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Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics

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Abstract

This study explores digital business transformation through the lens of four emerging technology fields: artificial intelligence, blockchain, cloud and data analytics (i.e., ABCD). Specifically, the study investigates the operations and value propositions of these distinct but increasingly converging technologies. Due to the dynamic nature of innovation, the potential of this ABCD hybridization, integration, recombination and convergence has yet to be considered. Using a multidisciplinary approach, the findings of the study show wide-reaching and diverse applications among a variety of vertical sectors, presenting exploratory research avenues for future investigation. The study also highlights the practical implications of these new technologies.

Keywords Digital transformation · Artificial intelligence · Blockchain · Cloud computing · Data analytics

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1 Introduction

> Pity the enterprise whose fortunes are tied exclusively to the analog world, be it producing film, renting videos, retailing books, or selling packaged software (Narayen 2018).

Digital business transformation (DBT) is a strategy that is gaining attention as companies are challenged to continually improve their business processes and capabilities. DBT stimulates new modes of working and interactions with customers, directly driving the creation of new business models. According to Weill and Woerner (2018), DBT can make firms future-ready and enhance average net revenues by 16% more than traditional firms. Evidence suggests that digitalization could add 1.25 trillion Euros to Europe's industrial value creation (Schweer and Sahl 2017) while Australia could generate $315 billion worth of economic opportunities (Alphabeta Advisors 2018). DBT refers to the use of technology to radically improve the firm performance of an enterprise (i.e., organizational performance, the functioning of the firm and outcomes of its operations) (Westerman and Bonnet 2015). DBT is an enabler of business transformation and has already introduced massive changes in business operations through better customer service, payments, business models and new methods of online engagement. In other words, it is not the use of technology as an end in itself that adds value but rather the application of technology to enhance user customer experience. As Grewal et al. (2020, p. 6) state that "Netflix might have demolished Blockbuster; Alibaba, Tencent, and Baidu might be issuing credible threats to traditional banks; and Amazon might have revolutionized businesses in a vast range of sectors, including supermarkets, publishing, and logistics. They have done so by gathering and leveraging information to enhance customer experiences".

DBT is a way of conducting business and transforming business from traditional to digital (Li 2018). It is more than just changing from a 'bricks and mortar' shop front for customers to a 'clicks and bricks' environment; digital transformation pervades all aspects of business by adopting cutting edge and often converging technologies. Thus, the goal of digital transformation is basically *business* transformation—using digital capabilities to transform a traditional enterprise into a top performer in the digital economy (Weill and Woerner 2018). The most digitally advanced firms, such as Google, Netflix, Uber and Airbnb, have successfully developed and leveraged their digitized, open and participative business models, incorporated in a connected ecosystem of producers and consumers. Goodwin (2015) describes DBT as an ecosystem of platform innovations, in which "Uber, the world's largest taxi company, owns no vehicles. Facebook, the world's most popular media owner, creates no content. Alibaba, the most valuable retailer, has no inventory. And Airbnb, the world's largest accommodation provider, owns no real estate." In this digital world, subscription services are preferred to ownership of assets or goods with little in the way of inventory requirements nor the costs associated with depreciation of those assets. Furthermore subscription models offer an on-going revenue stream and vast amounts of customer data which enables companies to constantly refine their offerings.

Although DBT can be wide in scope, this study focuses on digitizing the organization's business using four viable pathways which we put forward as ABCD technologies, that is Artificial Intelligence, Blockchain, Cloud and Data Analytics (Martin 2017). These technologies are expected to transform businesses of the future. Indeed, this is already happening. For example:

1. Organizations across all industries are investing in AI to automate value chain and serve customers, which is expected to reach $191 billion by 2025 with a compound annual growth rate of 36.6% (Markets and Markets 2019).

2. Gartner estimates blockchain technology is accelerating at a fast pace which will deliver business value of over $3 trillion by 2030 (Gartner 2019).
3. The dramatic rise of cloud migration suggests that this sector will reach $383 billion by 2020 (O'Neal 2018) with an annual growth rate of 22.8%.
4. A recent report suggests that 91.6% of Fortune 1000 companies are investing in big data analytics with 55% of firms investing greater than $55 million to address the fear of disruption (NewVantage Partners 2019).

Companies looking to digitally transform must determine how best to integrate ABCD technologies, and re-establish their operating model using a new more advanced way of doing business (Berman 2012). Because of recent technological changes, companies need to rethink the implications of ABCD technologies, which are the key to success in the emerging digital economy. There has been a paradigm shift in business strategy due to the emergence of next-gen technologies, given their emphasis on the provision of data, propelling insights toward competitive advantage. This study will focus on four viable pathways for transformation by exploring the merits and demerits of each. We choose ABCD as the critical next-gen technologies due to their interconnectivity and relationship to data-driven decision making in business. While firms have been applying ABCD technologies for business transformation in isolation, there is a paucity of research on their operational use cases, integrated applications, challenges and business opportunities (Kumar et al. 2020; Grewal et al. 2020). Thus, the study puts forward the following research questions, which are significant from a digital business transformation perspective:

- What are AI, blockchain, cloud computing and data analytics (ABCD) and how do they work?
- How do ABCD technologies operate to transform business?
- What are the opportunities and challenges that ABCD technologies provide?

To answer these exploratory questions, we discuss the nature and attributes of ABCD technologies that can transform the future of business. We have structured our discussion as follows. First, we define and discuss digital business transformation and its applications in various industries. Second, we discuss AI and its two applications: machine learning (ML) and deep learning (DL) with business cases. Next, we discuss blockchain, cloud computing and data analytics with applications. Examples of ABCD technologies already deployed in business are represented in tables in each section, providing evidence for the opportunities that have arisen for many varied vertical sectors by adopting a digital transformation strategy. Finally, we discuss the challenges and limitations of ABCD technologies and future research implications.

2 Literature review

2.1 Defining digital business transformation

Digital business transformation (DBT) is defined as the use of technology to radically improve the performance of organizations, redefine and recreate value propositions using Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) or, leveraging digital frontiers, such as smart devices, mobility or analytics for intra-/extra-/inter-business processes (Westerman et al. 2014). In a similar vein, von Leipzig et al. (2017) defined DBT focusing on transforming business models while Li (2018) highlighted new ways of doing business. Similarly, Basole (2016) and Singh and Hess (2017) explored emerging technological factors driving digital transformation. Sebastian et al. (2017) identified social, mobile, analytics, cloud and Internet of things (SMACIT) as fundamental driving forces of DBT. However, these studies primarily focused on the technological dimensions rather than linking them to business value, firm performance or strategic alignment. To address this gap, Nadeem et al. (2018) conducted a systematic review and found that digital transformation is intricately interlinked with digital business strategy (e.g., cross-functional integration, structural changes) and organizational capabilities (e.g., talent and operational capabilities). DBT focuses not only on incorporating robust technologies but also articulating a clear vision, transforming the business model, developing dynamic capabilities and understanding customers. In defining digital transformation, Kumar et al. (2020) focus on digital thinking across all operations, Davenport and Spanyi (2019) highlight customer-centric digital products and services and Verhoef et al. (2019) shed light on a new digital business model to create more value. Overall, we define DBT as the reconceptualisation of a business model using digital technologies to create, communicate and deliver value. Table 1 shows various dimensions of DBT definitions and their applications across industries.

