From data to action: How marketers can leverage AI

Article *in* Business Horizons · December 2019

DOI: 10.1016/j.bushor.2019.12.002

Colin Campbell
University of San Diego

Sean Sands
Swinburne University of Technology

Carla Ferraro
Monash University (Australia)

Hsiu-Yuan Tsao
National Chung Hsing University

Business Horizons (xxxx) xxx, xxx

ELSEVIER

Available online at www.sciencedirect.com

ScienceDirect

KELLEY SCHOOL OF BUSINESS
INDIANA UNIVERSITY
www.journals.elsevier.com/business-horizons

From data to action: How marketers can leverage AI

Colin Campbell [a,b,*], Sean Sands [b], Carla Ferraro [b], Hsiu-Yuan (Jody) Tsao [c], Alexis Mavrommatis [b,d]

[a] School of Business, University of San Diego, 5998 Alcala Park, San Diego, CA 92101, U.S.A.
[b] Swinburne University of Technology, Hawthorn, VIC 3122, Australia
[c] National Chung Hsing University, Taiwan
[d] EADA Business School, Barcelona, Spain

KEYWORDS
Artificial intelligence;
Machine learning;
Marketing function;
Marketing mix;
Consumer engagement;
Customer experience;
Customer journey

Abstract Artificial intelligence (AI) is at the forefront of a revolution in business and society. AI affords companies a host of ways to better understand, predict, and engage customers. Within marketing, AI's adoption is increasing year-on-year and in varied contexts, from providing service assistance during customer interactions to assisting in the identification of optimal promotions. But just as questions about AI remain with regard to job automation, ethics, and corporate responsibility, the marketing domain faces its own concerns about AI. With this article, we seek to consolidate the growing body of knowledge about AI in marketing. We explain how AI can enhance the marketing function across nine stages of the marketing planning process. We also provide examples of current applications of AI in marketing.

1. Artificial intelligence: Seeing the forest for the trees

New technologies have the potential to disrupt consumer behavior, management processes, and organizational strategy (Evans, 2017). Artificial intelligence (AI) is one such disruptive technology, affecting a diverse range of industries from health care to retail. AI involves the development of valuable, automated solutions to problems that would require the intervention of intelligence if completed by humans (Martínez-López & Casillas, 2013; Negnevitsky, 2004). AI is increasingly underpinning a vast array of customer-brand interactions. To optimize the customer experience,

* Corresponding author
E-mail addresses: colincampbell@sandiego.edu (C. Campbell), ssands@swin.edu.au (S. Sands), cferraro@swin.edu.au (C. Ferraro), jodytsao@dragon.nchu.edu.tw (H.-Y.(J.) Tsao), amavrommatis@eada.edu (A. Mavrommatis)

https://doi.org/10.1016/j.bushor.2019.12.002
0007-6813/

for instance, many firms employ AI and machine learning (ML) to predict customer demands, assist frontline service employees in serving customers, and allow simple service queries to be answered by bots.

AI is creating efficiencies on an unprecedented scale, leading to automated and interconnected business processes that have diverse implications for a wide range of business functions, including marketing. As a result, marketing managers need to consider reshaping internal capabilities, rethinking strategies, and how customer interactions might be transformed. While some firms are striving to lead all business decisions with consideration of AI (Baker, 2017; Wolska, 2017), others are struggling to see the forest for the trees and to navigate AI adoption. The purpose of this article is to consolidate the growing body of knowledge about AI in the field of marketing. Such understanding is critical given the frequent digital interactions between brands and customers (Bughin, McCarthy, & Chui, 2017), and will assist marketing managers in considering the adoption of AI.

AI offers a range of opportunities for the field of marketing (Martínez-López & Casillas, 2013). Indeed, research in the U.S. suggests a large proportion of business-to-consumer marketers are already taking advantage of AI and ML (Narrative Science, 2018). For those organizations that employ AI, it is primarily being used to target audiences, make product recommendations, and optimize advertising campaigns (Blueshift, 2018). But significant potential remains for marketers to leverage advanced AI capabilities, with only a small proportion—just 6%—reporting the use of such capabilities, which include personalizing campaigns, collaborative filtering, and predictive models (Blueshift, 2018). AI should be a consideration for all marketing managers as it represents the highest growth of any technology in marketing (Salesforce, 2017), is expected to increase in use (Columbus, 2018), and is predicted to have a $40 billion effect on marketing by 2025 (Reavie, 2018).

Although the vast majority of marketing managers believe AI has a revolutionizing potential, many are still unaware of the magnitude of the benefits or unsure how they can adopt AI to improve marketing (Demandbase, 2016; Reavie, 2018). In addressing these questions, we first provide a brief history of AI before offering a more in-depth analysis of AI and ML. Next, we outline the opportunities for applying AI to marketing strategy, including examples of current applications. Finally, we conclude with guidelines for what it takes to succeed in an AI-first business environment and provide thoughts for the potential growth of AI within the marketing discipline.

2. A primer: What marketers need to know about AI

2.1. AI is more than an evolution in statistics

The amount of data generated today by both humans and machines far outpaces humans' ability to absorb, interpret, and make complex decisions on the basis of that data (Hurwitz, Kaufman, & Bowles, 2015). AI can help address this problem. The rapid development of AI, coupled with cloud-based resources, connectivity, and platform-based business models (those focused on bringing parties together on a platform to exchange products and services for money), is leading to automated and interconnected business processes that have implications for customers and other stakeholders. For marketers, AI affords strong opportunities for innovative human—machine integration (Rust & Huang, 2014), with applications in advertising, strategy, logistics, and customer experience, to mention a few. For instance, AI can provide valuable insights about finding the right consumers, engaging with customers, and conducting return-on-investment analysis.

Because of the vast availability of data and the advent of increasingly cheaper and faster computing power, AI and ML also afford insights beyond those of traditional statistical methods. AI and ML do not apply rigid assumptions about the problem, nor about data distributions in general; they employ many approaches and techniques to find a solution. While AI and ML techniques can be based on deductive or inductive learning, the benefit of inductive learning is that not much prior knowledge is needed about the problem or the data. In contrast, traditional statistics is based on deductive learning (which relies on prior knowledge about data) and thus makes tight assumptions about the problem and nature of the data (Teboul, 2018). In other words, AI and ML methods enable learning from data and discard assumptions attached to statistical methodologies.

Given the business benefits of AI, there are myriad customer-focused applications increasingly observable in a range of industries, including retail, finance, healthcare, education, transportation, and communications. For example, virtual bots are turning customer service into self-service (Fluss, 2017), big-data AI applications are replacing portfolio managers (Javelosa, 2017), and social robots are replacing human greeters to welcome customers in service sectors (Choudhury, 2016). Indeed, growth in AI development and deployment is not expected to slow. McKinsey forecasts that by 2020, U.S. customers will manage 85% of their brand relationships without human interaction (Baumgartner, Hatami, & Valdivieso, 2016).

