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Data-Driven Understanding of Smart Service Systems Through Text Mining

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Abstract. Smart service systems are everywhere, in homes and in the transportation, energy, and healthcare sectors. However, such systems have yet to be fully understood in the literature. Given the widespread applications of and research on smart service systems, we used text mining to develop a unified understanding of such systems in a data-driven way. Specifically, we used a combination of metrics and machine learning algorithms to preprocess and analyze text data related to smart service systems, including text from the scientific literature and news articles. By analyzing 5,378 scientific articles and 1,234 news articles, we identify important keywords, 16 research topics, 4 technology factors, and 13 application areas. We define "smart service system" based on the analytics results. Furthermore, we discuss the theoretical and methodological implications of our work, such as the 5Cs (connection, collection, computation, and communications for co-creation) of smart service systems and the text mining approach to understand service research topics. We believe this work, which aims to establish common ground for understanding these systems across multiple disciplinary perspectives, will encourage further research and development of modern service systems.

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Keywords: smart service • smart system • smart service system • text mining • data-driven understanding

1. Introduction

Service systems in the transportation, retail, healthcare, entertainment, hospitality, and other sectors are configurations of people, information, organizations, and technologies that operate together for mutual benefit (Maglio et al. 2009). Service systems have become "smarter" over time as technologies have been increasingly used in the systems (Larson 2016, Watanabe and Mochimaru 2017). Smart service systems can be found in homes (Alam et al. 2012) and the energy (Strasser et al. 2015), healthcare (Raghupathi and Raghupathi 2014), and transportation sectors (Pelletier et al. 2011), among many others. As the concepts of service system and smartness intertwine, academia, industry, and government pay great attention to the concept of smart service system (e.g., Maglio et al. 2015, Larson 2016, NSF 2016, IBM Smarter Cities Challenge 2017). We believe this concept is meaningful in the development and use of technology, such as the Internet of Things (IoT), artificial intelligence (AI), and blockchain, as it represents the ultimate application and integration of technology for value creation.

Yet despite its importance, the concept of "smart service system" is unclear (Beverungen et al. 2017). What is it? What are the smart service system research areas and how are they related? What are the key technology factors of smart service systems? What are the main application areas and what does a smart service ecosystem look like? How can we define "smart service system"? The functions and operations of these systems depend on sensing (Sim et al. 2011), big data (Maglio and Lim 2016), computation (Lee et al. 2012), and automation (Jacobsen and Mikkelsen 2014), and should consider the customer (Wünderlich et al. 2013) and business aspects

(San Román et al. 2011). A search for "{TOPIC: (smart service system)}" in the Web of Science generates more than 5,000 results across engineering, computer science, information systems, control, transportation, healthcare, and other fields. Yet despite widespread application and the importance of research in this field, to our knowledge, in-depth understanding of such systems is still lacking in the literature.

A unified understanding of smart service systems across different fields may facilitate development and innovation. Furthermore, such understanding would promote the use, integration, and improvement of technologies from a broad and application-oriented perspective. Specifically, a generic definition or representation of a smart service system will promote mutual understanding among people of different backgrounds, thereby facilitating collaborative analysis and the development of such systems. Similarly, a comprehensive categorization of applications related to smart service systems can contribute to our understanding of system variety and lead to the creation of synergy between different applications. However, such integrative work is not easy to achieve because of the variety and volume of studies and applications related to smart service systems.

In this work, we develop an understanding of smart service systems by mining text related to these systems. The interdisciplinary body of text we analyzed includes scientific literature and news articles. The former discusses research topics and the technology factors of smart service systems; the latter describes application areas and business aspects. To capture the essence of the data, our analytics method uniquely incorporates metrics to measure the importance of the word-features of the data and unsupervised machine learning algorithms, such as spectral clustering (Von Luxburg 2007) and topic modeling (Blei et al. 2003). Our analysis of 5,378 scientific articles and 1,234 news articles identified significant keywords, research topics, technology factors (sensing, connected network, context-aware computation, and wireless communications), application areas, and a definition. Furthermore, we developed a conceptual framework of smart service systems and a hierarchical structure of smart service system applications by integrating our findings and those of existing studies.

Establishing common ground for central concepts is essential for science (Boehm and Thomas 2013). To integrate perspectives and capabilities for developing smart service systems, we provide a systematized view of dispersed knowledge about smart service systems, integrating such knowledge into a robust conceptualization of these systems and identifying key research topics, technology factors, and areas of application. Our findings contribute to the theory and practice of smart service systems. Our work is unique in that it uses a *data-driven* approach to understanding these systems. In terms of methodological contribution, it is, to our knowledge, the first study to accomplish data-driven understanding of a service research topic. Our research methodology can be applied to other topics in the future.

This paper is organized as follows. In Section 2, we review studies related to smart service systems and provide the conceptual foundations for this work. In Section 3, we describe the research methodology, including data collection and analysis methods. In Section 4, we describe the findings. In Section 5, we discuss the theoretical, managerial, and methodological implications of our work. In Section 6, we conclude with a discussion of future research issues.

2. Literature Review

As service systems become increasingly smarter through technological advances in many industries, researchers have investigated common characteristics of smart service systems. Table 1 lists several existing definitions or descriptions of smart service systems. These definitions and descriptions are consistent in that they specify the capabilities or requirements of such systems. We integrate existing perspectives on these systems to form the following definition: A smart service system is a service system capable of learning, dynamic adaptation, and decision making (Medina-Borja 2015) that requires an intelligent object (Allmendinger and Lombreglia 2005, Wünderlich et al. 2015) and involves intensive data and information interactions among people and organizations (Maglio and Lim 2016, Lim et al. 2018a). Smart service systems incorporate technologies for sensing, communication, and control, among others (NSF 2016), to effectively and efficiently consider the needs and context of stakeholders (Lim et al. 2016). Other keywords describing smart service systems in the literature include cognition, sustainability (Spohrer and Demirkan 2015), self-reconfiguration, connection (Carrubbo et al. 2015), wisdom, interaction (Barile and Polese 2010), people, real time (Gavrilova and Kokoulina 2015), user-centric (Geum et al. 2016), dynamic experience (Ostrom et al. 2015), autonomy (Maglio 2017), and elasticity (Moldovan et al. 2018). Different types of smart service systems, such as those found in homes (Alam et al. 2012), healthcare (Raghupathi and Raghupathi 2014), buildings (Agarwal et al. 2010), and transportation (Pelletier et al. 2011), have been realized in various forms in smart cities (Abella et al. 2017, Lim et al. 2018d).

In addition, IoT (Atzori et al. 2010), big data (Lim et al. 2018b), cloud computing (Iyoob et al. 2013), wearable devices (Patel et al. 2015), cyber-physical systems (Lee 2008), Industry 4.0 (Hofmann and Rüsch 2017), blockchain (Kshetri 2018), IoT-enabled servitization (Lim and Kim 2015), and service-oriented data use (Kim et al. 2018) are

Table 1. Existing Definitions or Descriptions of Smart Service System

Source	Definition or description
Barile and Polese (2010)	Smart service systems may be intended as service systems designed for a wise and interacting management of their assets and goals, capable of self-reconfiguration (or at least of easy inducted re-configuration) to perform enduring behavior capable of satisfying all the involved participants in time. . . . Because smart service systems inevitably involve multiple actors, the organizational configurations need to take account of network theory—especially the networking forces and enablers required to keep the system tight and focused towards its goals.
Massink et al. (2010)	Common recurring elements of smart service systems are: spaces; displays; sensors; users. Users will interpret information on displays and carry out actions as a result of what has been read.
Spohrer (2013)	Smart service systems are instrumented, interconnected, and intelligent. Instrumented means sensors, sensors everywhere—more of the information (real-time and historical, as well as Monte Carlo predictive runs) that stakeholders, providers, customers, governing authorities, etc.—need to make better win-win (value co-creation, capability co-elevating) decisions is available. Interconnected means people have easy access to information about a particular service system, as well as others that interact with it via value propositions, perhaps displayed on their smartphones. Intelligent means recommendations systems that work to provide stakeholders useful choices—for example, Watson-style recommendation systems, or Amazon-style recommendation systems.
Wünderlich et al. (2013)	Services delivered to or through intelligent products that feature awareness and connectivity are called "smart services" (Allmendinger and Lombreglia 2005). . . . The implementation of smart services is expected to result in substantial efficiency gains on both the provider's and the user's side from benefits such as cost reductions, increased flexibility, increased access, and time savings. . . . Smart interactive services comprises not only an embedded technology within the product that communicates object-to-object but also personal interactions between the user and the service provider employee as part of the smart service delivery process.
Carrubbo et al. (2015)	Smart service systems can be understood as service systems that are specifically designed for the prudent management of their assets and goals while being capable of self-reconfiguration to ensure that they continue to have the capacity to satisfy all the relevant participants over time. They are principally (but not only) based upon ICT as enabler of reconfiguration and intelligent behavior in time with the aim of creating a basis for systematic service innovation in complex environments. Smart service systems are based upon interactions, ties and experiences among the actors. Of course, among these actors, customers play a key role, since they demand a personalized product/service, high-speed reactions, and high levels of service quality; despite customer relevance, indirectly affecting every participating actor, smart service systems have to deal to every other actor's behavior, who's expectations, needs and actions directly affect system's development and future configurations. The smarter approach applied to healthcare is called "smarter healthcare." As IBM highlights, a smarter healthcare system is obtained through better connections for faster, more detailed analysis of data.
Gavrilova and Kokoulina (2015)	The term "smart" implies two main properties. First, it highlights anthropomorphic features of the smart service. For example, technology research company Gartner, Inc. claims that smart technologies are ". . . technologies that do what we thought only people could do. Do what we thought machines couldn't do" (Austin 2009). Second, term "smart" is usually related to artificial intelligence (i.e., intelligence of machine) "[. . .] because it is impractical to deploy humans to gather and analyze the real-time field data required, smart services depend on "machine intelligence" (Allmendinger and Lombreglia 2005). . . . Smart service systems often have the following characteristics of the intelligent system: Self-configuration (or at least easy-triggered reconfiguration), Proactive behavior (capability for prognosis or preventive actions, as opposed to the reactive behavior), Interconnectedness and continuous interactivity with internal and external system elements. . . . Smart service attributes include dynamic properties (without modelling of the changing environment; past-based modelling; stochastic modelling), intelligence (knowledge-based; data-based; content-based), Knowledge awareness (context-oriented; explicit knowledge; business intelligence), IT platform (mobile; SaaS; hybrid cloud; corporate servers), and elements (IT; people; hybrid).
Medina-Borja (2015)	A smart service system is a service system capable of learning, dynamic adaptation, and decision making based upon data received, transmitted, and/or processed to improve its response to a future situation.
Ostrom et al. (2015)	In the new technology-enabled service context, customers increasingly create their own experiences in a more dynamic and autonomous way. To respond to these challenges, how can services be designed with multiple channels, social media, and smart services, while enabling smooth service experiences for customers? How can services be designed for flexibility and co-creation, instead of focusing on predefined service scripts?
Spohrer and Demirkan (2015)	Smart service systems are ones that continuously improve (e.g., productivity, quality, compliance, sustainability, etc.) and co-evolve with all sectors (e.g., government, healthcare, education, finance, retail and hospitality, communication, energy, utilities, transportation, etc.). . . . Because of analytics and cognitive systems, smart service systems adapt to a constantly changing environment to benefit customers and providers. Using big data analytics, service providers try to compete for customers by (1) improving existing offerings to customers, (2) innovating new types of offerings, (3) evolving their portfolio of offerings and making better recommendations to customers, (4) changing their relationships to suppliers and others in the ecosystem in ways their customers perceive as more sustainable, fair, or responsible.