2.2 Digital business transformation in various industries

Digital business transformation using ABCD has already impacted various industries. For example, the healthcare industry has achieved positive outcomes from digital transformation enabling high-quality patient care, electronic health records (EHRs), digital imaging and prescriptions, giving more access to historical and real-time information to provide better and secure services (Haggerty 2017). DBT can transform health care in various ways, such as avoiding unnecessary hospital stays, improving care delivery models using big data analytics and reductions in cost. For example, Kaiser Permanente uses an electronic medical record service which is more consistent and provide better clinical practice than previous paper-based systems. The introduction of digital transformation in health care is said to reduce cost, improve patient outcomes and improve efficiency, thereby providing a benefit of $1.76 billion in Australia (Forsythe et al. 2016).

In addition to healthcare, sectors such as manufacturing where the main reason for digitalization is the reduction of cost, cloud applications play a vital role in internal management and communications (Schwertner 2017). Manufacturers are also using analytics to make the best use of equipment, reduce waste of materials and other inputs, advance supply chain networks and improve efficiency. For example, the automobile industry is struggling to compete against disruptive car manufacturers like Tesla and Faraday Future. Any long-established manufacturer now understands that it is vital to combine digital technologies with traditional processes to stay ahead of their competitors. For example, Audi gained massive advantages by applying digital transformation in sales, marketing and operations, enabling them to better meet local demand (Dremel et al. 2017). Metal plant companies use the power of digitalization to increase production rates by visualizing performance, streamlining operations and obtaining insights into causes of failures (Hartmann et al. 2015). Pharmaceutical manufacturers are now using less manufacturing space, and quality control has increased as easy detection of counterfeit medicines and chemicals can be provided. The consumer packaged goods industry has also achieved improvements through digital transformation by becoming closer to their customers and forming longer-lasting relationships that equate to repeat business and higher satisfaction (Kumar et al. 2020). Consumers experience faster response times through better channels of distribution with a huge reduction in cost. For example, instead of 40

Table 1 Definitions of digital transformations

Study	Definitions	Purpose(s)	Research areas
Ashwell (2017)	DBT can be referred to as the interrelationship between data, digital technology and people	Activity based intelligence (ABI) models for better understanding data and the use of information technology for understanding and countering organised criminal networks	Small and medium size companies. Consumer behaviour
Basole (2016)	DBT occurs through four tectonic technological factors such as mobile, social, analytics and cloud for reshaping businesses	Accelerating digital transformation through application programming interfaces (API)	Strategies for adopting an API ecosystem in business. Adopting API in machine learning and marketing analytics
Gölzer and Fritzsche (2017)	DBT can be explained in terms of Industry 4.0 which includes components such as Internet of things and big data solutions	Big data implication in industrial operations management	Customer service, e-commerce, customer demand
Heilig et al. (2017)	DBT can refer to digitalization and transformation of an organisation or a network of organisations through a variety of contexts: cultural, technological, governance strategy	Using game theory in maritime logistics environment through intra, inter and meta-level analysis for driving digital transformation in seaports	Operational management
Li (2018)	DBT refers to transforming/replacing traditional ways of doing business into a digital one	Transforming the creative industry through digital transformation	Creative industries such as architecture, advertising, publishing, design, fashion design, software, games development
Nadeem et al. (2018)	DBT links digital technologies with business strategy and organizational capabilities	Identify various sub-dimensions of digital technologies, digital business strategy and organizational capabilities	E-commerce

Table 1 continued

Study	Definitions	Purpose(s)	Research areas
Reddy and Reinartz (2017)	DBT is defined as the use of the Internet and computers for achieving economic value. In other words, it is the transformation of operations, interactions, configuration and wealth creation	Creating value through digital transformation	Manufacturing companies
Schwertner (2017)	DBT in business can refer to the application of technology for making new business models through processes and software systems, which can result in a profitable outcome	Applying technology in all aspects of business, especially in mature digital businesses through digital integration	General business management
Sebastian et al. (2017)	An aging company with legacy technology, needs to be digitalised by considering SMACIT (social, mobile, analytics, cloud and internet of things) to achieve digital transformation	Customer engagement, digitalized solution and technology-enabled assets for transforming business towards digitalization	General business management
Singh and Hess (2017)	DBT occurs when a company applies digital platforms using social media, mobile access, analytics and embedded devices	The roles that chief digital officers (CDO) should have in a company when shifting to digital transformation	Skills and competency needed for the chief digital officer. Identifying the important role CDOs should play in a company. Human-resource training on digitalisation
von Leipzig et al. (2017)	Digitisation shapes a part of Industry 4.0, which reshapes a business model for better efficiency and effectiveness through overcoming barriers of digitalisation	Analytics to gain competitive advantage, Developing a model for digitalisation for companies without a clear vision of incorporating digital strategy	Service sectors, reinventing their business model toward the creation of a strategic model that is driven by digital transformation

Table 1 continued

Study	Definitions	Purpose(s)	Research areas
Westerman et al. (2014)	DBT focuses on using emerging technologies to radically enhance firm performance	Identifies the core aspects of DBT as follows: operational processes (i.e., process digitisation, worker enablement, performance management), business models (i.e., digitally modified businesses, new digital businesses, digital globalization) and customer experience (i.e., customer understanding, top line growth, customer touch points)	Operations, marketing and sales, new business models and digital consumer behaviour

employees, ten employees can now do the same task within a shorter time frame, eventuating in far lower operating costs. The defence industry has also gained tremendous advantages through the introduction of digital tools which help their complex supply chain networks by enabling information sharing and collaboration among suppliers (Hartmann et al. 2015). Table 2 shows digital transformation as implemented in diverse industry sectors.

3 Drivers of digital transformation

3.1 Artificial intelligence (AI)

AI can be traced back to 1950 when English polymath Alan Turing invented a test to determine if the machine could mimic human cognitive functions (Batra et al. 2018), thus giving the world a preview of the possibilities which might become available with the advent of higher computing processing power. The theory of AI has been in development for many years, with its roots in 1956 (Cohen and Feigenbaum 2014). Several authors have explored the implications of AI (Nilsson 2014). It can be defined as machines which have human-like intellectual capacities (McGettigan 2016). It is a combination of computing technologies converging to enable rational decision-making in complex situations and contexts (Tredinnick 2017).

Over the years computers have been increasingly able to perform high level tasks which are comparable to humans, like solving mathematical problems, driving vehicles, understanding languages, and conducting commonsense reasoning. A machine that has AI capabilities must have a few core components, including the ability to conduct natural language processing (NLP), data retrieval from massive databases, proving mathematical theories, automatic programming, solving critical problems and diagnosing diseases (Nilsson 2014). Although three-quarters of executives believe that AI will help businesses further develop and enable them to achieve a competitive advantage, research states that companies are yet to put AI into