2.2. AI has different building blocks

AI is typically defined as technology that enables machines to learn from experience and perform human-like functions (Marr, 2018). We focus on ML because it underpins the functionalities AI affords (McCorduck, 2009). In broad terms, ML refers to software that is able to learn how to accomplish a task without explicit instruction. ML algorithms detect patterns and learn how to make predictions and recommendations by processing data and experiences rather than by receiving explicit programming instruction. ML is a powerful tool for mining large sets of data, providing marketers the opportunity to gain new insights into consumer behavior and to improve the performance of marketing operations (Cui, Wong, & Lui, 2006). ML is used in a wide variety of applications that power many aspects of modern society, including web searches, content filtering on social networks, and e-commerce recommendation systems (LeCun, Bengio, & Hinton, 2015). ML has emerged as the method of choice for developing practical software for computer vision, speech recognition, natural language processing, robot control, and other applications (Jordan & Mitchell, 2015). Table 1 provides a brief overview of AI and its subdomains of ML and deep learning, along with some key terms.

Machine learning can be subdivided into different forms, with the three key paradigms shown in Table 2. A discussion of each form follows (Chiu et al., 2018; Das, Doppa, Kim, Pande, & Chakrabarty, 2015; Davenport & Kirby, 2016).

2.2.1. Supervised ML

The most widely used ML methods are supervised learning methods (Jordan & Mitchell, 2015). An example of supervised learning would involve a system learning the difference between a koala

Table 1. AI subdomains and key terminology

Term	Definition
AI and AI Subdomains	
Artificial intelligence (AI)	The broad class of technology developed with the objective of collecting data in order to solve problems or make decisions.
Machine learning (ML)	An application of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.
Deep learning	A form of neural network that develops understanding by building successively more abstract representations of a data set. This occurs by separating a data set into different layers of abstraction or transformation and then searching for patterns, first within each layer and then between them.
Key AI Terminology	
Neural network	A form of AI model designed to approximate how the human brain operates. It works by breaking problems down into smaller components and then iteratively solving them, building on the findings of earlier stages.
Target leakage	When an AI model accidentally includes information that would not be known at the time of prediction. Because such information is often highly predictive of the outcome that is trying to be predicted, this produces overly optimistic estimates during model training of out-of-sample performance.
Feature engineering	Cleaning and manipulation of data that are input into an AI model. This includes simple tasks such as ensuring data are coded correctly (e.g., attaching days of the week to dates), as well more complex manipulations, such as creating transformations of or interactions between variables.
Ensemble model	A form of ML that combines several different models in order to improve prediction. This can be accomplished by using *blenders*, when several different models are run concurrently and their results are merged into a final prediction, or by *stacking*, when models are employed sequentially with one model's outputs forming inputs into another model.

Table 2. Comparison of key ML paradigms

	Supervised learning	Unsupervised learning	Reinforcement learning
Task defined?	Yes	No	Yes
Existing data needed?	Yes	Yes	No
ML actively makes decisions and assesses outcomes?	No	No	Yes
Occurs over time?	No	No	Yes

and a kangaroo. By examining dozens of labeled examples, the system can induce which features are useful for distinguishing between the two animals and thus improve its prediction. This same approach is used to train chatbots to identify common customer queries, and to train spam filters to identify unwanted emails.

More technically, supervised learning refers to situations when ML algorithms see data that includes both a series of predictor variables as well as an outcome. This data set can be split into training and holdout parts. The ML algorithm can then analyze the training set, looking for patterns between predictor variables and the particular outcome. Models relying on many different algorithmic approaches can then be compared by validating them using the holdout data. Supervised ML is focused on trying to predict a particular outcome and hinges on the existence of a data set composed of examples of predictor variables and known outcomes.

2.2.2. Unsupervised ML

While supervised learning involves analyzing data and attempting to predict a particular outcome, unsupervised learning involves analyzing data without trying to predict anything. Unsupervised learning is instead focused on understanding the underlying structural properties of a data set in order to discover useful representations of the input without the need for labeled training data (Jordan & Mitchell, 2015). Clustering, an unsupervised learning approach, focuses on finding associations between observed data in the absence of any explicit signs of association. Clustering enables rules to be developed to classify future data. Unsupervised ML can be used for segmenting customers and markets, classification, and detecting outliers. In sum, while unsupervised ML relies on a data set to operate, it is distinguished by its focus on finding structure rather than predicting a particular outcome.

2.2.3. Reinforcement ML

Reinforcement ML refers to situations where an existing data set does not exist, and an algorithm learns by taking different actions and evaluating their success or failure. In this instance, a learning system doesn't have a historical data set to draw upon, so immediate and continuous feedback enables the system to learn while building a data set. An example of reinforcement ML is advertising on Facebook with a conversion-tracking pixel installed. When an ad is first developed and flighted, Facebook's algorithm tests the ad across the full spectrum of targeting. As sales success occurs, the algorithm can analyze the data to better refine its targets, possibly by concentrating on a certain audience, during certain times of day, in certain geographic locations, and using certain on-screen placements. Reinforcement ML can also be used in developing recommendation systems and optimizing logistic flows.

2.2.4. Hybrid ML systems

Although the three ML paradigms help in understanding how ML operates, most current research involves a blend of these forms (Jordan & Mitchell, 2015). This approach often blends or stacks what are called ensemble models (see Table 1) in order to improve their prediction. For instance, a model might employ unsupervised ML to classify and organize data, then relate these classifications against an outcome using supervised ML. Likewise, supervised ML can be used to identify useful predictors, which can then be refined with reinforcement learning to yield better predictions going forward.

3. AI-enabled marketing: Opportunities and applications

Advances in the field of big data provide marketers the ability to collect and aggregate vast amounts of information, with the ultimate aim of turning data into insight or actionable strategy. AI can greatly assist marketers in this process by drawing conclusions from unstructured data about causes and effects within extremely large data sets. With the ability to detect and extrapolate upon patterns, AI can help marketers identify opportunities and act upon them in real time. As a means to provide an organizing framework and assist marketing professionals in understanding and determining effective uses for AI, we structure our discussion around nine components inherent to strategic marketing (Wood, 2011). We outline how AI might be leveraged at each stage, as well as the data and techniques that might best serve each stage. While we provide examples of current applications, it is important to note that the examples may have effects beyond a single stage because AI applications are often broad in nature. For instance, the use of AI to extract sentiment from customers in social channels could offer insight in a variety of stages. Table 3 provides a summary of AI's potential across each of the nine stages of the marketing plan.

3.1. Analyzing the current situation

Stage 1 involves analyzing the current situation and understanding macroenvironmental factors that can affect the organization, its marketing, and its stakeholders. At this step, marketing managers strive to develop an understanding of the current and future environment in which the company operates (Chaffey, 2004; Chaffey & Smith, 2012); managers can evaluate markets, the opportunities within them, and the threats arising from AI adoption decisions (Paschen, Pitt, & Kietzmann, 2020). Several tools available to marketers, such as SWOT or PESTLE analysis, can assist them in understanding the specific markets they operate in and the consumers they target. AI techniques, including social listening, can glean information on markets and consumers, particularly in terms of satisfaction, purchasing patterns, and product demand. From this perspective, AI affords marketers the opportunity to identify changes in competitor behavior (including pricing), estimate product demand, and assess customer sentiment (including customer satisfaction).

