2 Understanding Big Data and its application in the digital marketing landscape

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Introduction

The sheer volume of data on consumer behaviour and processes available to organisations is unprecedented. Computers and smart devices such as smartphones, smart cars, smart locks, smart refrigerators, smartwatches, smart speakers and other similar devices enabled by the Internet-of-Things (IoT) are emitting unstructured and structured data that enable organisations to generate consumer behavioural insights. These data can help in marketing strategy formulation while unlocking new market opportunities that were previously underexplored or unexploited (Erevelles, Fukawa, and Swayne, 2016).

Several leading global organisations have invested in using Big Data analytics to gain a competitive edge in the marketplace. For instance, online retail giant Amazon maintains data on its customers' names, addresses, payments and search histories in its data bank and uses its algorithms to improve customer relations for a seamless real-time customer experience across all online touchpoints (Liu *et al.*, 2020). American Express also uses Big Data to analyse and predict consumer behaviour. With access to Big Data, the predictive models enabled by Machine Learning (ML) capabilities allow for the superior application of both structured and unstructured data to better understand customer behaviour. Through sophisticated ML predictive models, organisations are able to apply Big Data in developing more personalised value propositions and warding off potential customer churn (Manglani, 2017). In the Business-to-Business (B2B) market, Rolls-Royce is using the data from IoT sensors on aircraft jet engines to provide a higher value proposition for their business customers by introducing the concept of Power by the Hour (PBH) or Engine-as-a-Service, meaning that value is derived via 'access to resources' rather than 'ownership of resources' (Shcherbakova, 2020). For a flat hourly rate per engine, Rolls Royce would handle installations, check-ups, maintenance and decommissioning. Preventative maintenance scheduling for these engines is automated based on the data received from the many sensors embedded in the engines. This pioneering approach to engine maintenance management forms the basis of the company's market leading CorporateCare® service. By adopting the PBH model, airlines transfer the engine maintenance responsibility to a vendor, which ensures that engine efficiency and safety remain at an optimal level. Airlines can then focus on their core competencies, which include customer service, route optimisation, pricing and marketing.

As Big Data becomes the new normal, organisations explore ways in which Big Data can be captured and used in marketing analytics to unleash new organisational capabilities and value propositions for customers. In this chapter, we explore the application of

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Big Data through the lens of the Marketing Mix. We extend the work by Fan, Lau, and Zhao (2015) via the expansion of their 5Ps framework (Product, Place, Promotion, Price and Process) with Physical evidence, Partnerships and People for contemporary marketing practice in both the B2B and the Business-to-Consumer (B2C) markets. We begin by addressing the following questions that help explain Big Data and its application to marketing practice:

- What does the term 'Big Data' mean, and how will the insights provided via Big Data analytics differ from what managers might generate from traditional analytics?
- What new insights does this new genre of marketing analytics provide for marketing decision-making?

These questions about Big Data are examined in the following sections of this chapter.

What is Big Data?

Big Data is the embodiment of several disciplines, such as quantitative studies, data science and business intelligence (Comm and Mathaisel, 2018). Big Data essentially consists of extremely large datasets. These datasets are made up of structured and unstructured data[1] that can be processed and analysed to reveal patterns and trends (Hazen *et al.*, 2014). Big Data typically refers to incredible amounts of data, much of which is unstructured data, and new ways of using data (Gandomi and Haider, 2015). There is a torrent of digital data, and this is changing the nature of doing business in a very fundamental manner. Big Data is often associated with large volumes of structured (e.g. transactional or historical data) and unstructured (e.g. behavioural) data that are generated by digital processes, SM exchanges, business transactions or machine-based activity and can be used by organisations to generate new insights for business gains (Erevelles, Fukawa, and Swayne, 2016).

Big Data includes the systems and processes governing data generation, collation, management, control and usage. Big Data is often characterised by high-volume, high-velocity and high-variety data (Laney, 2001). The volume (the amount of collected and generated data) is indicative of the magnitude of data; the velocity (the speed at which data are generated and processed) refers to the speed of data-processing rate and is realised via the digital processes with which Big Data is generated and the variety (number of data types) refers to new formats and types of data (Gnizy, 2020). Big Data presents itself in varied formats, from structured and numeric to unstructured text documents, video, audio and email data.