Table 2 Digital transformation in various industries

Firm	Type of industry	Product/services	Application of digital transformation
Audi ("Audi" 2016)	Automobiles	Audi City	The German giant gained 60% more sales by providing a digital experience in traditional showrooms in given locations, such as Berlin, London and Beijing
McKinsey Solutions ("Audi" 2016)	Management consulting	Software and technology-based analytics	McKinsey solutions provide software and analytic solutions to business for improving benchmarking, pricing and promotional strategies
KPMG ("Audi" 2016)	Business consulting	Watson cognitive computing platform	KPMG uses IBM's Watson computing platform to improve its professional services such as auditing. KPMG can now analyse a large amount of data providing the company with more insights
Kensho (World Economic Forum 2017a, b, c)	Technology	Analytic software	The company uses big data and machine learning for analyzing real-world events on financial markets, providing complex financial queries
Argos (World Economic Forum 2016)	Retail	Digital stores	The UK based retailer transformed five of its stores, providing customers with a quick and easy way to shop
Disney's magic bands (World Economic Forum 2016)	Entertainment	Smart wrist band	The company provided smart wrist bands for personalized customer experience in Disney World resorts, which led to a 20% increase in profit in 2014

practice (Rai 2020; Davenport and Ronanki 2018). One of the key reasons for this is data extraction. AI can only work through learning from a vast amount of existing data. For example, Airbus used their AI system to examine a production problem, calculate a vast amount of data, and come up with a solution and a recommendation (Ransbotham et al. 2017). Companies such as Bridgewater Associates are planning to use AI to automate key parts of their operation, while KPMG Australia is going to automate some of its auditing services, and law firm Baker & Hostetler will use AI to help boost their legal searches (Tredinnick 2017). In order to achieve fully-fledged AI: the first step is to use big data, the second is to apply analytics, and the third is prediction. AI needs data collection and storage in order to analyze and make predictions. Companies specializing in IT, marketing, finance, accounting and sales are using AI to become more competitive and efficient (Oana et al. 2017). For successful AI transformation, business needs to adopt a better data ecosystem with data governance, use cases with business value, analytics techniques and tools, workflow integration and an ambidextrous organizational culture (Chui 2017). As shown in Table 3, AI can be used in a wide range of different applications. Next, we consider one particular application in detail.

3.1.1 A case study on AI based digital transformation by Afiniti

Afiniti uses AI to predict patterns of interpersonal behavior for companies who are looking for success in human interaction. The aim is to replace the first in first out (FIFO) caller system which can cause drawbacks for customer service. Afiniti uses AI, big data analytics and machine learning (ML) algorithms to analyze human behavior and uses the outcomes for better pairing of customers with agents. Through their enhanced understanding of their customers, Afiniti's clients are able to tailor their services, ensuring better revenues and improved retention rates for companies like T-Mobile and Virgin (Afiniti 2018).

Afiniti collects data from different vectors of communication, call history and CRM records for customers around the world. It then combines interaction-level results from the client's data and uses specialized ML algorithms to identify different consumer behavior patterns and predicts outcomes from their historical behavior. As the number of interactions is quite low compared to the available data (which includes demographic data, interaction data and internal analytics), relying only on the ML algorithm can produce results that are unreliable. The system, therefore, runs the algorithm in real-time triggered by a consumer call. Afiniti runs the process in under 200 ms which allows the caller to be connected with the right agent. The outcomes of the call are recorded for future interaction with the customer, leading to a better service experience. Figure 1 shows the AI-based operations of Afiniti using private branch exchange (PBX) or automatic call distribution (ACD) software systems.

3.1.2 Machine learning as an application of AI

The term 'Machine Learning' (ML) was coined by Arthur Lee Samuel in 1995 (Syam and Sharma 2018). ML is widely considered the prerequisite for developing AI applications. It requires vasts amounts of data. It can be categorized as supervised learning where certain data are provided to have an outcome, but it is a different case for unsupervised learning where data are unstructured and unlabeled (Syam and Sharma 2018). Unsupervised machine learning trains a machine to discover hidden patterns and structures without a target variable (Lim et al. 2017). For example, the company M6D uses this technology to target potential consumers by displaying targeted advertising for hundreds of brands (Perlich et al. 2014). With the growth of real bidding exchanges, an advertiser can target specific customer leads, known in social

Table 3 Digital transformation cases using AI

Firms using AI	Type of industry and product	Applications of AI	Context
AIME (Artificial Intelligence Medical Epidemiology)	Healthcare	The AI-algorithm uses research and data such as insect borne-diseases, population density, wind speed direction, rain volume and other parameters to calculate the outbreak of a disease in a given area. This helped the startup to predict outbreaks such as the dengue virus 3 months in advance	USA
ROSS Intelligence	Legal research application	The AI app architected in a supercomputer uses natural language processing to answer legal questions. A similar task would take a legal assistant longer to complete. Law firms such as Baker and Hostetler are already using the app for their bankruptcy practice	USA
McCann Japan	Advertising and marketing agency	AI-CD β is an actual AI-based robot that works like an employee in the company, tasked to provide creative direction for the creation of commercials. The robot can recall historical adverts and help employees make better commercials	Japan
IVO	Technology product: mood box	A speaker called the mood box, which uses human mood to determine what kind of music a person might want to listen to. Users interact with the device by voice control and keep a diary of their moods using a speaker-controlled app	Hong Kong

Table 3 continued

Firms using AI	Type of industry and product	Applications of AI	Context
NotCo	Food manufacturing	The company uses AI to replicate meat and dairy products by using plant material. This is done by examining the molecular structure of the non-vegan products. The company's aim is to provide sustainable protein and help reduce water wastage and cruelty to animals	Chile
Webpage.ly	Web page design and digital service	The technology provides affordable alternatives for startup firms for their SEO operations by using algorithms. It analyses users' search behaviour and page rankings to suggest keywords that enables developers to produce higher impact on SEO content	Canada
Tes4Startup	Application	By using AI, Test4Startup can test the ability for a business to succeed by recommending strategies on pricing and competitors	Russia

apps as creating an impression. ML plays a vital role in the task by computing a massive amount of data about consumer behavior, making a decision and then finally delivering advertisements in near real-time. AI and ML have a positive impact on personal selling and sales management. While many believe that AI and machine learning will eliminate jobs, others believe that it will actually create over 2 million new jobs by 2025 (Syam and Sharma 2018). Sales management can become very efficient through ML with timely iterative detailed reporting, and service data that can ease a salesperson's job, allowing companies to translate discoverable patterns and trends into action.

In healthcare, ML can prescribe how many days a patient will stay in a hospital. This benefit not only helps a patient plan for home care requirements but also provides the hospital with efficient use of human resources and facilities. ML can significantly increase hospital bedding efficiency thereby enabling a hospital to serve more patients, improve doctor-nurse-theatre and scheduling of elective surgeries, and ultimately help with hospitals' long term strategic planning (Turgeman et al. 2017). Table 4 lists examples of the application of ML in a range of industries.

Fig. 1 How Afiniti operates using AI

3.1.3 A cases study on ML-based digital transformation by Netflix

Netflix does most of the computation for its recommendation system offline. It starts by mining data from the user, creating hypotheses to decide which model to initiate, and finally using different models to identify the match that is most appropriate to a user (Basilico and Amatrian 2013). The next step is to train the model through supervised machine learning algorithms. Netflix uses both supervised and unsupervised algorithms for their recommendation system (Basilico 2012). The learning happens in online, offline and nearline (an intermediary between online and offline computations) contexts, running massive amounts of data through Hadoop, a software application for storing and processing big data. In this process, the term signal is used for fresh information inputs in the algorithm, which can be done both online and offline. These data are gathered from live services related to user information, for example, data on what each customer has been watching (Basilico and Amatrian 2013). Figure 2 shows how Netflix ML algorithms are used for model training, offline computations, nearline computations and online computation (adapted from Basilico and Amatrian 2013). All the data is stored using Cassandra, EVCache and MySQL, for real-time usage and also for the purpose of prospective usage. Finally, the data is used to make recommendations to customers (Basilico and Amatrian 2013).