In analyzing the market, it is important for marketing managers to focus on competing brands, product alternatives, and available channels within the entire category landscape. Categories can develop rapidly with advancements in technology and available choices, leading to market volatility. Social media and online forums afford consumers the ability to research products most suitable to their specific needs. Oculus360 (2018), an AI-market and consumer-research agency, used ML to investigate consumer discussions in online forums. The research shows the importance of analyzing online conversations concerning the entire category rather than strictly focusing on one's own specific brand. Such insights are pertinent for broad situation analysis, providing a gauge of how well consumer segments are being served by one's own brand as well as competitors'.

3.2. Understanding markets and customers

Stage 2 involves understanding markets and customers, as well as gathering knowledge of microenvironmental factors that specifically affect the firm, including market-share trends, product/category demand, and customer characteristics, including needs, wants, behaviors, attitudes, brand loyalties, and purchasing patterns. At this stage, marketers aim to develop an understanding of the specific markets they operate in and the consumers they target, monitoring their behavior to track the success of previous stages in terms of key metrics. During this process, web analytics and traditional market research (customer satisfaction) are often engaged, with AI providing a vast array of opportunities beyond these. For instance, voice-of-customer programs are allowing marketers to move beyond interview-based data to also incorporate large amounts of unstructured customer data. Medallia is one customer-experience software provider that has integrated AI capabilities to mine customer preferences and data from the web, social media, mobile activity, and contact-center interactions (Dunwoodie, 2018). In this context, data can be analyzed and feedback provided in real time, allowing decisions and actions to be taken immediately.

Furthermore, AI is expanding the available sources of data that firms have access to and is extending traditional satisfaction metrics. An example of this was demonstrated at the 2019 Consumer Electronics Show in Las Vegas, where software developer Neurodata Labs and robotics manufacturer Promobot unveiled multimodal emotion detection for customer-experience management (Ponce de Leon, 2019). This is an AI system that is able to analyze a combination of human activities (e.g., facial expressions, body gestures, voice, eye movement, and heart rate) and determine a consumer's emotional state. The technology is being tested by a Russian bank,

Table 3. Marketing functions and AI potential

What AI Can Offer	Data Requirements	Examples of Current AI Implementations
Stage 1: Analyzing the current situation: Involves understanding macroenvironmental factors that can affect the organization, its marketing, and its stakeholders		
• Analysis, simplification, provision, and understanding of large unstructured data sets • Identification of anomalies (events) in the market • Recommender systems to identify likely future events (e.g., areas of potential growth) • Sentiment analysis	• External data, including census data, demographics, consumer confidence, macromarket trends, third-party data (e.g., news stories, stock prices, home sales), social-media discussions	• Sociocultural trends through online chatter • Stock-market prediction • Improved macroeconomic forecasting drawing on a wider array of indicators than present models
Stage 2: Understanding markets and customers: Entails gathering knowledge of microenvironmental factors that specifically affect the firm, including market-share trends, product/category demand, and customer characteristics: needs, wants, behaviors, attitudes, brand loyalties, and purchasing patterns		
• Identification of changes in competitor behavior (e.g., pricing) • Estimation of product demand • Assessment of customer sentiment (e.g., customer satisfaction, social media sentiment analysis)	• Internal data, including sales (current and historical, sales of own products), customer data (satisfaction, attitudes, demographics, etc.), market research (e.g., ad/promotion testing); External data, including market share, scanner data, sales (sales of competitors' brands, seasonality, weather, holidays), social-media comments, competitors' pricing and product availability (e.g., sales, stock-outs)	• Synthesis and understanding of customer comments, feedback, and interests • Market research using analysis of facial expressions, eye movements, and audio comments • Mapping the complexity of the customer journey and associated understanding of the effect of individual components (ads, touchpoint, and influencers) along the way • Detection of changes in competitor behavior (e.g., pricing, distribution) • Under Armour uses AI to perform consumer-sentiment analysis and social listening to understand what customers think of the brand and where the gaps in the market are
Stage 3: Segmenting, targeting, and positioning: Involves developing an understanding of customer segments and assisting with targeting and positioning decisions		
• Classification and clustering of customers into distinct segments	• Internal data, including loyalty and sales information, customer willingness to purchase, and brand	• Development of much smaller segments (moving toward true one-to-one marketing)

• Estimation of the probability of response to promotions • Improved targeting of ads • Product and brand recommendations	perceptions; External data, including demographics, census data, and location	• Clustering of consumers using vast data sets • Predictive modeling to optimize targeting decisions • Target received notoriety in 2012 for their ability to segment and target products to expectant mothers (Duhigg, 2012)
Stage 4: Planning direction, objectives, and marketing support: Entails developing longer-term goals and associated short-term objectives to support larger strategies		
• Provision of digital customer service (e.g., chatbots) • Estimation of the responsiveness of consumers to price changes and promotions • Combination of information from the macro- and microenvironments to better inform marketing objectives • Identification of those most likely to purchase	• Internal data, including historical data on areas of marketing (e.g., amounts, types, and locations of ads/sales support) and associated outcomes (e.g., site traffic, leads, sales); External data, including census data, demographics, consumer confidence, macro-market trends, and third-party data (e.g., news stories, stock prices, home sales)	• Estimation of sales and revenues (e.g., Aviso, DataRobot) as well as expected expenses of new and existing products • Estimation of the reactiveness of sales to ad spends, price changes, etc. • Travel-booking website Expedia used Amazon SageMaker AI to train its ML models to identify and highlight the most attractive hotel images in its data set; Expedia was then able to predict images that increased click-through and purchases
Stage 5: Developing product strategy: Involves creation of the suite of products sold by a firm		
• Identification of gaps in the market for new product development • Creation of more customized and boutique products • Awareness of what is in style or trendy and thus worth producing and selling • Assistance with designing and producing products customized to individual consumers	• Historical data on customers, their purchases, and associated outcomes (e.g., satisfaction, returns) in order to create recommendations; Databases of consumer profiles from which to estimate new customers' sizes/profiles depending on inputs; Information on trending products, topics, and styles from social media, press articles, etc.	• New product development (e.g., Choosy fast fashion) based on trends identified through analysis of social tagging • Hyper-individualized product customization (e.g., Zozo's clothes that are customized according to AI-enabled customer measurements)
Stage 6: Developing pricing strategy: Revolves around determining pricing strategies to maximize sales		
• Estimation of consumer price elasticity at both individual and collective levels	• Both historical and real-time sales, search, and price data on firm and competitor products	• Retailers such as Amazon use algorithms that automatically increase prices in response to spikes in demand

(*continued on next page*)

Table 3 (*continued*)