Big Data is transmitted at a break-neck speed and must, therefore, be analysed and processed at a fast pace to realise the benefits of real-time data analytics. Organisations are now adopting applications such as Hadoop, a software solution created by the Apache Software Foundation (Jabbar, Akhtar, and Dani, 2019). Hadoop is utilised as a Big Data batch processing[2] tool to derive insight from large datasets such as historical weblogs, past transactional data and sales data to develop customer profiles for traditional marketing activities (Hashem *et al.*, 2015). While Big Data batch processing tools such as Hadoop are designed to cope with Big Datasets, which have been collected over a period of time, real-time processing[3] of Big Data is concerned with the capacity of information systems to accept continuously streams of datasets for instantaneous decision-making where data-processing speed and efficiency are of the essence (Casado and Younas, 2014; Kitchens *et al.*, 2018). Apache Storm, an open source Big Data software solution also developed by the Apache foundation, is one example of an applications available to marketers in their quest to operationalise the use of Big Data for real-time marketing decision-making (Jabbar, Akhtar, and Dani, 2019).

Big Data involves three analytical categories: descriptive (what happened), predictive (what is probably going to happen) and prescriptive (what should be done) (Tonidandel, King, and Cortina, 2018; Gnizy, 2020). These are increasingly seen as a set of critical skills needed to augment organisational capabilities and business strategy (Hayashi, 2014). For example, organisations such as Walmart have applied predictive analytics to process data via Big Data systems in anticipating the impact of business trends on their product line pricing and organisational revenues (Gnizy, 2020).

The high-volume datasets emanating from Big Data can fuel large-scale organisational data systems, enabling contemporary marketing decision-making that challenges conventional marketing practice. Big Data analytics brings new mindsets to marketing practice and encourages proactive behaviour towards customers and markets (Baesens *et al.*, 2016; Tonidandel, King, and Cortina, 2018). While traditional marketing organisations have been accustomed to using traditional non-Big Data methods in marketing decision-making, Big Data's unique characteristics and the sophisticated interrogative analytics that it lends itself to enable marketers to go beyond traditional business intelligence (Gnizy, 2020). Hence, as Gnizy (2020) argues, Big Data analytics enable risk management and discover hidden facets and associations. Big Data also broadens the conceptions of market and strategy to encompass various aspects of improved knowledge or ideas pertaining to markets (competitors, customers and value creation) that non-Big Data systems (typically represented by structured or historical data stored in corporate databases such as customer information like contact details and transaction history) cannot detect, acquire, manage and process for the benefit of dynamic organisational marketing decision-making (Gnizy, 2020; Engelseth and Wang, 2018; Erevelles, Fukawa, and Swayne, 2016; Ghasemaghaei, 2018; Yang *et al.*, 2019). Unstructured data captured from consumer usage of SM platforms, Internet search, smart devices and locations can be stored alongside structured data such as transactions and sales information (Hashem *et al.*, 2015). As Big Data typically constitutes 95% of unstructured data, it is pivotal that marketers exploit the insights that can be gleaned from Big Data analytics, particularly that offered by the unstructured component of Big Data, in their quest for competitive advantage (Gandomi and Haider, 2015).

Big Data and its fusion with marketing practice

In marketing, the primary motivation in adopting Big Data is its potential usefulness for marketing decision-making purposes. In this section, we expand on the framework adapted from Fan, Lau, and Zhao (2015) to explicate the ways marketing practice is evolving in its application of Big Data in the contemporary management of the Marketing Mix.[4] We adopt the Marketing Mix framework as a lens for the discussion of Big Data applications in marketing decision-making for the reason that it is a well-known framework that encapsulates the principal components of tactical and strategic marketing decisions and is a framework that is well understood by marketing academics and practitioners alike. In this chapter, we advance the contributions made by Fan, Lau, and Zhao (2015) through complimenting their 5Ps framework (*Product, Place, Promotion, Price and Process*) with *Physical Evidence, Partnerships and People*, leading to the full 8Ps to align with contemporary marketing practice.