3.1.4 Deep learning as an application of AI

The power of deep learning (DL) was first realized in 2011 when an algorithmic breakthrough occurred providing better visual patterns that were six times more efficient than a human (Lemley et al. 2017). DL has the power to process data in their raw form, which is an ability absent in conventional machine learning. The powerful use of a complex algorithm set by DL has made it possible to improve tasks like visual object and speech recognition, object detection, drug discovery and genomics and much more. DL uses a backpropagation algo-

Table 4 Digital transformation cases using ML

Firms using machine learning	Type of industry and product	Applications of machine learning	Context
PlayerXP	Automated customer and community intelligence	Player XP uses ML to aid in the identifation of constructive feedback in mobile video game reviews by analyzing natural language, and helps filter unhelpful reviews	UK
Stanford University	Product: Autism Glass	The glass helps an autistic person to recognize emotion which makes social interaction easier	USA
Amazon	E-commerce	ML is used for product recommendation, supply chain management, forecasting and capacity planning. It scans sensitive data	Worldwide
Netflix	Online movie streaming	An algorithm called Dynamic Optimizer, helps reduce the amount of data it takes to stream videos	Worldwide
Google	Search engine	Google is taking a step further in ML by image enhancement, which fills in missing details in an image by zooming into project an enhanced reality	Worldwide
Salesforce	CRM	The company uses ML to predict customer behavior, recommend next actions to users and automate tasks. It uses customer data, captures sales activity, scores leads, delivers content and sends messages when customers are most likely to engage	Worldwide
Walmart	Anticipating customer need	Anticipate customer need by using facial recognition. By adopting biometrics, Walmart's ML technology can predict customer emotion and provide personalized services to them	USA

Table 4 continued

Firms using machine learning	Type of industry and product	Applications of machine learning	Context
North Face	Outdoor clothing retail	Highly personalized shopping experience by using IBM Watson. Consumers have to use a mobile application through which a virtual assistant can ask the consumer a series of questions to provide the best-personalized service	Worldwide

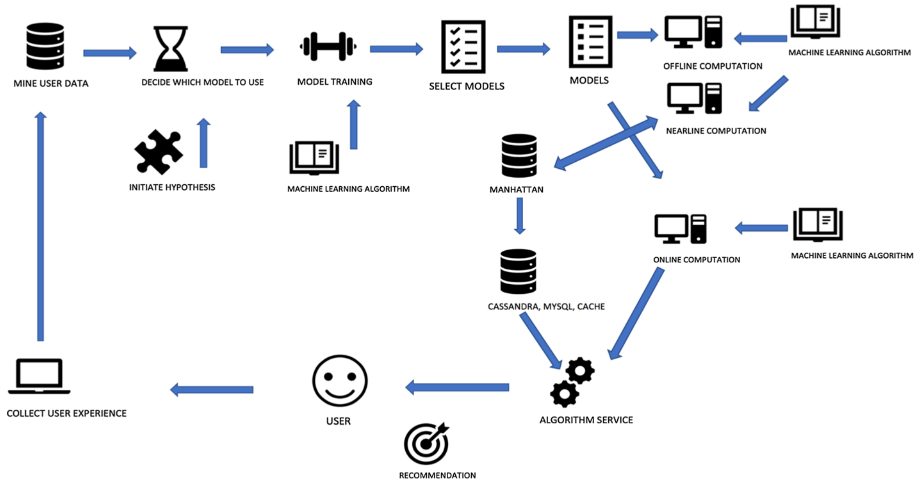

Fig. 2 Operations of Netflix using ML

rithm, which instructs how a machine can change its internal framework. It has outperformed ML at the prediction of potential drug molecules through better processing and recognition of image, videos and natural languages (LeCun et al. 2015).

The algorithms in DL have the capability of extracting high levels of data. DL enables the analysis and learning from a huge amount of unsupervised data, which makes it an important tool for big-data analytics. The algorithms used by DL are a deep architecture of consecutive layers where each layer provides a nonlinear transformation of its input and then provides a representation of its output (Najafabadi et al. 2015). These algorithms are significant because of their capacity to generate multiple representations with high-level features representing more abstract aspects of the data (Bengio 2013).

Neural Networks are often called DL as they perform more complex functions than traditional neural networks. Neural networks evolved through the availability of massively advanced hardware like commercial graphic processing units (GPUs) which helped speed up calculations in ML (Monroe 2017). Artificial neural networks are able to learn from what they see and then can generalize that knowledge to provide an example of something that they have never previously known. The networks have an input layer, an output layer and one

Table 5 Digital transformation cases using DL

Firms using deep learning	Type of industry and product	Applications of deep learning	Contexts
Affectiva	Automated customer & community intelligence	It uses DL to help identify human emotion from videos and images	UK
Gridspace	Product: Autism Glass	It uses DL networks for sophisticated speech recognition. DL is also used for reconditioning sophisticated speech, that identifies speakers, keywords, critical moments and time spent talking	USA
IBM Watson	Predictive modelling	IBM developed a computer system called Watson, which has the capability to process unstructured data and provide a solution to a problem from the findings	Worldwide
Novartis	Pharmaceutical company	The pharmaceutical giant is working with Intel to use deep neural networks for accelerating high content screening which will help to discover drugs faster	Worldwide
Zebra medical vision	Medical imaging startup	The company is raising money to use deep learning for building radiologist equipment	Israel
Atomwise	Pharmaceutical	The company is using deep learning for shortening the process of drug discovery and has raised over $45 million for the project	USA
Reason8	Mobile application	AI-powered service for automatic note-taking and preparation of summaries for in-person business meetings	Australia

or more hidden layers, and are full of nodes which are connected to each other (Lemley et al. 2017). In business, DL has become very popular in business processes such as CRM, human resources management (HRM), financial analysis, supplier management, fraud detection and in managing distribution channels (Necula 2017). DL has also been used to predict financial problems, such as risk management, construction portfolios, designing and pricing security which often involve large data sets. By applying DL, financial modeling can be done with far more precision than standard applications (Heaton et al. 2017). Table 5 lists examples of DL in different contexts.