What AI Can Offer	Data Requirements	Examples of Current AI Implementations
• Provision of dynamic pricing (e.g., surge pricing) and price discrimination. • Detection of anomalies (e.g., errors in pricing, fraud, or nonprofitable customers).		• Wise Athena leverages ML to analyze both own and competitor prices to help firms make optimal price and promotional decisions
Stage 7: Developing channels and logistics strategy: Involves determining logistics, distribution, and product stocking decisions		
• Prediction and optimization of distribution, inventory, store displays, and store layouts (both brick-and-mortar and online) • Enabling voice and visual search	• Data at the store level (historical and real-time sales, real-time inventory, in-store and web traffic data) and location level (local competitors, demographics of local catchment); Data on individual customers (historical sales, search history, any other customer-level data useful for making product recommendations); Historical customer service queries, responses, and satisfaction scores	• AI-driven stock and inventory management (e.g., Afesh) • Merchandising based on AI prediction (e.g., Celect) • Recommendation engines that show people what they want to see (e.g., Reflektion) • Use of AI-driven camera analysis to speed payment and optimize store layout and design. For instance, IMAGR makes SmartCart, an ordinary grocery cart with an AI computing video camera. The device tracks what goes into the cart, tallies the total along the way, and syncs that with payment information on the shopper's mobile phone • AI-enabled visual search (e.g., GrokStyle) • SapientRazorfish's COSMOS platform gleans information about a customer's profile and purchasing history. Sephora can then notify customers either by email, direct mail, or SMS when their favorite products are in stock or on sale, and even when customers are near one of their retail stores
Stage 8: Developing marketing communication and influence strategy: Focuses on serving customers the right promotion at the right time		
• Creation of different ads depending on permutations of content, and on related words	• Both historical and real-time data on ads, including their content (both text and images), placement, and performance; Information on	• Granify uses ML to identify shoppers ready to abandon a cart and to make real-time offers to encourage purchase

• Development of individualized promotional offers and ads • Running of AI-driven A/B testing • Optimization of ad placement • Reduction in cart abandonment • Contextual ad targeting • Optimization of ad retargeting • Keyword bidding and cost reduction • Automation and personalization of content creation	potential ad placements (e.g., costs, audience characteristics); Real-time data on customer behavior at all points along the consumer journey	• Watson Ads Omni enables marketers to deploy AI-powered interactive ad placements. Lego was the first brand to use Watson Ads Omni on Black Friday, 2018 (Sweeney, 2018) • Chinese video start-up Viscovery is developing AI technology that enables brands to display ads in videos specific to the content being watched (Caygill, 2017)
Stage 9: Planning metrics and implementation control: Involves identifying performance metrics, monitoring them, and then taking any needed corrective actions		
• Better prediction of expected revenues and profits, as well as their variability • Identification of metrics linked to key outcomes • Prediction of the effect of correct actions and, in some cases, automatically taking steps to diagnose, correct, and improve on poor results	• Both historical and real-time sales and marketing performance data; Real-time data facilitates diagnosing problems, while historical data enables prediction of corrective actions	• US financial software company Intuit uses ML enabled by Amazon Web Services for real-time fraud analysis • Identification of promotional and pricing mistakes

Rosbank, at their call center (Vilar, 2019). Data is collected from customers, including the number of pauses in speech, changes in voice volume, and the total conversation time, and converted in real time to a customer-satisfaction metric.

3.3. Segmenting, targeting, and positioning

Stage 3 involves segmenting, targeting, and positioning, which involves developing an understanding of customer segments and assisting marketing managers in their targeting and positioning decisions. In this process, marketers seek to group consumers according to certain criteria, enabling precise targeting of messages and the creation of brands and products that can best appeal to each segment. AI not only helps to predict customers' intent but can help marketers segment customers into more refined groups. Given the large heterogeneity of consumer tastes and preferences, the potential of segmentation is immense, from tailoring promotions and ads to making better product and brand recommendations. For example, in an attempt to improve its customer targeting, Harley-Davidson teamed up with U.S. marketing firm Adgorithms to use its platform, Albert. Albert uses AI and ML to automate and simplify marketing planning. Harley-Davidson provided Albert information on past customers, enabling the machine to create lists of similar audiences and match people who resemble their current buyers. The platform was responsible for 40% of Harley-Davidson's motorcycle sales and led to a ninefold increase in inbound calls (Power, 2017). AI is also being used to create personalized content targeted to individual consumers. In 2018, Wimbledon partnered with IBM to create a suite of tools and services, including two chatbots, on-site augmented-reality experiences, and a scoring and insights app (SlamTracker) that is tailored to the fan engaging with it (Moore, 2018).

Despite the benefits of using AI for segmenting, targeting, and positioning, marketers should be aware of the dangers of discrimination through AI. While businesses inherently discriminate in terms of to whom they offer products and services, AI can lead to unintended and illegal price discrimination through its emphasis on targeting different audiences. In the EU, it is now considered discriminatory behavior when algorithms are used to set prices on the basis of observable group characteristics. While a group may exhibit a general behavior, any individual within that group may not, and that person would therefore be discriminated against if observable group trends were used to determine pricing (Newell & Marabelli, 2015).

3.4. Planning direction, objectives, and marketing support

Stage 4 involves planning direction, objectives, and marketing support. This stage entails the development of longer-term goals and associated short-term objectives to support larger strategies. Wood (2011) noted that growth strategies, nongrowth strategies, objectives (marketing, financial, and societal), and customer service are important considerations within this stage. To assist growth strategies, AI and chatbots can be integrated into apps or social media to encourage consumer purchasing. One example is the Starbucks Barista bot for Facebook Messenger. The bot lets users place coffee orders via either voice command or a messaging interface.

One of the most common applications of AI in this stage is in customer service. In the United States, just 24% of customer service teams are using AI, but 56% report actively looking for ways to use AI (Salesforce, 2019). Including such applications as chatbots and text and voice analysis, AI use in customer service is forecasted to increase by 143% between 2019 and 2021 (Salesforce, 2019). Today, chatbots are being employed in customer service to address most simple queries. Chatbots reduce customer service costs, but their effect on customer satisfaction can be varied. Many consumers still prefer to speak with human agents for more complicated requests. In the U.K., nearly 50% prefer a human over a chatbot, and in the U.S., 40% prefer a human over a chatbot (Elliott, 2018). Despite consumer preferences for human interactions, AI can still provide back-end support in customer service. For instance, AI can act to assign agents to customers. This process can ensure that customers are connected with an agent who has the expertise to address the customer's needs. One such use would be classification systems that use natural-language processing to identify the problems customers report. By better matching agents with customers, AI can streamline the interaction and preserve value for firms.

3.5. Developing product strategy

Stage 5 involves the development of product strategy (i.e., the creation of the suite of products sold by a firm). At this stage, marketers use their understanding of target consumers and of the intended position for the brand to help develop successful products. This typically involves decisions about a product's design, features, quality, and customization. Opportunities for AI assistance in product strategy include identifying gaps for new product development, facilitating the production of products customized to consumers' specifications, and assisting with product delivery and logistics. AI can also identify which products to manufacture. Fast-fashion brand Choosy draws fashion inspiration almost exclusively from the top trending posts on Instagram, releasing 10 styles a week that customers can order before they go into production (Pallant & Sands, 2018). By creating only products that customers have committed to buying, Choosy avoids accumulating surplus stock and leverages the upside of mass customization while minimizing the downside.

Lily AI is another platform that assists in product configuration in online settings. In particular, Lily AI allows fashion retailers to encourage consumers to 'complete the look' at checkout. Lily AI's deep understanding of shoppers' choices about all apparel categories enables it to create real-time head-to-toe outfit suggestions that help retailers to increase basket size at checkout. AI is also being applied to product strategies within the store environment. U.S. shopping service Instacart uses ML to optimize in-store product selection, equating to thousands of hours of labor savings (Brandon, 2017). Fashion brand Levi's is employing algorithms to optimize how products are arranged in store and to improve size availability. Likewise, Nike is using geographical and behavioral data from its app to inform store offerings, and it is using clustering algorithms to provide advice on which items should be displayed together (McDowell, 2019). Product marketing is also being fine-tuned with AI, with Samsung engaging Crimson Hexagon's AI-powered audience-insights platform to understand what its existing and potential customers are saying on social media (Sentence, 2018). In this way, the analysis of user-generated conversations and associated images in social channels assists in learning "how consumers interact with their products, and thus how to create marketing campaigns that they can relate to" (Sentence, 2018).