Table 1. (Continued)

Source	Definition or description
Lim et al. (2016)	Smart service systems are those service systems in which connected things and automation enable intensive data and information interactions among people and organizations that improve their decision making and operations. Thus, transforming a service system into a smart service system means improving the decision making and operations within the service system with connected things and automation. As the definition indicates, a smart service system consists of four components: (1) connected things, (2) automation, (3) people and organizations, and (4) data and information interactions.
NSF (2016)	A "smart" service system is a system that amplifies or augments human capabilities to identify, learn, adapt, monitor and make decisions. The system utilizes data received, transmitted, or processed in a timely manner, thus improving its response to future situations. These capabilities are the result of the incorporation of technologies for sensing, actuation, coordination, communication, control, etc.
Larson (2016)	Until service science achieves the respect that comes with maturation and productive interaction among researchers from its sub-disciplines, our ability to foster substantial innovation in service systems will remain limited. That would be unfortunate, because such innovation could make these systems "smarter"—more sophisticated, nuanced, tuned to human needs, and augmenting human capabilities with supporting technology. Smarter systems, in turn, could help drive sustained economic growth by increasing our national productivity. They could create a steady stream of new jobs in numerous subdisciplines. They could help us to address serious social problems in arenas like healthcare, education, urban infrastructure, and national and global security. The definition of "service" can be further applied to artifacts such as "smart refrigerators" and "smart homes" that provide services that increase human quality of life.
Moldovan et al. (2018)	An elastic system (i.e., which may be equivalent smart service system in this paper) should leverage and combine developments from multiple fields of computer science, to achieve its goals. This multi-disciplinary approach provides to elastic systems the necessary capabilities to adapt and change with respect to the concerns and requirements of people, processes, and things over both physical and cyber worlds. ... An elastic system is composed of heterogeneous units (i.e., people, processes, and things) working together. ... Elastic systems should be built from replaceable self-contained units of functionality, each unit exposing its functionality through a well-defined interface. ... Elastic systems must have a strong focus on change, from design time, when elasticity capabilities are defined, to run-time and operation, when desired changes occur by enforcing the capabilities of different units. ... Elastic systems must also consider stakeholders' business requirements for achieving desired business goals.

all related to smart service systems. These terms emphasize the technological aspects of specific applications, whereas the term "smart service system" places the technology and people in the context of value creation. The smart service system concept may be comparable to existing technology-based service concepts in which "there is an interaction between customers and technology-embedded objects such as a computer, the Internet, or a machine at the moment of truth" (Noh et al. 2016, p. 202), such as technology-mediated service (Schumann et al. 2012) and information-intensive service (Lim and Kim 2014) concepts. Technology-mediated service (Schumann et al. 2012) or mobile service (Heo et al. 2017) emphasizes efficient delivery of information to people, whereas information-intensive service focuses mainly on creating information that helps people achieve their goals (e.g., exercise and transportation) and collecting the right data to create useful information (Lim and Kim 2015, Lim et al. 2018b). Such traditional technology-based service concepts focus on specific resources or activities of service systems, whereas the smart service system concept in our study focuses on the entire system of resources and activities to consider how capabilities operate together to increase mutual value (Beverungen et al. 2017). In summary, the smart service system concept depends on systems thinking (Frost and Lyons 2017) and value creation (Maglio and Lim 2016).

The studies cited suggest that there are various aspects of smart service systems. However, each study represents only the perspectives of the respective authors. For example, a definition in Table 1 can be limited to one or a few aspects of smart service systems, and most definitions may be subjective or limited. In addition, to our knowledge, no study provides an overview of the research and application areas of smart service systems, despite the merit of understanding the wide range of applications and research on these systems as a whole. As previously described, our objective is to develop a unified understanding of smart service systems based on a data-driven approach to reduce subjectivity and increase inclusiveness. Thus, we used a text mining method to aggregate knowledge and information from thousands of scientific and news articles.

3. Research Methodology

Developing a unified conceptualization of smart service systems is not easy given the variety and volume of the related studies and applications. Thus, we relied on a text mining method to develop our understanding of these systems. Text mining or text data mining is a process to discover previously unknown knowledge from textual data (Bird et al. 2009). Text mining methods have been used for many purposes on a wide range of document types, such as technology trend analysis with patent data (Yoon and Park 2004), customer understanding with customer opinion (Jansen et al. 2009), feedback (Ordenes et al. 2014), review (Mankad et al. 2016) or even related patent data (Lim et al. 2017), and understanding specific research fields with scientific documents (Jo et al. 2007). Recent studies apply machine learning algorithms to text data to discover previously unknown knowledge from the data. For example, a clustering algorithm can be applied to identify unknown categories of documents (e.g., Aggarwal and Zhai 2012), and a classifier can be applied to automate the classification of spam mails and identify significant words (Yu and Xu 2008). A notable algorithm for text mining is the topic modeling algorithm, which discovers hidden topics of a set of documents, using for example, latent Dirichlet allocation (LDA) (Blei et al. 2003) and non-negative matrix factorization (NMF) (Lin 2007). Visualization is key to interpretation of text data analysis results because most of the text mining cases involve numerous features and require semantic interpretation (Lim et al. 2017). For example, a visualization of the network between different keywords is useful to understand the key links between the keywords and to efficiently categorize the keywords (e.g., Park and Yoon 2015).

Text mining is an appropriate method for achieving our research objective because we want to comprehensively explore aspects and areas of smart service systems and such work is difficult for people to do alone. In addition, despite the insights from experts, the subjective identification and categorization of key aspects and areas of smart service systems can be difficult to evaluate. A data-driven approach, such as text mining with metrics and machine learning algorithms, can be an excellent alternative (Blei et al. 2003, Mankad et al. 2016, Zhuge and Wilks 2017, Antons and Breidbach 2018). Moreover, the human analysis built on the analytical findings from massive amounts of documents often generates rich insights and implications (Ordenes et al. 2014, Lim et al. 2017). In relation to this, we collected and analyzed a comprehensive set of 5,378 scientific articles and 1,234 news articles. Sections 3.1 and 3.2 explain the data collection and analysis methods, respectively.

3.1. Collection of Scientific and News Data

Text data obtained from the scientific literature and news articles contain useful information about smart service systems. In this study, the sources of scientific data included titles, abstracts, and keywords of journal articles, review papers, proceeding papers, and book chapters about smart service systems. The news data included introductions, compliments, and critiques. The literature data may represent the research topics and technology factors of smart service systems, whereas the news data may show the application areas and business aspects. Hence, these two types of data complement each other in strengthening our understanding of the academic and practical aspects of these systems, from which theoretical and managerial insights can be derived.

Table 2 shows an overview of data collection in this study. The five queries used for literature data collection were {TOPIC: (smart) AND TOPIC: (service) AND TOPIC: (system)}, {TOPIC: ("smart service")}, {TOPIC: ("smart services")}, {TOPIC: ("smart system")}, and {TOPIC: ("smart systems")}. A total of 6,488 items were collected, including 2,688 articles, 149 reviews, 3,851 conference papers, and 147 book chapters. As of May 7, 2016, these data were the "full" population (i.e., not a sample) of the smart service system literature identified from the Web of Science Core Collection databases of the Science Citation Index Expanded (SCIE) (1945–), Social Sciences Citation Index (SSCI) (1987–), Conference Proceedings Citation Index—Science and Social Science and Humanities (1990–), Book Citation Index—Science and Social Science and Humanities (2005–), and Emerging Sources Citation Index (2015–). The Web of Science Core Collection includes quality papers, and all the papers show characteristics of smart service systems. Unlike existing systematic reviews of selected papers, we collected all available data from the databases first and then excluded data of little relevance and nonimportant features in a semiautomatic and statistical manner.

Table 2. Overview of Data Collection

Data type	Data source	Collection method	Content of data	Collected items
Literature data	Web of Science Core Collection	Download all data found with the five queries through the Web of Science data provision service	The title, abstract, and keywords of article	6,488 items
News data	Websites of news service providers	Search for 126 keywords through the Google News service and get the title and content of news from the websites of news service providers	The title, content, and keywords (if specified) of article	1,256 items

Deciding from what part of the documents to collect text data for analysis, such as from the abstract only or full text, is crucial in text mining application research. We used text data composed of title, abstract, and keywords, following existing studies (e.g., Xie and Miyazaki 2013, Noh et al. 2015). For example, Noh et al. (2015) showed that using abstract data rather than description data was effective in their text mining-based patent analysis. They also stated that the analysis result was not sensitive to the part of the documents from which the text data was collected. Nonetheless, we consider their study as one case, and we believe that the decision should depend largely on the research objective, constraint, and available data.

We considered four specific conditions in deciding to use the title, abstract, and keywords only, i.e., to reduce noise, increase signal, maximize efficiency, and accept limited accessibility to full texts. First, the body of a paper involves considerable noise for text mining. If we include text data in the introduction or discussion section, controlling noise from the words, such as "may," "within," and "TDD" can be very difficult (researchers include many general English words and acronyms in the body of their paper). These words disturb the statistical and semantic analyses of text data. Second, our assumption is that researchers intentionally include signal words (e.g., "system," "data," "health," and "city") in the title, abstract, and keywords to highlight the main characteristics of their paper. Third, the proper analysis of text data from the introduction or discussion section requires significant preprocessing effort because of the first and second conditions. The speed of analytics also becomes very slow. The initial vector space of the literature data included 28,302 word-features, although we only included titles, abstracts, and keywords. Finally, collecting full text data from academic articles is very difficult because of data protection and cost. Although we may have access to data, many publishers do not provide data in an HTML format, requiring additional processing. Above all, we did not have access to *all* data because of cost, which is fundamentally why we selected the Web of Science service to download available data.

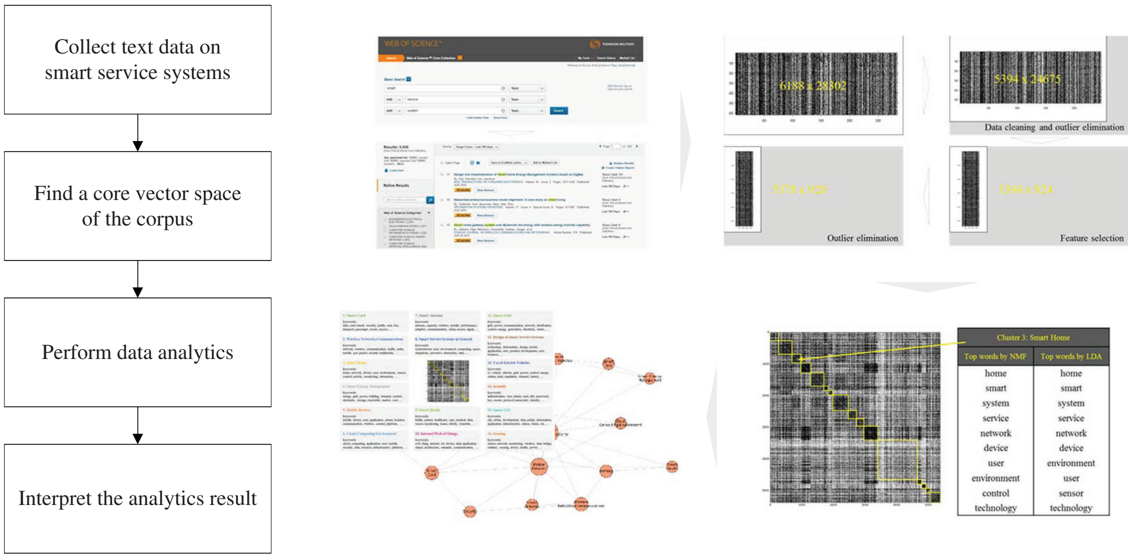
For news data collection, we searched for relevant two-word phrases that contain "smart" that we identified in the scientific data, particularly those that indicate "application areas" of smart service systems (e.g., "smart grid," "smart power," "smart home," "smart transportation," and "smart parking"): This resulted in a list of 352 phrases. We then searched news articles from Google News (language = "English," region = "USA") using this list. We finally obtained a set of 126 keywords that was useful in analyzing the application areas in terms of number, technological intensity, and overlap of search results (i.e., we found that 226 phrases were not used often in news articles, and do not represent technology-based service or overlap with others). Data were collected from the websites of news service providers using 126 keywords by getting the title and content. Articles that could not be used without permission were excluded. We collected the 10 most relevant items for each keyword, according to Google, only if the article actually discussed an application related to smart service systems. Data were not collected if the article only introduced goods or showed financial information.

We relied on the Google News platform service for data collection to ensure the freshness, diversity, textual richness, originality, and consistency of the content (Google 2017a). Five criteria were attributed to our research objective to understand "application areas" of smart service systems. First, we considered advanced applications as of data collection time, May 22 to June 7, 2016. Most of the analyzed news articles were published between the end of 2015 and the middle of 2016; some articles were published before 2015 and discussed outdated but still significant topics, such as smart aircraft. Second, we considered various kinds of applications. The types of news on smart service systems include review of specific technologies and relevant applications, comparison of different applications in the same market, and prospects of a future lifestyle. We confirmed that the Google News platform was suitable to find all these types of news. Third, we considered rich information in terms of applications. Fourth, we considered original rather than summary or integrated articles. The news highly recommended in the platform qualified the third and fourth criteria. Fifth, we considered news about applications in the United States only because consideration of one specific region of competition reduces the variability from differences in lifestyle and policy. Moreover, we wanted to ensure that no human editors are involved in news recommendation. Google has improved the reliability and comprehensiveness of its service to meet the five criteria (Google 2017b).

