View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by AIS Electronic Library (AISeL)

Association for Information Systems

AIS Electronic Library (AISeL)

ICIS 2019 Proceedings

Governance, Strategy and Value of IS

The Impact of Deep Learning on Organizational Agility

Haining Wang
University of Warwick, phd18hw@mail.wbs.ac.uk

Jimmy Huang
Warwick Business School, jimmy.huang@wbs.ac.uk

Zhewei Zhang
Warwick Business School, zhewei.zhang@wbs.ac.uk

Follow this and additional works at: https://aisel.aisnet.org/icis2019

Wang, Haining; Huang, Jimmy; and Zhang, Zhewei, "The Impact of Deep Learning on Organizational Agility" (2019). *ICIS 2019 Proceedings*. 26.
https://aisel.aisnet.org/icis2019/governance_is/governance_is/26

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICIS 2019 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

The Impact of Deep Learning on Organizational Agility

Short Paper

Haining Wang
Warwick Business School
University of Warwick
Coventry CV4 7AL
United Kingdom
eric.wang.18@mail.wbs.ac.uk

Jimmy Huang
Warwick Business School
University of Warwick
Coventry CV4 7AL
United Kingdom
Jimmy.Huang@wbs.ac.uk

Zhewei Zhang
Warwick Business School
University of Warwick
Coventry CV4 7AL
United Kingdom
Zhewei.Zhang@wbs.ac.uk

Abstract

Artificial intelligence advances business model, strategizes competitive resources, and impacts on organizational agility. Deep learning as a subset of AI brings changes in different aspects that substantially influences organizational capabilities. We argue that deep learning enables new conceptualization of organizational agility. We will conduct a case study in a leading Chinese FinTech company to inductively ground these impacts.

Keywords: Artificial Intelligence, Deep Learning, Organizational Agility.

Introduction

In recent years, deep learning becomes a predominant machine learning method used in a wide range of artificial intelligence designs that can produce remarkably accurate results (Goodfellow Bengio and Courville 2016). Similar to other machine learning methods, deep learning relies on algorithms (Schmidhuber 2015), and can make data-driven predictions (Deng and Yu 2014). In particular, deep learning can automatically manipulate data without human control on the rules (Chollet 2017), in turn generating immediate, customized, and accurate results. One of the most significant influences of deep learning is on how firms formulate dynamic capabilities, one of which organizational agility has been drawn to our attention.

Deep learning distinguishes itself from other prevailing machine learning methods in its ability to process unlabeled data (LeCun Bengio and Hinton 2015). Common machine learning methods require labelled data to perform tasks whereas deep learning can process natural data in raw forms (Domingos 2012). Such ability requires deep learning to exhibit a particular way of data collection, data analysis, and algorithms. First, data should be collected in large quantity and variety so that deep learning can gain sufficient information (Najafabadi et al. 2015). Second, analysis has been transformed by deep learning to an exceptionally data-driven and evidential process (McAfee and Brynjolfsson 2012). Third, deep learning algorithms (e.g. neural networks) empower the machine to resemble human by learning tacit decisions (Bengio Courville and Vincent 2013). Through these particular changes, deep learning enables the machine to control decision-making over human; and potentially leads to data and machine management over human and knowledge management. As a result, deep learning enables firms to become agile that is inherently data-driven and machine-based.

Organizational agility captures the capability of firms to quickly sense and respond to market dynamics (D'Aveni et al. 2010; Jaworski and Kohli 1993; Overby et al. 2006). Park et al. (2017) conceptualize organization agility as a sense-response process loop, which entails sequence in steps (sensing, decision-making, and responding). Both sensing and responding can be improved by applying business intelligence techniques (Park et al. 2017) whereas improvement in decision-making requires efficient communication amongst involved stakeholders (Kester et al. 2011). The key difference is that decision-making step is necessarily involved with human. If deep learning can be trained to incorporate decision-making criteria to the rules, machine can individually and automatically generate organizational agility.

This research looks into "what is the impact of deep learning on organizational agility?" We answer this research question by examining deep learning functionalities and their linkages to the key steps of organizational agility. Each functionality enables a particular way of using data, and each linkage makes a difference to each step of organizational agility. The aggregation of these changes enables a re-conceptualization of organizational agility.