3.6. Developing pricing strategy

Stage 6 involves developing a pricing strategy to maximize sales. In developing a pricing strategy, marketers decide how much to charge for products and services, strive to understand consumer price sensitivity, and map competitor pricing. AI can assist in a number of ways, including estimating consumer price elasticity, enabling dynamic pricing (e.g., surge pricing), and detecting pricing anomalies (including pricing errors, cases of fraud, and nonprofitable customers). AI enables marketers to track buying trends and determine more competitive product price points in an attempt to nudge customers at the point of decision (Arevalillo, 2019). Amazon collects and analyzes data at multiple points along the customer's journey, from prepurchase (including products viewed or searched for, reviews, and page visits) to purchase (including all purchase histories and wish lists) and postpurchase (including returns and service interactions). AI and ML assist Amazon in collecting all of this customer data and understanding what shoppers are looking for and the prices they are willing to pay (Ke, 2018).

Some firms are using dynamic pricing, supported by big data and AI, to help gain a competitive pricing advantage. In the hotel context, dynamic pricing can allow the issue of underoccupancy to be addressed by adjusting pricing to balance supply and demand and to maximize profit (O'Hear, 2017). To assist in pricing decisions, Airbnb employs AI and ML to help hosts make pricing decisions about their property. Pricing is a complex process for hosts given traditional demand factors, such as seasonal changes, local events, and location, as well as the fact that each listing exhibits unique property characteristics (Hill, 2015). Airbnb provides pricing assistance with an ML algorithm that makes pricing suggestions for each date that a host makes a property available. For brands that want to ensure their pricing is competitive, AI can develop a pricing index against competitors' catalogs and pricing, allowing relative price to be benchmarked.

3.7. Developing channels and logistics strategy

Stage 7 involves the development of a channel and logistics strategy, including determining optimal logistics, distribution, and product stocking. At this stage, marketers strive to decide between direct sales channels, whole channels, or retail channels. In some instances, AI can provide access to new channels to market. One social commerce app, Browzzin, combines AI and visual-recognition technology with the power of influencers to drive sales as the app transforms posted images into shoppable content (Dorfer, 2019). Shoppable-content platforms like Browzzin and Pinterest's visual search feature are examples of deep learning augmenting the shopping experience via image classification. Such technologies allow consumers to take pictures of things they see in stores, on a commute, or at a friend's, and then they make the items in the pictures shoppable. In this way, consumers can shop anywhere or anytime, which creates new opportunities for companies to engage consumers outside of traditional channel locations. Similar developments will also likely occur in the B2B sales process, which is undergoing substantial transformations fueled by advances in AI and ML (Paschen, Wilson, & Ferreira, in press).

With regard to logistics strategy, marketing managers are concerned with ensuring the delivery of products so they are available to customers at the right place and at the right time. From this perspective, decisions need to be made to estimate demand at particular locations, including at the store level (considering historical and real-time sales, real-time inventory, and in-store and web-traffic data) and location level (considering local competitors and demographics of local catchment). AI allows marketers to predict and optimize distribution, inventory, store displays, and store layouts (both brick-and-mortar and online). Today, retailers are able to employ AI-informed planograms, or dynamic plans that recommend the ideal number and placement of inventory within a store (McDowell, 2019). Further benefits to logistic management include cognitive procurement and predictive merchandising, which assist with stock and inventory management. At Walmart, some stores have started testing autonomous robots that scan shelves for spaces that need replenishing (McDowell, 2019). In the future, it is feasible that robots and drones will transform last-mile delivery.

3.8. Developing marketing communications and influence strategy

Stage 8 involves the development of marketing communications and influence strategy, with a specific focus on serving customers the right promotion at the right time. At this stage, marketers work to create and enhance brand meaning in the eyes of customers, as well as to inform them of product offerings. This involves careful development, targeting, and placement of communications in order to convey an effective message to the correct set of customers while minimizing costs. A diverse range of opportunities exists for AI within the broad domain of marketing communications, including conducting AI-driven A/B ad testing, contextual ad targeting, AI-optimized ad retargeting, keyword bidding, and automation and personalization of content creation. In terms of data requirements, marketers should seek historical data to optimize placement and creation of ads, as well as real-time data about customer behavior at the point of purchase. Current applications at this stage include AI-powered interactive ad placements (Sweeney, 2018) and the ability to display ads in videos specific to the content being watched (Caygill, 2017). For Black Friday 2018, LEGO engaged Watson Ads Omni to create AI-powered interactive ads (Sweeney, 2018). The AI system was trained with the knowledge of a wide range of different LEGO products, with ads crafted to consumers depending on their specific interests and needs. The benefit of such an application is that the brand can have meaningful, one-on-one conversations with consumers along their paths to purchase.

In terms of AI-generated content creation and the development of personalized content, 20th Century Fox and the NBA provide interesting use cases. In 2016, 20th Century Fox collaborated with IBM Watson to create the first AI-created trailer for the movie Morgan. Watson analyzed hundreds of thriller and horror trailers to learn what aspects make them suspenseful, and it suggested appropriately thrilling moments for inclusion in the trailer (IBM, n.d.). Taking content creation one step further, the NBA has worked with AI to develop personalized content. In 2015, the NBA partnered with U.S. sports-tech firm WSC Sports to offer fans near-instant highlight clips from games via NBA websites. Using AI, highlight packages were developed for every player in a game, enabling the NBA to deliver personalized highlights to a global audience—for instance, sending clips of Australian-born NBA stars to Australian viewers who were previously underserved by traditional broadcast footage (NBA, 2015).

3.9. Planning metrics and implementation control

Finally, Stage 9 involves developing planning metrics and implementation control, and specifically striving to identify and monitor performance metrics and then taking any necessary corrective actions. To this end, marketers use metrics to assess how their efforts are working, to identify problems, and to increase efficiency. Key aspects of this task include identifying and measuring relevant metrics and deciding how to respond to abnormalities. In terms of data requirements, both historical and real-time environmental sales and marketing performance data can be used to diagnose and help predict corrective actions and variability. Two key benefits of AI in planning and implementation are that human operators are not required to command or analyze outputs and that

AI works on a trial-and-error basis. Algorithms are able to pick up detailed information by mimicking the behavior of the human brain, and marketers are able to understand, anticipate, analyze, and act to solve problems.

A key way in which AI is being used at this stage of the marketing function is in A/B testing—for instance, in the context of assessing advertising or online features. A key benefit of A/B testing underpinned by AL and ML is that websites, ads, and other online assets can self-optimize in real time as a result of AI assessment of behavior and reactions to a multitude of different variations. ML algorithms can continuously collect data and deliver the optimized variations to individual users in real time, allowing for the best performing aspect to carry through. HSBC used this method to drive 100% more click-throughs on their mobile homepage (Adobe, 2019). The company tested AI-driven dynamic content against static content on its mobile app home page. The personalized results drastically outperformed their static peers in terms of click-through rates to product pages. The efficacy of a range of campaigns can be tested with AI assistance. Many consumers use their phones or other devices while they watch TV. If a TV advertising campaign airs and customers use devices in parallel to ad exposure, the immediate response to the campaign can be assessed. For example, with the data for when each individual ad airs, marketing managers can assess metrics relating to the specific call to action, such as site traffic, and compare the airing times to user response immediately.

