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Investigating How the Cloud Computing Transforms the Development of Industries

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ABSTRACT The Internet of Things (IoT) transforms many fields, including the educational, logistics, and manufacturing industries. The IoT is an internet framework whereby a large number of devices or equipment are connected and synchronized using gateways, third-party technologies, and software in machine-to-machine and cloud computing networks. With the flourishing development of IoT, cloud computing plays an essential role in its application layer. Cloud computing technology has been widely applied in various industries and developed as particular cloud computing types: education as a service (EaaS), logistics as a service (LaaS), and manufacturing as a service (MaaS). The applicability of cloud computing in various industries has attracted significant attention from researchers and professionals. This study investigated the technical trends of emerging cloud computing technologies and surveyed 3,697 cloud computing-related studies from 2010 to 2019. The findings indicate that intelligence and automation are the core issues that drive research on cloud computing. The main types of research are critical review, system design, and systematic analysis. Cloud computing services (e.g., XaaS, EaaS, LaaS, MaaS) are related to big data, analytical technologies, service orientation, and IoT. This study applied machine-learning algorithms to analyze educational, logistic, and manufacturing data and yielded results with more than 90% accuracy and AUC. This study used various devices such as laptops, tablets, and smartphones to configure and review machine-learning models using third-party cloud platforms, which are infinitely scalable and flexible for data analytics, thereby allowing users to make quicker predictions and decisions focused on business needs.

INDEX TERMS Cloud computing, machine learning, education as a service (EaaS), logistics as a service (LaaS), manufacturing as a service (MaaS).

I. INTRODUCTION

In 2000, the MIT Auto-ID Center proposed the framework of the Internet of Things (IoT) [1]. The IoT European Research Council defined IoT as the connection of devices, physical objects, and humans at any time, in any place, with anything on the Internet [2], [3]. The IEEE IoT Initiative recently proposed that the standard of IoT framework involves descriptions of various IoT domains [4]. IoT can be considered as an infrastructure that connects devices and objects with networks and databases; it is expected to revolutionize many industries [5]. IoT provided a machine-to-machine (M2M) and human-to-machine (H2M) architecture for advanced metering infrastructure (AMI) [6]. The smart grid is a typical IoT application that involves data communications, data acquisition and data analytics from users, distribution substations, and transmission lines [7], [8]. The high costs of infrastructure maintenance and equipment procurement may influence business revenue in industries.

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This IoT concept is classified as follows: perceptron layer, network layer, and application layer. Cloud computing is performed on the application layer of IoT, providing virtualized computing resources over the internet. Most companies, such as Cisco, Microsoft, and Amazon, provide cloud services to different industries, such as education, manufacturing, and logistics (see Figure 1).

Using cloud computing services, a user can access virtual resources instead of buying physical infrastructure and computing resources. Such services provide a configurable and extensible infrastructure that supports different types of inputs (e.g., customer needs, device control, and sensors) and outputs (e.g., indicators, analyzer, and actuators). Cloud computing comprises three categories of cloud computing services: Platform as a Service (PaaS), Infrastructure as a Service (IaaS), and Software as a Service (SaaS). Cloud computing has developed new kind services: Education as a Service

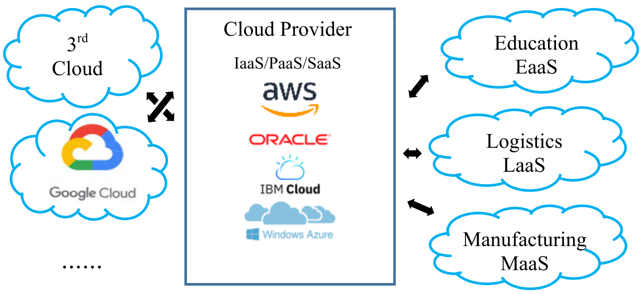

FIGURE 1. The current cloud computing ecosystem.

(EaaS), Logistics as a Service (LaaS), and Manufacturing as a Service (MaaS), for different industries. Cloud computing is essential to every industry. For the education industry, cloud computing offers users adaptive learning strategies and real-time learning activities; e.g., massive open online courses. For the logistics industry, logistical problems can be estimated, visualized, and analyzed on the cloud to optimize logistics strategies, such as vehicle rental projects. For the manufacturing industry, cloud computing provides the convenience method, which is not constrained by factory location or time. Manufacturing processes and equipment can be analyzed and visualized promptly on a cloud platform, e.g., the successful GE aircraft predictive maintenance case. Accordingly, famous companies such as IBM and Microsoft provide cloud computing tools that can be applied quickly in many fields. Microsoft Azure Machine Learning Studio is a cloud-based analytics tool designed to simplify ML procedures for the user. This study surveyed cloud computing-related research and applied ML to data obtained from different industries. The goals were as follows:

- to investigate current cloud computing-related tools and business applications
- to survey current cloud computing-related research through keyword analysis
- to apply cloud computing to predictions for different issues in the fields of education, logistics, and manufacturing

This study aims to develop the cloud technology and survey the studies related to cloud computing. Session 2 investigates the technical trends of emerging cloud computing technologies. Session 3 assesses cloud computing-related literature. Session 4 applies the main ML algorithms to analyze the data in education, logistics, and manufacturing industries. Session 5 describes the dataset, evaluation criteria, and analytics results. Session 6 discusses effect of cloud computing on different industries. Session 7 concludes with this study's significance, limitations, and future work.

II. SURVEY OF CLOUD COMPUTING TECHNIQUES

Cloud computing services, such as IaaS, PaaS, and SaaS, provide cloud-based applications to users who perform tasks using the cloud. Cloud computing takes different forms (e.g., EaaS, LaaS, MaaS). The phrase "as a service" attracts significant attention from users. The idea of "Everything as

TABLE 1. The main cloud computing software from different report.

Source	The main cloud company
G2	AWS, Google, Oracle Compute Cloud Service, Microsoft Azure, IBM Cloud, DigiOcean, Alibaba Cloud
Bloomberg	Alibaba Cloud, Amazon Web Services, Google Cloud, IBM Corp. Microsoft Corp
PPaT Inc.[12]	SAS Predictive Analytics, Google Cloud, Oracle, Microsoft, IBM Predictive Analytics

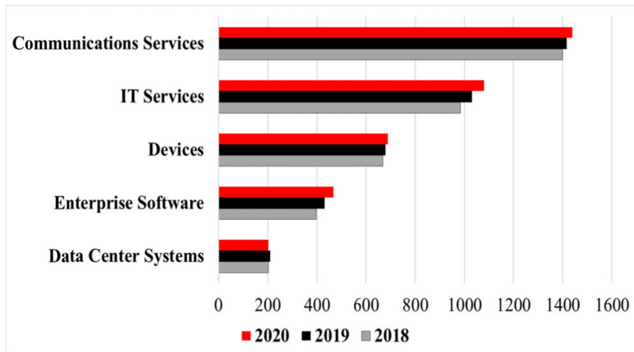

FIGURE 2. The trend of the global IT S pending Forecast (billion US dollars) [9].

a Service" (XaaS) transforms industries. Figure 2 shows the worldwide IT Spending Forecast from the 2019 Gartner Report. Cloud computing is taking on more than hundreds of billions of dollars of work. Gartner Inc. predicts that global IT spending is expected to reach $3.79 trillion USD in 2019, which is an increase of 1.1% from the previous year [9]. Technavio has stated that the global IaaS market would grow by 101.56 billion USD at a compound annual growth rate (CAGR) close to 28% during 2019–2023. MarketsandMarkets^{TM} forecasts that the market size of cloud-related services will grow to 9.47 billion USD by 2022 at a CAGR of 24.5% during 2017–2022 [10]. Another report indicated that the worldwide cloud computing market size will increase to 623.3 billion USD by 2023 at a CAGR of 18% [11]. These business reports indicate that cloud computing has a great influence on the global marketplace.

A. CLOUD COMPUTING PROVIDERS

Table 1 shows the main cloud computing providers mentioned by different consulting institutions. Microsoft, IBM, Amazon, Oracle, Alibaba, and SAS are common cloud service providers; they offer numerous cloud computing applications (e.g., Microsoft Azure, IBM, Google, and Oracle Compute Cloud Service) that can be employed in various scenarios according to the different requirements of different industries. Based on the integrated results, we investigated these software functionalities. Most providers offer cloud infrastructure (e.g., Google Cloud), communications services (e.g., Azure IoT Gateway), data centers (e.g., Microsoft Azure Data Lake), and data analytics (e.g., SAS predictive analytics module, IBM SPSS modular).

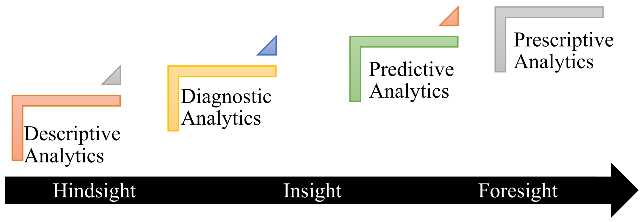

FIGURE 3. The evolution of data analytics.

B. DATA ANALYTICS AND CLOUD COMPUTING

Data analytics is essential for cloud computing. Cloud computing involves aspects such as data collection, data analytics, and visualization. Microsoft, Gartner, Information Builders, and other business consulting institutions classify data analytics into four as follows: descriptive, diagnostic, predictive, and prescriptive. Figure 3 demonstrates the evolution of data analytics. Predictive analytics has been conducted widely, e.g., GE engine predictive maintenance. Predictive analytics is essential in various fields; this study has applied it to different issues in education, logistics, and manufacturing.