Theoretical Background

Artificial Intelligence, Machine Learning and Deep Learning

Artificial intelligence (AI) enables the machine to exhibit human intelligence including the ability to perceive, reason, learn, and interact, etc. (Rai et al. 2019; Russell and Norvig 2016; Nilsson 2014). Essentially, AI is a broad concept that captures the intelligent behavior of the machine. Machine learning empowers the machine to "learn" without explicit programming (Samuel 1959). This learning process is accomplished by machine itself through collecting data, analyzing data and making predictions. So machine learning is a subset of AI and serves as a technique to operationalize AI. The principle of machine learning incorporates training algorithm to enable machines to learn how to make accurate predictions. There are four training categories of machine learning algorithms: supervised, semi-supervised, unsupervised and reinforcement (LeCun Bengio and Hinton 2015). Deep learning is defined as a category of machine learning algorithm that can derive structure from raw data in a multi-layered manner (Deng and Yu 2014). It can use all four training approaches to achieve respective functions. The way deep learning process data and generate result resembles how human brain identifies patterns, categorizes information types (Schmidhuber 2015).

Deep learning is essentially data-driven (Molnar et al., 2018) and is enabled by algorithms, architecture, learning weights (Honegger, 2018), and high volume of data input (McAfee and Brynjolfsson 2012). These characteristics of deep learning have allowed business from increasing domains to establish new competitive resources and enhance business competitiveness (Agarwal and Dhar 2014) through unprecedented algorithm capabilities. For example, deep learning with neural network algorithm has helped traveling industry in price forecasting (Elliott 2017), healthcare system in disease diagnosis (Chen and Asch, 2017), and financial services in credit risk detection (Pasquale 2015). The uniqueness and strength of deep learning attribute to multilayered architecture and diverse propagation, which enhance accuracy (Goodfellow Bengio and Courville 2016) in result.

Changes Induced by Deep Learning

Specifically, deep learning influences organizational behavior in human-machine relationships through several aspects of changes. First, changes are reflected in the way by which data is collected. Increasing functionalities of digital devices allow people to collect data with significantly larger quantity and diversity (Newell and Marabelli 2015). Data collected from digital devices and can be traced and recorded is, termed as "digital trace data" (Wu and Brynjolfsson 2009). Digital trace data is not only rich in quantity but also in diversity so that deep learning can comprehensively enhance the accuracy in result.

Second, data analysis is a subsequent and critical aspect that follows the data collection, and contributes to the value capture and creation of the data. Data analysis includes data mining and statistical analysis (Chen et al. 2012). These functions are mainly supported by algorithms that can classify, cluster, and regress data. Typically, deep learning uses neural networks-based algorithm to conduct data classification and pattern generation. This advanced capability in algorithm empowers deep learning to explore and leverage unique data features in a superior way.

Third, algorithm is regularly updated so that the machine can exhibit increasing intelligence (Schmidhuber 2015). The cause of algorithm advancement should attribute to the use of big data. With more information extracted from big data, deep learning can improve the algorithm capability and intensify the influences. In particular, neural networks-based algorithm can essentially improve to perform as human brain with hidden neurons and multi-layered structure (LeCun Bengio and Hinton 2015; Honegger 2018). The direction of algorithm advancement can be considered as human-like reasoning and machine-level speed.

Organizational Agility

Organizational agility refers to the capability of a firm to quickly sense and respond to its external environment (D'Aveni et al. 2010; Overby et al. 2006). Cockburn (2006) stated that organizational agility must have a light and supple structure so that timely change can be maneuvered. Therefore, agile firms can constantly prepare themselves for competitive actions, which facilitate the value creation, value capture and competitive performances (Sambamurthy et al. 2003) in volatile environments (Prahalad 2009).

Most scholars have conceptualized organizational agility with two imperative components: sensing and responding (Nazir and Pinsonneault 2012; Overby et al. 2006). If either component is limited, the overall agility will be impeded (Tallon et al. 2018). Firstly, sensing refers to scanning business cues from external environment so that firms can prepared to maneuver strategy, solidify competitiveness and enhance performance (Daft and Weick 1984; Thomas et al. 1993). The scanning process should effectively filter and extract useful information, so that firms can then decide to follow up with actions (El Sawy 1985).

