IT innovation adoption research did not consider many external characteristics. Studies were primarily internal focused. Government, power, and environmental uncertainty were the most commonly used determinants. Over the past two periods there has been a growing focus on institutional pressures, including coercive, normative, and mimetic pressures, as enterprises are increasingly embedded in social networks and influenced by the external context.

In addition to the frequency of determinant occurrence, we also identified the top (best) and worst determinants in enterprise level IT innovation adoption research based on their predictive power corresponding to the approach identified by [25], as shown in Tables 13 and 14. Predictive power was determined by the ratio of number of times the determinant was studied and the number of times it was found significant. Predictors were considered significant in quantitative studies if they were statistically significant (at $p<0.05$) as well as in a broader sense of "indicating importance" for qualitative studies. Determinants studied more than 5 times and with a predictive power of 0.7 or higher were considered top (best) predictors. Determinants studied more than 5 times and with a predictive power of 0.3 or lower were considered poor (worst) predictors. Our results show that organizational size and top management support were two of the most prominent positive predictors of IT innovation across all functional disciplines; the most negative predictor of IT innovation was cost. The results also show that there were differing top predictors in each functional discipline, indicating the diversity in determinant emphasis. Top determinants in Category II, for example, include IT innovation determinants, such as relative advantage, compatibility, and complexity. There were also no overlapping worst predictors across functional disciplines. However, two rather unusual findings emerged. Contrary to other functional disciplines, organizational innovativeness (in Category I) and organizational size (in Category III) were found to be poor predictors of IT innovation.

4. Research implications

Our text analytic review of the multi-disciplinary literature of IT innovation adoption by enterprises reveals several underexplored areas. In this section, we consider these areas and, in particular, focus on (1) emerging IT innovation, (2) enterprise analysis perspective, (3) transformation perspective, and (4) advancement of text analytic approaches for literature mining.

4.1. Emerging IT innovation

Our results show that the majority of research has focused on well-established enterprises and often well understood IT innovations; very little work has examined emerging technologies, such as mobile/wireless technologies, social media, or Web 2.0, for example. Emerging IT innovations have the potential to radically transform enterprises. They have been shown to lead to new means of data and information access, transmission, and exchange as well as new

Table 5
Meaning extraction rules.

Rule #	Class	Rule	Display	Example
1	Factors studied in relationship to Adoption	[1] near [2] 1: {Factor}; 2: Adoption	[1] is a factor studied in relationship to Adoption	IT Readiness is a factor studied in relationship to Adoption
2	Factors increasing Adoption	[1] near [2] near [3] 1: {Factors}; 2: {Indicates Encourages}: 3: Adoption	[1] increases Adoption.	IT Readiness increases Adoption
3	Factors significantly increasing Adoption	[1] near [2] near [3] near [4] 1: {Factors}; 2: {Indicates Encourages}; 3: {Indicates Significant}; 4: Adoption	[1] significantly increases Adoption	IT Readiness significantly increases Adoption
4	Factors increasing Adoption (with detail)	[1] near [2] near [3]; 1: {Factors}; 2: {Indicates Encourages}: 3: Adoption	[1] [2] Adoption	IT Readiness Facilitates Adoption
5	Factors significantly influencing adoption	([1] near [2] near [3]) ∪ ([4] near [5] near [6]) 1: {Factors}; 2: {Indicates Encourages}; 3: {Adoption}; 4: {Factors}; 5: {Indicates Significant}; 6: {Adoption}	[1] significantly influences Adoption	Top Management Support significantly influences Adoption.
6	Factors significantly increasing Adoption (with detail)	[1] near [2] near [3] near [4]; 1: {Factors}; 2: {Indicates Encourages}; 3: {Indicates Significant}; 4: Adoption	[1] [2] Adoption and is [3]	IT Readiness Strengthens Adoption and is Highly Critical
7	Factors decreasing Adoption	[1] near [2] near [3]; 1: {Factors}; 2: {Indicates Discourages}: 3: Adoption	[1] decreases Adoption	Complexity decreases Adoption
8	Factors decreasing Adoption (with detail)	[1] near [2] near [3]; 1: {Factors}; 2: {Indicates Discourages}: 3: Adoption	[1] [2] Adoption	Complexity Hinders Adoption
9	IT Technologies studied in relationship with Adoption	[1] near [2]; 1: {IT Technologies}; 2: Adoption	[1] has been studied with Adoption	Customer Relationship Management has been studied with Adoption
10	IT Technologies associated with increasing Adoption	[1] near [2] near [3]; 1: {IT Technologies}; 2: {Indicates Encourages}; 3: Adoption	[1] is associated with increasing Adoption	Supply Chain Management is associated with increasing Adoption