4. Getting it right: From AI foundations to an AI orientation

While AI holds many possibilities for marketers, achieving its potential is not easy. A firm's journey from an AI foundation to an AI orientation is akin to the DIKW Pyramid (Zins, 2007), which describes the hierarchical relationship between Data, Information, Knowledge, and Wisdom. At the base of the pyramid, firms must first have or develop certain foundational abilities to collect data. From here, AI and ML functionality transforms useful and relevant data into information. This information, when blended with context, expertise, and intuition, becomes knowledge. Finally, wisdom adds value, which requires the mental function of judgment (Wallace, 2007).

A data foundation requires firms to have robust systems capable of tracking relevant data in real time. They must also be able to store data for historical analysis because the data requirements for AI are quite high (Chui et al., 2018). While collecting data may seem easy, it is important to note that many IT systems are not designed for data pulls. For instance, many advertising agencies' systems are designed to track an individual client's performance, not to extract data from campaigns. Similarly, many businesses suffer from data silos. Many systems do not use a common tracking ID number, or worse, they arrange data in fundamentally different ways, necessitating custom software for data sets to be merged. While some forms of ML (e.g., reinforcement) can operate without training data sets, accessing historical data sets is valuable.

In developing an AI foundation, firms will also need to be aware of the increasingly important challenges of privacy and regulation. Consumers are understandably growing more concerned about what data is being collected from them and how it is being used by marketers. In response, firms such as Apple are proactively choosing to restrict what consumer data is collected and how it is used. While some workarounds are possible, such restrictions necessarily impose constraints on what data scientists can potentially achieve with ML. A similar concern lies in privacy-related regulation. In Europe, the General Data Protection Regulation (GDPR) came into effect in May of 2018. The regulation requires the highest privacy settings by default, unless a user explicitly consents to their data being used. Such defaults restrict both the amount and quality of data available for use in AI applications. In the U.S., concern is also growing, in part because of Facebook's continued data breaches and harvesting of data without consumer consent (Doffman, 2019). U.S. regulation has yet to follow the EU's example, although it may if consumer concern continues to grow. Furthermore, ML must also be monitored to ensure compliance with antidiscrimination laws (Chui et al., 2018; Newell & Marabelli, 2015). For instance, in the U.S., lenders cannot use race-based predictions of loan defaults as a reason for loan denial, and in the EU, insurers are no longer able to use statistical evidence about gender differences to set premiums (Newell & Marabelli, 2015).

In addition to data, firms looking to leverage AI also need to consider their human capital. While AI requires skilled data scientists, other complementary functions are also necessary. While data scientists are often highly skilled statisticians, their expertise should be supplemented by deep awareness of the firm, its markets, and its customers in order to build optimal models. While ML algorithms are highly adaptable on their own, correctly coding or transforming data can still lead to significant improvements in performance. For instance, while many data sets include a calendar date, adding in a categorical variable denoting which day of the week each day corresponds to can be highly predictive of sales at some businesses, such as restaurants. As such, best practice often marries data scientists with managers who have deep business and strategic knowledge. Software and software engineers are also important considerations. While many open-source statistical computing programs have ML plug-ins available, their use requires considerable expertise to run, assess, and implement models (Demandbase, 2016). Even more user-friendly options, such as the automated ML platform DataRobot, still require software engineers to integrate resulting learnings into firm systems for on-the-fly implementation. This reflects the broader choice between buying or building IT architecture. It is also important to be aware that ML models can drift over time and require periodic recalibration and retraining (Chui et al., 2018).

Once the foundational aspects of AI implementation—data, human capital, and software—are present, firms must still work to develop an AI orientation within their broader culture. For some, such cultural shifts will require a completely different approach to decision making, from top down to bottom up and from long-range planning to short-term reactions (Merendino et al., 2018). This entails both philosophical shifts and more pragmatic considerations. At a macro level, business orientations need to shift toward a culture of continual improvement through testing and learning. While initial benefits from AI are often modest, with continual improvement they can compound over time into much larger gains. This includes adopting a data-driven approach to mining historical data for clues on paths forward, as well as developing sets of testable possibilities that AI can experiment upon. To evolve a business's processes in order to emphasize this constant mining of existing data and ceaseless running of AI tests can sometimes represent a large departure from existing organizational cultures. This requires training employees in the basic capabilities and opportunities of AI so that they can better identify possible business opportunities, understand output, and act upon findings (Chui et al., 2018; Demandbase, 2016). Internal marketing programs to garner buy-in and share ideas and successes can also be helpful.

While the success of developing an AI orientation often depends on a firm's ability to foster cross-functional collaboration, this is very difficult to achieve. While considerable research explores how to develop such competencies—generally in the context of developing a new product (Morgan & Liker, 2006; Sethi, Smith, & Park, 2001)—the role of incentives is also an important consideration. How AI resource costs and benefits are apportioned can encourage different behaviors among employees. For instance, if the budget for AI expenditures is charged back to departments, it might cause subtle resistances to usage, especially in early stages when benefits are less clear. This can be potentially mitigated if benefits from AI cost savings accrue back to the individual departments that implement them. Should such savings be taken away, this might instead dissuade use. Similarly, managers are encouraged to consider how AI factors into the metrics by which teams and departments are assessed. Rather than simply using dollar amounts as targets, firms might also set targets for efficiency gains. Likewise, rather than evaluating immediate benefits, teams and departments might be better evaluated in terms of the opportunity or potential value their changes can bring.

Because understanding and implementation of AI is continuing to evolve, maintaining an AI orientation requires constant monitoring of industry best practices. Managers may want to increase funding for AI-related conferences and educational opportunities, as well as encourage sharing of insights across functional units. Careful design of incentives and performance metrics can help encourage participation in such efforts. Finally, managers should lead by example, themselves staying abreast of best practices and championing their own AI initiatives.

5. What's next? Thoughts for the future of AI

There is no doubt that AI is becoming increasingly integrated into marketing practice, enabling companies to reduce process times and engage with individual consumers at scale. But in many ways, AI is still in its infancy, and not all brands are equally predisposed to implementing AI. Many marketers likely fear relinquishing control to AI, and across many industries, there are widespread concerns that AI will take jobs away from workers. But the rapid development of AI technologies will see jobs change and adapt, though not necessarily decline, to the evolving needs of companies. For instance, as AI is responsible for more analytical tasks, analytical skills will likely become less important. In contrast, jobs requiring other skill sets, such as intuition or empathy, are likely to increase in importance (Huang & Rust, 2018). In essence, to progress to the point where AI can add wisdom, human judgment will be required.

With the multitude of opportunities for AI integration within marketing, some may fear that AI will replace human work roles within the profession. But at a broad level, the automation afforded by AI technologies will allow marketers the ability to invest their time in creativity rather than process. For service agents, AI will result in an elevation in tasks, allowing AI to improve the prioritization of service agents' work (Salesforce, 2019). At a more granular level, AI affords marketers with new tools to engage, satisfy, and retain customers.