Secondly, responding refers to the actions that specify the way to manage resources and gain competitiveness in face of environmental changes (Daft and Weick 1984). These actions include new products or services line, new operational models, new cooperation partners, new segments of customers, and even redesigning of organizational structure (D'Aveni 1994; Thomas et al. 1993). Therefore, other competitors may sense these actions as new market changes and react accordingly.

Thirdly, Park et al. (2017) highlight decision-making as another component of organizational agility. It exists and works between sensing and responding from an information process perspective. Decision-making refers to interpreting scanned information in a way that firms can clearly define opportunities and threats (Thomas et al. 1993). This step requires human (e.g. executives, top managers etc.) to analyze and plan on how to make full use of opportunities and alleviate threats (Houghton et al. 2004; Kester et al. 2011). Therefore, the extent to which decision-making can be agile will determine the firm's overall agility.

Fourthly, Park et al. (2017) also demonstrate the relationship among these three components as a process or a loop with sequence and steps. Sensing, decision-making, and responding works in this specific sequence and compose a unit for a firm to demonstrate organizational agility. It captures how information flows between the organization and environment. Therefore, all three components should be agile enough to contribute to the organizational agility.

Organizational Agility and IT

IS literature mainly focus on IT as an enabling factor of organizational agility. IT is considered as a crucial infrastructure that equips firms with adaptability (Haeckel 1999) to ever-changing conditions (Lucas and Olson 1994). Sambamurthy et al. (2003) state that IT enables digital options that can be used to quickly sense market opportunities. Overby et al. (2006) argue that digital options can be either knowledge-based or process-based. While knowledge-based digital options refer to technology that can help firm access and utilize information to gain competitiveness; process-based digital options refer to infrastructure that firm can possess to coordinate information. Knowledge-based digital options can mostly support sensing and process-based digital options can mostly support responding. In particular, IT helps firms to access, filter and organize customer data so that firms can effectively sense the market (Chakravarty et al. 2013). IT enables firms to coordinate communication so that firms can realize efficient decision-making (Lu and Ramamurthy 2011). Furthermore, IT helps firms to organize and store data so that firms can make timely responses (Wixom and Watson 2001).

Changes in technology have led to changes in the way we conceptualize organizational agility and IT. Building on the work of Park et al. (2017), we are particularly interested at examining how new technology affects the three key components of organizational agility, namely sensing, decision-making, and responding. Specifically, we aim to extend the extant literature by exploring how firms utilize new technology to scan business cues from the environment, so that firms can initiate decision-making and responding steps to maneuver strategy, competitiveness and performance (Daft and Weick 1984; Thomas et al. 1993). We elaborate these changes and their impact on organizational agility in turn.

Changes in technology can influence the sensing capability of firms. Sensing can be better supported by IT infrastructure capability (Lu and Ramamurthy 2011). The comprehensiveness of information acquired and the speed of information processed altogether determine the quality of sensing. Decision-making step refers to the process to assess opportunities and threats from what has been sensed from the external environment (Thomas et al. 1993). Changes in technology provide firms with more efficient coordination of information (Chan et al. 2006) and communication of people (Okhuysena and Bechky 2009). Also, technology changes enable internal integrations that aim at structural standardization and explicit knowledge (Nazir and Pinsonneault 2012). Therefore, changes in technology can affect decision-making through infrastructure and/or organizational structure. Afterwards, responding step is conducted as an organizational action to the market with strategy and/or products. Changes in technology can influence the extent to which responses are accurate, customized, and timely. The quality of responding depends on the data analysis and coordination with decision-making. Technology can bring in advanced analytic and processing power of data to enhance the responding capability. Also, since responding and decision-making work in sequence, technology changes, which can fundamentally improve decision-making, will improve responding accordingly.