organizational structures. Emerging IT innovations may also lead to new administrative IT requirements and responsibilities, such as security policies and enterprise device management. An avenue for potential research in enterprise-level IT innovation is therefore a more focused understanding of the particular factors, processes, and contexts that characterize emerging IT innovation. Unquestionably, adoption of emerging IT innovations often contains some level of risk and uncertainty. A study of emerging IT innovation adoption would therefore provide additional insights into how enterprises manage risks and make cost–benefit tradeoffs.

4.2. Enterprise analysis perspective

The IT innovation adoption literature has predominantly focused on a single organization or firm. However, enterprises are increasingly connected to other firms and often embedded in complex value networks [8]. While studies rooted in institutional and resource dependency theory have provided some insight into the contextual factors that shape IT innovation adoption in inter-firm contexts, such as supply chains, there still is a dearth of studies that has examined how IT innovation adoption occurs in extended enterprises. Potential topics include an examination of factors and processes of IT innovations that span both geographical and administrative boundaries, such as global manufacturing enterprises and open innovation networks.

4.3. Transformation perspective

IT innovations have the potential of fundamentally transforming the enterprise [7]. Much of the existing research, however, has failed to explore the implications of IT innovation adoption on IT-enabled enterprise transformation. Future studies may want to examine in what ways IT innovation adoption shapes organizational processes, business models and strategies, and even entire industries and markets. Similarly, it could be explored how enterprise transformation has led to IT innovation adoption.

4.4. Advancement of text analytic approaches for literature mining

Text analytics is a promising method for literature mining. It leverages existing IS tools and databases to search, explore, and make sense of large complex sets of structured and unstructured information. Our study illustrates the applicability of text analytics to a specific topic domain in the organizational and management sciences, but can be easily extended to other topics and fields. Compared to other literature analysis approaches (e.g. meta-analyses, bibliometric studies, and co-citation analysis), text analytics has its advantages, but also certain limitations. The primary limitation is in the comprehensiveness and sophistication of the term catalog required to run text analytics. While many tools incorporate sophisticated dictionaries and some text learning methods, text analytics could greatly benefit from advanced textual engineering capabilities. In this paper, we seeded our analysis using a comprehensive list of factors and determinants identified in previous studies. A future opportunity of text analytics would be to automatically identify and add additional topic-relevant keywords and phrases. A second limitation of text analytics is its lack of document layout understanding. Unless document layout data is specifically identified, text analytics does have some challenges in interpreting tabular results. Despite these limitations, in contrast to the traditional literature review approaches, current text analytics capabilities enable researchers to far more quickly gain an in-depth understanding of topic patterns, keywords, and relationships of large corpus of data. It also enables researchers to ask alternate questions and receive answers by leveraging search and filter mechanism without having to re-read the entire dataset.

5. Conclusions

This study provided a comprehensive multi-disciplinary classification and analysis of the scholarly development of the enterprise-level IT innovation adoption literature. We identified 472 articles from leading journals over the past three decades and classified them by functional discipline, publication, research methodology, and IT type. We introduced and applied text analytic methods to this document repository to identify salient adoption determinants and their relationships, discover research trends and patterns across disciplines, and suggest potential areas for future research. Our paper makes several important contributions. From a theoretical perspective, this paper contributes to our overall understanding of IT innovation adoption by enterprises and the impact of organizational, technological, and environmental determinants. From a methodological perspective, we demonstrate the design, applicability, and value of text analytics for multi-disciplinary knowledge discovery and literature reviews. Our study is one of the few studies in the organizational and management sciences that has used text analytics for gaining insights into a broad set of literature.