3.2. Analysis of the Scientific and News Data

Figure 1 shows the analysis process of the literature data. Before conducting data collection and analysis, we performed multiple pilot studies using small sets of literature and news data to develop effective data analysis methods. This approach enabled us to develop a method for finding a "core vector space." One challenge in text mining is to identify meaningful data and word-features in the context in question; for example, the initial set of 6,488 scientific articles included numerous minimally relevant data and nonimportant word-features, such as "Synthesis and Characterization of Shape-Memory Polyurethane-Polybenzoxazine Compounds" (Erden and Jana 2013) and "notwithstanding," respectively. A core vector space is one without nonrelevant data and

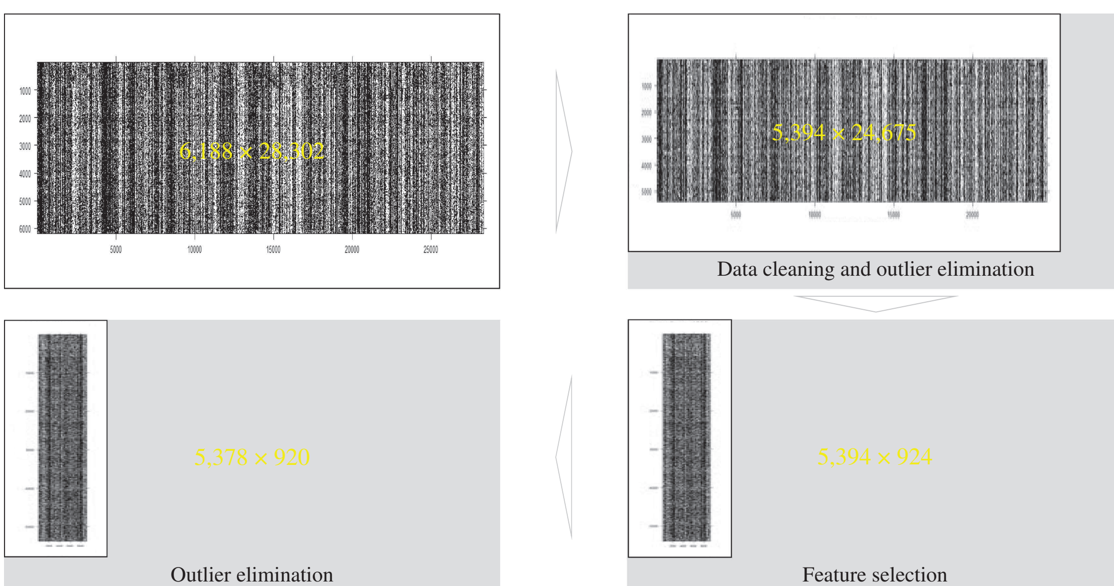
Figure 1. Overview of Data Analysis



nonimportant word-features, i.e., a homogenous vector space in terms of smart "service" systems for "people." We used bibliographical and statistical analyses to find a core vector space of the initial data.

Figure 2 illustrates the process for finding a core vector space in the scientific article data. There are three steps in this process. The black cell indicates that the corresponding word (column) appears in the datum (row). First, we cleaned the data. There are popular techniques for preprocessing textual data and transforming it into a numerical form. These techniques include stop word elimination, lemmatization, and stemming to exclude nonmeaningful words and standardize the form of words in the documents; vector space representation of the data, which usually refers to the creation of a document-term matrix; the use of term frequency–inverse document frequency (TF–IDF) rather than simple frequency to meaningfully reflect the feature value of an item; and measurement of the similarity between data using metrics such as cosine similarity, the Jaccard coefficient, and the Pearson correlation coefficient (Bird et al. 2009). Using such techniques, we deleted data where the abstract or title information was missing or was a duplicate. We eliminated a word if it was included in the list of stop words (e.g., "it" and "for"). Next, we changed the font to lowercase (e.g., from "Smart" to "smart"), lemmatized all the words (e.g., from "processes" to "process"), and applied other customized rules developed

Figure 2. An Illustration of How to Find a Core Vector Space



from the pilot studies to address the specific problems of the data (e.g., do not lemmatize "glasses" to "glass"). Outlier data were also eliminated from the list of irrelevant fields defined in the pilot studies (e.g., "microscopy," "biophysics," "spectroscopy," and "physics"). As a result of the first step, a total of 5,394 items were chosen from the original 6,188 items.

Second, we selected only the word-features that may represent "smart service systems" based on TF–IDF values, which represents the importance of a word considered in the article and in the entire data set. For example, "external," "require," and "provide" may not be important in the article entitled "Robotic Automated External Defibrillator Ambulance for Emergency Medical Service in Smart Cities" (Samani and Zhu 2016); we found the top four words of this article were "city," "ambulance," "emergency," and "robotic" according to their TF–IDF values across the 5,394 articles. We used the normalized TF–IDF calculation from the Python Scikit-Learn Library (Pedregosa et al. 2011) after testing its performance in pilot studies. From the union of the top "four" words in the data, we selected the words that appeared at least twice across the data set. See Appendix A for a detailed description of our word-feature selection process (e.g., the logic, metrics, and process used for the selection of "four" words).

Third, we eliminated outliers by calculating the cosine similarities between data items after recalculating TF–IDF values with the 924 word-features that represent "smart service systems." The pairwise similarity comparison matrix (i.e., $5{,}394 \times 5{,}394$ matrix) was derived and the mean of vectors were calculated, with smaller mean value indicating less similarity. We then checked the least similar data by manually reading the content of each article, deleting those that were not relevant; for example, one deleted item was "Evaluation of Pneumonia Severity and Acute Physiology Scores to Predict ICU Admission and Mortality in Patients Hospitalized for Influenza" (Muller et al. 2010). Sixteen outliers were eliminated, resulting in a core vector space with 5,378 articles and 920 word-features.

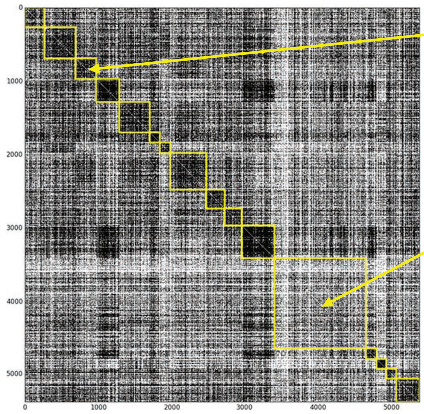
After finding the core vector space, we examined the data through descriptive analyses, such as representative word analysis (e.g., ranking the 920 words and visualizing word clouds) using the five metrics in Table A.1 in Appendix A and word association rule mining (Agrawal and Srikant 1994). We then performed unsupervised machine learning, network analysis, and factor analysis. First, we performed spectral clustering (Von Luxburg 2007) to identify key research topics of smart service systems. Spectral clustering is based on graph partitioning and uses the Laplacian matrix derived from a similarity matrix of data. This algorithm was chosen based on the pilot studies through testing the effectiveness of various clustering algorithms to sample data, which include spectral clustering, affinity propagation clustering (Frey and Dueck 2007), agglomerative clustering (Beeferman and Berger 2000), density-based spatial clustering of applications with noise (Birant and Kut 2007), and k-means clustering (Hartigan and Wong 1979) after principal component analysis (PCA) (Jolliffe 2002). The mean of silhouette coefficient (Rousseeuw 1987) of the entire data set was our performance metric for algorithm testing.

The graph-partitioning problem in spectral clustering is an NP-hard problem, requiring use of a heuristic algorithm, meaning that the clustering result and the score of the mean silhouette coefficient changes with each run. We checked the average of 10 iterations. Figure A.2 in Appendix A shows that the average values based on the cosine and Euclidean distance are high when the number of clusters is 14 and 16. We compared both cases by checking the cluster representation words determined by the five metrics in Table A.1. We also reviewed data of each cluster for manual evaluation. Finally, we arrived at an optimal number of 16 clusters.

In interpreting the 16 clusters, we first identified the top 100 word-features with clear differences among the clusters using chi-squared and F values. These 100 features include the words of a specific application area of smart service system (e.g., "city" and "home") and the general words used for a smart service system (e.g., "cloud," "scheme," and "sensor"). This simple analysis implies that the clusters may represent such topics as "smart city," "smart home," "cloud computing," and "sensing." We then used topic modeling algorithms and the five metrics in Table A.1 to identify sets of top words that represent each cluster. In the pilot studies, we tested the effectiveness of the two-topic modeling algorithms, i.e., NMF and LDA, through manual checks of the different number of topics. We chose both algorithms because they did not dominate one another in most cases. We also reviewed the contents of the top and bottom representative data of each cluster during interpretation, which were identified based on the cosine similarity between each item and the centroid of its cluster, as well as the data sources (e.g., journals and proceedings) of each cluster to assess the homogeneity of the cluster; a cluster may be homogeneous if the top and bottom data discuss a similar topic and the data sources are highly correlated.

We also used a visualization method adapted from Longabaugh (2012) to interpret the result of spectral clustering (see Figure 3). The left side of Figure 3 shows a binary adjacency matrix. The black cell indicates that the corresponding adjacency score of cosine similarity is larger than the mean of all values in the matrix (i.e., an average similarity between data). Each cluster is highlighted by a yellow border. The density of the

Figure 3. Interpretation of Clustering Result



Cluster 3: Smart home	
Top words by NMF	Top words by LDA
home	home
smart	smart
system	system
service	service
network	network
device	device
user	environment
environment	user
control	sensor
technology	technology

Cluster 12: Design of smart service systems	
Top words by NMF	Top words by LDA
system	system
service	service
smart	smart
technology	technology
information	information
design	model
model	application
management	management
application	design
control	new

area represents homogeneity of the cluster, whereas the size indicates the number of items in the cluster. Thus, the cluster may indicate a broad topic if the density is low and the size is large. Opposite results were found for specific topics. The homogeneity and size were considered when each cluster was interpreted and named based on its top representative words determined by the NMF and LDA algorithms and the five metrics. The right side of Figure 3 illustrates the interpretation and naming. We also performed a network analysis and an exploratory factor analysis to the clustering result for further interpretation. This is introduced in Section 4 in detail.

The analysis of news article data was similarly conducted. See Appendix B for further detail on finding a core vector space of news data. In this case, the core vector space contained 1,234 data (rows) and 256 features (columns). Unsupervised machine learning was applied to the vector space, similar to the scientific data; Figure B.1 in Appendix B shows that the average scores of mean silhouette coefficient based on the cosine and Euclidean distance converge at "n_clusters = 56." After examining and interpreting the 56 clusters in detail, we deleted one that pertained to news on market reports rather than an application area. In the end, 55 areas of smart service system application were identified.

4. Findings

This section describes the findings of our data analysis. Section 4.1 describes the basic attributes of smart service systems that were identified by the significant keywords of smart service systems and their statistical relationships. Section 4.2 describes 16 research topics related to these systems and their relationships, which were identified by clustering the scientific literature data. Section 4.3 proposes four factors that constitute a smart service system along with a system definition based on the factors that were identified by analysis of seven clusters that represent generic aspects of these systems. Section 4.4 describes 13 application areas that consist of 55 subareas related to smart service systems and their ecosystems based on clustering of news data.

4.1. Basic Attributes of Smart Service Systems

We rank the 920 word-features from the scientific literature on smart service systems using scaled standardized values of the five metrics in Table A.1 in Appendix A. Figure 4 shows the words, i.e., word clouds, which we identified for these systems based on overall score; the right side shows the word cloud with the full list of 920 word-features, and the left shows the top 100 words. The figure suggests that our five metrics capture meaningful keywords. Table 3 shows the result of association-rule mining on the 920 word-features. The support, confidence, and lift values represent the degree of association between the words on the left-hand side (LHS) and right-hand side (RHS). In Table 3, the rows are ordered by the lift value showing a dependency between the two sides. Table 4 shows the top 10 research areas in Web of Science and the top 10 sources (i.e., journals, proceedings, or books) of the 5,378 scientific articles.