III. CLOUD COMPUTING-RELATED STUDIES

Varghese's studies indicated the importance of cloud computing and demonstrated its evolution in recent years [13]. Cloud computing has been widely applied to different industries. XaaS is considered to be an innovative concept, and computing services have developed into various types: EaaS, LaaS, and MaaS. To obtain a deeper understanding of cloud computing-related trends, this study analyzed the comprehensive profiles of cloud computing, XaaS, EaaS, LaaS, and MaaS, by using studies found using Google Scholar. The Publish or Perish (PoP) software was used to survey the relevant studies published during 2010–2019. We initially used PoP to obtain the related studies; the obtained result was manually reviewed and subsequently filtered for the top 20 most cited papers. The keywords of these top citation papers were included in this study and present the current technology trend.

A. CLOUD COMPUTING

This study used the keywords "cloud computing" and obtained 999 academic-related studies. Mell et al. defined cloud computing as a model for allowing convenient and on-demand network connected to several configured computing components (e.g., storage, servers, and services) that can be rapidly deployed the resource with optimal management effort [14]. Standard cloud computing offers cloud infrastructure, online web GUIs, data applications, and data analytics. Cloud computing offers diverse types of services, is flexible, and can scale to meet users' needs. Stergiou et al. integrated cloud computing and IoT technologies to demonstrate how the former could improve the functions of the latter [15]. Zhang et al. applied deep learning in the Industrial IoT (IIoT) [16]. Some researchers have argued that cloud computing technologies have created a "ubiquitous" trend of mobile devices being employed to accomplish tasks promptly [17]–[19]. Related studies have indicated that cloud computing has the potential to transform information and communication technologies by shaping how hardware is designed and purchased as well as making software more valuable as a service [19], [21]. Table 2 lists the cloud computing-related studies and their current citation statuses. Those with high citations focus on IoT, big data, data collection, analytics technology, and visualization. The common keywords include "modeling and simulation," "big data," "web," "visualization," "data center," "security and privacy," "IaaS," "SaaS," "PaaS," and "mobile." Security [22]–[33], data access control [28]–[33], data processing [31], and service-oriented application [34] are key challenges for cloud computing. Developing the advanced security toolkit to address these challenges is an important avenue for future studies on cloud computing.

B. EVERYTHING AS A SERVICE (XAAS)

Botta proposed the cloud computing IoT (CC-IoT), which integrates cloud computing and IoT [36]. XaaS is a cloud computing service that involves various services through a network. The cloud's resources are sold as services to applications, such as scientific and industrial intelligent analytics (e.g., smart factory), on an XaaS cloud platform [37]. This study searched using the keywords of "Everything as a Service" and obtained 570 academic-related studies. Some research argues that the development of service systems has continuously evolved, as have the services used in various fields [40], [42]–[44]. XaaS is concerned with social science, which aims to enhance co-creation and value creation [42]. XaaS is used for data access and communication [40]. Value co-creation is determined by the social community; it is reproduced in the sociality framework [43]. XaaS can form as various services based on the industry's character for co-creation and value creation in service. Table 3 shows their current citation statuses. Those with high citations focus on service orientation, value creation, security, data applications, and networks. XaaS has been applied to marketing, e-learning, GIS, and manufacturing. The common keywords, which include "service," "value co-creation," "data," "visualization," "data service," and "information system." XaaS is transforming the development of the various industries and cloud computing technologies. For the cloud computing, more comprehension of various issues is required between the demand (user side) and supply (service provider). [24]. This study surveyed various industrial issues (e.g., education, logistics, and manufacturing) that could affect the different roles of cloud computing and used real data in ML to form different cloud computing services on a cloud platform.

C. EDUCATION AS A SERVICE (EAAS)

In today's complex and highly competitive education environment, the need to develop sustainable strategies and technologies has led to the creation of computing services. Some studies argue that the attitudes and behaviors of students

TABLE 2. The cloud computing studies.

Cites	Year	Description of the study
13484	2011	The National Institute of Standards and Technology establishes various computing definitions [14].
10230	2010	The roles of cloud service and related elements are clearly described for broader definitions of cloud computing [19].
3645	2011	The CloudSim, a simulation framework that can enhance quality of service in cloud computing, is proposed [21].
3477	2010	Cloud computing is stated to face challenges related to privacy security and data confidentiality [22].
3164	2012	Fog computing is a new type of computing service via the edge of the network. It has been used to support IoT applications characterized by latency requirements for mobility [19].
2569	2011	Current security issues related to cloud computing are noted, and Internet protocols are applied to communicate between the cloud and the end user [23].
2433	2011	Cloud computing is shown to be employed in many fields [24].
2216	2010	The development of public auditability for existing cloud data storage services has already been promoted in the cloud computing field [25].
2152	2012	Cloud computing has positive effects on cost saving and energy efficiency under dynamic workload conditions [26].
1966	2013	Mobile cloud computing has been widely utilized for different applications, such as mobile learning and mobile gaming [27].
1954	2010	A security scheme that can offer systematical and complete data access control in cloud environment is proposed [28].
1745	2012	The proposed security framework, which involves LDAP and SSO, creates a security mesh in the cloud environment [29].
1630	2013	The proposed distributed application may run on two or more network computers in some cloud-based embodiments [30].
1448	2015	The large amount of data processing is essential for cloud computing [31].
1402	2013	Cloud computing may address some problems in mobile computing, such as mobility, resource scarcity and disconnections [17].
1388	2010	The proposed analytical model is used to compare energy usage in the mobile device and the cloud platform [18].
1314	2012	Cloud computing is considered a major trend for the manufacturing industry by providing the distributed resources to a centralized management framework [32].
1302	2010	Cloud service providers should have effective access control policies and well-understood common federated policies to ensure that applications do not lead to any security breaches [33].
1247	2010	Service-oriented architecture enabling technologies and the resources for cloud computing are formed as cloud computing services [34].
1215	2010	Cloud computing has been extensively employed to support functional areas such as supply chains and marketing [35].

while learning primarily determine the students' perceptions of the service quality provided [54], [63]. IBM has characterized EaaS as advanced cloud computing that incorporates infrastructure and platform software with additional business

TABLE 3. The XaaS studies.

Cites	Year	Description of the study
1705	2013	Analytically defining the roles of the user and the service providers is used to enable co-creation and value creation in service [38].
1683	2010	Customers, managers, and employees are prominent components for the increasingly technical sophistication of service sciences [39].
1661	2010	This proposed approach offers the nomadic/general user high-speed downstream Internet access within the network framework [40].
1511	2013	Morozov proposed the term "solutionism," which describes the belief that all problems can be solved through computation technologies [41].
1419	2010	The understanding of customer value creation is essential for service science [42].
1283	2011	The service providers get opportunities to co-create service value with their end users [43].
1089	2011	For the current service logic, the participants have flexibility to configure and tune their roles within dynamic service systems [44]d.
1003	2010	The service systems thinking approach is related with the relationships, networks, and value creation [45].
953	2016	IoT provides low-cost services, high performance, versatility, and openness for device connectivity [36].
932	2011	The crowd-funding is an innovative service type, which consumers connect their financial together via the Internet [46].
864	2013	Internet is one of the speculative channels, which can connect the people around the world together [47].
857	2011	The service-learning approach is used for children interact with technology in the media design [48].
827	2015	The proposed method aims to design, develop and implement Internet service provider architectures [49].
798	2012	Googlization demonstrates platform economy and its challenge [50].
776	2012	The use of Internet can result in time and cost savings [51].
747	2010	The proposed system presented user and geographical information within the social network on the collaborative service [52].
698	2010	Value creation can come from a resource collaboration and integration, as suggested by the customer-dominant logic) [53].

processes. Microsoft has argued that EaaS can provide extensible and proactive services to optimize the educational environment and increase problem solving ability. EaaS-related applications have been used extensively, and typical examples are Microsoft Cloud Service and IBM Educational Cloud Service. This study analyzed the comprehensive profiles of studies of EaaS by using the keywords of "Education as a Service." The survey obtained 1,599 EaaS-related studies. EaaS has been developing continuously in the past 10 years and offers cloud infrastructure, online web GUI, and data applications. The educational environment could be local, national, or global, as well as in the classroom or the cloud. Johnson indicated that EaaS is the business model of a delivery system that unbundles the components of higher education and offers students the option to pay for only those courses that they want and need [54]. EaaS remains extensible; it can be scaled to fit users' requirement and has been applied in medical and power education [55], [56]. Some studies argue that the EaaS model would result in a "student-driven" trend and retain students through services that make their training obvious [57], [58]. Some research used machine learning techniques to forecast secondary school student performance [59], [60]. Table 4 shows the current citation statuses of the studies. Those with high citations focus on distance education, student satisfaction, big data, IoT, and analytics technology. The common keywords include "big data," "IoT," "e-learning," "customer satisfaction," "higher education," "new managerialism," and "cloud computing." The use of digital technologies to increase the quality of education service is accomplished by providing access to resources and enabling remote collaboration between students and teachers [58].