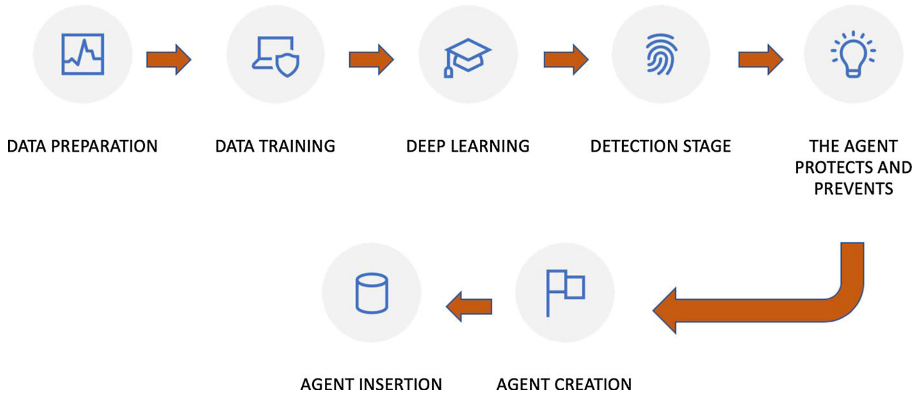

Fig. 3 Operations of deep instinct using DL

3.1.5 A case study on DL based digital transformation by Deep Instinct

Deep Instinct, one of the first deep learning companies in the world is focused on cybersecurity. Using the power of DL based predictive capabilities, Deep Instinct can help companies protect themselves from cyber threats, advanced persistent threats and zero-day threats, and can run on servers, mobile devices and across a company's endpoints. At the preparation stage, data samples are prepared for the deep learning neural network which contains several labeled files like malware, mutation etc. (Deep Instinct. 2018). Second, at the training stage, raw data is trained through Graphics Processing Units (GPUs) which is faster than using central processing units (CPUs). For example, data can be trained within 3 days as opposed to weeks. Third, at the deep learning stage, the data is run through DL algorithms. Fourth, at the detection stage, the neural networks begin to detect cyber threats through a continuous training process. Fifth, at the prediction stage, the deep learning brain can now predict the level of cyber threat a file may pose. Sixth, at the agent creation stage, the brain can turn terabytes of insight into megabytes of instincts. At the seventh stage, at the agent insertion stage, the agent is domain agnostic; hence it can be used for mobile device endpoints and servers. Finally, at the agent protection and prevention stage, the agents check each and every file, macros, scripts etc. The process is so fast that the users are not affected by its processing which takes less than a millisecond. The ability of the agent allows the uncorrupted files to run freely in the system with the ability to detect any type of threat (Fig. 3).

3.2 Blockchain as a driver of digital business transformation

Drawing on advanced cryptography, blockchain works as an open-source distributed database (Kirkland and Tapscott 2016). Bitcoin is one of the most popular applications of blockchain that runs on an open ledger (Kumar et al. 2020). This open-source platform allows anyone to change the underlying code providing the opportunity for all participants to see what is actually happening. In other words, it is a true peer-to-peer (P2P) system which does not require intermediaries to authenticate or settle transactions. The system can record any structured information, for example, who paid whom, who owns money to whom or which light sourced power from which power source (Iansiti and Lakhani 2017). Blockchain is typically unhackable, which makes it a trusted platform although recent studies (e.g., Orcutt 2019) have reported the security concerns on some platforms.

The blockchain can actually reduce costs, for example, the cost of verifying the details of a transaction and remove the cost of intermediaries (Michelman 2017). A blockchain transaction works by representing a transaction as a block in the system, which is then broadcast to every party in the network. When those who are in the network approve the transaction, the block gets added to the chain, providing an ineradicable and transparent record of a transaction, e.g., moving money from one party to another (Crosby et al. 2016).

The architecture of blockchain consists of continuous blocks in a sequential form which holds transactions and records like those in a traditional public ledger. Blockchain is made up of decentralized ledger technology (DLT), which is maintained by a peer-to-peer networks, thus not being controlled or owned by any one particular authority. It is tamper-resistant, and the user cannot lose control of the digital identities even if they lose access (Dunphy and Petitcolas 2018). In addition to decentralization, blockchain technology has three further recognized characteristics: persistency, anonymity, and auditability. Persistency in the blockchain is where falsification can be captured easily as transactions are checked, recorded in blocks and distributed to the whole network. Anonymity in the blockchain supports users as they are able to generate as many addresses as they want to avoid real identity exposure. Finally, auditability in the blockchain allows users to track and trace any transaction by accessing any nodes in the distributed network providing tracing improvement and transparency of the data (Zheng et al. 2016). Overall, blockchain works on five principles that determine the operation of this technology: irreversibility of records, computational logic, transparency with pseudonymity, distributed database and peer-to-peer networks (Iansiti and Lakhani 2017). Table 6 shows digital business transformation cases using blockchain.

3.2.1 A case study on blockchain-based digital transformation in banking

There are several issues with cross-border payments. One of the biggest challenges is the payment investigation time which could be reduced by using distributed ledger technology (DLT) (FARGO 2016). An example of blockchain as used by FARGO with ANZ bank is the Nostro Reconciliation process, where two banks are involved in transactions using different currencies for cross-border payments. Figure 4 shows the steps in the process which are discussed in the following.

The first step of the process is to connect two or more entities via nodes. The purpose of the nodes is to keep connection with each entity thus requiring a peer-to-peer network to be established (Mills et al. 2016). Figure 4 shows the Nostro reconciliation process of two banks, Bank A and B, where Bank A holds a Nostro account with Bank B and trades in Bank B's currency. In the first step, Bank A will start its transaction with Bank B via SWIFT (a network which is used for transferring funds). At the same time, Bank A must create a linked request in the distributed ledger for starting the transaction with Bank B, which records each and every transaction via SWIFT. The records can later be confirmed by Bank B during cash disbursement (Fargo 2016). Now Bank B can view all the transactions between Banks A and B in real-time which previously used to take 24 h (Fargo 2016). In the third step, Bank B disburses funds and simultaneously confirms requests in the distributed ledger system which notifies Bank A immediately. The advantage of distributed ledger technology in payment transparency is that it confirms the settlements between the financial entities and identifies delays or problems with the transactions more quickly given the transparency.

Table 6 Digital business transformation using blockchain

Firms using blockchain	Type of industry and product	Applications of blockchain	Contexts
FedEx	Courier delivery service	Use blockchain to track high-value cargo and solve problems regarding payments	World Wide
Burger King	Fast food chain	The brand uses blockchain technology by introducing Whopper coins to fuel their reward program. Customers can hold on to their reward or sell them	Russia
Mastercard	Financial services	Using blockchain for secure payment at point-of-sale (PoS). Although this is yet to be established the financial giant is heavily exploring blockchain technology	USA
JP Morgan	Financial services	The financial giant wants to use blockchain to tackle the issue of international financial transactions, and lower the cost of operation	World Wide
Huawei Technologies	Mobile company	The mobile giant wants to use blockchain for privacy and security	World Wide
Bank of America	Financial services	Bank of America hopes to use blockchain for more transparent financial services for both consumers and business. Recently they have patented 9 more blockchain related technologies	World Wide
EY (Ernst and Young)	Professional services	In April 2018 one of the big four audit firms, EY, announced a pilot test for their blockchain technology which will analyze cryptocurrency transactions	World Wide
Ubiquity	Legal services	The complication in the legal process of transferring real estate has been simplified using blockchain	USA
Transactivgrid	Energy distribution	Reducing the costs of energy distribution by allowing members to locally produce and sell energy	USA
Essential	Travel	This firm is developing a new system for the Dutch government to securely store passenger data	Netherlands

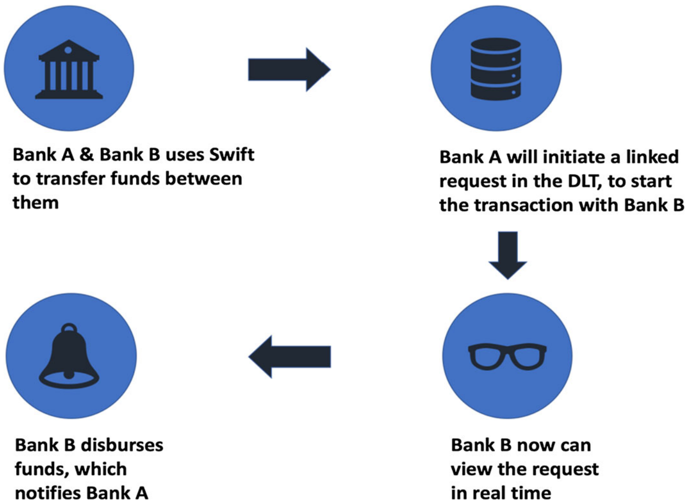

Fig. 4 Blockchain operation between two banks

3.3 Cloud computing as a driver of digital business transformation

Microsoft has reported a 36% growth in their net income in the last quarter of 2019 to $11.6 billion through the growth of its cloud business model (i.e., Azure) competing against Amazon, Salesforce and Oracle. Benlianet al. (2018) state that cloud computing is an evolved computing system and business model for providing information technology, infrastructure components and applications. According to Bhushan and Gupta (2018), cloud computing is a computational model that has the ability to process on-demand access to networks with a shared pool of resources (hardware/software), which are customizable and where a minimum amount of intervention is required from the service provider. Avram (2014) identifies some commonalities in defining cloud computing, such as the business model is based on pay per use, the space in the cloud is elastic and can have the illusion of being an infinite resource, and finally, it is a self-service interface where resources are virtualized.