These tables and figures show some of the basic attributes of smart service systems. For example, Table 3 indicates that a smart service system requires technologies for networking, data and information processing, control, communications, devices, and applications to provide specific functions to system users. Table 4 shows relevant research fields (e.g., telecommunications and automation) and specific application areas (e.g., energy

Figure 4. Word Clouds of the Smart Service System Literature Measured Based on the Five Metrics

Word cloud with the full list of top 100 words

Word cloud with the full list of 920 words

Table 3. A Number of Top Rules in the Result of Association Rule Mining Sorted by the Lift Value

Rank	LHS	⇒	RHS	Support	Confidence	Lift
1	{smart, user}	⇒	{service}	0.284	0.936	1.069
…	…	…	…	…	…	…
9	{device, smart}	⇒	{service}	0.234	0.916	1.046
…	…	…	…	…	…	…
13	{communication, smart}	⇒	{service}	0.228	0.911	1.040
…	…	…	…	…	…	…
19	{network, smart}	⇒	{service}	0.319	0.909	1.038
…	…	…	…	…	…	…
22	{information, smart}	⇒	{service}	0.282	0.908	1.037
…	…	…	…	…	…	…
29	{control, system}	⇒	{smart}	0.203	0.958	1.030
…	…	…	…	…	…	…
45	{data, system}	⇒	{service}	0.270	0.889	1.015
…	…	…	…	…	…	…
50	{new}	⇒	{service}	0.247	0.887	1.013
…	…	…	…	…	…	…
53	{application, smart}	⇒	{service}	0.299	0.887	1.012
…	…	…	…	…	…	…

Table 4. Top 10 Research Areas and Journals Related to Smart Service Systems

Web of Science research area	Frequency	Source	Frequency
Engineering, Electrical, and Electronic	2,117	*IEEE Transactions on Smart Grid*	74
Telecommunications	1,316	*Journal of Medical Systems*	52
Computer Science, Information Systems	1,257	*International Journal of Distributed Sensor Networks*	52
Computer Science, Theory, and Methods	1,148	*IEEE Transactions on Consumer Electronics*	51
Computer Science, Artificial Intelligence	736	*Wireless Personal Communications*	48
Computer Science, Hardware, and Architecture	602	*IEEE Communications Magazine*	35
Computer Science, Software Engineering	444	*Renewable and Sustainable Energy Reviews*	34
Computer Science, Interdisciplinary Applications	377	2012 *IEEE Power and Energy Society General Meeting*	24
Energy and Fuels	345	*Personal and Ubiquitous Computing*	23
Automation and Control Systems	317	*Multimedia Tools and Applications*	22

and health). Figure 4 shows these attributes in more detail; the top words to describe smart service systems include "network," "data," "user," "application," "technology," "information," "device," "grid," "energy," "power," "environment," "communication," "mobile," "management," "sensor," "control," "ubiquitous," "real-time," and "interaction." Figure 4 also demonstrates the utility of the five metrics in Table A.1 for examining the core attributes of a topic.

4.2. Sixteen Research Topics Related to Smart Service Systems

Figure 5 shows 16 research topics related to smart service systems (i.e., 16 clusters of literature data). Some topics represent generic aspects of these systems, whereas others address specific application areas. We describe the seven generic and nine application clusters in the next two paragraphs. The studies we referenced for each cluster were selected from the top 10 representative items of the cluster, as determined by mean cosine similarity of an item to other items, and reviewed by the authors.

The seven generic topics (clusters) are as follows: Topic 8 (Cluster 8) is "smart service systems in general," which addresses context-awareness (Gu et al. 2005), delivery to users (Dimakis et al. 2010), smart devices and environment (Cho and Yoe 2010, Crotty et al. 2008), and other general characteristics of smart service systems (e.g., ubiquitous computing and pervasive environment). Topic 12 is "design of smart service systems," which addresses components (Gessner et al. 2009), engineering (Lopes and Pineda 2013), design strategy (Kreuzer and Aschbacher 2011), customer perspective (Wünderlich et al. 2015), and other knowledge for the design of these systems (e.g., design model, approach, and process). Topic 16 is "sensing," which addresses the user-centric sensor design (Chen et al. 2004), data gathering (Neves et al. 2010), aggregation (Sim et al. 2011), and other issues on sensing and data monitoring in smart service systems. Topic 10 is "Internet/Web of Things," which addresses the IoT (Singh et al. 2014), Web of Things (Mainetti et al. 2015), and other issues on the connectivity of objects in these systems. Topic 2 is "wireless networks/communications," which addresses traffic control (Malavasi et al. 2003), optimal allocation (Levorato and Mitra 2011), multiaccess (Blum et al. 2011), and other issues on wireless networking and communications. Topic 5 is "mobile devices," which addresses mobile phone use (Yadav and Naik 2013), information distribution (Noor 2009), location-based functions (Fei et al. 2015), and other issues on mobile devices and networks. Topic 6 is "cloud computing/environment," which addresses cloud computing availability (Lee et al. 2012), security (Getov 2012), authentication mechanism (Kim and Moon 2014), and other issues on infrastructure or platform that enable cloud functions in these systems.

Figure 5. 16 Research Topics of Smart Service System

1. Smart Card
Keywords:
data, card, transit, security, public, user, bus, transport, passenger, secure, access, …

7. Smart Antenna
Keywords:
antenna, capacity, wireless, mobile, performance, adaptive, communication, cdma, access, signal, …

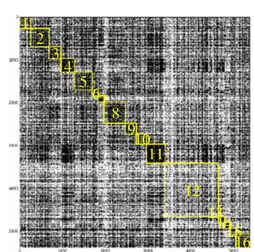
11. Smart Grid
Keywords:
grid, power, communication, network, distribution, control, energy, generation, electricity, meter, …

2. Wireless Networks/Communications
Keywords:
network, wireless, communication, traffic, radio, mobile, qos, packet, security multimedia, …

8. Smart Service Systems in General
Keywords:
contextaware, user, environment, computing, space, ubiquitous, pervasive, interaction, data, …

12. Design of Smart Service Systems
Keywords:
technology, information, design, model, application, new, product, development, user, business, …

3. Smart Home
Keywords:
home, network, device, user, environment, sensor, control, activity, monitoring, interaction, …



13. Use of Electric Vehicles
Keywords:
EV, vehicle, electric, grid, power, control, energy, station, load, regulation, demand, battery, …

4. Smart Energy Management
Keywords:
energy, grid, power, building, demand, control, electricity, storage, renewable, market, cost, …

14. Security
Keywords:
authentication, user, attack, card, RFID, password, key, secure, protocol, anonymity, identity, …

5. Mobile Devices
Keywords:
mobile, device, user, application, phone, location, communication, wireless, content, platform, …

9. Smart Health
Keywords:
health, patient, healthcare, care, medical, data, sensor, monitoring, home, elderly, wearable, …

15. Smart City
Keywords:
city, urban, development, data, public, information, application, infrastructure, citizen, future, iot, …

6. Cloud Computing/Environment
Keywords:
cloud, computing, application, user, mobile, security, data, resource, infrastructure, platform, …

10. Internet/Web of Things
Keywords:
web, thing, internet, IoT, device, data, application, object, architecture, semantic, communication, …

16. Sensing
Keywords:
sensor, network, monitoring, wireless, data, bridge, realtime, sensing, device, health, power, …

The nine application topics (clusters) are as follows: Topic 3 is "smart home," which addresses the elements (e.g., Yu et al. 2011), design (Anbarasi and Ishwarya 2013), trends (Alam et al. 2012), and ecology (Crowley and Coutaz 2015) of home monitoring, control, and automation using specific sensors, devices, and environment. Topic 9 is "smart health," which addresses the management of patient health (Mukherjee et al. 2014), the collection and use of personal health records (Chung and Park 2016), required devices (Goyal et al. 2012) in health care and management systems, and other issues in technology-based health monitoring and care. Topic 4 is "smart energy management," which addresses the efficient use of energy (Colak et al. 2012), distribution of renewable energy (Byun et al. 2011), regional energy management (Cai and Li 2014), system design (Strasser et al. 2015), and other issues pertaining to efficient control of energy demand and consumption. Topic 11 is "smart grid," which addresses aspects of power and communication (Lo and Ansari 2012), security (Amin 2012), services (Chen 2011), trend (El-Hawary 2014) in smart grids, and other issues on energy control through distributed infrastructure network. Topic 13 is "use of electric vehicles," which addresses fleet management (Hu et al. 2016), interactions through smart grids (Mwasilu et al. 2014), business models (San Román et al. 2011), efficient charging (Sbordone et al. 2015), sharing (Lee and Park 2013) of electric vehicles, and other issues on modern vehicle use systems. Topic 14 is "security," which addresses authentication (Lee 2013a), smart card use (Lee 2013b) in security systems, applications in the health industry (Mishra et al. 2014), and other issues on smart schemes against specific attacks. Topic 15 is "smart city," which addresses the concept (Su et al. 2011), architecture (Anthopoulos and Fitsilis 2014), and worldwide applications (e.g., Pérez González and Dıaz Dıaz 2015) of smart cities, and other issues on (public) data-driven digital urban systems and the infrastructure or environment for these systems. Topic 1 is "smart card," which addresses the applications and benefits (Bagchi and White 2005, Pelletier et al. 2011) of smart cards. Topic 7 is "smart antenna," which addresses the design (Kawitkar and Shevgaonkar 2003), evaluation (Wong et al. 1988), use (Herscovici and Christodoulou 2001), and other aspects of smart antennas.

Figure 6 shows a network of the relationships among the 16 research topics. We first identified the centroids in the clusters for the network analysis and computed the cosine similarities between the centroids. Given that all clusters are highly related, the similarity scores are generally high and all nodes (clusters) are connected; thus, we identified the top 3 most relevant clusters from each cluster, and connected only these to observe the most significant relationships between the research topics; size of node represents the network degree (i.e., relationship strength). The nodes in the center represent generic aspects of smart service systems (e.g., sensing and wireless communications), whereas the nodes in the boundaries pertain to specific application fields (e.g., smart home and energy). The former nodes have strong relationship values (i.e., connected with many other nodes), whereas the latter are weaker and connected through the former. The relationship between a specific

Figure 6. Relationship Among the 16 Topics

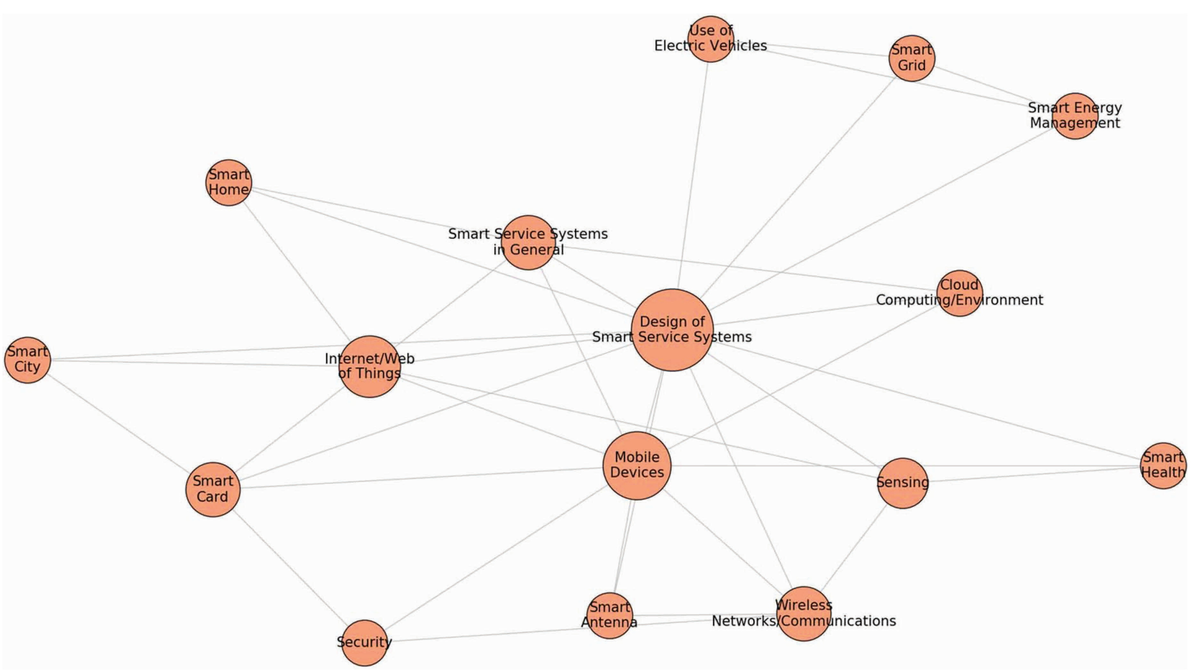
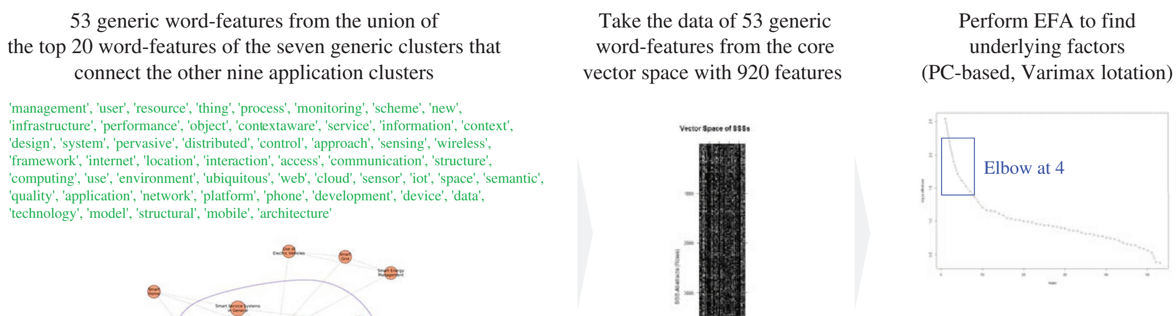


Figure 7. Factor Identification of Smart Service System



	FA1	FA2	FA3	FA4
wireless	−0.029	−0.041	0.523	0.191
network	0.007	−0.087	0.429	0.109
communi cation	0.011	−0.069	0.331	−0.005
mobile	−0.04	0.154	0.319	−0.217
…	…	…	…	…

pair of nodes has implications. For example, "smart grid," "smart energy management," and "use of electric vehicles" are highly relevant. "Design of smart service systems" is one of the top three relevant topics to all the other research topics, except "security." This reflects the fact that smart service system design is always a fundamental issue in technology development and application.