The development of AI will also lead to a gap between early adopters and laggards. Research suggests that early adopters will likely be those organizations with a strong digital base and, as such, a higher propensity to invest in AI (Bughin et al., 2017). For early adopters, there will be additional challenges associated with forging a new path in the largely uncharted application of AI in business. These organizations may require unforeseen resources. For example, tech companies like Facebook and Twitter have hired human-rights directors to proactively address social and political issues raised by emerging technology (Lomas, 2018). While AI laggards will not face such challenges, the customer experience they provide may suffer—though customers who want to resist AI or who prioritize privacy may find laggard firms attractive (Newell & Marabelli, 2015).

Regardless of the rate of AI adoption, any future AI-marketing integration will be best served by balancing AI and human intelligence. Given the unique strengths and weaknesses of both AI and humans, blending them together provides the seamless end-to-end experience consumers expect (Forrester, 2017). The most immediate integration of AI and human intelligence will likely occur within customer service via AI-assisted human agents. By combining the speed of computer programs with the deep knowledge and understanding of human service agents, companies can resolve customer problems more quickly. Over time, it may become increasingly hard to tell humans and AI agents apart in service contexts.

Beyond operational marketing functions, AI will likely effect drastic shifts in consumption practices as we know them. Even today, societal changes enabled by AI have shifted consumption behavior in some categories. Now, rather than purchase movies or music, consumers subscribe to Netflix or Spotify, with these platforms offering a vast array of titles and convenience, all curated to individual users by intelligent recommendation systems. One day, we may not own products in the traditional sense but instead subscribe to them, and AI-enabled platforms will deliver us food, clothing, and other necessities as and when we need them (Press, 2019). Such business models will continue to advance the relevance of access over ownership. These shifts will be important for businesses to consider as they pursue the growing market of consumers engaging in alternative forms of consumption.

Acknowledgment

We gratefully acknowledge Dr. Taylor Larkin for his machine-learning expertise.

References

Adobe. (2019 September 16). *AI-powered personalization — Above expectation, beyond imagination*. Available at https://www.adobe.com/insights/ai-powered-personalization.html

Arevalillo, J. M. (2019). A machine learning approach to assess price sensitivity with application to automobile loan segmentation. *Applied Soft Computing*, *76*, 390—399.

Baker, R. (2017 March 1). Domino's to become an 'artificial intelligence first' business. *Ad News*. Available at http://www.adnews.com.au/news/domino-s-to-become-an-artificial-intelligence-first-business#0mPiDLEUG9Sg5FBA.99

Baumgartner, T., Hatami, H., & Valdivieso, M. (2016 May). The new world of sales growth. *McKinsey & Company*. Available at https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/the-new-world-of-sales-growth

Blueshift. (2018). *Activating customer data for AI powered marketing*. Available at https://downloads.blueshift.com/report-customer-data-for-ai/

Brandon, J. (2017 July 12). Instacart AI helps personal shoppers buy groceries faster. *VentureBeat*. Available at https://venturebeat.com/2017/07/12/instacart-ai-helps-personal-shoppers-buy-groceries-faster/

Bughin, J., McCarthy, B., & Chui, M. (2017 August 28). A survey of 3,000 executives reveals how businesses succeed with AI. *Harvard Business Review*. Available at https://hbr.org/2017/08/a-survey-of-3000-executives-reveals-how-businesses-succeed-with-ai

Caygill, D. (2017 November 20). Six trends brands should know about for 2018 and the tech they need to craft responses. *Campaign*. Available at https://www.campaignlive.co.uk/article/six-trends-brands-know-2018-tech-need-craft-responses/1450488

Chaffey, D. (2004). *E-business and e-commerce management*. London, UK: Financial Times-Prentice Hall.

Chaffey, D., & Smith, P. R. (2012). *Emarketing excellence: Planning and optimizing your digital marketing* (4th ed.). Abingdon, UK: Routledge.

Choudhury, S. R. (2016 May 24). Softbank's Pepper robot gets a job waiting tables at Pizza Hut. *CNBC*. Available at https://www.cnbc.com/2016/05/24/mastercard-teamed-up-with-pizza-hut-restaurants-asia-to-bring-robots-into-the-pizza-industry.html

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., et al. (2018, April). *Notes from the AI frontier: Insights from hundreds of use cases*. New York, NY: McKinsey Global Institute.

Columbus, L. (2018 May 14). 77% of marketing execs see AI adoption growing this year. *Forbes*. Available at https://www.forbes.com/sites/louiscolumbus/2018/05/14/77-of-marketing-execs-see-ai-adoption-growing-this-year/#51c6e4267ef8

Cui, G., Wong, M. L., & Lui, H. K. (2006). Machine learning for direct marketing response models: Bayesian networks with evolutionary programming. *Management Science, 52*(4), 597–612.

Das, S., Doppa, J. R., Kim, D. H., Pande, P. P., & Chakrabarty, K. (2015). Optimizing 3D NoC design for energy efficiency: A machine learning approach. In *Proceedings of the 2015 IEEE/ACM international conference on computer-aided design* (pp. 705–712). Austin, TX: IEEE.

Davenport, T. H., & Kirby, J. (2016). Just how smart are smart machines? *MIT Sloan Management Review, 57*(3), 21–25.

Demandbase. (2016 December 13). *80 percent of all marketing executives predict artificial intelligence will revolutionize marketing by 2020*. Available at https://www.demandbase.com/press-release/marketing-executives-predict-artificial-intelligence-will-revolutionize-marketing-2020/

Doffman, Z. (2019 April 18). 1.5m users hit by new Facebook privacy breach as extent of data misuse exposed. *Forbes*. Available at https://www.forbes.com/sites/zakdoffman/2019/04/18/facebook-illegally-harvested-data-from-1-5m-users-as-it-leveraged-its-data-machine/#31649c436a2e

Dorfer, S. (2019 May 31). *Shoppable content: AI app Browzzin*. Available at https://www.stylus.com/kppfqb

Duhigg, C. (2012). How companies learn your secrets. *New York Times Magazine*. Available at https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html?pagewanted=1&_r=1&hp

Dunwoodie, B. (2018 July 12). How AI is impacting the voice of the customer landscape. *CMS Wire*. Available at https://www.cmswire.com/customer-experience/how-ai-is-impacting-the-voice-of-the-customer-landscape

Elliott, C. (2018 August 27). Chatbots are killing customer service. Here's why. *Forbes*. Available at https://www.forbes.com/sites/christopherelliott/2018/08/27/chatbots-are-killing-customer-service-heres-why/#466539aa13c5

Evans, G. L. (2017). Disruptive technology and the board: The tip of the iceberg. *Economic and Business Review, 3*(1), 205–223.

Fluss, D. (2017). The AI revolution in customer service. *DestinationCRM*. Available at https://www.destinationcrm.com/Articles/ReadArticle.aspx?ArticleID=115528

Forrester. (2017). Forrester study reveals benefits of artificial intelligence with the human touch. *Genesys*. Available at https://www.genesys.com/collateral/forrester-study-reveals-benefits-of-artificial-intelligence-with-the-human-touch

Hill, D. (2015). How much is your spare room worth? *IEEE Spectrum, 52*(9), 32–58.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172.