D. LOGISTICS AS A SERVICE (LAAS)

LaaS is prevalent in the manufacturing, [76]–[79], transportation, and international trade sectors. Some researchers have indicated that cyber-physical systems (CPSs) depends on communication, computation, and control infrastructures to support the efficient use of logistics resource [76]. Logistics service providers have been dedicated to developing cloud computing within a few years to cope with the growing IT demands of logistics. Related studies on the influence of cloud computing in the logistics management have presented critical strategies for clouds to migrate to the logistics industry when the existing logistics information systems move to cloud systems [81], [82]. LaaS is a cloud computing service that involves various services through a network. Most of the LaaS-related studies mentioned the cloud manufacturing issue [78], [83], [95].This study used the keywords of "Logistics as a Service." and obtained 133 academic-related studies. Table 5 shows their current citation statuses. Those with high citations focus on CPSs, cloud manufacturing, distribution management, logistics management, and cloud-based systems. The common keywords, which include "cloud manufacturing," "cyber-physical system," and "cloud computing."

E. MANUFACTURING AS A SERVICE (MAAS)

Cloud computing is transforming the traditional manufacturing industry. Cloud users can request services related to product design, manufacturing, validation, quality management, and all the stages of a product's life cycle [32]. MaaS combines advanced technologies (e.g., cloud computing [99], [101], [102], IoT [100], and data science) and service-oriented technologies [83], [99]–[108]. Cloud computing is aiding the evolution of manufacturing processes and equipment maintenance. Many researchers have endeavored to leverage manufacturing performance with the advancement and power of the new ICT technologies. MaaS is a cloud computing service that involves various services through a network. This study used the keywords of "Manufacturing as a Service." and obtained 396 academic studies. Table 6 shows their current citation statuses. Those with high citations focus on Industry 4.0, big data analytics, manufacturing, and digital twins. The common keywords include "IoT," "cloud computing," "CPS," "big data," and "Industry 4.0." Most of the MaaS-related studies aim to realize the complete sharing, optimal on-demand use, and efficient allocation of the

TABLE 4. The EaaS studies.

Cites	Year	Description of the study
2866	2016	The influence of online learning in higher education is studied [54].
1025	2011	Learners can access informal and formal learning from schools and institution [61].
432	2012	Globalization causes the transformation of education and the ordering of EaaS, and provides a way of researching education [62].
346	2010	Students' satisfaction differs with the quality of offered services and the learning environment [63].
331	2013	The transformative service focuses on the relationship between service entities' influences and the users' satisfaction [57].
265	2011	The development of education is driven by educational data from computing tools [64].
221	2016	The presented multilayered security system can be beneficial for the volume, veracity, and velocity of big data from cloud-based services [65].
197	2010	Improving students' achievements through school counselors' collaboration is more effective in the neighbor community [66].
164	2012	For EaaS, teachers play an important role, as they are responsible for the cultural and social reproduction of capitalism and ideological control [67].
159	2013	Much research has emphasized the importance of business processes, services and data portability for cloud adoption [68].
153	2018	The presented fog-driven IoT architecture can deal with the challenge of medical IoT applications, such as scalability, information management, security, and privacy [55].
150	2012	The development of early childhood education aims to participate in a collective wider community, working with aspects of ethics of care–for human and the planet [56].
121	2010	Globalization impacts international education and the education decisions being taken within transnational networks [69].
119	2018	The core of EaaS is integrating, creating and communicating knowledge for a variety of learners [70].
108	2015	Higher education in some countries is facing pressure to conform to a market-led discourse [71].
105	2015	Higher education is not only about obtaining professional knowledge but about generating the impression that employers and colleges want different things [72].
102	2011	Cloud providers should advocate cloud API standards to enhance learning objects interoperability and portability as they rely on educational cloud services [73].
101	2010	Student loyalty is key for the future educational services in the increasingly competitive and globalized education service industry [74].
95	2013	The user-friendly platform is the essential requirement that needs to be a part of the service provided to avoid dissatisfying users [58].
93	2011	Value-creating activities are dynamically inter-related to create students' learning experiences, which benefits the education institutions' brand [75].

TABLE 5. The LaaS studies.

Cites	Year	Description of the study
163	2017	The aim of the manufacturing industry is comprehensive servitization, since service-oriented frameworks and IoT have been proposed with the rise of advanced cloud computing and the logistics industry [83].
151	2015	Cloud manufacturing is an innovative manufacturing business strategy, which is transforming the current service-oriented manufacturing process [84].
144	2017	The current manufacturing industry is becoming more service-oriented and highly collaborative [85].
75	2013	Top-management support, communication, costs, processing time, and environmental issues are the key factors for reverse supply chains [86].
65	2015	With computers deeply impacting modern manufacturing systems, related technologies (e.g., CPSs) are flourishing [87].
60	2016	Industry 4.0 integrates the common trend of digitalization and the networking of data and information [88].
59	2014	Cloud computing is used for cloud smart city logistics, which provide on-demand logistics infrastructure for intelligent city [89].
42	2012	In the logistics sector, each type of service has distinct requirements for service fulfillment that are applied in the specified architecture [90].
33	2012	Logistics information system has been increasingly considered as one of an important driving forces for economic development [91].
33	2010	The decided transportation parameters products can be used for modeling and also in LaaS [92].
30	2013	Increased availability of existing resource allocation and optimizing the size of the provided handling equipment fleet are increasingly important in today's logistics industry [93].
28	2017	Demanufacturing and remanufacturing include the set of knowledge-based methods and technologies to repeatedly utilize resources [94].
26	2018	Manufacturing resources from different providers are formed as cloud services such as logistics cloud [76].
23	2013	Users fulfilling requirement via cloud manufacturing platform is a current industry trend [95].
15	2016	The topological structure of cloud-based manufacturing networks includes the logistics as a service [77].
14	2018	Customers have on-demand access to services (e.g., LaaS) via cloud manufacturing [78].
13	2011	The LaaS function is employed in humanitarian assistance operations for the deployment of multiple services [96].
13	2017	Logistics as a service is a utilization of arranging and integrating all manufacturing resources involved in the entire life cycle of the cloud manufacturing services [79].
11	2015	Semantic integration is essential for information and communication technologies and automation technologies [97].
11	2014	The users can select the data security level to make the correct judgments regarding risk for their enterprise [98].

TABLE 6. The MaaS studies.

Cites	Year	Description of the study
452	2011	Cloud manufacturing platforms included public, private, hybrid and community service platforms [99].
411	2014	IoT and cloud computing are used to generate a service-oriented manufacturing model for the sharing of various manufacturing resources [100].
401	2013	Cloud manufacturing includes on-demand service, ubiquitous access, real-time scalability, resource deployment, and virtualization [101].
386	2014	Cloud manufacturing could allocate capabilities and resources at lower support and maintenance costs [102].
294	2010	The purpose of solutions focuses on environmental, functional, economic, and social dimensions [103].
284	2012	The cloud manufacturing services include software resources, various manufacturing resources and capability services [104].
242	2013	Cloud technology takes advantage of production scalability, openness, rapid reaction, and resource allocation in manufacturing [105].
224	2015	Cloud computing technology enables cloud-prognosis for the manufacturing industry [106].
179	2017	Optimizing different traditional and emerging database management systems on the cloud environment for distributed processing, computing, storage, and access is essential for cloud computing services [107].
163	2017	To develop the manufacturing system, the involvement of advanced manufacturing approach/techniques is fundamental and indispensable [83].
146	2011	Service is essential for the manufacturing industry. Services and products are integrated into the service system for offering an efficient product/service to customers [108].
144	2017	Cloud manufacturing is involved with the entire manufacturing process, from order management and product design to distribution processing and equipment maintenance [85].
134	2018	Industry 4.0 is extensive the evolution from embedded solution to cyber-physical systems [109].
95	2017	Industry 4.0 is characterized by the solution of CPSs in the manufacturing field [110].
94	2014	The connecting cloud and network is presented as an effective cloud computing application in the manufacturing industry [111].
87	2013	Industrial automation systems aim to be agile, and cloud computing is the promising technologies for manufacturing automation [112].
77	2014	The advanced manufacturing technologies include the standard requirements and analytical technologies for applying the components of the new technologies [113].
73	2013	Economic globalization has transformed the organization of the global economy toward greater functional interdependence and integration through cross-border economic activity [88].
67	2017	Cloud manufacturing is an innovation that combines the cloud platform, semantic web, service-orient technologies, and virtualization and analytics tools for resource sharing [114].
67	2018	The utilization of innovation technologies to strengthen the competitiveness of the manufacturing industry has become a popular trend worldwide [115].

different manufacturing process [100], [101], [104]. Studies focused on improving MaaS are concerned with service science, prognosis [106], big data [107], [115], and industrial automation [112]. The concepts of digital twins and big data have received significant attention in recent years [115].

IV. APPLYING THE CLOUD COMPUTING SERVICE IN THE INDUSTRIES

This study investigated EaaS, LaaS, and MaaS by applying a ML model to predict UCI data from various sources.

The standard procedure for data analytics was employed to preprocess and model the predicted issues for the learning performance of students, vehicle acceptability, and semiconductor manufacturing processes. ML algorithms were used to solve and integrate these issues into different cloud computing solutions to achieve the goals of EaaS, LaaS, and MaaS.

A. PROCEDURE OF KNOWLEDGE DISCOVERY IN DATABASES (KDD)

KDD is the process of acquiring potential useful information by analyzing or mining data collections. This widely-used technique of data analytics is based on procedures that analyze data from different sources. The standard procedures are selecting a target dataset, preprocessing data, transforming data formats, training models, and evaluation. To achieve the goal of cloud computing, this study leveraged Microsoft Azure ML Studio for pattern identification to predict different datasets in various industries. Microsoft Azure ML Studio has numerous users and is considered to be a popular application. Users can build, evaluate, preprocess, model, and run their data analytics projects with Microsoft Azure ML tools. Figure 4 illustrates the procedures of KDD.