4.3. Factors and Definition of Smart Service Systems

Having identified some attributes and research topics on smart service systems, we now ask: What factors constitute the "core" structure or architecture of a smart service system? Figure 7 illustrates our process of identifying the key factors. We identified a set of 58 word-features, which are the union of the top 20 word-features in the seven generic clusters using the geometric mean of the standardized five metric values (i.e., overall score). We then excluded "home," "energy," "traffic," "study," and "smart" from the full set of 58 word-features because they may be considered too general or too application-oriented. The remaining 53 generic word-features, such as "user," "thing," "Internet," "context-aware," "control," "sensing," "wireless," "location," "interaction," "access," "communication," "computing," "data," and "architecture," may represent the core structure of smart service systems. We used the data from 53 generic word-features from the vector space of 920 features to perform an exploratory factor analysis (Thompson 2004). PCA-based factor identification with varimax rotation enabled us to identify underlying factors. The elbow analysis of the eigenvalue graph on the right panel of Figure 7 indicated that four was an appropriate number of factors. According to the factor loading of the 53 word-features, these four factors are "sensing," "connected network," "context-aware computing," and "wireless communications."

Thus, we propose the following data-driven definition of a smart service system based on these four factors and the list of 53 generic words: *A smart service system is a service system that controls things for the users based on the technology resources for sensing, connected network, context-aware computing, and wireless communications*. Examples of resources include specific environment, infrastructure, devices, and applications (software). Examples of things to be controlled include specific objects, processes, and users. The definition and examples were derived from a data-driven approach, which consists of important words statistically and semantically identified from the literature data. Our findings indicate that representative examples include smart home, energy management, health, and city systems. More examples are introduced in the next section.

4.4. Application Areas and an Ecosystem of Smart Service Systems

This section describes the results of our analysis of the news data. As described previously, 55 clusters were identified from the news data. Cluster interpretation was performed using the approach applied to the scientific data. We categorized the 55 clusters into 13 areas by analyzing the pair-wise cosine similarities between clusters and reviewing the original 126 keywords used for the collection of news data. We relied on our reading of each item (i.e., knowledge from the data collection process) in the categorization. Table B.1 in Appendix B shows the 13 application areas and 55 subareas related to smart service systems. We validated the 13 areas using the NMF and LDA topic modeling algorithms by setting the number of topics to 14. As expected, one topic was related to the deleted cluster of market report news (see Section 3.2 about this cluster); the other 13 topics were highly consistent with our categorization.

Figure 8. Ecosystem of Smart Service Systems

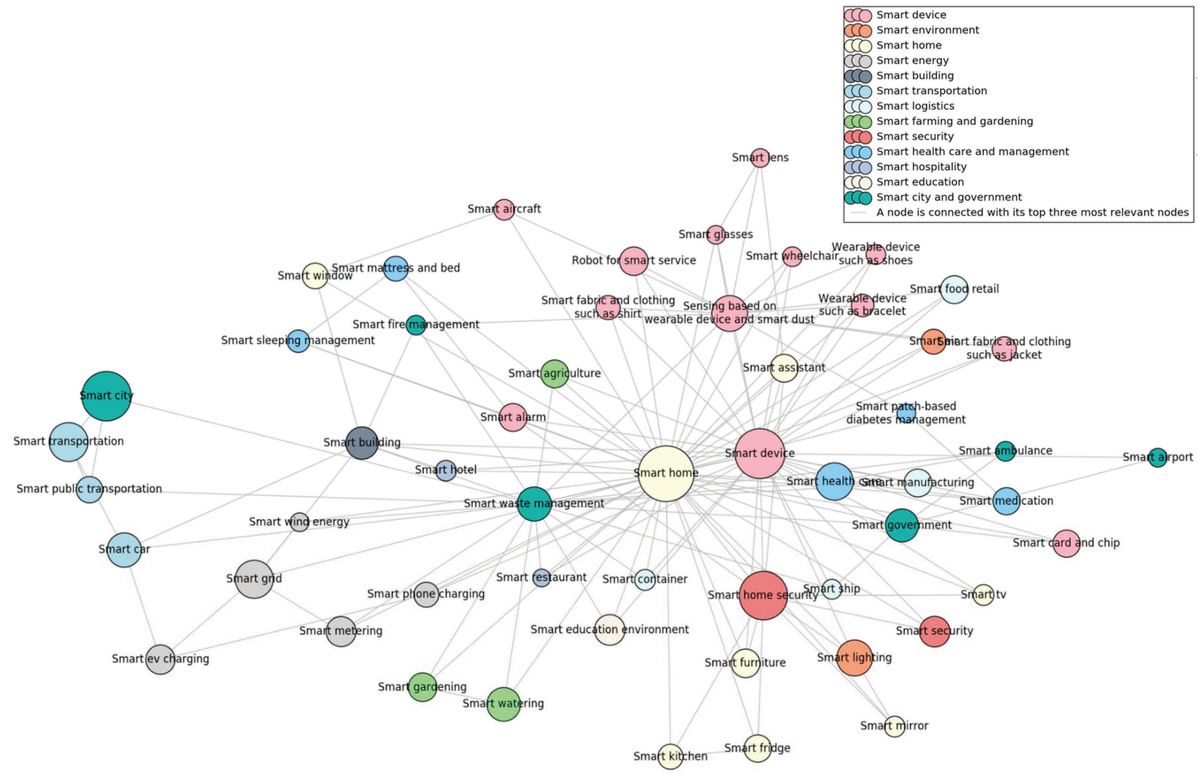


Figure 8 illustrates the relationship among the 55 subareas. Network analysis was performed using the approach used in the case of scientific literature data, except that node size here represents the number of items (i.e., size) of the cluster rather than network degree. The figure represents an *ecosystem* of smart service systems. Some key implications are as follows: First, smart devices are critical resources that facilitate delivery of various smart service systems to users. Second, smart homes incorporate various technologies by positioning at the center of different smart service systems to make living smarter. Third, a smart service system is related to other systems across different contexts of the users (e.g., smart health in smart home and smart transportation in smart city) and resources (e.g., smart device and environment). Thus, achieving synergy between different smart service systems will effectively streamline the development and operations of the systems.

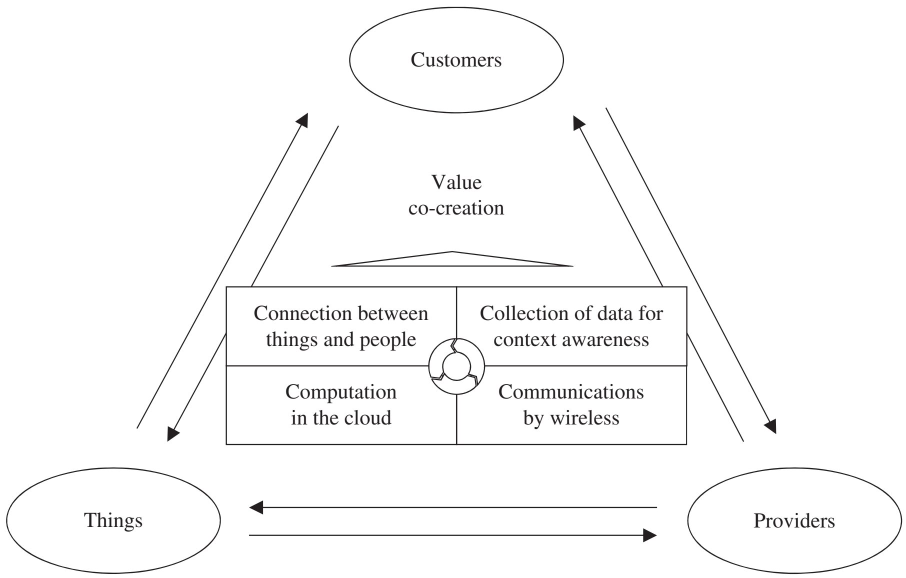
5. Discussion

5.1. Connection, Collection, Computation, and Communications for Co-Creation

In this section we clarify the concept of smart service systems by integrating the four technology factors identified from the scientific literature and findings from existing studies on service systems and smart service systems. Customers create their own value based on offerings from firms (Normann and Ramirez 1993), thus enabling them to apply their competencies in the context of firm resources (Prahalad and Ramaswamy 2000). This means that value may be co-created between customers and firms (Prahalad and Ramaswamy 2002) or generally among multiple actors (Lim et al. 2012). As such, service is "the application of competences (knowledge and skills) by one entity for the benefit of another" (Vargo and Lusch 2004, p. 14), and service systems are "value creation configurations of resources, including people, information, and technology" (Vargo et al. 2008, p. 145). This fundamental concept of a service system shows that, in smart service systems, resources are integrated for four technology factors (i.e., sensing–collection, connected network, context-aware computing, and wireless communications) to enhance the socio-economic factor (co-creation) for system participants, such as customers and providers.

Thus, we propose that smart service systems may be understood along five dimensions, which we call the 5Cs. They are: (1) connection, (2) collection, (3) computation, (4) communications, and (5) co-creation. Figure 9 illustrates smart service system mechanisms (i.e., how a smart service system works) based on these 5Cs, and Table 5 provides a detailed description of the 5Cs. The lines in Figure 9 represent data and information interactions: Smart service systems combine technology resources (e.g., specific device, environment, infrastructure,

Figure 9. Conceptual Framework for Smart Service Systems



and software) for the (1) connection of things and people, (2) collection of data for context awareness, (3) computation in the cloud, and (4) communications to automate or facilitate for (5) the value co-creation activities between customers and providers. The circle at the center represents continuous system control and development, as data and information interactions in a service system are iterative and stakeholders can develop their relationships and continuously improve value co-creation through a cycle of monitoring and learning. This feature shows the importance of service system thinking for using various technologies. The direction of the evolution of smart service systems is clear, i.e., continuous development of the value co-creation loop by integrating technologies for connection, collection, computation, and communications.

The first four dimensions represent the technological resources of smart service systems; the fifth represents the application objective. The first four dimensions contribute to increasing opportunities for active value co-creation. As we become more connected, encounters for value co-creation increase; as we collect and compute more quality data (quality in terms of variety and volume), the informational or intellectual resources for value co-creation increase; and as we communicate more efficiently and effectively, the frequency and intensity of value co-creation increases. In short, the 5Cs theoretically describe what constitutes "smartness" in modern service systems. The real advantage of considering the full-service system in terms of the 5Cs is that it helps us focus on value creation among stakeholders, which can be facilitated by means of technology. Smart people and organizations create value by connecting relevant things and people's concerns, by collecting and computing data, and by communicating with things and people to address concerns. This mechanism applies in describing and developing any type of smart service system (see Table 6). Our perspective is consistent with existing definitions of the smart service system in Table 1 (for example, see the definitions of Spohrer 2013, and Barile and Polese 2010). Compared with existing studies of these systems, our clarification is significant because it confirms, aggregates, and simplifies insightful but subjective expert perspectives *based on data*.