Changes in Organizational Agility by Deep Learning

Based on the identification of deep learning functionalities, changes in data collection, data analysis, and algorithms can collectively influence how organizational agility works in current theorization. With particular approaches in data collection, data analytics and algorithms, deep learning can be trained to speedily appropriate more comprehensive information (Chollet 2017) in sensing, to learn from what executives behave towards gathered information (Schmidhuber 2015) and become an "executive" to complete decision-making step, and to generate faster and more accurate responses (Goodfellow Bengio and Courville 2016). The way deep learning operates essentially controls all three components of organizational agility. Deep learning can fundamentally accomplish each task in an automatic manner where sequential actions can largely become simultaneous actions. Thus, deep learning is highly likely to change how we theorize organizational agility.

Theoretical Development

To develop a comprehensive understanding, we aggregate all the changes led by deep learning (Wu and Brynjolfsson 2009; Chen et al. 2012; Schmidhuber 2015) with current debates and perspectives of organizational agility (Lu and Ramamurthy 2011; Nazir and Pinsonneault 2012; Chakravarty et al. 2013; Park et al. 2017). Essentially, we aim to capture how organizational agility works based on deep learning implementation. This approach of theorizing will uncover how deep learning functionalities influence the key steps of organizational agility. Understanding such influence contributes not only to the reconceptualization of organizational agility but also to the impact of deep learning.

From the current literature, we have categorized three streams of influences (A1-A3, B1-B4, C1-C2) in Figure 1, and explain each stream in turn, first, in stream A, sensing is influenced mainly by how data is collected and analyzed through deep learning. Indeed, deep learning requires vast amounts of data to operate in an effective way. Given that most data acquired by firms is essentially digital trace data, the variety and quantity of acquired data can significantly affect the effectiveness of how firms sense the market. Also, firms gradually implement cloud computing to store and manage data resources. The capability of cloud infrastructure and functions facilitates efficient management of data resources, thereby further supporting deep learning to use digital trace data within the firm (Li et al. 2017). Another aspect change is data-driven analysis, which enables better exploitation of digital trace data. So machines can reach and analyze all possible data resources in order to exhibit data-driven sensing function.