Cloud-based computing has emerged as a mixture of three major trends of a computing system through the Internet: service orientation, virtualization and standardization (Sharma et al. 2015). It has the power to provide highly scalable distributed computing systems (Wang et al. 2020; Xia et al. 2020). It can be described as a platform that enables on-demand network access from a shared pool of computing resources which are configurable and requires minimum management effort (Almorsy et al. 2016). Undoubtedly, it is a disruptive technology which has transformed the IT sector and Internet services (Botta et al. 2016). The ultimate benefit of using cloud computing is that the user can scale up or down the usage of cloud according to their needs and are charged accordingly, minimizing the cost of doing business globally (Sabi et al. 2016). Cloud computing offers three types of services: (1) Infrastructure as a Service (IaaS), such as cloud-based storage services available on demand (e.g., Amazon Elastic Computing Cloud) (2) Platform as a Service (PaaS), such as operating system supports and software development frameworks (e.g., Google AppEngine), and (3) Software as a Service (SaaS), such as storage processing and network resources allowing consumers to control applications (e.g., Joyent and Salesforce CRM). Along with the three service models, cloud computing has five characteristics and four deployment models. The five characteristics are on-demand self-service, broad network access, resource pooling, rapid elasticity and measured service (Battleson et al. 2016). The deployment models are private cloud, community cloud, public cloud and hybrid cloud. Kushida et al. (2015) depict cloud computing as a revolutionary technology that has transformed the location of computing and how software and tools are produced for business processes.

Businesses across the world are being transformed through cloud technology due to lower infrastructure costs, more innovation and significant digitization (Lemley et al. 2017). Bo (2018) states that cloud technology enables necessary business agility by increasing efficiency in the system. Cowen et al. (2016) report that cloud technology increases return on capital by improving operations and quality of service. Marković et al. (2014) describe how cloud computing can transform businesses in healthcare and education. Kasemsap (2015) reports that it is important to combine cloud computing with the supply-chain process to achieve maximum efficiency with customers and suppliers. Cao et al. (2017) link cloud technology with supply chain optimization by highlighting demand access, security and back up, sharing real time inventory and sales information, scalable services and payment arrangements. Table 7 lists examples of cloud computing applications.

3.3.1 A case study on cloud computing-based digital business transformation

Figure 5 shows a cloud computing-based service as presented in the Adobe Creative Cloud system. The illustration derived from Armbrust et al. (2010) depicts the relationship between the cloud provider and the user. As a provider of SaaS, Adobe Creative Cloud provides a subscription to the user to install the application system. The cloud provider and SaaS provider could be the same entity, as in this Adobe Creative Cloud instance. The SaaS user is the end end-user of the cloud, such as an Adobe Photoshop user. Adobe Creative Cloud for enterprise runs on the Amazon Web Service (AWS), which makes collaboration and operation easier and flexible for the users. The users can run Adobe Creative Cloud services such as Adobe Photoshop and Illustration in desktop and mobile applications, where an end-user can download the app from Adobe Cloud service using a license. The cloud service provides various features such as collaborating in the cloud service for project management, accessing fonts and stock images. The services in the cloud can be accessed through users' unique identification, hence only the users entitled to the service has the power to access it and share content with the chosen audience.

3.4 Data analytics as a driver of digital business transformation

Data analytics has gained momentum in recent years due to the emergence of big data. According to Akter and Wamba (2016, p. 178), it is a "holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage". Big data is beyond the capacity of conventional database systems (Dumbill 2013) as the data do not fit the structure of databases' architecture, hence an alternate way is required to process and gain value from the data. Due to the size and incompatibility of processing big data using existing information systems, advanced information technologies are required to extract maximum value from the data.

With the constant progression and evolution of data and computing power, big data has been effectively used for business or data analytics (Wamba et al. 2015). Both big data and traditional analytics explore ways to extract value-added information from different data

Table 7 Digital transformation cases using cloud computing

Firms	Uses of cloud computing	References
Microsoft	Microsoft has successfully leveraged cloud-based innovations to host machine learning and artificial intelligence to give an edge to its business customers through customer relationship management and supply chain management software	Duff (2020)
Adobe system	Offering cloud-based subscription called creative clouds, Adobe has experienced customer growth and stronger customer relationships. Adobe studied years of industry trends before moving towards cloud-based product and service offerings	Cohen (2017)
Goldman & Sachs	Adopting a private cloud infrastructure has led Goldman & Sachs to improve risk management for their derivative products and business	Seth and Kaplan (2016)
The Hartford	Using a private cloud to reduce costs, The Hartford was able to bring products and services to the market faster and meet the needs of customers and agents	Guido (2014)
Delhaize America	The company is using big data analytics on cloud computing to learn the impact of local weather on category sales	Guido (2014)
Pearson	The education group is using an enterprise wide cloud strategy to provide web-oriented educational products to South Africa and China	Guido (2014)
Intercontinental Hotels	The Intercontinental Hotel Group is using cloud computing to boost its customer service and email marketing activities to a greater extent	McDonald (2016)
Commonwealth Bank Australia	The Australian banking giant is planning to move 9000 virtual machines to the private cloud for better operational activity and for better delivery of services	Sharwood (2018)
DHL	The supply chain giant uses SAAS to upload data which can provide real-time insight to risk management	(Murphy (2015)
Capital One	Using AWS has helped Capital One to support faster innovation and enhance the customer experience. The company made savings through shifting resources, found value in data and recovered faster from failures. Working with AWS helped the bank to launch products within weeks instead of months, providing cutting edge customer service solutions by using data to feed machine learning analysis	(Amazon 2020)
Qantas	By using Microsoft Azure, Qantas provides a unified solution for better operations and customer service. Azure helped generate personalized services and connected employees all over the world	Doniz (2018)

Fig. 5 Cloud computing-based service by Adobe

sources in order to gain a competitive advantage (Battisti et al. 2019; Camilleri 2019; Shams and Solima 2019). However, traditional analytics differ from big data analytics on four dimensions: volume, variety, velocity and accessibility (Morabito 2015). Volume represents a disproportionately large amount of data and the smaller data storage requirements of businesses. These entities need to obtain large quantities of data from ubiquitous, heterogeneous and constantly evolving sources and devices to generate effective and meaningful information for accurate and precise decisions (Wamba and Akter 2019). Variety refers to different types of data collected from business entities, which could include structured, semi-structured and unstructured data. Due to the dynamic nature of big data, velocity relates to the rate of data generated and analyzed, and sometimes includes real-time analytics. Accessibility is defined as the capacity to acquire data from various sources (Ohlhorst 2013; Sathi 2012). However, many researchers tend to replace accessibility and include veracity as the fourth dimension of big data, and describing the dimensions as the 4Vs. Veracity is related to trustworthiness and access to a complete set of data as the uncertainty, complexity, inconsistency and anonymity of big data could influence its reliability. In recent times, another two dimensions, value and variability, have been proposed by other authors, characterizing big data as 6Vs (Akter et al. 2019). Variability is linked to heterogeneity of big data as they could be generated due to differential velocity. Lastly, the economic value related to the type of data dictates the value dimension of big data. Data in the unprocessed form is useless until it is examined using appropriate analytics to extract meaningful information.