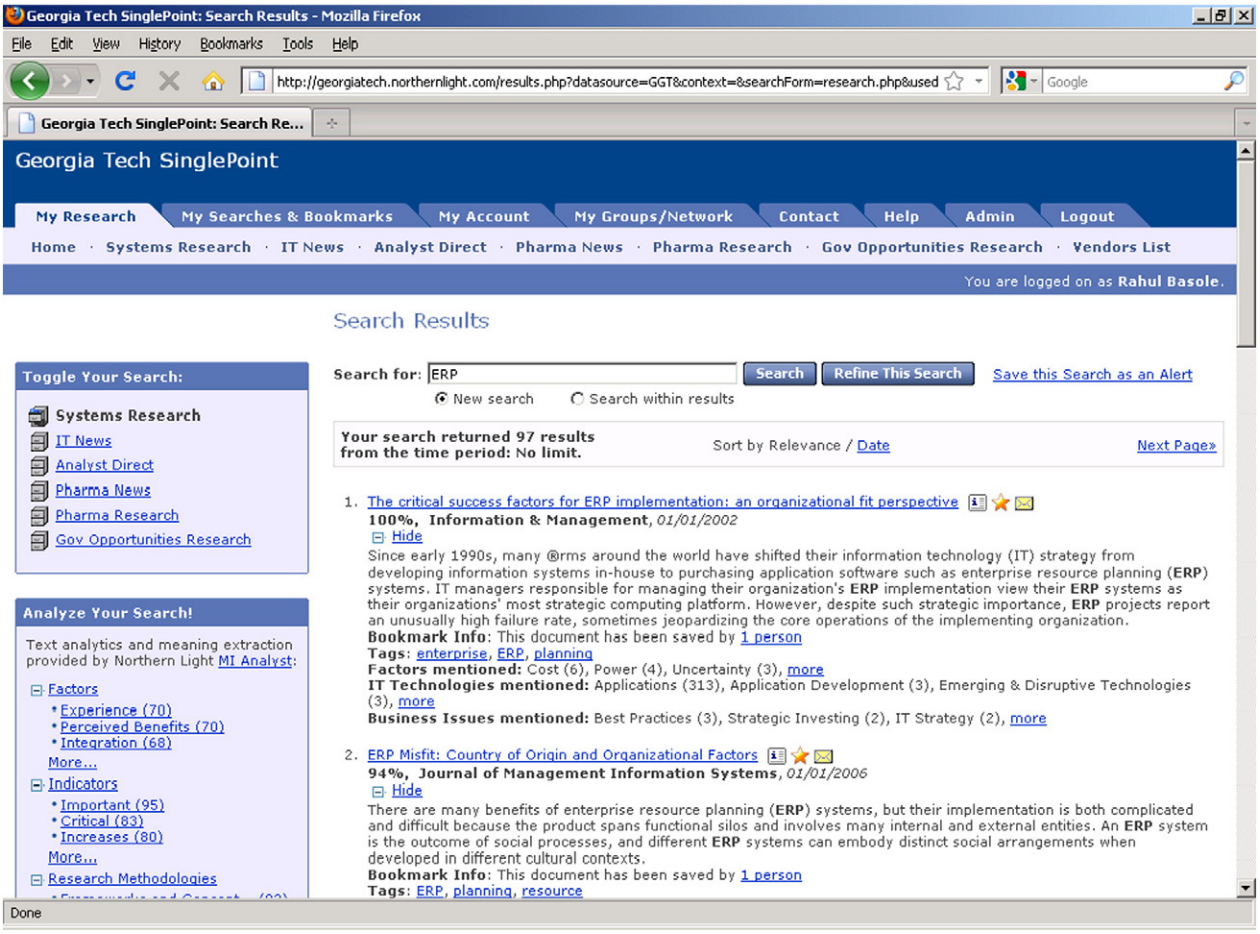

Fig. 3. Screenshot of Northern Light portal.

Our approach can easily be applied to other topical areas or functional domains, thus providing a systemic mean to evaluate the growing and increasingly multi-disciplinary body of knowledge.

Our study does have some limitations. First, we did not set a common starting date across journals since our objective was to be inclusive of all relevant articles. This may have impacted our comparative analysis of journals since some have been in circulation longer than others. Another limitation is the inclusion of the relatively larger number of IS/CS journals. This may have skewed our results since there is a greater probability that an article on IT innovation adoption exists in IS/CS. However, our goal was to identify articles in high quality journals applicable to the study of IT innovation adoption. From a text mining perspective, one challenge we faced was when results in a study were summarized in a table format, but only one occurrence of determinant significance occurred; based on our proximity approach multiple determinants could have been deemed significant. Understanding the "layout" of a document thus becomes important and an interesting

Table 6
Distribution of articles by year of publication and functional discipline category.

Category	1977–79	1980–89	1990–99	2000–08	Total	% of total
I	2	15	82	209	308	65.3
II	1	8	23	42	74	15.7
III	1	8	21	19	49	10.4
IV	0	1	1	6	8	1.7
V	0	1	3	29	33	7.0
Total	4	33	130	305	472	
% of total	0.8	7.0	27.5	64.6		

Table 7
Top 25 journals publishing enterprise adoption of IT innovation research.