Similar to Fan, Lau, and Zhao (2015), we begin the discussion in this section by identifying the types of data sources for marketers to use in obtaining Big Data to aid in marketing decision-making. We then explicate some of the methods that are currently being employed by marketers in the analysis of Big Data and, finally, provide an overview of application examples to give the reader an idea of the evolution caused by the adoption of Big Data in the practice of marketing management.

The Marketing Mix concept has endured through time due to its ability to identify the multitude of decision types marketing managers can use to better serve their clientele. As is typical for the Marketing Mix, Big Data examples can fall under multiple 8P categories, for example, sensors in vehicle engines can be used to manage product design (Product), distribution challenges (Place) and after-sales service (Process). Furthermore, we include User-Generated Content (UGC) and electronic Word-of-Mouth (eWOM) under the Promotion category because they offer a significant contribution to Big Data. Although eWOM and UGC are, strictly speaking, not directly under the control of an organisation, many companies aim to harness this valuable data for their purposes, for example, through social Customer Relationship Management (social CRM) as a Process with which to guide the People assets of the organisation. The discussion then concludes with explanations of Big Data applications for each of the 8P Marketing Mix categories.

Product

In the product decision-making realm of the Marketing Mix, Big Data is beginning to influence marketing decisions in areas as diverse as new product design and development, reputation or brand management, product lifecycle management and quality management. For example, in the consumer electronics industry, Big Data has been applied by major organisations, including Xiaomi and Lenovo, to accelerate the pace of NPD programs in responding to today's dynamic and evolving marketplace (Tan and Zhan, 2017). Big Data has allowed for product features and functions to be added to a product that customers are willing to pay for while eliminating otherwise undesirable product features (Sun and Huo, 2019; Urbinati *et al.*, 2019).

In the semiconductor industry, Intel monitors product quality attributes through Big Data interfaces, which enables the organisation to significantly reduce the validation time for testing before bringing the product to market. Intel fuses intelligence derived from Big Data with AI to significantly increase new product quality and reduce NPD time. In test execution, Big Data analytics coupled with AI allows Intel to locate faults more efficiently while eliminating redundant tests in their NPD programs. This approach reduces the number of tests performed by 70%, enabling complex semiconductor products to reach the market more quickly without compromising product quality (The Innovation and Enterprise, 2020 – see Further reading).

Using Big Data, brand marketing campaigns are able to more accurately analyse brand strength through a brand's reputation in the marketplace. Making the linear approach to collecting data redundant, the new approach to brand marketing is utilising circular data analysis via a variety of data touch points. Marketers are able to monitor the 'Likes' or 'Re-tweets' of potential customers, which allows the data analytics system to identify crucial metrics that set aside specific parameter results and aid in the marketer's understanding of the customer's preference for the brand.

Price

A greater understanding of the buying behaviour of our customers can help organisations find the optimal price that a customer is willing to pay at any given time, place or circumstance. Manual practices for setting prices are time-consuming and make it impossible for marketers to visualise dynamic pricing patterns for their products and thus optimise pricing and unlock value. Pricing decisions based on factors such as product costs, product margins, competitor prices and quantity discounts are simplistic and inadequate in the current reality of emerging marketing practices. At its core, a pricing decision is essentially a Big Data issue (Feng, Li and Zhang 2019; Gerlick and Liozu, 2020; Steinberg, 2020).