Table 6 shows that the 5Cs are useful in describing the main characteristics of a smart service system. Describing these systems using the 5Cs provides a basis for interconnecting different fields with emphasis on applications. Recent concepts, such as IoT, big data management, AI, cloud computing, blockchain, and wearable devices, are related to smart service systems, and each corresponds to one or more system attributes. For example, wearable devices, such as smartphones, wristbands, and watches, which serve mainly as data collection and information delivery channels, are related to collection and communications. AI is linked to computation, whereas IoT and blockchain relate more to connection. Moreover, each of the research fields related to smart service systems, such as, electronic engineering on connection and collection, computer science and industrial engineering on computation and communications, and marketing and business on co-creation, may focus on one or more of the system attributes and seek synergy with different fields related to other attributes.

As with any large scale initiative for change, the transition to smarter service systems is difficult. Nevertheless, a strategy toward smarter service systems can be developed based on the 5Cs. First, the native value co-created through the service system in question must be identified because it represents the mission or target of

Table 5. 5Cs of Smart Service System

5Cs	Description
Connection	Connection between things and people is the first attribute a smart service system should manage. Connected things include tangible goods directly used by customers, as well as dedicated infrastructures generally required by customers and providers; these goods and infrastructures can be connected to other things. We are living in a connected world; the buzzwords "IoT," "Connected Car," or "Connected Home" reflects our ability and desire to better control things around us. The development of a connected network of people and things, which is the base infrastructure for the system, is the groundwork for collection and communications in a smart service system. In fact, a connected network represents the network of "data sources" for smart service systems. Where to collect data is directly relevant to data use (i.e., purpose of service system) and to the scope and potential of a service system. IoT matters because IoT is really about creating a cyber-physical infrastructure for connection. Technologies for data analytics, cloud computing, and mobile communications, among others, can effectively work together only with a connection infrastructure.
Collection	Collection of data from connected people and things is the second attribute of a smart service system. Data include condition traces of engineering systems, event logs of business processes, health and behavioral records of people, and bio-signals of animals. Given our capability for continuous monitoring and learning from data, data are the core resources for context awareness. The term "smart" mainly pertains to information actions rather than to physical or interpersonal actions; hence this term is inevitably related to the use of data. A major distinction between traditional and recent data collection is the data source (i.e., engineering systems versus human systems). In other words, current sensing methods include physical plus social sensing. In this article, physical sensing refers to a process conducted using physical sensors, whereas social sensing includes any type of sensing enabled or conducted by people without using physical sensors. Examples of social sensing include data collection from social network services, surveys, interviews, queries, and documents. Physical and social sensing from things and people within a service system produce data that indicate behaviors and operations of people, operations and condition management of organizations and things, and interactions within a service system. Data-use contributes in making these effective and efficient.
Computation	Computation is the third key attribute of smart service system. Computational processes involve the use of specific algorithms and expert knowledge for decision making. Computation is the prerequisite for data and information communications in a connected network because these processes transform raw data into standardized data or information that enable machine-understandable data or human-understandable information. The key functions of smart service systems, such as context awareness, predictive and proactive operations, adaptation, real-time and interactive decision making, self-diagnosis, and self-control, can be created only through computation on specific data. This often requires several pre-tasks for data analytics, such as analysis planning, data cleaning, anonymization, aggregation, integration, and storage. Two of the key requirements of computation of smart service systems are cloud computing availability and security because of the distributed nature of connections in a smart service system.
Communications	Communications by wireless between people and things is the fourth attribute of a smart service system. The contexts of communications include both machine-to-machine actuation and machine-to-human guidance; thus, the issues of this attribute encompass not only the issues of communications of machine-understandable data but also human-understandable information, such as visualization methods and other information delivery methods through auditory, olfactory, palate, and tactile stimulation in physical, virtual, and augmented reality. Although the same goods, infrastructures, and stakeholders can be involved in multiple service systems, interactions are relatively unique in each service system. Although technologies for connection, collection, and computing are fulfilled in a specific service system, the key to transforming such system into a smarter service system or to creating a new smart service system lies in improving the unique interactions within the system in question. As such, the communications technology that facilitates interactions is crucial in any smart service system; the communications technology is circulating blood of the system.
Co-creation	Co-creation of value between customers and the provider of a service system is the fifth attribute of a smart service system. Value creation is the core purpose and central process in economic exchange. Any type of socio-technical service system involves value co-creation that brings different stakeholders together to jointly produce a mutually valued outcome. In this respect, the development and use of technologies ultimately aim for enhanced value creation or for creation of new value. Examples of value co-creation stakeholders include customers of IT goods, manufacturers, government agencies of infrastructure, and application developers.

technology development and use. Second, connectivity within the service system must be improved in terms of scope, size, depth or trust because the connected network represents the capability and potential of the service system. Third, the right kind of data must be collected through physical and social sensing. Moreover, the quality of the data must be managed because data content is directly connected to the scope and potential of the service system. Fourth, data must be integrated and analyzed through computation using appropriate data analytics processes because the computing method determines the smartness and accuracy levels of the service system; the creation of information from data is directly related to the value and attractiveness of any

Table 6. Main Characteristics of the 11 Types of Smart Service Systems

Smart service system	What the service system automates or facilitates (according to the 5Cs)
Smart home	Value co-creation activities of residents and related stakeholders through in-home or home-around connectivity, collection of living-related data, computation for context awareness, and wireless communications within or through a technology-equipped house
Smart energy	Value co-creation activities of energy users, producers, and other stakeholders through connectivity, collection of energy operations data, computation to optimize energy usage, and communications between machines, facilities, etc.
Smart building	Value co-creation activities of building occupants, managers, and other stakeholders through connectivity, collection of work-related and building operations data, computation for comfort and performance optimization, and communications within or through a technology-equipped building
Smart transportation	Value co-creation activities of drivers, riders, and other stakeholders through connectivity between vehicles, roads, and other infrastructures; collection of vehicle operations and health data; computation for safety and efficiency, and communications between vehicles, people, etc.
Smart logistics	Value co-creation activities of manufacturers, distributors, and other stakeholders through connectivity between facilities, vehicles, and goods; collection of production and logistics data; computation for optimal operations management; and communications between facilities, vehicles, people, etc.
Smart farming	Value co-creation activities of farmers, agriculture companies, and other stakeholders through connectivity between living properties and farming equipment, collection of condition and environment data, computation for optimal health management, and communications within or through a technology-equipped farm
Smart security	Value co-creation activities of property owners and protectors by the connectivity, collection of property condition and environment data, real-time computation for surveillance, and real-time communications between the stakeholders
Smart health	Value co-creation activities of patients, healthy people, healthcare providers, and other stakeholders through connectivity between people, devices, and health care environment; collection of health-related data; computation for diagnosis and prognosis; and communications within or through technology-equipped people, living, and care environment
Smart hospitality	Value co-creation activities of guests and service providers through connectivity between people and service environment, collection of stay-related data, computation for context awareness, communications within or through technology-equipped hospitality environment
Smart education	Value co-creation activities of students, teachers, and other stakeholders through connectivity between people, devices, and education environment; collection of study-related data; computation for maximal learning and satisfaction; communications within or through technology-equipped education device and environment
Smart city and government	Value co-creation activities of citizens, public infrastructures, government agencies, and other stakeholders through connectivity among people and organizations, collection of data for public purposes, computation for optimal administration and living conditions of citizens, and communications between stakeholders

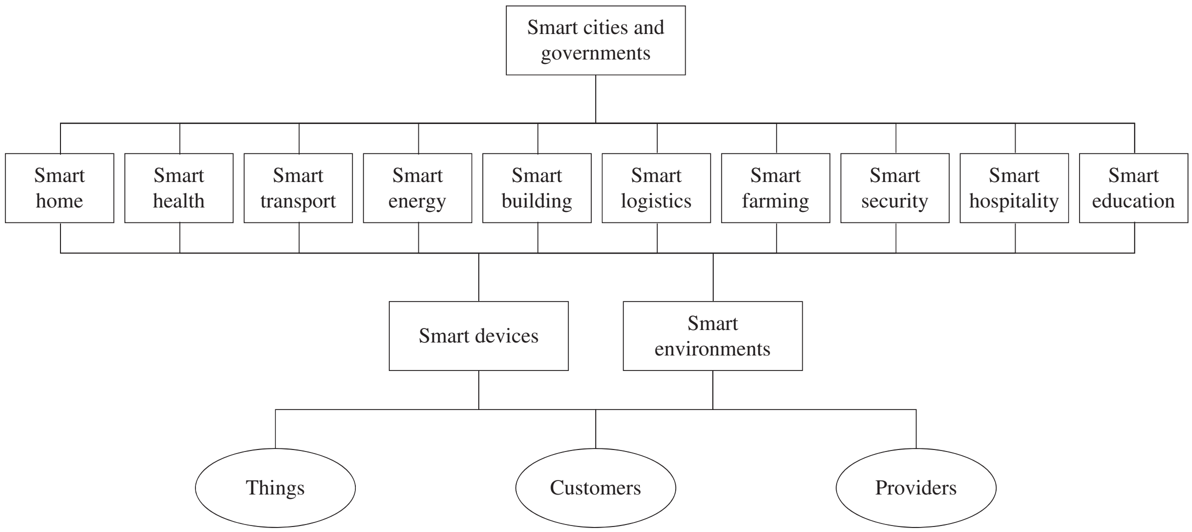
service system. Fifth, communications between machines and humans must be improved to facilitate easy and spontaneous data collection as well as to increase the efficiency and acceptability of information delivery to customers.

We do not propose the 5Cs as the exhaustive list of dimensions of smart service systems. Researchers may identify different dimensions from different studies. Human actions in service systems can be categorized as informational, physical, and interpersonal (Apte and Mason 1995). The automation of such actions, which has evolved from automated teller machines for banking services to warehouse robots for shipping services, has made these services smarter (Maglio and Lim 2016). We think the current status of most smart service systems is mainly at the level of the automation of informational actions. The emergence of autonomous service systems (Maglio 2017) with the automation of physical actions and interactions, such as self-driving cars and fully automated buildings, may force us to extend our 5Cs of smart service systems to include *control*, a 6th "C" (Maglio and Lim 2018). Automation of interpersonal (emotional) actions in the distant future may force us to further extend, with *care*, to a 7th "C."

5.2. Hierarchical Structure of Smart Service System Applications

The 13 application areas in Section 4.4 can be distinguished according to the type of application. Smart device and environment are resource-type areas that are required in any kind of smart service system. Smart home, energy, building transportation, logistics, farming and gardening, security, health care and management, hospitality, and education are business system-type areas. Smart city and government systems are a public administration-type area. As shown in Table A.1 in Appendix A, common keywords of the 55 subareas include

Figure 10. Hierarchical Structure of Smart Service System Applications



"device," "product," "app," "data," and "information." This list implies that the essence of smart service system applications, which have been discussed in various news articles, is to use a device or product with a smartphone application to collect data from people and objects and to deliver information to them.

Based on the categorization of the 13 areas and the conceptual framework in Section 5.1, Figure 10 shows a hierarchical structure of smart service system applications. Things, providers, and customers are connected by using smart devices and environment, which are key resources that collect data and facilitate delivery of various smart business systems to customers. The stakeholders then co-create value through smart business systems. Smart cities and governments comprise 10 types of smart business systems, i.e., smart home, health, transportation, energy, building, logistics, farming, security, hospitality, and education service systems. Figures 9 and 10 are useful for describing a smart service system. For example, we can define a smart home as a service system that automates or facilitates value co-creation activities (e.g., lighting, cooking, temperature control, garage opening, and exercising) between residents and related stakeholders through connectivity enabled by in-home or home-around devices and environment, collection of living-related data, computation for context awareness, and wireless communications achieved within or through a technology-equipped house.

5.3. Text Mining Approach to Understand Service Research Topics

From a research methodology perspective, our study provides a successful example of the collection, analysis, and interpretation of large text databases for understanding a service research topic. This study is unique because we aimed to minimize subjectivity in processing and aggregating text about smart service systems. The identification of important word-features describing these systems, the clustering analyses, and the factor analysis were based on the algorithms designed through pilot studies; only the parameter setting and analysis result interpretation were conducted by humans with data analysis results for decision making. Nonetheless, existing studies and our preliminary knowledge of smart service systems provided a basis for the research method design and the analysis result interpretation. We believe many service research topics can be similarly addressed using text from customers, researchers, and other stakeholders.