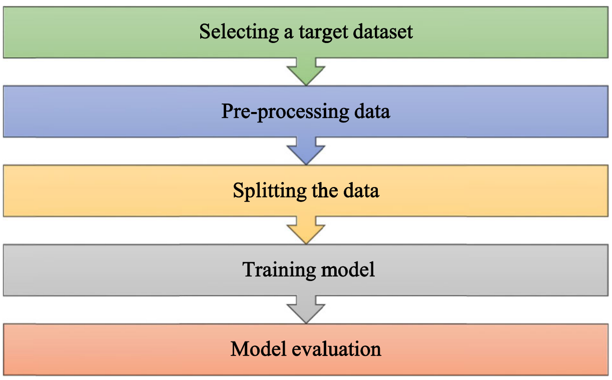

FIGURE 4. The procedure of KDD.

B. MACHINE-LEARNING MODELING

In this study, the support vector machine (SVM), tree-structure algorithm, and classifier-related algorithm were employed in predictive analytics. We also used the ensemble learning method to enhance the accuracy of the algorithm. Ensemble learning combines multiple decision models to generate better predictive performance than could a single decision model. The aim of ensemble-based model is the combination of a group of weak learners to form a strong learner and improve the overall performance for increasing the accuracy of the model.

1) TWO-CLASS bOOSTED DECISION TREE

The two-class boosted decision tree algorithm is an example of ensemble learning and relies on the ensemble of trees to forecast. Succeeding trees adjust the errors of preceding trees. The algorithm starts with an empty ensemble of weak learners. The current output of the ensemble is obtained for each training instance. This output is the aggregate of the outputs of all the weak learners in the multiple model. Next, the gradients in the loss function for each instance is estimated by the model. The algorithm uses the examples to fit a weak learner, and the gradient is simply defined as the target function. The learning rate is used to combine the weak learners together to create a strong predictive model. The algorithm is repeated until it reaches a terminal condition.

2) TWO-CLASS SVM

A two-class SVM is based on an SVM algorithm used to analyze input data and recognize patterns in a multi-dimensional feature space. The classifier initialized by this module is suitable for choosing between two outcomes that depend on categorical and continuous input variables. These machines require labeled data and assign new examples into one category or another while mapping them onto the same space.

3) TWO-CLASS LOGISTICS REGRESSION

A two-class logistic regression algorithm is a supervisory, learning algorithm that predicts the probability of a binary event's occurrence using a logistic function. Logistic regression assumes a logistic distribution of the observation where the probability that an observation is classified as one of two categories is based on the independent variables. The algorithm aims to exploring the optimal solution for $\alpha\{0\}, \ldots, \alpha\{r-1\}$ by estimating the objective function of the parameters with the given independent variables.

$$prob(x; \alpha_0, \ldots, \alpha_r - 1) \tag{1}$$

Equation 1 is the logistic distribution function, x is an r-dimensional vector representing all the features of one instance, and $\alpha\{0\}, \ldots, \alpha\{r-1\}$ are the parameters of the logistic distribution.

4) TWO-CLASS BAYES POINT MACHINE

A two-class Bayes point machine algorithm approximates the Bayes-optimal decision of linear classifiers by choosing a generalization performance classifier. The machine stochastically approximates the center of solution space; thus, the machine is not prone to overfitting the training data.

5) TWO-CLASS DECISION FOREST

A two-class decision forest algorithm is an ensemble learning algorithm intended for classification tasks. The ensemble mechanism is based on the general principle of not relying on a single model but creating multiple related models and combining them in some way to enhance performance. Generally, multiple ensemble trees provide better coverage and accuracy than can single decision trees.

C. PROCEDURE FOR DATA ANALYTICS

In this study, the procedure for data analytics involved importing open data, preprocessing and selection, training the data, evaluating the model, and formulating accurate solutions

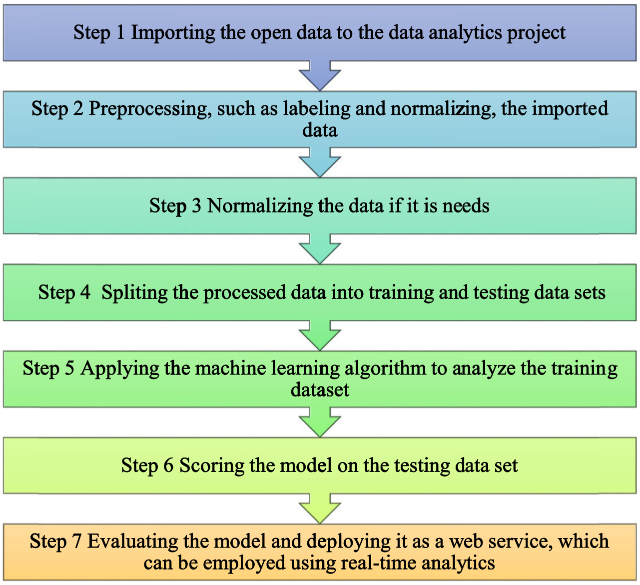

FIGURE 5. The procedure of the data analytics used in this study.

TABLE 7. The list of dataset.

Dataset	Description	Instances
Educational dataset [59]	The data comprising thirty-three attributes, e.g., grades, social related features, and self-perception of learning.	649
Logistical dataset [116]	The data has seven attributes, including the size of luggage boot, buying price, number of doors, passenger capacities, safety of the car, car acceptability.	1728
Manufacturing dataset [117]	The data has 591 features containing method, classifications, and time stamp for each instance.	1567

from the observed results. Figure 5 shows the various processing steps.

D. DATA SOURCES

The results demonstrate cases of how cloud computing could be applied in the educational, logistical, and manufacturing fields. The dataset was taken from the UCI ML repository [59], [116], [117]. Table 7 exhibits the dataset description. The educational case developed an EaaS to predict the performance of students learning mathematics. The logistical case developed a LaaS for a vehicle selection problem with data imported to the cloud and used to forecast preferences. The manufacturing case was for predicting yield failure in a semiconductor manufacturing process. The training model was developed as a MaaS.

V. RESULTS

This study applied cloud computing to education, logistics, and manufacturing. The results show how Microsoft Azure ML Studio could assist developers in creating a cloud ML model for these industries.

TABLE 8. The traditional academic guide.

AUC Range	The level of discrimination
0.7–0.8	acceptable discrimination
0.8–0.9	excellent discrimination
0.9–1.0	outstanding discrimination

A. EVALUATION CRITERIA

This study used accuracy, the receiver operating characteristic curve (ROC), and the area under the curve of the ROC (AUC) to evaluate the analytics.

1) ACCURACY

The key parameters are true negative (TN), false negative (FN), true positive (TP), and false positive (FP). Equation 2 is the formula for estimating the accuracy, which is the number of correct assessments divided by the number of all assessments.

$$\text{Accuracy} = \frac{(\text{TN} + \text{TP})}{(\text{TN} + \text{TP} + \text{FN} + \text{FP})} \tag{2}$$

2) ROC

ROC is a probability curve plotted with the false positive rate (FPR) on the x-axis against sensitivity on the y-axis. Equations 3 and 4 are the formulas of sensitivity and FPR, respectively:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}} \tag{4}$$

3) AUC

Accuracy is measured using the AUC, for which a value closer to 1 represents a near-perfect test but less than 0.5 represents a worthless test. Table 8 shows the traditional academic guide for classifying the accuracy of a diagnostic test.

B. EaaS: PREDICTION OF STUDENTS' LEARNING PERFORMANCE

The related literature contains applications of educational data mining to predict students' learning performance [59]. Most of the studies used grades as the decision variable. We used educational data analytics to predict learning performance, such as failing or passing a course in mathematics. Initially, we preprocessed data by labeling the target variable according to the final grade variable (G3). The preprocessed data were normalized by the min–max method to scale the data between 0 and 1. Equation 5 is the formula of normalization.

$$z = \frac{x - \min(x)}{[\max(x) - \min(x)]} \tag{5}$$

Table 9 shows the results of the experiment and analysis of the performance. The trained model could be deployed as a

TABLE 9. Results of analytics in education case.

Algorithm	Accuracy	AUC	Main Parameter	Data (Train/Tes)
Two-class Bayes point machine	0.96	0.9	Iteration = 500 Random Number Seed= 2342	70/30
Two-class Logistic regression	0.97	0.9	L1 Weight=0.949 L2 Weight=0.193	70/30
Two-class boosted decision tree	0.96	0.9	Learning Rate = 0.06 Number of leaves=2 Minimum leaf instances=4 Number of trees= 436	70/30
Two-class SVM	0.97	0.9	Iterations=92 Lambda=1.32272007 E-05	70/30
Two-class decision forest	0.95	0.9	Maximum depth of decision trees = 14 Minimum number of samples per leaf = 1 Number of random splits per node = 68 Number of decision trees = 15	70/30

web service or the data can be imported directly, then the teacher can predict the students' performance and create an adaptive learning strategy on the cloud. The result shows that this EaaS can offer educators real-time analytics anytime and anywhere.