Hence, marketers are increasingly bringing themselves to adopt dynamic pricing approaches, a market-driven demand-based approach to pricing that engages a flexible pricing practice in which the actual price for a product is based on a complex analysis of current market conditions. Demand, seasonality and competitor actions are among the factors that moderate the actual price level of a product at any given time (Jiang and Li, 2020; Augustin and Liaw, 2020). In the United States, the practice of dynamic pricing among major league baseball teams demonstrates the robustness and the effectiveness of Big Data-driven dynamic pricing models that improve revenue management. Prices are set at multiple times of day, incorporating many Big Data variables, including weather, ongoing work around the ballpark that may be a cause of inconvenience for patrons, teams on the rise in the league, the potential for a record-setting event (hits, homeruns or plays), trending conversations about a game on SM, and what tickets are selling for in secondary marketplaces, such as StubHub and TicketMaster, the largest fan-to-fan ticket marketplaces (see Erevelles, Fukawa, and Swayne, 2016). Hence, Big Data allows organisations to manage their pricing to capture the willingness of fans to pay more for a special game while mitigating the tendency for parallel-market opportunistic organisations or individuals to exploit pricing discrimination practices that may otherwise exist and thus distort an organisation's pricing strategies.

Place

The 'place' or 'distribution' aspect of the Marketing Mix typically involves logistical considerations such as warehouse management, inventory management, packaging and order tracking. The ubiquitous use of Location-Based Services (LBSs) enabled by mobile technology provides marketers with location- and time-specific user information for its target markets. The location-based information of target customers is seen as having fundamental ramifications for the four leading logistics considerations, that is, inbound transport, outbound transport, inventory management and warehousing activities (Onstein *et al.*, 2020; Ashayeri and Rongen, 1997; Christopher, 2011). Innovations associated with the application of location-based information systems to enable the matching of supply and demand in marketplaces have been shown to significantly reduce the costs associated with the aforementioned logistical consideration that is fundamental for the movement of goods from production and warehousing facilities to the target market for consumption (Christopher, 2011). A demand-driven supply chain's ability to respond rapidly to demand variability based on the movement of its target market, which is aligned with supply, is even more pronounced in services-based industries (Onstein *et al.*, 2020). Balancing the supply and demand sides of a service industry is a critical success factor because this industry provides products that are more intangible, perishable, inseparable and variable than physical goods. In this sense, the application of real-time location-based Big Data will result in lower working capital requirements and drive stronger sales and profit. For example, functions such as barcode reading, videos, pictures and messages are inherent capabilities of most smartphones today and optimise supply chain operations at very little cost. Location data captured by mobile phones makes it easy to track shipments with precision using devices' location capabilities linked to the central corporate system over the Internet. Drivers can map shorter or less congested routes to make timely delivery and this, in turn, significantly optimises fleet utilisation (asset utilisation) in the courier services such as UPS and Federal Express.

The recent outbreak of the COVID-19 global health pandemic has brought to prominence the role of Big Data in tracing the movement of people to help contain the speared of infections amongst the population in a country, state, city or smaller geographic boundaries. Big Data has been pivotal in revealing the patterns and provide insights into the spread and control of this virus based on the movement of members of the society. Several modalities of digital data including patient location, proximity, patient-reported travel, co-morbidity, patient physiology and current symptoms made possible by the location capabilities inherent to smartphones can be digitised and used for generating actionable insights at both community and demography levels (Haleem *et al.*, 2020), resulting in the more efficient allocation of critical resources for better utilisation of public health services.

The use of location-based Big Data is not merely limited to the movement of humans but is also increasingly pertinent to the monitoring of the movement of 'things' in the age of the IoT. Modern vehicles are already equipped with a multitude of sensors and on-board computers that alert drivers to the imminent need for servicing. Hence, after-sales maintenance and the spare parts market for motor vehicles are probably the area where sensor based, product-in-use data can already produce the greatest strategic gains for organisations. Considering the fact that the same brand of vehicles can utilise differing design principles, it is no wonder that the vehicle after-sales maintenance and spare part manufacturers are struggling with the 'bullwhip'[5] effect. For example, variance in the demand for spare parts by vehicle end-users due to, for example, unanticipated changes in the conditions where the vehicles are used (e.g. long-term drought and dust causing problems with the engine) creates significant fluctuations in demand for spare parts manufacturers and vehicle servicing operators. These bullwhip effects could be reduced if on-board computers signalled a vehicle after-sales support network of these changed (long-term) location specific weather conditions and the impact they are having on specific engine parts. Moreover, a quick reaction (i.e. preventative maintenance) to engine sensor warnings could also result in localised repairs to stop the damage altogether, which is an example of superior customer service (Andersson and Jonsson, 2018; Giannakis and Louis, 2016).