Rank	Journal title	Category	# of articles	%
1	Information and Management	I	52	11.0
2	European Journal of Information Systems	I	31	6.6
t-3	Communications of the ACM	I	26	5.5
	Journal of Management Information Systems	I	26	5.5
t-5	IEEE Transactions on Engineering Management	II	25	5.3
	Electronic Markets	I	25	5.3
	Technovation	V	25	5.3
8	Information Systems Research	I	20	4.2
9	Management Science	II	15	3.2
t-10	Journal of Computer Information Systems	I	13	2.8
	Journal of Strategic Information Systems	I	13	2.8
t-12	Decision Support Systems	I	12	2.5
	MIS Quarterly	I	12	2.5
	OMEGA	II	12	2.5
t-15	Journal of Global Information Management	I	10	2.1
	Journal of Information Technology	I	10	2.1
	Journal of Org. Computing & E-Commerce	I	10	2.1
18	Decision Sciences	II	8	1.7
t-19	Communications of the AIS	I	7	1.5
	Information Systems Journal	I	7	1.5
t-21	European Journal of Operational Research	II	6	1.3
	Information Systems Management	I	6	1.3
	Journal of Business Research	III	6	1.3
	Strategic Management Journal	III	6	1.3
t-25	Harvard Business Review	III	5	1.1
	Journal of Electronic Commerce Research	I	5	1.1
	Journal of Marketing	III	5	1.1
	Organization Science	III	5	1.1

Table 8
Frequency by research method and category.

Research method	Frequency						Examples
	I	II	III	IV	V	Total[a]	
Speculation/commentary	0	0	0	0	0	0	n.a.
Frameworks and conceptual model	162	38	28	3	5	236	[48]
Literature analysis	6	3	3	0	0	12	[25]
Case study	39	1	1	0	2	43	[36]
Survey	176	49	16	6	6	253	[29]
Field study	24	5	1	0	1	31	[23]
Field experiment	0	0	0	0	0	0	n.a.
Laboratory experiment	0	0	0	0	0	0	n.a.
Mathematical model	43	21	18	6	3	91	[26]
Qualitative research	10	0	2	0	1	13	[4]
Interview	66	7	6	0	1	80	[47]
Secondary data	2	3	1	0	1	7	[51]
Content analysis	3	0	0	0	0	3	[40]

[a] Total more than 472 as studies may use multiple research methods.

Table 9
Frequency by IT innovation type and category.

IT innovation type	Frequency						Examples
	I	II	III	IV	V	Total[a]	
Applications	263	62	30	7	15	377	[30]
Application development	47	9	4	0	0	60	[44]
Data and knowledge management	74	13	12	0	3	102	[46]
Electronic commerce and electronic business	187	28	15	3	9	242	[61]
Enterprise architecture	18	1	2	1	0	22	[3]
Hardware	56	24	15	3	4	102	[11]
Mobile/wireless	12	0	2	0	2	16	[41]
Networking and communications	65	14	5	0	2	86	[31]
Platforms	3	0	0	0	1	4	[18]
Security	12	1	0	0	1	14	[13]
Storage	0	0	0	0	0	0	n.a.
Virtualization	1	0	0	0	0	1	[33]

[a] A total more than 472 studies may examine multiple IT innovation types.

Table 10
Occurrence of firm characteristics.

1977–79 (n = 4)	1980–89 (n = 32)	1990–99 (n = 134)	2000–08 (n = 290)
Strategy (100%)	Experience (53%)	Experience (69%)	Experience (72%)
Organizational structure (75%)	Integration (44%)	Integration (54%)	Infrastructure (58%)
Experience (50%)	Strategy (44%)	Strategy (42%)	Integration (51%)
Performance gap (50%)	Organizational structure (41%)	Infrastructure (40%)	Strategy (47%)
Financial resources (25%)	Organizational size (19%)	Organizational structure (31%)	Trust (37%)
Slack resources (25%)	Infrastructure (16%)	Top management support (21%)	Top management support (24%)
User involvement (25%)	Top management support (12%)	IS planning (13%)	Financial resources (22%)
Top management support (25%)	Maturity (12%)	Human resources (12%)	Human resources (18%)
	Organizational culture (12%)	Organizational size (11%)	Organizational structure (17%)
	Financial resources (9%)	Trust (10%)	Maturity (16%)
	IS planning (9%)	Financial resources (10%)	Organizational readiness (9%)
	User involvement (9%)	Maturity (10%)	Organizational size (9%)
	Communicability (6%)	User involvement (10%)	User involvement (8%)
	Technology policy (6%)	Organizational culture (9%)	IT resources (7%)
	Trust (6%)	Communicability (4%)	IS planning (6%)

Table 11
Occurrence of IT innovation characteristics.