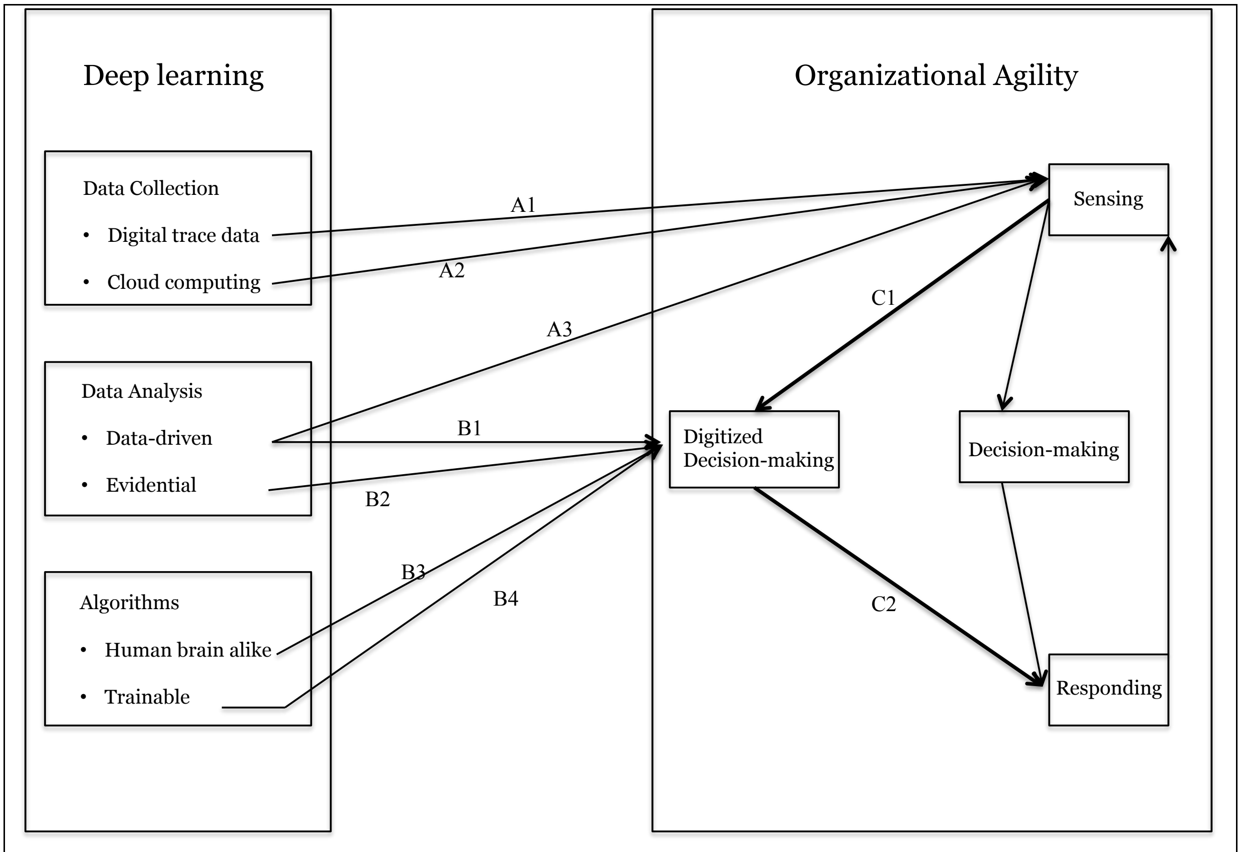

Figure 1. Research Model

Second, in stream B, changes in data analysis and algorithms led by deep learning can lead to a form of digitized decision-making. From the aspect of data analysis, executives are faced with exponentially increasing amounts of data to analyze so that more information can be considered and more effective decisions can be made. However, human cannot possible deal with ever-increasing data in a short amount of time. Deep learning can indeed accommodate such intensive workload in an efficient manner. Therefore, machine-generated decisions are data-driven and evidential whereas human-generated decisions are hardly data-driven and but experiential. Deep learning lead such change in data analysis can put forward to a digitized decision-making status.

In terms of algorithms, capabilities of algorithms can determine the degree of intelligence machines possess. In particular, neural network is a commonly used deep learning algorithm that can mostly resemble human. The mechanism of how neural network functions simulate human brain where neurons and multi-layered structure altogether enable tacit way of reasoning. Also, this type of algorithm can be constantly trained to exhibit ideal accuracy and effectiveness. Therefore, neural networks-based algorithm enables machines to largely digitize decision-making process.

Third, in steam C, new form of organizational agility potentially can exist due to different aspects of changes led by deep learning. It is clear that current conceptualization of organizational agility is a unit loop of sensing, decision-making and responding. However, given the changes induced by deep learning a new form of decision making, termed by us as "digitized decision-making process", will be developed.

Through the digitized decision-making process, conventional decision-making that is performed by human will gradually be handed over to the machine. Therefore, the machine will gain full autonomy over each step of organizational agility. Therefore, current conceptualization of organizational agility with its three key steps occurring in a particular order should be revised in the context of deep learning. All three proposed steams will be reviewed after the data collection and remains to be confirmed or modified.

Methodology

Research Setting

To identify changes in organizational agility as a result of deep learning implementation, we select a leading Chinese FinTech company to contextualize such change and analyze the collected data. This case is selected because it is particularly suitable for disclosing and enriching relationships and logic (Eisenhart and Graebner 2007) between deep learning and organizational agility constructs. FinTech companies provide a typical setting for answering this research question for several reasons. First, deep learning implemented in this company supports its business model different from traditional financial services. The loan assessment of a bank is basically undertaken by mixing human and machine (Lummer and McConnell 1989), whereas credit assessment in this FinTech company employs machines that use deep learning to accomplish this type of task. Second, FinTech business places credit assessment as a vital procedure in that accurate selection of users guarantees the corresponding business revenue. So the role of deep learning in the credit assessment can influence organizational agility by changing the process of sensing, responding and decision-making. Third, financial service has been creating disruptive influences with data-driven technologies (Huang et al. 2017). Deep learning implemented in many FinTech companies entails such disruptive influences. Aggregated changes led by deep learning can impact current theorization of organizational agility. This serves as a critical contribution on agility theory in current digital age.