However, the challenge that persists for location-based Big Data analytics is its currency in accurately predicting customers' locations. Both spatial and temporal data should be taken into consideration (temporal moving pattern mining for LBS) (Fan, Lau, and Zhao, 2015). A large volume of spatial and temporal data will need to be processed within a very short time period, practically in a matter of seconds, before customers move to new locations. Given the context-specific importance of location-based Big Data, this information will only be rendered valuable if the currency of the data can be guaranteed to enable context-relevant marketing decision-making. Thus, the 'velocity' issue regarding Big Data remains one of the most challenging aspects of location-based Big Data.

Promotion

As marketing information systems interface and integrate with consumer technologies such as SM Platforms, it is fair to argue that Promotion is the Marketing Mix element most impacted by the advent of Big Data and its application to marketing practice. The advent of Programmatic Marketing for targeted, real-time online display advertising can only be explained by the harnessing of Big Data in an information infrastructure which supports real-time processing frameworks that enable media buying on the 'fly' based on user web sessions and preferences (Jabbar, Akhtar, and Dani, 2019). Such integration provides solutions based on the analysis of information about consumers' preferences, opinions and needs. In other words, the scope of Big Data acquisition for marketing communications application permeates a wide range of marketing communication mix decision-making.

Big Data has become so fundamental to basic marketing communication decisions that it is beginning to influence programmatic media buying, granular audience segmentation and targeting and the execution of real-time trigger marketing campaigns (Chen *et al.*, 2019; Ford, 2019; Jabbar, Akhtar, and Dani, 2019). For example, marketers have increased consumers' awareness of their brands via the application of Big Data in recommender systems in the e-commerce context. Product marketing via online platforms such as Amazon and Ebay has targeted audiences using Online Consumer Reviews, where the sentiment mining of Big Data is applied for the efficient placement of digital advertisements in the e-commerce marketplace (Salehan and Kim, 2016; Chong *et al.*, 2017). Unfortunately, not all online reviews are accurate or truthful because some reviews are deliberately designed to either increase the popularity of a brand or discredit a competitor's brand – these fake reviews can distort a brand's reputation (Reyes-Menendez, Saura, and Martinez-Navalon, 2019). Sentiment analysis, a subfield of Natural Language Processing (NLP), can help automate the detection of fake reviews. By analysing the positive–neutral–negative meanings of the text and identifying content similarities between reviews, this review spam can be removed. Many e-commerce systems also link reviews to past purchases to identify fake reviews. Online sales and promotional platforms are dynamically managing their fake review detection systems in addressing the data distortions contributed by review spam (Chong *et al.*, 2017; Nair, Shetty, and Shetty, 2017).

Television ads can now be targeted at the household level via Programmatic Advertising as TV stations migrate their broadcast technologies from analogue to Internet-based technologies (Lee and Cho, 2020). This has resulted in real-time, automatic bidding for advertising opportunities online, accounting for two-thirds of the total digital video spend in the United States in 2019 (Malthouse, Maslowska, and Franks, 2018). However, due to the limitations of the current technologies used in Big Data analysis, the challenges posed by the very nature of Big Data (i.e. volume, variety, velocity and veracity) call for a dynamic and more scalable, multi-tiered, automated system for Big Data-enabled decision-making systems (Kumar, Shankar, and Alijohani, 2019).

Process

The most significant impact of Big Data is the automation of marketing processes. Real-time Big Data analytics involves the processing of a continuous stream of data inputs from a variety of sources for instantaneous marketing decision-making with low information latency (Kitchens *et al.*, 2018). The drive to automate marketing processes will mean that typical marketing activities, including but not limited to website buying, ad-slot buying, online publishing, customer profiling, targeting, search engine optimisation and content generation, will experience significant disruption (Jabbar, Akhtar, and Dani, 2019). The confluence of real-time processing within programmatic marketing calls for marketers to re-examine their existing marketing processes and invest in cloud-based infrastructure for scalable, real-time marketing analytics and automated decision-making (Hazen *et al.*, 2014).