C. LaaS: VEHICLE SELECTION ANALYTICS

The transportation tool plays an important role in logistics management. Some studies were dedicated to solving car rental logistics [118]. Estimating the preferences for particular cars was also a key issue. This case aimed to predict if a car was acceptable by analyzing its details. Table 10 shows the results of the experiment and analysis of the performance. These classification algorithms were employed to predict vehicle acceptability (unacceptable/acceptable). The features were used as the input and the vehicle was used as the decision variable. The trained model could be integrated into a vehicle rental logistics maintenance system via a web service and a logistics manager could predict the data and retrain the model promptly.

D. MaaS: YIELD FAILURE PREDICTION IN SEMICONDUCTOR MANUFACTURING PROCESS

The manufacturing case aimed to forecast yield failure predictions for a semiconductor manufacturing process. We processed the dataset by handling the missing values and used the mutual information (MI) to filter the features. MI is a score that measures the mutual dependencies among variables by maximizing the mutual information between the target variables and joint distribution in a multi-attribute dataset. Table 11 shows the results of the experiment and analysis of the performance. In this case, failure was a decision variable. The data from a semiconductor manufacturing process was

TABLE 10. The result of analytics in the logistics case.

Algorithm	Accuracy	AUC	Main Parameter	Data (Train/Test)
Two-Class Bayes Point Machine	0.96	0.9	Iteration = 500 Random Number Seed = 2342	70/30
Two-Class Logistic Regression	0.96	0.9	L1 Weight = 0.015 L2 Weight = 0.024	70/30
Two-Class Boosted Decision Tree	0.98	0.9	Learning Rate = 0.15 Number of leaves = 6 Minimum leaf instances = 47 Number of trees = 233	70/30
Two-Class SVM	0.94	0.9	Iterations = 92 Lambda = 1.32272007E−05	70/30
Two-Class Decision Forest	0.98	0.9	Maximum depth of decision trees = 14 Minimum number of samples per leaf =2 Number of random splits per node = 945 Number of decision trees = 15	70/30

imported for predictive maintenance. The trained result could be connected to a third-party application via a web service to support real-time analysis in a cloud-based environment. The trained model could be used as a MaaS by a manufacturing manager to pre-plan and pre-schedule maintenance work, as well as reduce maintenance costs for spare parts. The MaaS can assist users in predicting the remaining life of equipment, reduce unplanned forced outages, and minimize the risk of catastrophic failures.

VI. DISCUSSION

Some professionals and researchers are dedicated to realizing the goal of XaaS, which consists of an extensive variety of applications that can be accessed on-demand over a network. This study has demonstrated the application of ML to data in different industries and developed an EaaS, LaaS, and MaaS on a cloud computing platform via a web browser instead of utilizing these services in an internal physical environment with infrastructure and servers to process the data. However, cloud computing also involves network security, data collection, data analytics, data connectivity, data visualization, and related value-added applications. The utility and security of a cloud environment are discussed next.

A. UTILIZING CLOUD COMPUTING SERVICES

This study showed how cloud computing could affect different industries. In some specific industries, such as manufacturing, logistics, education, and medical, an enterprise's profile can be authorized only on a local server. Cloud computing may not be suitable for all industrial fields in diverse environments. Fog computing and edge computing may be suitable for a specific industrial field. Fog computing aims to distribute the utilization of cloud computing to a network edge. Fog computing is ideal for IoT and real-time

TABLE 11. The result of analytics using MaaS.

Algorithm	Accuracy	AUC	Main Parameter	Data (Train/Test)
Two-class Bayes point machine	0.90	0.9	Iteration = 500 Random Number Seed = 2342	70/30
Two-class Logistic regression	0.90	0.9	L1 Weight = 0.497 L2 Weight = 0.963	70/30
Two-class boosted decision tree	0.97	0.9	Learning Rate = 0.33 Number of leaves = 36 Minimum leaf instances = 7 Number of trees = 182	70/30
Two-class SVM	0.90	0.9	Iterations = 92 Lambda = 1.32272007E−05	70/30
Two-class decision forest	0.94	0.9	Maximum depth of decision trees = 4 Minimum number of samples per leaf = 1 Number of random splits per node = 14 Number of decision trees = 27	70/30

connectivity applications. GE, Intel, Dell and other enterprises from hardware, software are considered as key role in the development of fog commuting. Some researchers have indicated that the distributed cloud system could increase the utilization of the network in the future [13]. Edge computing offers computing power, as well as memory, closer to a user's location. Oracle, IBM, Microsoft, Advantech the main service providers also proposed the edge-based solution (e.g., Oracle tactical edge cloud, Microsoft Azure IoT Edge). Both types of computing will be considered in a future study. We will train a model on the cloud but also retrain it on the edge. This study was limited by its data sample; data from diverse industries will be employed for data analytics in future studies.

B. SECURITY ISSUES

Forrester's report estimated that, by the end of 2018, half of the businesses around the world will have used at least one cloud service. This study has not only realized a cloud computing service but also investigated the effects of devices on a cloud computing environment by using tablets and smartphones to access the environment. The cloud means that everything is not constrained by space, time, or device. The cloud services must comply with network security standards to guarantee the integrity of the data of an enterprise and protect any user that contracts such services. Some studies surveyed the security challenges of cloud computing [23]. Some researchers have indicated that cloud computing service users must be aware the risks of data breaches in a cloud-based framework [23]. Validating the verification of a user who is trying to access a cloud application when the user signs out of a platform or changes a device is necessary for cloud computing. This study surveyed our account, which was validated on a cloud platform, by changing our device to access the cloud service. Our case studies have shown that the cloud computing environment validated our account when we changed our device, then validated our use of the account information. The survey's results show that the cloud has multi-factorial authentication, which means more credentials that discriminate and verify access.

VII. CONCLUSION

Cloud computing has a growing market that many enterprise and organizations are adopting to enable their digital transformation. This study not only surveyed cloud computing technologies but also current cloud computing services research such as EaaS, LaaS, and MaaS. In Google Scholar, results were obtained from 3,697 academic papers published from 2010 to 2019. We used descriptive statistics, PoP, and CiteSpace to analyze these studies. The recently proposed concept of XaaS has quickly developed into diverse types of services, such as EaaS, LaaS, and MaaS. The findings show that the studies have a high number of citations. Classification algorithms based on the standard KDD procedure were used to analyze the imported data. The results show that data from different industries can be imported into an authorized cloud platform and the different algorithms had significantly high accuracy. In the education case, this study predicted the performance of students learning mathematics. The trained results could aid instructors or teachers in personalizing individual learning activities and materials. In the logistics case, vehicle acceptability could be forecasted. The trained model could assist car rental managers in formulating rental strategies. In the manufacturing case, this study predicted equipment failure and assisted in the formulation of predictive maintenance strategies. Many consulting institutions have emphasized the importance of cloud computing. This study utilized cases from different industries to demonstrate that cloud technologies offered users multiple alternatives for on-demand infrastructure so that enterprises can avoid investing in expensive and complex resources.

Adequate integrated cloud computing services and ICT are prerequisites for keeping pace with the rapid rise of complexity in various industries. This study successfully demonstrates that using ML for training models on the cloud can generate diverse cloud computing services, such as EaaS, LaaS, and MaaS. Cloud platforms could provide personalized and flexible environments for different industries and assist in data analysis and strategy formulation. The trained results could be integrated with third-party ML tools, such as TensorFlow. Further, Python can be used for ML analysis workflow. Trained modeling can be generated as a web service for real-time analysis. This study surveyed how cloud computing is changing the way industries practice decision-making and problem solving with dynamically virtualized and scalable resources provided as a service over the network communication. The cloud platform is infinitely flexible for data analytics, thereby giving users to make efficient analytics focused on users' needs. Developers can configure cloud data analytics using a mobile phone and tablet. However, the data set in this study is limited, and more industries' data should be included in future studies. We plan to conduct further research to repeat this analysis in other industries to investigate how ensemble learning algorithms can transform different industries. Future work could also investigate the potential of edge computing formed from the ubiquitous devices in wearable object, device and other embedded objects, as such embedded computing will become more powerful and convenience in diverse industries [17], [27], [35].

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REFERENCES

[1] S. Sarma, D. L. Brock, and K. Ashton, "The networked physical world," Auto-ID Center, Cambridge, MA, USA, White Paper MIT-AUTOID-WH-001, 2000, pp. 1–16.

[2] A. Ghasempour and T. K. Moon, "Optimizing the number of collectors in machine-to-machine advanced metering infrastructure architecture for Internet of Things-based smart grid," in *Proc. IEEE Green Technol. Conf.*, Kansas City, MO, USA, Apr. 2016, pp. 51–55.

[3] *Internet of Things Strategic Research Roadmap*. Accessed: Jul. 30, 2019. [Online]. Available: http://www.internet-of-things-research.eu/pdf/IoT_Cluster_Strategic_Research_Agenda_2009.pdf

[4] *Towards a Definition of the Internet of Things (IoT)*. Accessed: Jul. 30, 2019. [Online]. Available: https://iot.ieee.org/images/files/pdf/IEEE_IoT_Towards_Definition_Internet_of_Things_Revision1_27MAY15.pdf

[5] N. Gershenfeld, R. Krikorian, and D. Cohen, "The Internet of Things," *Sci. Amer.*, vol. 291, no. 4, pp. 76–81, 2004.

[6] A. Ghasempour, "Optimum number of aggregators based on power consumption, cost, and network lifetime in advanced metering infrastructure architecture for Smart Grid Internet of Things," in *Proc. IEEE Ann. Consum. Commun. Netw. Conf.*, Las Vegas, NV, USA, Jan. 2016, pp. 295–296.