In particular, our core vector space finding method can provide the following utilities to use a text mining approach for understanding a service research topic: (i) intuitive understanding of the importance of words through the use of metrics, (ii) quick elimination of the features that disturb statistical and semantic analyses, (iii) substantial reduction of calculation time for machine learning, and (iv) easy interpretation of machine learning results with reduced number of features and cognitive loads. When we applied the LDA topic modeling with the 30 topics to the initial literature data set of the 6,188 by 28,302 matrix, the analysis generated irrelevant, too specific or nongranular topics because of the presence of nonimportant features. Examples include the irrelevant topic with the keywords of "material," "polymer," and "chemical"; the specific topic with "cdd," "entrez," and "default"; and the nongranular with "provisioning," "subscriber," and "email." The same topic modeling to the core vector space of the 5,378 by 920 matrix eliminated these issues. We believe the core vector space finding method can be used for effective and efficient applications of text mining.

6. Concluding Remarks

Our work advances understanding of smart service systems by mapping dispersed knowledge from scientific literature and news data to achieve a more systemized and integrated conceptualization. Our work identifies key research and applications areas of smart service systems. Furthermore, our work recognizes the multidimensional smartness (i.e., the 5Cs) of modern service systems. Such empirical findings are consistent with the information we can read from existing studies or news. For example, the journal names and research areas in Table 4 are highly relevant to our findings. This fact implies that our findings make sense, from a semiautomated analysis of big text data, which naturally and clearly reflects the existing structure of smart service system research and application. As such, our contribution is to aggregate and confirm the key concepts and areas of broad studies and applications of smart service systems based on data. We believe our work is important because of the ongoing and intensive discussion among researchers about the definition of "smartness" in modern service systems. We hope our work will bring some clarification and elaboration to this issue. In addition, our data-driven research method can be used in future studies to understand other service research topics.

Nonetheless, we see several limitations to our work that can be addressed in future research. First, our findings depend on data, which means the results may change if the source and time of data collection change. For the scientific data, our strategy was to use all available data from the Web of Science Core Collection databases; the scope and source of data can be expanded to other databases (e.g., Scopus) or reduced to specific domains (e.g., IEEE journals) depending on the purpose. Likewise, different search keywords could be used for news data collection. We collected literature and news data from May and June 2016; data in 2021 will undoubtedly show different research topics, application areas, and factors of smart service system. For example, we believe applications of virtual reality and blockchain technologies will be significant by that time.

Second, our work did not provide detailed information on each research topic, application area or factor of smart service systems. A systematic review of existing literature for a specific topic may be valuable to analyze smart service systems in more detail. The analysis of abstracts, titles, and keywords was appropriate to achieve our research objective (i.e., examining broad studies on smart service systems and developing a high-level concept of the entire literature), but full text analysis may be appropriate if the research objective is focused on a specific topic.

Third, from the perspective of used data, data collection from news articles was performed manually to avoid legal conflicts. Thus, some irrelevant data may have been included in the data set through human error. Automated news collection through the Lexis-Nexis service may be advantageous in terms of quality control. Although this study analyzed the broad aspects of smart service systems, an analysis of user perspectives on these systems is not provided here. Surveys or interviews with users may be done in the future to further develop our understanding. Patent data can be analyzed for an in-depth analysis of technological aspects of smart service systems. We excluded patent data because technological aspects can also be obtained from the scientific literature, and a patent analysis would likely involve an extremely large volume of data, which would require a separate study. Other types of data on smart service systems, such as company profiles, can be used to investigate other aspects of these systems.

Fourth, the analysis method of the current work should be interpreted and validated through additional test cases; for example, the method for identifying a core vector space should be applied and continuously improved in different contexts (e.g., supervised learning context with different data). Comparison of the analyses of abstracts versus full text from the same papers may facilitate development of a selection and processing strategy for applying text mining to service research. Finally, the findings obtained from text mining should be incorporated with real research and development projects related to smart service systems. We have conducted such projects with the industry and the government, such as those about smart cars and transportation, health, and building systems (e.g., Lim and Kim 2014; Kim et al. 2018; Lim et al. 2018a, b, c). An integration of the current study and such projects will further facilitate development of smart service systems.

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Appendix A

Here we describe our method of word-feature selection in some detail. Words in an output of scientific documents can be categorized as follows:.

- Type 1: acronym words developed by the authors, such as "TDD" and "IMSS"

- Type 2: words of the overall topic (smart service system), such as "system," "data," "health," and "city"
- Type 3: words frequently used in scientific documents, such as "existing" and "way" and general English words, such as "may" and "within."

Feature selection requires including Type 2 words and excluding Type 1 and Type 3 words. Type 1 words tend to have very high TF-IDF values because they appear several times in an item but are not present in other items. Type 3 words have low values for the opposite reason. Type 2 words, which appear several times in many items, generally have high TF-IDF values. Identifying meaningful keywords from each item using TF-IDF is useful to filter out some Type 3 words (i.e., too general words). Selecting keywords that were found as a top word at least twice across the data set is useful in excluding Type 1 words (i.e., extremely case-sensitive words).

One issue is deciding on the number of keywords to be selected from each item. Given that we aim to select a minimum number of keywords for efficiency of computation and interpretation, we need to determine a number that can appropriately represent an article. To do this, we calculated the average significance values of different keyword sets according to the number of keyword selections from each article and analyzed the loss of significant features. Significance value was calculated based on the five metrics in Table A.1, which were defined through experiments on various candidates in pilot studies. Figure A.1 indicates the substantial difference between the average significance of the four-keyword case and the five-keyword case (all metrics have an elbow at point K5 and multiple elbows are repeated from this point). The findings indicate the substantial difference between the average significance of the four-keyword case and the five-keyword case, which means the latter starts to include many nonsignificant keywords. Thus, we chose four as the minimum number of keywords to select from each item (i.e., excluding Type 3 words). Then we selected the keywords that were found at least twice in the 5,394 articles (i.e., excluding Type 1 words). In pilot studies, we found that setting this parameter value as greater than two could exclude many Type 2 words. As a result, 2,439 word-features were selected from the original 24,675 features.

At this point, we found that the reduced data set with 2,439 word-features still contained redundancies, such as "existing," "way," and "smms," indicating the need to filter out additional Type 1 and Type 3 words. We identified such words assuming that all words are generated from a Gaussian mixture model (GMM) (Bishop 2006). A GMM-based clustering method can be used to categorize a word-feature with other word-features that share similar distributions (see Pedregosa et al. 2011). We checked the distribution of words in the reduced data set by renormalizing TF-IDF values with 2,439 features. We observed from the pilot studies that the GMM-based clustering method can categorize several Type 2 words that have certain distributions. We also observed that Type 1 and Type 3 words do not correlate with other Type 1 and Type 3 words without some Type 2 words. Given that the number and types of distributions under the reduced data set are unknown, we performed GMM-based clustering using an arbitrary large number of clusters (100) to identify a set of Type 1 and Type 3 words that are not correlated with other Type 2 words. This approach is useful to eliminate many nonimportant Type 1 and Type 3 words. Because GMM is a probabilistic model, clustering results change each run, and so clustering analysis was performed 10 times and the words commonly determined nonimportant were extracted; this loose strategy was used so as to not lose Type 2 words (i.e., to reduce the Type I decision error; Montgomery 2005). We identified and removed many nonimportant features, such as "existing," "way," "within" (Type 3) "ugs," "dsms," and "smms" (Type 1). A total of 1,515 features were removed, leaving 924. Figure A.2 shows the analysis result used in determining the optimal number of clusters of the literature data.

Table A.1. Five Metrics for Word-Feature Selection

Metric	Description	Characteristic
Metric 1	Mean of the TF-IDF scores of a word-feature across data	High value indicates that the word is generally important across many data
Metric 2	Mean of the cosine similarities of a word-feature to other features	High value indicates that the word is close to many other words, meaning that the word may be a representative word of the corpus
Metric 3	Cosine similarity between a word-feature and the centroid of features	High value indicates that the word is close to the artificial word that is the center of all words (i.e., the word that may represent the corpus)
Metric 4	Mean of the dot product scores of a word-feature to other features	Metric 4 was designed to consider both Metric 1 and 2 at the same time because the dot product score is the multiplication of the cosine similarity and the vector magnitude which is proportional to Metric 1. Thus, the high value may indicate that the word is close to many other words and important across many data at the same time.
Metric 5	LDA score of a word-feature for the single topic of entire data set	Metric 5 represents the probability of the word presence in describing the topic. Thus, the high value indicates that the word may represent the topic of the corpus

Figure A.1. Loss of Important Features According to the Number of Representative Word Selections from Each Article

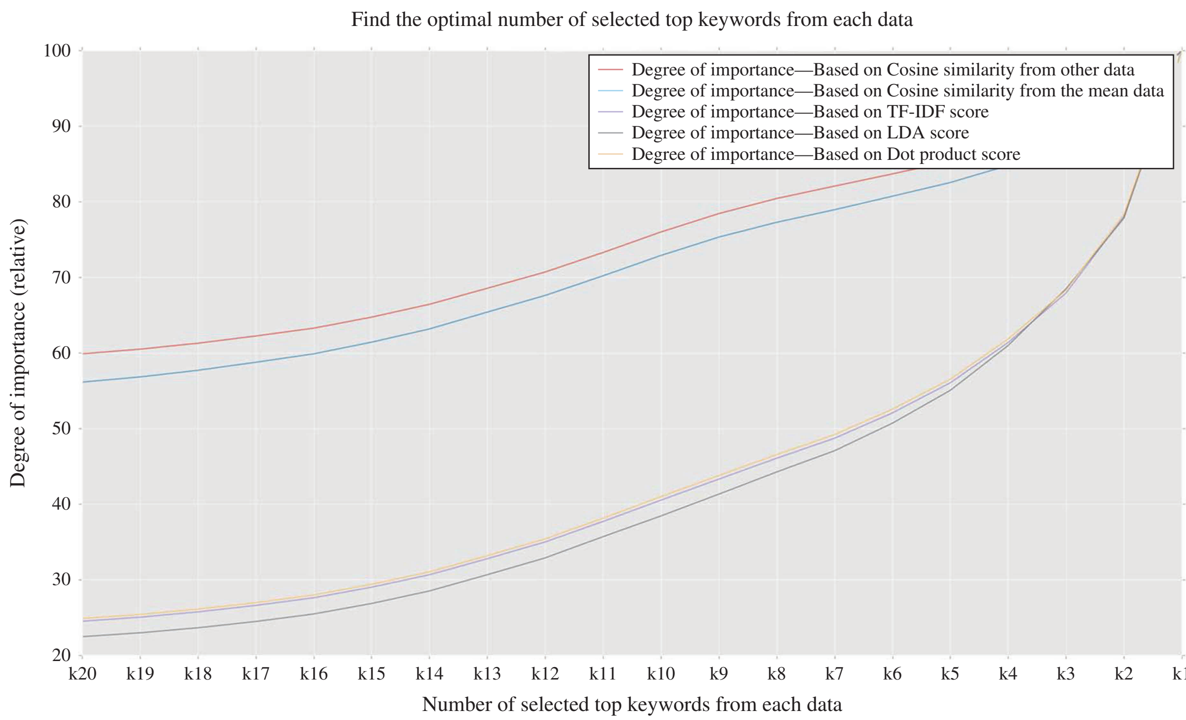
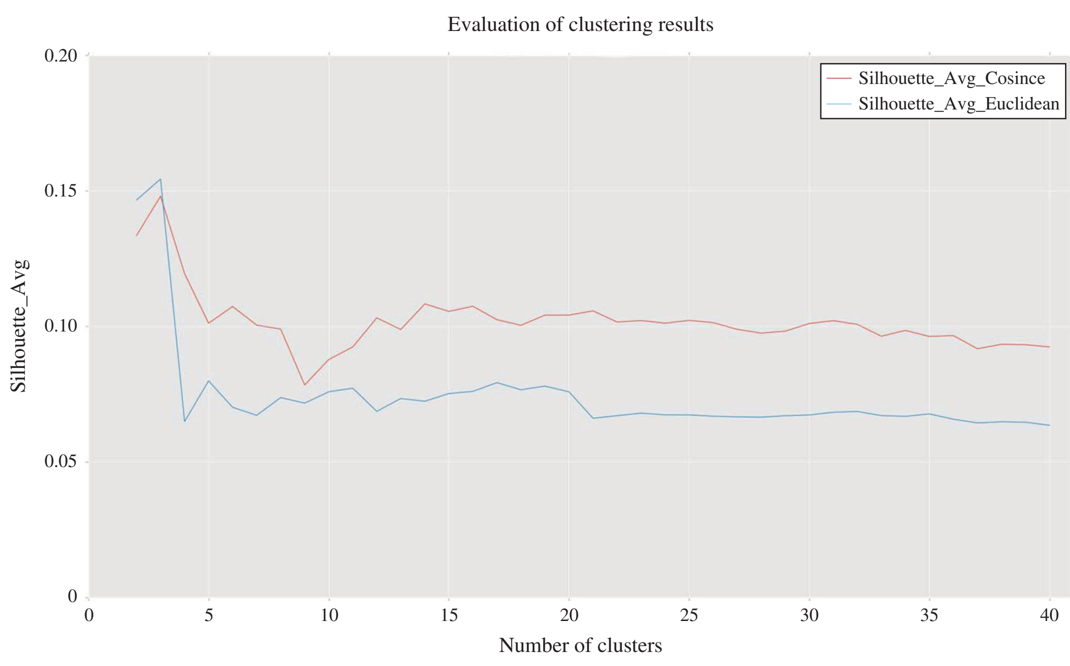