Consumers, automation and monetization are considered the three main drivers for big data (Sathi 2012). In recent times, big data has experienced further growth due to the Internet of Things (IoT), which includes machine intelligence. Due to the interconnected nature of networked technologies and smart devices, IoT can facilitate rapid and constant exchange of realtime data, with the potential for improving functionality and upscaling processes, leading to the generation of new and better products and services (Xia et al. 2012; Kopetz 2011; Gubbi et al. 2013). Big data opens up new opportunities and generates added operational and financial value (Ohlhorst 2013; Morabito 2015; Sathi 2012). As a result, companies can use their resources to achieve better outcomes utilizing the potential of big data. Cost-efficiency and effectiveness, improved decision making and exploring new opportunities are considered the three main benefits of big data analytics (Davenport 2014). Technologies related to big data can be adopted in large companies to strengthen traditional technologies. It can significantly improve efficiency by increasing productivity and product quality by improving values (Manyika et al. 2017). Production data can be analyzed to map the optimum use of resources, i.e., time, human workforce and raw materials. Big data can improve pre/post-production stages of the supply chain and combine production data with other functions, thereby improving overall efficiency and effectiveness (Feinleib 2014; Ohlhorst 2013). Big data analytics can be utilized in more effective and faster decision-making and provide opportunities to reach evidence-based decisions. Data-intensive companies such as Google, eBay, Amazon and Facebook generate additional revenue and adopt new value-streams through big data analytics. Information from large data sets can transform business models, boost innovation capabilities and productivity, and open up new markets using data-driven approaches (Gobble 2013; Davenport 2014; Chen et al. 2012). Table 8 shows use cases of big data analytics.

4 Discussion and conclusions

While this study provides some primary understanding of ABCD technologies drawing on literature and case studies, the applications of these technologies demonstrate that more research is required to understand their dynamic nature. The findings show that although the four technologies have individualized benefits, more business value could be derived from harnessing their interconnectivity to accelerate business growth and productivity. Also, ABCD technologies are driving the development of transformative business models with new platforms that automate processes, match demand and supply, dynamically price and make real-time decisions. This section discusses some of the challenges and limitations of these technologies from various stakeholders' point of view.

With regard to *AI*, this paper highlights positive business-oriented use cases and applications. However, there are widespread concerns, such as ethics, privacy and algorithmic bias (Larson 2019). The danger of AI has already been highlighted by Elon Musk in the context of regulatory oversight and its safe use (Metz 2018). Due to these issues, customers tend to have less trust in AI because they think AI cannot "feel" (Gray 2017). Research shows that people do not trust AI-based decisions or answers such as medical diagnosis, financial planning or hiring (Davenport 2018). Although AI, ML and DL are at the peak of their hype cycle, it is argued autonomous systems should not replace humans. In a similar spirit, the CEO of IBM proposes AI equates to man "plus" machines instead of man "versus" machines (Carpenter 2015), in what could be described as human–robot teaming and collaboration. According to Davenport (2018), full disclosure and transparency about the intelligent agent or hybrid systems (both human and automated device) should clarify the roles of human and machine, because the majority of customers have a negative perception towards bots and virtual assistants, though studies have shown that certain demographics would much rather chat in an online window with both than actually speak to a call center representative and be on long hold waiting times. Also, ensuring accuracy, replicability and reliability in AI algorithms is critically important whether in self driving cars or diagnosing patients with AI. Yet some of the grandest challenges will have to do with AI-based business productivity tools that listen to every conversation and translate speech to text, see every movement and process that movement against a set of known behaviours, and identify individuals without their consent (even if they are a single suspect amongst many). While AI has a high degree of accuracy based on a quality and diverse data set, it can also make mistakes which are generally known as false negatives and false positives in the literature. Individuals who are subject to errors through ill-defined algorithms can experience asymmetric effects. Through longer term training of diverse data sets, it is said that errors will decrease in size and frequency, making systems more reliable. Controversy has struck AI systems presently being used in law enforcement, and courts of law, where AI is used to determine both eligibility for arrest or even sentencing time periods (Re and Solow-Niederman 2019). As unstructured data in the form of visual analytics becomes analyzable through sophisticated AI, the algorithms

Table 8 Digital transformation cases using data analytics

Firms	Cases on analytics applications	References
McDonald's Corporation	Sales data is utilized to optimize the drive-thru experience, trickle down to kitchen operations, the supply chain, menu suggestions, personalized menus and deals based on customer purchase history	Elmes (2019)
JP Morgan Chase & Co	Several artificial intelligence and machine learning programs optimize some of JP Morgan Chase's processes, including algorithmic trading and commercial-loan agreements interpretation. There is a reduction of the time needed to review documents: tasks which previously required about 360,000 h of work, now take just a few seconds to complete	Aleksandrova (2019)
CitiBank	Use of real-time machine learning and predictive modeling to analyze big data to pinpoint fraudulent behavior and minimize financial risk for online banking providers. CitiBank can spot suspicious transactions, e.g., incorrect or unusual charges, and promptly notify users about them. Apart from being useful for consumers, the service also helps payment providers and retailers monitor all financial activity and identify threats related to their business	Aleksandrova (2019)
Microgaming	Accurately determines the odds and personalizes games for different types of players, tracking player statistics and incorporating these into the personal gaming experience	Vickery (2016)
Netflix	Netflix collects data from its 151 million subscribers, and implements data analytics models to discover customer behavior and buying patterns. Then, they use that information to recommend movies and TV shows based on subscriber preferences	Dixon (2019)
Booking.com	Data contained in the "Booking.com Analytics" is harnessed by a proprietary logic that converts it into a prioritized list of actionable business advice. Also, Booking.com thinks that partner hotels can quickly peruse the opportunities, select the most relevant options for their property, and instantly implement them to enhance their listing and grow their business through their Booking.com portal	Sklyar and Kharchenko (2019)
Dignity Health	Uses a big data and advanced analytics platform to predict potential sepsis cases at the earliest stages, when intervention is most helpful	Beall (2020)
Express scripts	Analyze individual patient data and alert health care workers to serious side effects before a medication is prescribed	Beall (2020)

for example, conducting people searches may well be governed at a state/provincial level supported by legislation.