[7] A. Ghasempour, "Internet of Things in smart grid: Architecture, applications, services, key technologies, and challenges," *Inventions J.*, vol. 4, no. 1, pp. 1–12, 2019.

[8] A. Ghasempour, "Advanced metering infrastructure in smart grid: Requirements, challenges, architectures, technologies, and optimizations," in *Smart Grids: Emerging Technologies, Challenges and Future Directions*, J. Lou, Ed. New York, NY, USA: Nova Science, 2017.

[9] Gartner. (2019). *Gartner Says Global IT Spending to Grow 1.1 Percent in 2019*. Accessed: Jul. 30, 2019. [Online]. Available: https://www.gartner.com/en/newsroom/press-releases/2019-04-17-gartner-says-global-it-spending-to-grow-1-1-percent-i

[10] Marketsandmarkets.com. (2019). *Global Cloud Migration Services Market Contemplated to Grow $9.47 Billion in 2022*. Accessed: Jul. 30, 2019. [Online]. Available: https://www.marketsandmarkets.com/pdfdownloadNew.asp?id=266815130

[11] Reportlinker.com. (2019). *Cloud Computing Market by Service, Deployment Model, Organization Size, Workload, Vertical And Region—Global Forecast to 2023*. Accessed: Jul. 30, 2019. [Online]. Available: https://www.reportlinker.com/p05749258/Cloud-Computing-Market-by-Service-Deployment-Model-Organization-Size-Workload-Vertical-And-Region-Global-Forecast-to.html

[12] PAT RESEARCH: B2B Reviews, Buying Guides & Best Practices. (2019). *Top 52 Predictive Analytics & Prescriptive Analytics Software—Compare Reviews, Features, Pricing in 2019—PAT RESEARCH: B2B Reviews, Buying Guides & Best Practices*. Accessed: Jul. 30, 2019. [Online]. Available: https://www.predictiveanalyticstoday.com/top-predictive-analytics-software/

[13] B. Varghese and R. Buyya, "Next generation cloud computing: New trends and research directions," *Future Gener. Comput. Syst.*, vol. 79, pp. 849–861, Feb. 2018, doi: 10.1016/j.future.2017.09.020.

[14] P. Mell and T. Grance, "The NIST definition of cloud computing," *Nat. Inst. Standards Technol.*, vol. 53, no. 6, p. 50, 2011.

[15] C. Stergiou, K. E. Psannis, B.-G. Kim, and B. Gupta, "Secure integration of IoT and cloud computing," *Future Gener. Comput. Syst.*, vol. 78, pp. 964–975, Jan. 2018, doi: 10.1016/j.future.2016.11.031.

[16] H. Li, K. Ota, and M. Dong, "Learning IoT in edge: Deep learning for the Internet of Things with edge computing," *IEEE Netw.*, vol. 32, no. 1, pp. 96–101, Jan./Feb. 2018, doi: 10.1109/mnet.2018.1700202.

[17] N. Fernando, S. Loke, and W. Rahayu, "Mobile cloud computing: A survey," *Future Gener. Comput. Syst.*, vol. 29, no. 1, pp. 84–106, Jul. 2013.

[18] K. Kumar and Y.-H. Lu, "Cloud computing for mobile users: Can offloading computation save energy?" *Computer*, vol. 43, no. 4, pp. 51–56, 2010, doi: 10.1109/mc.2010.98.

[19] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, "Fog computing and its role in the Internet of Things," in *Proc. 1st Ed. MCC Workshop Mobile Cloud Comput.*, 2012, pp. 13–16.

[20] M. Armbrust, A. Fox, R. Griffith, A. D. Joseph, R. Katz, A. Konwinski, G. Lee, D. Patterson, A. Rabkin, I. Stoica, and M. Zaharia, "A view of cloud computing," *Commun. ACM*, vol. 53, no. 4, p. 50, 2010. Accessed: Jul. 31, 2019, doi: 10.1145/1721654.1721672.

[21] R. Calheiros, R. Ranjan, A. Beloglazov, C. De Rose, and R. Buyya, "CloudSim: A toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms," *Softw., Pract. Exper.*, vol. 41, no. 1, pp. 23–50, 2010, doi: 10.1002/spe.995.

[22] Q. Zhang, L. Cheng, and R. Boutaba, "Cloud computing: State-of-the-art and research challenges," *J. Internet Services Appl.*, vol. 1, no. 1, pp. 7–18, 2010, doi: 10.1007/s13174-010-0007-6.

[23] S. Subashini and V. Kavitha, "A survey on security issues in service delivery models of cloud computing," *J. Netw. Comput. Appl.*, vol. 34, no. 1, pp. 1–11, 2011, doi: 10.1016/j.jnca.2010.07.006.

[24] S. Marston, Z. Li, S. Bandyopadhyay, J. Zhang, and A. Ghalsasi, "Cloud computing—The business perspective," *Decis. Support Syst.*, vol. 51, no. 1, pp. 176–189, 2011.

[25] C. Wang, Q. Wang, K. Ren, and W. Lou, "Privacy-preserving public auditing for data storage security in cloud computing," in *Proc. IEEE INFOCOM*, Mar. 2010, pp. 1–9.

[26] A. Beloglazov, J. Abawajy, and R. Buyya, "Energy-aware resource allocation heuristics for efficient management of data centers for Cloud computing," *Future Gener. Comput. Syst.*, vol. 28, no. 5, pp. 755–768, 2012, doi: 10.1016/j.future.2011.04.017.

[27] H. T. Dinh, C. Lee, D. Niyato, and P. Wang, "A survey of mobile cloud computing: Architecture applications and approaches," *Wireless Commun. Mobile Comput.*, vol. 13, no. 18, pp. 1587–1611, 2013.

[28] S. Yu, C. Wang, K. Ren, and W. Lou, "Achieving secure scalable and fine-grained data access control in cloud computing," in *Proc. IEEE INFOCOM*, Mar. 2010, pp. 534–542.

[29] D. Zissis and D. Lekkas, "Addressing cloud computing security issues," *Future Gener. Comput. Syst.*, vol. 28, no. 3, pp. 583–592, 2012, doi: 10.1016/j.future.2010.12.006.

[30] P. Nickolov, B. Armijo, and V. Miloushev, "Globally distributed utility computing cloud," U.S. Patent 8 429 630, Apr. 23, 2013.

[31] I. Hashem, I. Yaqoob, N. Anuar, S. Mokhtar, A. Gani, and S. U. Khan, "The rise of 'big data' on cloud computing: Review and open research issues," *Inf. Syst.*, vol. 47, pp. 98–115, Jan. 2015, doi: 10.1016/j.is.2014.07.006.

[32] X. Xu, "From cloud computing to cloud manufacturing," *Robot. Comput.-Integr. Manuf.*, vol. 28, no. 1, pp. 75–86, 2012, doi: 10.1016/j.rcim.2011.07.002.

[33] H. Takabi, J. B. D. Joshi, and G.-J. Ahn, "Security and privacy challenges in cloud computing environments," *IEEE Security Privacy*, vol. 8, no. 6, pp. 24–31, Nov./Dec. 2010, doi: 10.1109/msp.2010.186.

[34] T. Dillon, C. Wu, and E. Chang, "Cloud computing: Issues and challenges," in *Proc. 24th IEEE Int. Conf. Adv. Inf. Netw. Appl. (AINA)*, Apr. 2010, pp. 27–33.

[35] R. Buyya, J. Broberg, and A. Goscinski, *Cloud Computing [Recurso Electrónico]*. Hoboken, NJ, USA: Wiley, 2011.

[36] A. Botta, W. Donato, V. Persico, and A. Pescapé, "Integration of cloud computing and Internet of Things: A survey," *Future Generat. Comput. Syst.*, vol. 56, pp. 684–700, Mar. 2016.