Data collection

This research aims to conduct a case study with multiple qualitative data collection methods, including semi-structured interview, archival document and observation. The theory building takes place from recursively interpreting data, clustering constructs, and associating literature (Eisenhardt and Graebner 2007). A holistic single-case study will be conducted because this is a phenomenally emergent case (Yin 2003). Semi-structured interview will be conducted with working staff from different departments such as technical, marketing and strategy. The data analysis will follow a four-step, grounded, iterative process (Langley 1999; Strauss and Corbin 1998) in order to generalize a theoretical result. The intermediate stage of analysis is based on the principle of axial coding (Strauss and Corbin, 1998), as the new concepts are generated with the textual evidence and relevant literature. Then, a preliminary conceptual framework of how deep learning enables new form of organizational agility.

To conduct semi-structured interviews, we select informants who are knowledgeable, but share diverse perspectives towards deep learning, which helps to limit the bias in data collection (Eisenhart and Graebner 2007). We aim to use purposeful sampling (Kumar Stern and Anderson 1993) of all key informants who undertake tasks related to or influenced by deep learning implementation. The semi-structure interview attempts to capture (1) what changes led by deep learning have been realized; (2) how agile the firm is (through three elements: sensing, decision-making, and responding; and (3) how deep learning substantially changes above-mentioned three elements of organizational agility. All the interviews will be recorded and transcribed. Field notes will be taken during each interview and observation. Purposeful sampling can support continuous comparison of data across all the informants (Glaser and Strauss 1967). In general, our approach requires an iterative manner in data collection, data analysis and new informants seeking based on revealed information. This process ends when the data analysis reaches "theoretical saturation" (Glaser and Strauss 1967). Therefore, we can ensure the quality of the data for the emerging theory through the grounding process.

Preliminary Findings

We have conducted a preliminary meeting with this Chinese FinTech company, and have gained fundamental understandings in the deep learning implementation within the firm. Deep learning-supports financial services that are capable of reaching, benefiting and extending customers in exceptionally agile manner. The utilization of deep learning manifests two important points. First, the process of deep learning is entirely data-driven. Rules are solely based on data (answers can be understood as labeled data). Second, decisions are determined by machine. In the deep learning process, rules are derived from data and contribute to the management of data. The capability of machine is surpassing human by learning trivial management skills from data as human, by dealing with vast amount of data in a shorter time than human, and by generating accurate decisions than human. Since this is just a short and preliminary meeting with the company, these findings are limited but in accordance with our theoretical development. We aim to thoroughly conduct data collection soon to comprehensively disclose the theoretical framework.

Expected Progress

Current stage of this research has already identified several key aspects of changes led by deep learning. These changes and the way they influence the key constructs of organizational agility offer a promising opportunity to re-theorize organizational agility. So we are inspired to discover how organizational agility functions after the implementation of deep learning. We have gained access to a leading Chinese FinTech company and aim to collect qualitative data from in September. During that time, over 30 semi-structured interviews will be conducted. In addition, archival document and observation will be used as two additional sources of data collection. In October and November, we will conduct data analysis. A preliminary discussion to reflect data analysis and theoretical development will be produced. The full paper is expected to complete in the early quarter of next year. We believe this research will yield significant and novel contribution to the IS field.

Expected Contribution

This paper will contribute to current IS research by theorizing the impacts of deep learning on organizational agility. We have critically identified key theoretical constructs that are enabled by the implementation of deep learning, as well as their potential influence on the three steps of organizational agility. As highlighted in the theoretical development section, in-depth theorization of deep learning impacts will be based on the data collection and analysis in the following step. The prospected findings will shed light on the reconceptualization of organizational agility in the context of deep learning implementation.

Reference

Agarwal, R. and Dhar, V., 2014. “Big data, data science, and analytics: The opportunity and challenge for IS research,” *Information Systems Research* (25:3), pp. 443–448.

Bengio, Y., Courville, A. and Vincent, P., 2013. “Representation learning: A review and new perspectives,”.*IEEE transactions on pattern analysis and machine intelligence* (35:8), pp.1798-1828.

Chan, Y.E., Sabherwal, R. and Thatcher, J.B., 2006. “Antecedents and outcomes of strategic IS alignment: an empirical investigation,” *IEEE Transactions on engineering management* (53:1), pp.27-47.