Hurwitz, J. S., Kaufman, M., & Bowles, A. (2015). *Cognitive computing and big data analytics*. New York, NY: John Wiley & Sons.

IBM. (n.d.). *The quest for AI creativity*. Available at https://www.ibm.com/watson/advantage-reports/future-of-artificial-intelligence/ai-creativity.html

Javelosa, J. (2017, March 30). Major firm announces it's replacing its employees with AI. *Futurism*. Available at https://futurism.com/major-firm-announces-its-replacing-its-employees-with-a-i

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255–260.

Ke, W. (2018, November 2). Power pricing in the age of AI and analytics. *Forbes*. Available at https://www.forbes.com/sites/forbesfinancecouncil/2018/11/02/power-pricing-in-the-age-of-ai-and-analytics/#6ce8b9fc784a

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.

Lomas, N. (2018, September 16). Facebook is hiring a director of human rights policy to work on "conflict prevention" and "peace-building." *TechCrunch*. Available at https://techcrunch.com/2018/09/16/facebook-is-hiring-a-director-of-human-rights-policy-to-work-on-conflict-prevention-and-peace-building/

Marr, B. (2018 February 14). The key definitions of artificial intelligence (AI) that explain its importance. *Forbes*. Available at https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that-explain-its-importance/#4eebeecc4f5d

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management, 42*(4), 489–495.

McCorduck, P. (2009). *Machines who think: A personal inquiry into the history and prospects of artificial intelligence*. Natick, MA: AK Peters.

McDowell, M. (2019 March 12). Stores get smart about AI. *Vogue Business*. Available at https://www.voguebusiness.com/technology/artificial-intelligence-physical-stores-kering-nike-alibaba

Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., et al. (2018). Big data, big decisions: The impact of big data on board level decision-making. *Journal of Business Research, 93*, 67–78.

Moore, M. (2018 July 14). Wimbledon 2018: How IBM Watson is serving up the best viewer experience. *TechRadar*. Available at https://www.techradar.com/news/wimbledon-2018-how-ibm-watson-is-serving-up-the-best-viewer-experience

Morgan, J. M., & Liker, J. K. (2006). *The Toyota product development system*. New York, NY: Productivity Press.

Narrative Science. (2018 January 17). *Artificial intelligence (AI) adoption grew over 60% in the last year: Executive survey shows almost two-thirds of enterprises harnessed AI in 2017*. Available at https://narrativescience.com/company-annoucements/artificial-intelligence-ai-adoption-grew-over-60-in-the-last-year/

NBA. (2015). *NBA teams up with WSC Sports Technologies to provide next-gen video highlights to fans worldwide*. Available at http://pr.nba.com/nba-wsc-sports-technologies-partnership

Negnevitsky, M. (2004). *Artificial intelligence: A guide to intelligent systems* (2^{nd} ed.). New York, NY: Addison-Wesley.

Newell, S., & 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), 3–14.

Oculus360. (2018 March 1). *Using AI to analyze your brand's category*. Available at https://www.o360.ai/blog/using-ai-to-analyze-a-brand-category?hsCtaTracking=1a0f5798-

592d-445c-b8b3-31e122a70676%7Cf1c6b498-0a32-4ced-9a9c-dd8f3ceb236b

O'Hear, S. (2017 December 13). The price is right! Pace raises £2.5M to automate hotel room pricing based on demand. *TechCrunch*. Available at https://techcrunch.com/2017/12/13/pace-pricing/

Pallant, J., & Sands, S. (2018 September 12). The paradox of choice. Why made-to-order might not solve the fashion industry's problems. *The Conversation*. Available at https://theconversation.com/the-paradox-of-choice-why-made-to-order-might-not-solve-the-fashion-industrys-problems-102442

Paschen, U., Pitt, C., & Kietzmann, J. (2020). Artificial intelligence: Building blocks and an innovation typology. *Business Horizons, 63*(2) (XXX—XXX).

Paschen, J., Wilson, M., & Ferreira, J. (2019). Collaborative intelligence: How human and artificial intelligence create value along the B2B funnel. *Business Horizons, 63*(3) (in press).

Ponce de Leon, S. (2019 January 12). At CES, AI robots can read your emotions. *Grit Daily*. Available at https://gritdaily.com/ai-emotion-bots/

Power, B. (2017 May 30). How Harley-Davidson used artificial intelligence to increase New York sales leads by 2,930%. *Harvard Business Review*. Available at https://hbr.org/2017/05/how-harley-davidson-used-predictive-analytics-to-increase-new-york-sales-leads-by-2930

Press, G. (2019 December 9). 120 AI predictions for 2019. *Forbes*. Available at https://www.forbes.com/sites/gilpress/2018/12/09/120-ai-predictions-for-2019/#43092141688c

Reavie, V. (2018, August 1). Do you know the difference between data analytics and AI machine learning? *Forbes*. Available at https://www.forbes.com/sites/forbesagencycouncil/2018/08/01/do-you-know-the-difference-between-data-analytics-and-ai-machine-learning/#5c50edac5878

Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science, 33*(2), 206—221.

Salesforce. (2017). *State of marketing: Insights and trends from 3,500 global marketing leaders*. Available at https://www.salesforce.com/content/dam/web/en_us/www/assets/pdf/datasheets/salesforce-research-fourth-annual-state-of-marketing.pdf

Salesforce. (2019 April 9). *State of service: 2019's changing customer service trends*. Available at https://www.salesforce.com/au/blog/2019/04/state-of-service-2019-s-changing-customer-service-trends.html

Sentence, R. (2018 June 28). *How Samsung uses social listening for product marketing and sentiment analysis*. Available at https://econsultancy.com/how-samsung-uses-social-listening-for-product-marketing-sentiment-analysis/

Sethi, R., Smith, D. C., & Park, C. W. (2001). Cross-functional product development teams, creativity, and the innovativeness of new consumer products. *Journal of Marketing Research, 38*(1), 73—85.

Sweeney, E. (2018 October 2). IBM's interactive AI ads reach more sites, brands. *Industry Dive*. Available at https://www.marketingdive.com/news/ibms-interactive-ai-ads-reach-more-sites-brands/538558

Teboul, W. (2018 July 20). *Why use machine learning instead of traditional statistics?* Available at https://towardsdatascience.com/why-use-machine-learning-instead-of-traditional-statistics-334c2213700a

Vilar, H. (2019 March 12). UK's Nationwide analyses customer interactions with SAS. *Fintech Futures*. Available at https://www.bankingtech.com/2019/03/uks-nationwide-analyses-customer-interactions-with-sas/

Wallace, D. P. (2007). *Knowledge management: Historical and cross-disciplinary themes*. Santa Barbara, CA: Libraries Unlimited.

Wolska, K. (2017 May 19). *From mobile first to AI first — Google I/O 2017 conference*. Available at https://medium.com/appchance/from-mobile-first-to-ai-first-google-i-o-2017-conference-c93247d8c234

Wood, M. B. (2011). *The marketing plan handbook*. New York, NY: Pearson.

Zins, C. (2007). Conceptual approaches for defining data, information, and knowledge. *Journal of the American Society for Information Science and Technology, 58*(4), 479—493.