[37] Z. Cai, X. Li, and J. N. D. Gupta, "Heuristics for provisioning services to workflows in XaaS clouds," *IEEE Trans. Services Comput.*, vol. 9, no. 2, pp. 250–263, Mar. 2016, doi: 10.1109/tsc.2014.2361320.
[38] C. Grönroos and P. Voima, "Critical service logic: Making sense of value creation and co-creation," *J. Acad. Marketing Sci.*, vol. 41, no. 2, pp. 133–150, 2012, doi: 10.1007/s11747-012-0308-3.
[39] B. Schneider, D. E. Bowen, P. P. Maglio, C. A. Kieliszewski, and J. C. Spohrer, "Winning the service game: Revisiting the rules by which people co-create value," in *Handbook of Service Science*. New York, NY, USA: Springer, 2010, pp. 31–60.
[40] P. Bender, P. Black, M. Grob, R. Padovani, N. Sindhushayana, and A. Viterbi, "CDMA/HDR: A bandwidth efficient high speed wireless data service for nomadic users," in *The Foundations of the Digital Wireless World*. Singapore: World Scientific, 2009, pp. 161–168. Accessed: Jul. 31, 2019, doi: 10.1142/9789814287517_0016.
[41] E. Morozov, *To Save Everything, Click Here*. New York, NY, USA: PublicAffairs, 2013.
[42] A. Ostrom, A. L. Ostrom, M. J. Bitner, S. W. Brown, K. A. Burkhard, M. Goul, V. Smith-Daniels, H. Demirkan, and E. Rabinovich, "Moving forward and making a difference: Research priorities for the science of service," *J. Service Res.*, vol. 13, no. 1, pp. 4–36, 2010, doi: 10.1177/1094670509357611.
[43] C. Grönroos, "Value co-creation in service logic: A critical analysis," *Marketing Theory*, vol. 11, no. 3, pp. 279–301, 2011, doi: 10.1177/1470593111408177.
[44] B. Edvardsson, B. Tronvoll, and T. Gruber, "Expanding understanding of service exchange and value co-creation: A social construction approach," *J. Acad. Marketing Sci.*, vol. 39, no. 2, pp. 327–339, 2010, doi: 10.1007/s11747-010-0200-y.
[45] R. Lusch, S. Vargo, and M. Tanniru, "Service, value networks and learning," *J. Acad. Marketing Sci.*, vol. 38, no. 1, pp. 19–31, 2009. Accessed: Jul. 31, 2019, doi: 10.1007/s11747-008-0131-z.
[46] A. Ordanini, L. Miceli, M. Pizzetti, and A. Parasuraman, "Crowdfunding: Transforming customers into investors through innovative service platforms," *J. Service Manage.*, vol. 22, no. 4, pp. 443–470, 2011, doi: 10.1108/09564231111155079.
[47] A. Dunne and F. Raby, *Speculative Everything: Design, Fiction, and Social Dreaming*. Cambridge, MA, USA: MIT Press, 2013.
[48] A. Bryant, N. Schönemann, and D. Karpa, "Children and the media: A service-learning approach," in *Integrating Service-Learning Into the University Classroom*. Sudbury, MA, USA: Jones and Bartlett Publishers, 2011.
[49] J. V. Nguyen, "System and method for designing, developing and implementing Internet service provider architectures," U.S. Patent 9 087 319, Jul. 21, 2015.
[50] S. Vaidhyanathan, *The Googlization of Everything*. Berkeley, CA, USA: Univ. of California Press, 2012.
[51] A. Johnson, *A Short Guide to Action Research*. Boston, MA, USA: Pearson/Allyn and Bacon, 2012.
[52] Y. Zheng, X. Xie, and W.-Y. Ma, "Geolife: A collaborative social networking service among user location and trajectory," *IEEE Data Eng. Bull.*, vol. 33, no. 2, pp. 32–39, 2010.
[53] K. Heinonen, T. Strandvik, K. Mickelsson, B. Edvardsson, E. Sundström, and P. Andersson, "A customer-dominant logic of service," *J. Service Manage.*, vol. 21, no. 4, pp. 531–548, 2010, doi: 10.1108/09564231011066088.
[54] L. Johnson, S. A. Becker, and M. Cummins, *The NMC Horizon Report: 2016 Higher Education Edition*. Austin, TX, USA: New Media Consortium, 2016.
[55] B. Farahani, F. Firouzi, V. Chang, M. Badaroglu, N. Constant, and K. Mankodiya, "Towards fog-driven IoT eHealth: Promises and challenges of IoT in medicine and healthcare," *Future Generat. Comput. Syst.*, vol. 78, pp. 659–676, Jan. 2018, doi: 10.1016/j.future.2017.04.036.
[56] I. Duhn, "Making 'place' for ecological sustainability in early childhood education," *Environ. Educ. Res.*, vol. 18, no. 1, pp. 19–29, 2012, doi: 10.1080/13504622.2011.572162.
[57] L. Anderson, A. L. Ostrom, C. Corus, R. P. Fisk, A. S. Gallan, M. Giraldo, M. Mende, M. Mulder, S. W. Rayburn, M. S. Rosenbaum, K. Shirahada, and J. D. Williams, "Transformative service research: An agenda for the future," *J. Bus. Res.*, vol. 66, no. 8, pp. 1203–1210, 2013, doi: 10.1016/j.jbusres.2012.08.013.
[58] G. Dominici and F. Palumbo, "How to build an e-learning product: Factors for student/customer satisfaction," *Bus. Horizons*, vol. 56, no. 1, pp. 87–96, 2013, doi: 10.1016/j.bushor.2012.09.011.
[59] P. Cortez and A. M. G. Silva, "Using data mining to predict secondary school student performance," EUROSIS-ETI, Ghent, Belgium, Tech. Rep., Apr. 2008, pp. 5–12.
[60] A. M. Shahiri, W. Husain, and N. A. Rashid, "A review on predicting student's performance using data mining techniques," *Procedia Comput. Sci.*, vol. 72, pp. 414–422, Dec. 2015, doi: 10.1016/j.procs.2015.12.157.
[61] M. Moore and G. Kearsley, *Distance Education*. Belmont, CA, USA: Wadsworth Cengage Learning, 2012.
[62] M. Lawn and S. Grek, *Europeanizing Education*. Oxford, U.K.: Symposium Books, 2012.
[63] T. Gruber, S. Fuß, R. Voss, and M. Gläser-Zikuda, "Examining student satisfaction with higher education services: Using a new measurement tool," *Int. J. Public Sector Manage.*, vol. 23, no. 2, pp. 105–123, 2010.
[64] J. Ozga, *Fabricating Quality in Education*. London, U.K.: Routledge, 2011.
[65] V. Chang, Y.-H. Kuo, and M. Ramachandran, "Cloud computing adoption framework: A security framework for business clouds," *Futur. Gener. Comput. Syst.*, vol. 57, pp. 24–41, Apr. 2016, doi: 10.1016/j.future.2015.09.031.
[66] J. Epstein and F. Van Voorhis, "School counselors," *Roles Develop. Partnerships Families Communities Student Success' Prof. School Counseling*, vol. 14, no. 1, p. 2156759X1001400, 2010, doi: 10.1177/2156759x1001400102.
[67] M. Lawn and J. Ozga, "The educational worker? A re-assessment of teachers," in *Schools, Teachers and Teaching (RLE Edu N)*, vol. 45. Abingdon, U.K.: Routledge Library Editions, 2012.
[68] V. Chang, R. J. Walters, and G. Wills, "The development that leads to the cloud computing business framework," *Int. J. Inf. Manage.*, vol. 33, no. 3, pp. 524–538, 2013.
[69] S. Moutsios, "Power, politics and transnational policy-making in education," *Globalisation, Soc. Edu.*, vol. 8, no. 1, pp. 121–141, 2010, doi: 10.1080/14767720903574124.
[70] B. Ruben, *Quality in Higher Education*. 2018. Accessed: Jul. 31, 2019, doi: 10.4324/9781351293563.
[71] K. Lynch, "Control by numbers: New managerialism and ranking in higher education," *Crit. Stud. Edu.*, vol. 56, no. 2, pp. 190–207, 2014, doi: 10.1080/17508487.2014.949811.
[72] R. Craig, *College Disrupted: The Great Unbundling of Higher Education*. New York, NY, USA: St. Martin's Press, 2015.
[73] P. Kalagiakos and P. Karampelas, "Cloud computing learning," in *Proc. 5th Int. Conf. Appl. Inf. Commun. Technol. (AICT)*, pp. 1–4, 2011.
[74] S. Carvalho and M. de Oliveira Mota, "The role of trust in creating value and student loyalty in relational exchanges between higher education institutions and their students," *J. Marketing Higher Edu.*, vol. 20, no. 1, pp. 145–165, 2010, doi: 10.1080/08841241003788201.
[75] M. Pinar, P. Trapp, T. Girard, and T. Boyt, "Utilizing the brand ecosystem framework in designing branding strategies for higher education," *Int. J. Educ. Manage.*, vol. 25, no. 7, pp. 724–739, 2011, doi: 10.1108/09513541111172126.
[76] Y. Liu, L. Wang, X. Wang, X. Xu, and L. Zhang, "Scheduling in cloud manufacturing: State-of-the-art and research challenges," *Int. J. Prod. Res.*, vol. 57, pp. 1–26, Oct. 2018, doi: 10.1080/00207543.2018.1449978.
[77] X. Wen and X. Zhou, "Servitization of manufacturing industries based on cloud-based business model and the down-to-earth implementary path," *Int. J. Adv. Manuf. Technol.*, vol. 87, nos. 5–8, pp. 1491–1508, 2014, doi: 10.1007/s00170-014-6348-8.
[78] J. Siderska and K. Jadaan, "Cloud manufacturing: A service-oriented manufacturing paradigm. A review paper," *Eng. Manage. Prod. Services*, vol. 10, no. 1, pp. 22–31, 2018, doi: 10.1515/emj-2018-0002.
[79] X. Yao, J. Zhou, Y. Lin, Y. Li, H. Yu, and Y. Liu, "Smart manufacturing based on cyber-physical systems and beyond," *J. Intell. Manuf.*, vol. 30, no. 8, pp. 2805–2817, Dec. 2017, doi: 10.1007/s10845-017-1384-5.
[80] F. Lin, K. Sandkuhl, N. Shilov, A. Smirnov, V. Tarasov, and A. Krizhanovsky, "Logistics-as-a-service: Ontology-based architecture and approach," *Investigación Operacional*, vol. 34, no. 3, pp. 188–194, 2014.
[81] J. Jung and H. Kim, "Deployment of cloud computing in logistics industry," *J. Digit. Converg.*, vol. 12, no. 2, pp. 163–171, 2014, doi: 10.14400/jdc.2014.12.2.163.
[82] U. Arnold, J. Oberlander, and B. Schwarzbach, "Advancements in cloud computing for logistics," in *Proc. Federated Conf. Comput. Sci. Inf. Syst. (FedCSIS)*, 2013, pp. 1055–1062.