1977–79 (n = 4)	1980–89 (n = 32)	1990–99 (n = 134)	2000–08 (n = 290)
Complexity (100%)	Complexity (56%)	Cost (62%)	Cost (62%)
Cost (50%)	Cost (47%)	Complexity (46%)	Complexity (57%)
	Compatibility (28%)	Compatibility (31%)	Compatibility (41%)
	Image (16%)	Relative advantage (22%)	Relative advantage (26%)
	Relative advantage (9%)	Image (15%)	Image (22%)
	Trialability (6%)	Trialability (11%)	Perceived benefits (18%)
	Ease of use (3%)	Ease of use (10%)	Ease of use (14%)
	Perceived benefits (3%)	Perceived benefits (6%)	Trialability (13%)
		Perceived usefulness (6%)	Perceived usefulness (11%)
		System quality (2%)	Result demonstrability (1%)
			System quality (1%)

Table 12
Occurrence of external characteristics.

1977–79 (n = 4)	1980–89 (n = 32)	1990–99 (n = 134)	2000–08 (n = 290)
Government (50%)	Power (53%)	Power (57%)	Dependency (83%)
Power (50%)	Competitive pressure (41%)	Uncertainty (45%)	Power (68%)
Uncertainty (50%)	Government (41%)	Competitive pressure (37%)	Competitive pressure (56%)
	Uncertainty (37%)	Government (36%)	Government (52%)
	Dependency (3%)	Dependency (7%)	Uncertainty (39%)
	Environmental complexity (3%)	Social network (3%)	External pressure (15%)
		Environmental complexity (2%)	Vendor support (8%)
		Vendor support (2%)	Social network (6%)
		Customer interaction (1%)	Interconnectedness (5%)
			Coercive pressure (3%)
			Competitive intensity (3%)
			Normative pressure (3%)
			Customer interaction (2%)

Table 13
Top predictors of IT innovation adoption by functional category.

Category		Relationship	# of times studied (n)	# of times significant (s)	Predictive power (n/s)
I	Organizational culture	(+)	9	8	0.89
	Vendor support	(+)	9	8	0.89
	Internal pressure	(+)	7	6	0.86
	User involvement	(+)	6	5	0.83
	Organizational size	(+)	63	49	0.78
	External pressure	(+)	23	18	0.74
	Top management support	(+)	57	44	0.77
	Cost	(+)	174	130	0.75
	Perceived benefits	(+)	151	93	0.75
II	Organizational size	(+)	15	13	0.87
	Relative advantage	(+)	13	11	0.85
	IS/IT infrastructure	(+)	5	4	0.80
	Compatibility	(+)	19	15	0.79
	Complexity	(−)	22	17	0.77
	Top management support	(+)	12	9	0.75
III	Leadership	(+)	6	5	0.83
	Compatibility	(+)	11	9	0.82
	Relative advantage	(+)	5	4	0.8
	Complexity	(−)	13	10	0.77
IV	Cost	(−)	9	8	0.89
	Experience	(+)	7	6	0.86
	Organizational size	(+)	5	4	0.80
V	Cost	(−)	6	5	0.83

Table 14
Worst predictors of IT innovation adoption by functional category.

Category		Relationship	# of times studied (n)	# of times significant (s)	Predictive power (n/s)
I	Interconnectedness	(+)	7	1	0.14
	Organizational innovativeness	(+)	6	1	0.17
	Communicability	(+)	6	1	0.17
	Maturity	(+)	14	3	0.21
II	Perceived usefulness	(+)	5	1	0.2
	Integration	(+)	14	4	0.29
	Government	(+)	7	2	0.29
III	Image	(+)	5	0	0
	Strategy	(+)	10	1	0.1
	Integration	(+)	8	1	0.13
	Organizational size	(+)	11	2	0.18
	Competition	(+)	11	3	0.27

future research for text analytics. While text mining could have also been used to automatically extract articles from online databases, without any editorial filtering, our analysis was seeded with articles and journals identified in an earlier comprehensive study conducted by the authors. Each of these limitations presents intriguing opportunities for future research.

Appendix A. References of studies included in analysis

In consideration of page length, the list of 472 references will be available online.

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