Recently, Programmatic Marketing for online display advertising has become an example of a marketing communication process that has been increasingly automated via the acquisition and use of real-time Big Data. Although in its infancy, Programmatic Marketing is likely to accelerate and refine the automation, algorithmic decision-making and developments in advertising technologies, leaving behind traditional media approaches that in comparison, are unprofitable and less efficient (Jabbar, Akhtar, and Dani, 2019; McGuigan, 2019). In customer service processes, the introduction of Chatbots and virtual assistants powered by NLP and AI can answer routine customer enquiries and release human employees for more complex tasks (Kietzmann, Paschen, and Treen, 2018; Reshmi and Balakrishnan, 2018; Urbinati *et al.*, 2019).

In an industrial setting, embedding sensors into manufacturing plants can help alert managers of possible manufacturing problems and service requirements. Furthermore, embedding sensors into machinery sold to monitor product performance can be offered as an additional service to the end-user to prevent expensive breakages and production downtime. Such predictive maintenance can form a cornerstone of loyal clientele during the crucial period after the end of warranty periods (Andersson and Jonsson, 2018; Urbinati *et al.*, 2019).

Physical evidence

In website design, the Physical evidence (everything the customers see when interacting with a business online including the virtual elements of the product or service and the layout or interior design of the virtual shops) incorporates the entire brand's visual representation online as well as the use of, for example, colours, images and fonts to reflect the brand values. Google Analytics can help web masters improve their website's Physical evidence by identifying bounce and conversion rates and overall engagement with the website content. Data from A/B testing (Google Optimize) can be used to refine the brand style in advertisements and Landing Pages (Kietzmann, Paschen, and Treen, 2018).

The introduction of the Amazon Go store in Seattle in 2018 provides an illustrative insight into the potential for Big Data in disrupting the retail industry. Amazon Go is a new prototype of a futuristic retail store based on the 'Just Walk Out' technology. With only a smartphone app linked to a credit card, a customer could enter the store, select merchandise from the aisles and just walk out – no lines, no waiting and no cashier. The entire customer shopping experience is facilitated by the stream of real-time Big Data enabled by technologies such as computer vision, data science, ML and sensor-based information technologies (Ives, Cossick, and Adams, 2019).

Partnerships

Partnerships, in a marketing context, typically explore the synergies that can be achieved by supply chain partners; for example, the effective and efficient use of Big Data can minimise the bullwhip effect in supply chains (Hofmann, 2017). A success story of a firm that has harnessed the power of Big Data analytics into their supply chain partnership arrangements is Walmart (Sanders, 2016). Using batch processing Big Data analytics, Walmart has learned a great deal about customer preferences. For example, they learned that before a hurricane, consumers stock up on food items that do not require cooking or refrigeration. By collaborating with their supplier partners, Walmart is able to stock such items at their stores in advance of a hurricane. Such Big Data analytics enables Walmart to win pricing and distribution concessions from its suppliers, and this, in turn, gives the retailer and its partners a significant advantage over competing supply chain networks (Sanders, 2016; Anshari *et al.*, 2019).

People

Big Data analytics enables large-scale dataset integration, supporting people management decisions for the effective deployment of human talent in marketing operations. Talent analytics is now emerging as a methodology that allows for the identification of patterns in workforce activity data, allowing more efficient workforce management (Marler and Boudreau, 2017). The benefits derived from talent analytics in terms of value creation are clear, in particular (1) identifying a causal relationship between training expenditure and profitability and (2) justifying the need for an organisation to set up training in specific areas of human talent development that can improve organisational profitability (Nocker and Sena, 2019).

However, the human talent for data-driven marketing operations is dynamic, and new marketing careers, such as data scientists and data analysts, are likely to become common. Given the dynamism of Big Data and its emerging importance in marketing practice, Data Scientists will play an integral role in helping perform the greater statistical, querying, scripting, scraping, cleaning, warehousing and training activities needed in the data-heavy functions of marketing.