The implications of *blockchain* technology are fascinating due to the decentralization of user data and achieving consensus through a public network of participants to ensure the accuracy of information (Kumar et al. 2020). However, it is critical to evaluate its core promises, such as transparency, security, decentralization and immutability in transactions. While firms across the world are experimenting with meaningful scalability of this technology, further work needs to be completed, such as establishing a common standard, technical capability, and digitization of assets (Carson et al. 2018). Kumar et al. (2020) suggests that blockchain technology needs to pass three tests, viz. the decentralization test (i.e., political, architectural, commercial and contractual), the crypto asset test and finally, the business model test. Since assets, trust, ownership, money, identity and contracts (ATOMIC) are all programmable in the blockchain domain, it is important to manage how to create and capture value from each of these components. According to Wamba and Queiroz (2020), "[d]espite the numerous potential benefits of blockchain, blockchain related concepts (e.g., enablers, adoption, implementation, etc.) are still to be well mastered by a good number of managers. The challenges about how they can ensure that blockchain adds value to their organizations and the supply chain management [SCM], remain unanswered". While many tout the auditability of the blockchain to be one of its greatest strengths, re: transparency, there are inevitably cybersecurity matters to address. The main challenge for the blockchain arguably is ensuring that a trusted system is not riddled with counterfeit blocks or counterfeit data permeating from fake and illegitimate transactions or sources of transactions that is not only unchangeable on the public ledger, but is used to drive vital decisions that then further corrupt the digital ecosystem. Auditability becomes near impossible in an environment that bases everything on the digital with no way to recalibrate what is fact and not fiction.

Although *cloud computing* has evolved dramatically, challenges revolve around standards and interoperability of this platform. According to Kathuria et al. (2018), cloud computing can be based on technology capability, cloud service portfolio capability (cloud service offerings, market offerings), or cloud integration capability (legacy synchronization, legacy consistency) to influence business value and firm performance. Since cloud computing is the backbone of digital transformation, it is critical to research the interconnectivity between cloud computing and the Internet of Things, AI, blockchain, data analytics, and crowdsourcing to develop an innovative business model. Recent failures in cloud implementation have been caused by poor integration and lack of business value. Cloud computing hacks have also been behind some of the biggest retail data breaches in online customer history, rendering service level agreements (SLAs) between the business and cloud computing providers as void. When data of hundreds of millions of customers is compromised, it is a serious issue to be dealt with through the courts, although end-users are left scrambling when their identity credentials are stolen, and class action law suits take 5 or more years to determine. Mandataory data breach notification (MDBN) principles and regulations seek to empower Privacy and Data Commissioners around the world to enforce disclosure of data breaches to consumers who have been compromised in deep hacks where personal identifying information (PII) has been stolen (e.g., credit card numbers, name, date of birth, login and password details), but critics of MDBN note that after a commensurately small penalty to ecommerce service providers, it is back to business as usual. The same can be said for IOT devices that are placed in key public locations within business and customer sites to drive innovation, producing speech or video analytics of sentiment among employees, visitors and customers (e.g., museums). What are the means by which business can convey to citizenry that their tools are conducting real-time data collection and analysis? What are the legal and ethical considerations and how can businesses keep pace with evolving societal expectations? Thus, future research should investigate these factors and their implications for the strategic business value of digital transformation and clear processes towards consent.

Although *data analytics* are transforming business operations, firms need to address challenges in both managerial and technological contexts to extract value from large data sets (Michael and Miller 2013). With regard to technology, incompatible IT infrastructure and data architecture can impede the ability to store, analyze and derive effective information from data sets, which comprise structured, semi-structured and unstructured data. In addition, there are serious challenges arising from incompatible technologies related to enterprise-wide platforms for sharing big data and its analytics with a given organization and its sectoral system as well as the inconsistency of internal and external databases. Acquisition of data from third parties can also pose the risk of data being outdated and of diminished value. Missing, incomplete or inaccurate data, often known as "dirty data" can also act to corrupt models and algorithms, simply by skewing results. It is important that acquired data meet two important criteria: understanding and quality. To extract insights from collected data, it is essential that analytics possess the ability to comprehend and to differentiate relevant data from unconnected and misleading data so that appropriate decision-making processes can happen.

Overall, DBT implementation needs to focus on how to integrate ABCD and other emerging technologies (e.g., Internet of Things) for various business functions in hybrid modes, integration, recombination and in convergence. For example, cloud based accounting gains momentum if it is fuelled by AI, big data and blockchain based financial reporting (Ionescu 2019). In order to develop a holistic platform using innovative technologies, Gill et al. (2019) propose a framework showing how to integrate AI, IoT and blockchain for next-generation cloud computing environment. Similarly, recent studies highlight the connection between AI, deep learning, and blockchain as complementary technologies for digital transformation (Arora et al. 2020; Ekramifard et al. 2020). This integration can help firms develop customer relationship management, supplier relationship management and innovative business models. For example, cutting edge, cloud-hosted AI platforms like Microsoft's Genee, Oracle's Crosswise or Salesforce's Einstein aim to achieve competitive advantage in their respective marketplaces through predictive and prescriptive analytics (Kumar et al. 2020). The fundamental applications of emerging technologies (e.g., AI, augmented technology, sensors, IOT and robotics) and insights into how to integrate these processes can better explain the behavioral consequences for customers and employees (Davenport and Spanyi 2019; Grewal et al. 2020; Verhoef et al. 2019). Table 9 lists some of the research questions that are relevant to the development and deployment of ABCD technologies and their interconnectivity for business transformation and operational excellence.

5 Conclusion

Using a multidisciplinary perspective, this study puts forward ABCD technologies as the fundamental building block for the future of digital business transformation (DBT). To answer the research questions on DBT using ABCD technologies, we started with a discussion clarifying the DBT concept and its implications for various industries. Next, we introduced AI, blockchain, cloud and data analytics with operational use cases and applications. Since their operational effectiveness will determine the future of DBT, the findings shed light on various challenges and opportunities. A critical question for firms is to establish interconnectivity

Table 9 Future research questions for digital business transformation using ABCD technologies

Digital transformation research streams	Relevant theories	Future research questions
Digital transformation strategy, culture, leadership, and organization	Resource-based theory (Barney 1991)	How to ensure fairness and ethics in AI, trust in the blockchain, cloud security and privacy of analytics?
	Dynamic capability theory (Teece et al. 1997)	How can organizations ensure digital transformation and strategic business alignment between ABCD technologies?
	Competitive strategy (Porter and Millar 1985)	How can organizations better incorporate functional differences into their digital transformation culture?
Operations management of ABCD technologies	Transaction cost theory (Williamson 1979, 1981)	How can organizations better use ABCD technologies to achieve operational excellence and sustainable growth?
		How to develop and deploy AI systems that prevent and detect an algorithmic bias?
ABCD technology infrastructure, privacy and security of digital transformation	IS success theory (Delone 2003; DeLone and McLean, 1992)	What are the capabilities of data governance, security and privacy for digital transformation using ABCD technologies?
	Sociomateriality of IT (Orlikowski 2007)	How can a firm leverage ABCD technologies to enhance firm performance?
		What should be the drivers of integration, hybridization, recombination and convergence of/between ABCD technologies?
Business value	IT business value (Melville et al. 2004), the business value of analytics (Wixom et al. 2013)	How does ABCD adoption/continuance vary across firms/industries?
		How do ABCD and organizational decision-making process jointly influence business value?
		How can firms leverage ABCD technologies to adapt to business models?

among these technologies to reap the ultimate benefits. In essence, these processes of innovation include: hybridization, integration, recombination and convergence. Due to the nascent stage, this study summarized the initial emergence of ABCD technologies and their impact on digital transformation through business use cases. We hope researchers will explore these cases in greater depth in addressing the research questions posed in Table 9.

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