[83] F. Tao, Y. Cheng, L. Zhang, and A. Y. C. Nee, "Advanced manufacturing systems: Socialization characteristics and trends," *J. Intell. Manuf.*, vol. 28, no. 5, pp. 1079–1094, 2017, doi: 10.1007/s10845-015-1042-8.
[84] L. Ren, L. Zhang, F. Tao, C. Zhao, X. Chai, and X. Zhao, "Cloud manufacturing: From concept to practice," *Enterprise Inf. Syst.*, vol. 9, no. 2, pp. 186–209, 2015, doi: 10.1080/17517575.2013.839055.
[85] L. Ren, L. Zhang, L. Wang, F. Tao, and X. Chai, "Cloud manufacturing: Key characteristics and applications," *Int. J. Comput. Integr. Manuf.*, vol. 30, no. 6, pp. 501–515, 2017, doi: 10.1080/0951192x.2014.902105.
[86] J. R. Huscroft, B. T. Hazen, D. J. Hall, J. B. Skipper, and J. B. Hanna, "Reverse logistics: Past research, current management issues, and future directions," *Int. J. Logistics Manage.*, vol. 24, no. 3, pp. 304–327, 2013.
[87] C. Yu, X. Xu, and Y. Lu, "Computer-integrated manufacturing, cyber-physical systems and cloud manufacturing—Concepts and relationships," *Manuf. Lett.*, vol. 6, pp. 5–9, Oct. 2015, doi: 10.1016/j.mfglet.2015.11.005.
[88] B. Lüthje, S. Hürtgen, P. Pawlicki, and M. Sproll, *From Silicon Valley to Shenzhen*. Lanham, MD, USA: Rowman & Littlefield Publishers, 2013.
[89] K. Nowicka, "Smart city logistics on cloud computing model," *Procedia—Social Behav. Sci.*, vol. 151, pp. 266–281, Oct. 2014, doi: 10.1016/j.sbspro.2014.10.025.
[90] G. Prockl, A. Pflaum, and H. Kotzab, "3PL factories or lernstatts? Value-creation models for 3PL service providers," *Int. J. Phys. Distrib. & Logistics Manage.*, vol. 42, no. 6, pp. 544–561, 2012, doi: 10.1108/09600031211250587.
[91] Z. Chu, "Logistics and economic growth: A panel data approach," *Ann. Regional Sci.*, vol. 49, no. 1, pp. 87–102, 2011, doi: 10.1007/s00168-010-0434-0.
[92] D. Collado-Ruiz and H. Ostad-Ahmad-Ghorabi, "Fuon theory: Standardizing functional units for product design," *Resour., Conservation Recycling*, vol. 54, no. 10, pp. 683–691, 2010, doi: 10.1016/j.resconrec.2009.11.009.
[93] M. Klumpp, U. Clausen, and M. ten Hompel, *Logistics Research and the Logistics World of 2050*. Berlin, Germany: Springer, 2013, pp. 1–6.
[94] T. Tolio, A. Bernard, M. Colledani, S. Kara, G. Seliger, J. Duflou, O. Battaia, and S. Takata, "Design, management and control of demanufacturing and remanufacturing systems," *CIRP Ann.*, vol. 66, no. 2, pp. 585–609, 2017, doi: 10.1016/j.cirp.2017.05.001.
[95] L. Ren, L. Zhang, C. Zhao, and X. Chai, "Cloud manufacturing platform: Operating paradigm, functional requirements, and architecture design," *Sustain. Manuf.*, pp. 501–515, Apr. 2013. Accessed: Jul. 31, 2019, doi: 10.1115/msec2013-1185.
[96] J. A. Vohr, "Haiti disaster relief: Logistics is the operation," *Military Rev.*, vol. 91, no. 4, pp. 76–82, 2011.
[97] S. Strzelczak, "Ontology aided manufacturing and logistics," in *Open Knowledge Driven Manufacturing and Logistics—The eScop Approach*. Warsaw, Poland: OWPW, 2015, pp. 111–213.
[98] Y. Wang, S. Ma, and L. Ren, "A security framework for cloud manufacturing," in *Proc. ASME Int. Manuf. Sci. Eng. Conf.*, Detroit, MI, USA, Jun. 2014, doi: 10.1115/MSEC2014-4082.
[99] F. Tao, L. Zhang, V. C. Venkatesh, Y. Luo, and Y. Cheng, "Cloud manufacturing: A computing and service-oriented manufacturing model," *Proc. Inst. Mech. Eng. B-J. Eng. Manuf.*, vol. 225, no. 10, pp. 1969–1976, 2011.
[100] F. Tao, Y. Cheng, L. D. Xu, L. Zhang, and B. H. Li, "CCIoT-CMfg: Cloud computing and Internet of Things-based cloud manufacturing service system," *IEEE Trans. Ind. Informat.*, vol. 10, no. 2, pp. 1435–1442, May 2014.
[101] D. Wu, M. Greer, D. Rosen, and D. Schaefer, "Cloud manufacturing: Strategic vision and state-of-the-art," *J. Manuf. Syst.*, vol. 32, no. 4, pp. 564–579, 2013, doi: 10.1016/j.jmsy.2013.04.008.
[102] L. Zhang, Y. Luo, F. Tao, B. H. Li, L. Ren, X. Zhang, H. Guo, Y. Cheng, A. Hu, and Y. Liu, "Cloud manufacturing: A new manufacturing paradigm," *Enterprise Inf. Syst.*, vol. 8, no. 2, pp. 167–187, 2012. Accessed: Oct. 28, 2019, doi: 10.1080/17517575.2012.683812.
[103] F. Nordin and C. Kowalkowski, "Solutions offerings: A critical review and reconceptualisation," *J. Service Manage.*, vol. 21, no. 4, pp. 441–459, 2010, doi: 10.1108/09564231011066105.
[104] F. Tao, Y. J. LaiLi, L. D. Xu, and L. Zhang, "FC-PACO-RM: A parallel method for service composition optimal-selection in cloud manufacturing system," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2023–2033, Nov. 2013, doi: 10.1109/TII.2012.2232936.
[105] X. V. Wang and X. Xu, "An interoperable solution for cloud manufacturing," *Robot. Comput.-Integr. Manuf.*, vol. 29, no. 4, pp. 232–247, 2013, doi: 10.1016/j.rcim.2013.01.005.
[106] R. Gao, L. Wang, R. Teti, D. Dornfeld, S. Kumara, M. Mori, and M. Helu, "Cloud-enabled prognosis for manufacturing," *CIRP Ann.*, vol. 64, no. 2, pp. 749–772, 2015, doi: 10.1016/j.cirp.2015.05.011.
[107] C. Yang, Q. Huang, Z. Li, K. Liu, and F. Hu, "Big data and cloud computing: Innovation opportunities and challenges," *Int. J. Digit. Earth*, vol. 10, no. 1, pp. 13–53, 2017.
[108] J. Gao, Y. Yao, V. Zhu, L. Sun, and L. Lin, "Service-oriented manufacturing: A new product pattern and manufacturing paradigm," *J. Intell. Manuf.*, vol. 22, no. 3, pp. 435–446, 2011.
[109] L. Xu, E. Xu, and L. Li, "Industry 4.0: State of the art and future trends," *Int. J. Prod. Res.*, vol. 56, no. 8, pp. 2941–2962, 2018, doi: 10.1080/00207543.2018.1444806.
[110] Y. Liu and X. Xu, "Industry 4.0 and cloud manufacturing: A comparative analysis," *J. Manuf. Sci. Eng.*, vol. 139, no. 3, p. 034701, 2016, doi: 10.1115/1.4034667.
[111] I. Mezgár and U. Rauschecker, "The challenge of networked enterprises for cloud computing interoperability," *Comput. Ind.*, vol. 65, no. 4, pp. 657–674, 2014, doi: 10.1016/j.compind.2014.01.017.
[112] O. Givehchi, H. Trsek, and J. Jasperneite, "Cloud computing for industrial automation systems—A comprehensive overview," in *Proc. 18th IEEE ETFA*, Sep. 2013, pp. 1–4.
[113] G. Tassey, "Competing in advanced manufacturing: The need for improved growth models and policies," *J. Econ. Perspectives*, vol. 28, no. 1, pp. 27–48, 2014, doi: 10.1257/jep.28.1.27.
[114] G. Adamson, L. Wang, M. Holm, and P. Moore, "Cloud manufacturing—A critical review of recent development and future trends," *Int. J. Comput. Integr. Manuf.*, pp. 347-380, 2017. Accessed: Jul. 31, 2019, doi: 10.1080/0951192x.2015.1031704.
[115] Q. Qi and F. Tao, "Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison," *IEEE Access*, vol. 6, pp. 3585–3593, 2018, doi: 10.1109/access.2018.2793265.
[116] M. Bohanec and V. Rajkovic, "Knowledge acquisition and explanation for multi-attribute decision making," in *Proc. 8th Int. Workshop Expert Syst. Appl.*, 1988, pp. 59–78.
[117] D. Dua and C. Graff. (2019). *Archive.ICS.UCI.Edu*. Accessed: Oct. 28, 2019. [Online]. Available: http://archive.ics.uci.edu/ml
[118] Y. Yang, W. Jin, and X. Hao, "Car rental logistics problem: A review of literature," in *Proc. IEEE Int. Conf. Service Oper. Logistics, Inform. (IEEE/SOLI)*, vol. 2, Oct. 2008, pp. 2815–2819.

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