Conclusions and the future convergence of Big Data and AI

This chapter expands on the work of Fan, Lau, and Zhao (2015) by outlining major Big Data developments across the full suite of the eight Marketing Mix variables, where Big Data is already enabling improvements across all fundamental marketing decisions. As is typical for the Marketing Mix, some of the examples cited could serve as an example of multiple Marketing Mix variables; for example, the IoT trackers embedded in a corporate vehicle fleet could be classified as a Product feature or a Process feature. This chapter also tackled the difficult balance between considering 'People' as such and also as the object of Big Data collection and analysis.

In the future, a deeper relationship between Big Data and AI is to be expected. How else could marketeers make sense of the volume of Big Data? Some of our examples would not be possible without this. AI can support managers in automated decision-making at the operational and tactical levels, especially in stable business environments (Duan, Edwards, and Dwivedi, 2019). Overall, AI-empowered systems are becoming increasingly important for strategic management (Goul, Sidorova, and Satz, 2020), and the volume of AI-enabled decisions will increase because the datasets used for decision-making are growing exponentially and are often unstructured. This is where the cognitive features of the automatic processing of data, specifically ferreting sentiment insights from data with NLP and ML, are invaluable (D'Arco *et al.*, 2019). However, humans for now are still better at 'thinking outside the box', dealing with unstructured strategic decisions and learning from challenges. Future research is aiming to replicate this through the development of Deep Learning (a subset of ML) (Duan, Edwards, and Dwivedi, 2019).

One of the greatest challenges to future AI-empowered automation is the human mind. Already, the GDPR[6] legislation bans the automated processing of person-identifiable data to the detriment of that individual, for example, for mortgage refusal (Article 22 of the GDPR). Moreover, the closer to our daily routines Big Data and AI come, for example, IoT, IoP or wearable technology, the greater the demand for ethical design principles will be (Kumar *et al.*, 2020). In other words, AI governance is gaining momentum; Google applies responsible AI technology developments with 'explainability, fairness appraisal, safety considerations, human–AI collaboration and liability frameworks' (Goul, Sidorova, and Saltz, 2020, p. 5255). Hence, an essential development aim for AI should be the ability to provide human-like justifications based on data for decision-making (Kumar *et al.*, 2020).

Key lessons for future research

- Big Data comes from varying sources, from IoT-embedded sensors to SM content
- Core marketing decision can be improved with the AI-assisted analysis of Big Data
- Big Data with AI enhances competitive strategy formulation
- Future AI development must incorporate ethical design principles

Further reading

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Notes

1 Unstructured data is either machine generated or human generated. For example, data emitted from IOT devices, social media applications, website metrics and search engines are classified as unstructured data.

2 **Batch processing** involves the processing of large volumes of data which has been collected over a significant period of time. It is a popular method for processing Big Data typically used in applications where data naturally fit in a specific time window (Casado and Younas, 2014).

3 **Real-time processing** is defined as an approach that requires a continuous stream of inputs for the processing and outputs of data (Casado and Younas, 2014).

4 The term 'marketing mix' is a foundation model for businesses, historically centered around product, price, place and promotion and had been extended to include people, physical evidence, partnerships and processes to cater for services marketing. The marketing mix has been defined as the 'set of marketing tools that the firm uses to pursue its marketing objectives in the target market'.

5 The bullwhip effect refers to distorted information from one end of a supply chain affecting another, leading to tremendous inefficiencies in the form of excessive inventory investment, poor customer service, lost revenues, misguided capacity plans, ineffective transportation and missed production schedules (Lee, Padmanabhan, and Whang, 1997).

6 The General Data Protection Regulation (GDPR) is a regulation in EU law on data protection and privacy in the European Union (EU) and the European Economic Area (EEA). It also addresses the transfer of personal data outside the EU and EEA. The GDPR's primary aim is to give control to individuals over their personal data and to simplify the regulatory environment for international business by unifying the regulation within the EU. GDPR. (2018). *General Data Protection Regulation*. Available at: https://gdpr-info.eu/ (accessed 5 October 2020).

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