Chakravarthy, A., Grewal, R., and Sambamurthy, V., 2013. “Information technology competencies, organizational agility, and firm performance: Enabling and facilitating roles,” *Information Systems Research* (24:4), pp.976–997.

Chen, J.H. and Asch, S.M., 2017. “Machine learning and prediction in medicine—beyond the peak of inflated expectations,” *The New England journal of medicine* (376:26), pp.2507.

Chen, H., Chiang, R.H. and Storey, V.C., 2012. “Business intelligence and analytics: From big data to big impact,” *MIS Quarterly* (36:4), pp.1165-1188.

Chollet, F., 2017. *Deep Learning with Python*. Manning Publications.

Cockburn, A., 2006. *Agile software development: the cooperative game*. Pearson Education.

D’Aveni, R. A., 1994. *Hypercompetition: Managing the dynamics of strategic maneuvering*. New York, NY: The Free Press.

D'Aveni, R.A., Dagnino, G.B. and Smith, K.G., 2010. “The age of temporary advantage,” *Strategic management journal* (31:13), pp.1371-1385.

Daft, R.L. and Weick, K.E., 1984. “Toward a model of organizations as interpretation systems,” *Academy of Management Review* (9:2), pp.284-295.

Deng, L. and Yu, D., 2014. “Deep learning: methods and applications,” *Foundations and Trends® in Signal Processing* (7:3), pp.197-387.

Eisenhardt, K.M. and Graebner, M.E., 2007. “Theory building from cases: Opportunities and challenges,” *Academy of Management Journal* (50:1), pp.25-32.

Elliott C (2017) New artificial intelligence promises to make travel a little smarter. Does it? Washington Post (June 22), http://wapo.st/ 2towCjX?tid=ss_tw&utm_term=.acde7d2bff94.

El Sawy, O.A., 1985. “Personal information systems for strategic scanning in turbulent environments: can the CEO go on-line?” *MIS Quarterly* (9:1) pp.53-60.

Glaser, B.G. and Strauss, A.L., 1967. “The constant comparative method of qualitative analysis,” *The discovery of grounded theory: Strategies for Qualitative Research* (101), pp.158.

Goodfellow, I., Bengio, Y. and Courville, A., 2016. *Deep learning*. MIT press

Haeckel, S.H., 1999. *Adaptive enterprise: Creating and leading sense-and-respond organizations*. Harvard business press.

Hedman, J., Srinivasan, N. and Lindgren, R., 2013. “Digital traces of information systems: Sociomateriality made researchable,” in the *Proceedings of Thirty Fourth International Conference on Information Systems, Milan*.

Honegger, M., 2018. “Shedding Light on Black Box Machine Learning Algorithms: Development of an Axiomatic Framework to Assess the Quality of Methods that Explain Individual Predictions,” *arXiv preprint arXiv:1808.05054*.

Houghton, R., El Sawy, O.A., Gray, P., Donegan, C. and Joshi, A., 2008. “Vigilant information systems for managing enterprises in dynamic supply chains: Real- time dashboards at Western Digital,” *MIS Quarterly Executive* (3:1), pp.4.

Huang, J., Henfridsson, O., Liu, M.J., Newell, S., 2017. “Growing on steroids: rapidly scaling the user base of digital ventures through digital innovation,” *MIS Quarterly*. (41:1), pp.301–314.

Jaworski, B.J. and Kohli, A.K., 1993. “Market orientation: antecedents and consequences,” *Journal of Marketing* (57:3), pp.53-70.

Kester, L., Griffin, A., Hultink, E.J. and Lauche, K., 2011. “Exploring portfolio decision-making processes,” *Journal of Product Innovation Management* (28:5), pp.641-661.

Kumar, N., Stern, L.W. and Anderson, J.C., 1993. “Conducting interorganizational research using key informants,” *Academy of Management Journal* (36:6), pp.1633-1651.

Langley, A., 1999. “Strategies for theorizing from process data,” *Academy of Management Review* (24:4), pp.691-710.

LeCun, Y., Bengio, Y. and Hinton, G., 2015. “Deep learning,” *nature* (521:7553), pp.436.