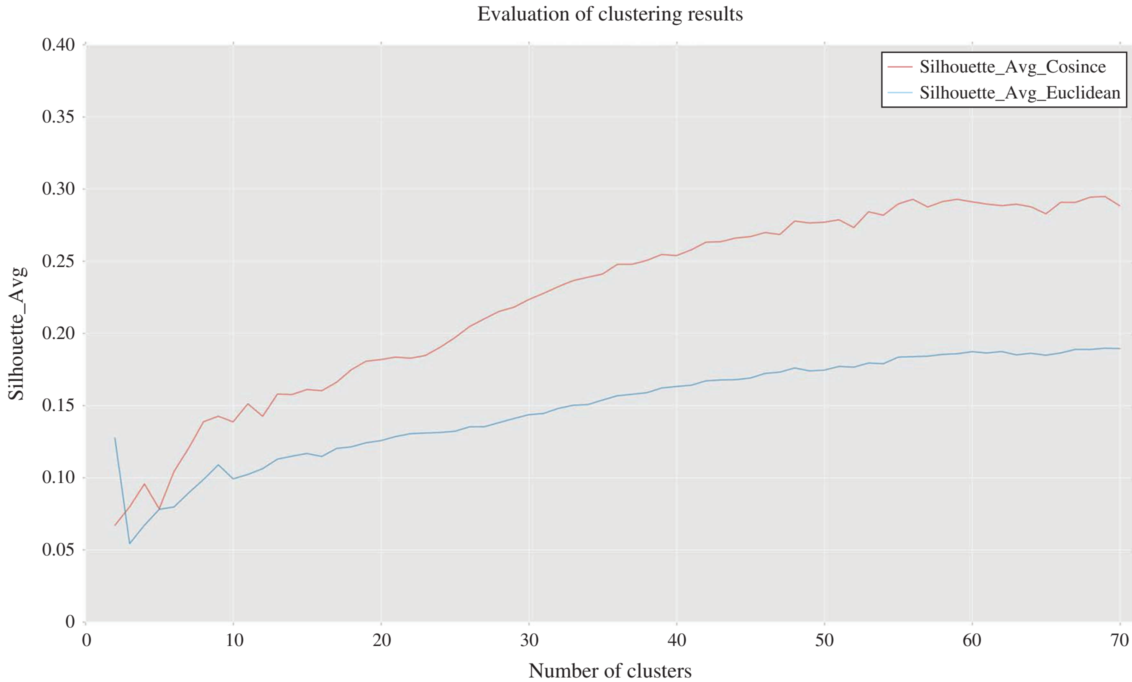
Figure A.2. Evaluation of the Clustering Results of Literature Data



Appendix B

As with the scientific literature data, we cleaned the news data and deleted duplicate items. However, the feature selection algorithm used for the news data differs from the one used for the scientific data. We identified the same number of keywords (four) from each scientific article but a different number of keywords from each news article. This difference is because some news articles can be distinguished with one or two keywords (e.g., name and brand of the introduced good) and others may require many keywords if the news discusses a general topic (e.g., an overall introduction of smart home). Moreover, the length of news articles varies much more compared to the length of scientific abstracts, titles, and keywords. Thus, we used a minimum number of keywords from a news article using the following algorithm.

Figure B.1. Evaluation of the Clustering Results of News Data



First, we calculated the TF-IDF values of the entire data set. Second, we identified the top word of an item, called the "original datum," with the highest TF-IDF value. Third, we generated the artificial "new datum" that contains the top word with the same TF-IDF value. Fourth, we calculated the cosine similarities of the new datum to all items in the entire data set. Fifth, we considered the word as representative of the original datum if the original datum was most similar to the new datum. If the two data are not most similar, we returned to the second step and included the next top word with next highest TF-IDF value to the new datum. We then performed the consecutive steps until the requirement of the fifth step was satisfied. This algorithm enabled us to identify one or more keywords for each item that can distinguish it from other items. Sixth, we considered the next ranked word for each item in addition to the identified minimum number of keyword(s) to provide at least two keyword considerations for each article. This step was performed to secure a sufficient number of Type 2 words. We repeated the above steps to identify representative words for all items in the data set. Finally, we selected the keywords that were representative of an item at least "three times" across the data set because news data involved many Type 1 words (i.e., case-sensitive words), such as company name and news location.

Figure B.1 shows the analysis result used in determining the optimal number of clusters of the news data (Section 3.2). Table B.1 shows 13 areas and 55 subareas related to smart service systems, which were identified from the news data.

Table B.1. Keywords of the 13 Areas and 55 Subareas Related to Smart Service Systems

13 areas	55 subareas	Representative keywords
Smart device	Smart device	device, product, IoT, data, wearable, security, home, connected, service, consumer, authentication, and information
	Sensing based on wearable device and smart dust	sensor, dust, device, data, body, clothing, information, walker, living, wearable, and Internet
	Smart alarm	alarm, smart, clock, pebble, home, device, product, watch, app, bed, sleep, connected, system, and wearable
	Smart wheelchair	wheelchair, smart, system, sensor, technology, device, connected, information, family, electric, home, IoT, patient, and data
	Wearable device such as bracelet	bracelet, smart, wearable, device, app, technology, product, body, connected, sensor, Fitbit, watch, and apple
	Wearable device such as shoes	shoe, smart, technology, data, app, product, device, sensor, system, information, wearable, Samsung, connected, and watch
	Smart fabric and clothing such as jacket	smart, fabric, jacket, technology, clothing, sensor, wearable, google, consumer, product, and health

Table B.1. (Continued)

13 areas	55 subareas	Representative keywords
	Smart fabric and clothing such as shirt	smart, shirt, clothes, clothing, sensor, data, Hexoskin, wearable, app, body, technology, device, health, thread, fabric, connected, and information
	Robot for smart service	robot, smart, Zenbo, home, technology, system, machine, Asus, drone, logistics, device, supply, chain, data, and product
	Smart lens	lens, smart, Google, eye, contact, device, technology, glasses, camera, sensor, patent, system, data, and Samsung
	Smart glasses	glasses, smart, technology, device, product, wearable, app, blind, camera, eye, and data
	Smart card and chip	card, smart, chip, technology, security, data, system, EMV, bank, information, ID, key, and device
	Smart aircraft	aircraft, smart, window, technology, air, sensor, system, passenger, seat, patent, vehicle, data, and device
Smart environment	Smart air	air, smart, home, data, app, sensor, system, uHoo, energy, device, health, product, technology, service, and room
	Smart lighting	lighting, smart, light, LED, bulb, technology, system, product, home, street, app, sensor, energy, and power
Smart home	Smart window	glass, window, smart, technology, building, light, energy, room, system, product, and sensor
	Smart mirror	mirror, smart, sensor, home, Microsoft, app, house, information, device, voice, and care
	Smart furniture	furniture, table, smart, technology, home, system, device, charging, product, Ikea, room, Samsung, and Internet
	Smart home	smart, home, device, app, technology, system, product, sensor, house, Amazon, living, building, and service
	Smart assistant	Google, home, smart, assistant, device, echo, amazon, app, technology, product, information, Microsoft, service, consumer, say, and system
	Smart tv	tv, smart, Samsung, app, device, room, video, system, hub, living, Verizon, and Internet
	Smart kitchen	kitchen, smart, cooking, cook, food, app, pan, device, technology, connected, home, appliances, sensor, fridge, product, refrigerator, and grill
	Smart fridge	fridge, smart, refrigerator, home, Samsung, family, door, hub, camera, app, device, appliances, touchscreen, technology, lg, product, food, kitchen, and connected
Smart energy	Smart grid	energy, smart, grid, system, power, solar, technology, microgrid, electric, home, data, and management,
	Smart phone charging	battery, smart, case, iPhone, Apple, charging, power, device, system, product, technology, energy, charger, electric, and app
	Smart metering	smart, meter, energy, metering, system, technology, billing, power, home, data, service, consumer, government, and supply
	Smart EV charging	charging, charger, EV, power, smart, electric, vehicle, system, technology, energy, battery, solar, grid, car, home, and product
	Smart wind energy	blade, wind, energy, system, technology, power, smart, service, sensor, data, controller, and machine
Smart building	Smart building	smart, building, parking, system, technology, energy, security, home, data, car, sensor, city, management, service, and information
Smart transportation	Smart car	car, vehicle, technology, smart, road, system, electric, transportation, service, traffic, data, Internet, information, sensor, and connected
	Smart public transportation	bus, transport, smart, system, city, vehicle, technology, service, urban, passenger, transportation, government, card, road, traffic, and information
	Smart transportation	transportation, smart, technology, vehicle, traffic, city, system, bridge, road, car, highway, service, information, and connected
Smart logistics	Smart manufacturing	manufacturing, smart, factory, product, technology, system, data, plant, service, connected, chain, management, supply, and information
	Smart container	container, smart, can, technology, system, service, data, product, supply, management, bottle, chain, information, waste, and security
	Smart ship	ship, smart, data, service, technology, system, connected, information, Hyundai, logistics, Internet, passenger, and room
	Smart food retail	shelf, smart, food, consumer, label, technology, labeling, information, sensor, GMO, system, and data

Table B.1. (Continued)

13 areas	55 subareas	Representative keywords
Smart farming and gardening	Smart gardening	plant, smart, system, garden, water, home, sensor, device, app, technology, light, led, farm, and watering
	Smart agriculture	agriculture, farmer, climate, smart, farm, food, technology, climatesmart, system, data, information, service, and management
	Smart watering	water, smart, irrigation, system, controller, watering, sprinkler, home, garden, sensor, lawn, device, data, hub, technology, connected, product, and plant
Smart security	Smart security	camera, smart, home, video, surveillance, security, app, system, device, cam, technology, product, sensor, card, and service
	Smart home security	home, smart, system, device, door, security, house, connected, lock, app, technology, garage, product, Internet, and consumer
Smart healthcare and management	Smart patch-based diabetes management	patch, insulin, smart, device, glucose, patient, system, app, sensor, body, health, data, and technology,
	Smart mattress and bed	mattress, bed, sleep, smart, app, technology, Balluga, sensor, body, home, system, product, and alarm
	Smart medication	medication, patient, pill, smart, app, health, device, system, technology, doctor, data, care, information, sensor, service, home, and family
	Smart sleeping management	sleep, bed, smart, device, app, light, technology, data, alarm, mattress, sensor, system, body, product, and wearable
	Smart healthcare	healthcare, health, patient, smart, technology, hospital, care, system, device, data, doctor, service, product, home, and information
Smart hospitality	Smart restaurant	restaurant, guest, system, smart, food, technology, service, data, app, table, consumer, hospitality, device, and management
	Smart hotel	hotel, guest, room, smart, technology, hospitality, service, system, Samsung, device, tv, lighting, building, energy, light, consumer, connected, and door
Smart education	Smart education environment	student, smart, school, classroom, campus, education, technology, system, Internet, service, device, information, and building
Smart city and government	Smart city	city, smart, technology, government, service, urban, system, data, energy, building, management, information, traffic, citizen, and transportation
	Smart waste management	system, smart, waste, management, technology, service, city, sensor, data, device, home, information, and IBM
	Smart government	service, smart, government, data, citizen, system, technology, security, information, city, ID, management, Dubai, and authentication
	Smart airport	airport, smart, technology, passenger, service, information, government, traffic, data, security, region, and consumer
	Smart fire management	fire, data, building, technology, system, city, information, smart, sensor, service, Internet, and alarm
	Smart ambulance	ambulance, patient, smart, vehicle, paramedic, hospital, service, system, Dubai, data, technology, care, doctor, car, health, information, and road

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