Li, P., Li, J., Huang, Z., Li, T., Gao, C.Z., Yiu, S.M. and Chen, K., 2017. “Multi-key privacy-preserving deep learning in cloud computing,” *Future Generation Computer Systems* (74), pp.76-85.

Lu, Y. and K.(Ram) Ramamurthy, 2011. “Understanding the link between information technology capability and organizational agility: An empirical examination,” *MIS quarterly* (35:4), pp.931-954.

Lummer, S.L. and McConnell, J.J., 1989. “Further evidence on the bank lending process and the capital-market response to bank loan agreements,” *Journal of Financial Economics* (25:1), pp.99-122.

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D., 2012. “Big data: the management revolution,” *Harvard business review* (90:10), pp.60-68.

Molnar, C., 2018. “Interpretable machine learning,” *A Guide for Making Black Box Models Explainable*.

Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R. and Muharemagic, E., 2015. "Deep learning applications and challenges in big data analytics," *Journal of Big Data* (2:1), p.1.

Nazir, S. and Pinsonneault, A., 2012. "IT and firm agility: an electronic integration perspective," *Journal of the Association for Information Systems* (13:3), p.2.

Newell, S. and Marabelli, M., 2015. "Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'," *The Journal of Strategic Information Systems* (24:1), pp.3-14.

Nilsson, N.J., 2014. *Principles of artificial intelligence*. Morgan Kaufmann.

Okhuysen, G.A. and Bechky, B.A., 2009. "10 coordination in organizations: an integrative perspective," *Academy of Management annals* (3:1), pp.463-502.

Overby, E., Bharadwaj, A. and Sambamurthy, V., 2006. "Enterprise agility and the enabling role of information technology," *European Journal of Information Systems* (15:2), pp.120-131.

Park, Y., El Sawy, O.A. and Fiss, P., 2017. "The role of business intelligence and communication technologies in organizational agility: a configurational approach'" *Journal of the association for information systems* (18:9), p.1.

Pasquale, F., 2015. Digital star chamber. *Aeon (August 18, 2015), available at https://aeon. co/essays/judge-jury-and-executioner-the-unaccountable-algorithm [https://perma. cc/AT2Y-FS3J].*

Prahalad, C.K., 2009. In volatile times, agility rules. *Business Week*, *4147*, p.80.

Rai, A., Constantinides, P. and Sarker, S., 2019. "Editor's Comments: Next-Generation Digital Platforms: Toward Human–AI Hybrids," *MIS Quarterly* (43:1), pp.iii-ix.

Russell, S.J. and Norvig, P., 2016. *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited,.

Sambamurthy V, Bharadwaj A, Grover V., 2003. "Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms," *MIS Quarterly* (27:2), pp.237–263.

Samuel, A., 1959. "Some Studies in Machine Learning Using the Game of Checkers," *IBM Journal of Research and Development* (3:3), pp.210-229.

Schmidhuber, J., 2015. "Deep learning in neural networks: An overview," *Neural networks* (61), pp.85-117.

Strauss, A. and Corbin, J., 1998. *Basics of qualitative research techniques*. Thousand Oaks, CA: Sage publications.

Tallon, P.P. and Pinsonneault, A., 2011. "Competing perspectives on the link between strategic information technology alignment and organizational agility: Insights from a mediation model," *MIS Quarterly* (35:2), pp.463-486.

Tallon, P.P., Queiroz, M., Coltman, T. and Sharma, R., 2018. "Information technology and the search for organizational agility: A systematic review with future research possibilities," *The Journal of Strategic Information Systems* (28:2), pp.218-237.

Thomas, J.B., Clark, S.M. and Gioia, D.A., 1993. "Strategic sensemaking and organizational performance: Linkages among scanning, interpretation, action, and outcomes," *Academy of Management Journal* (36:2), pp.239-270.

Wixom, B.H. and Watson, H.J., 2001. "An empirical investigation of the factors affecting data warehousing success," *MIS Quarterly* (25:1), pp.17-41.

Wu, L. and Brynjolfsson, E., 2009. "The future of prediction: how Google searches foreshadow housing prices and quantities," *ICIS 2009 Proceedings*, p.147.

Yin, R., 2003. Case study research: Design and methods (3rd ed.). Thousand Oaks, CA: Sage.