Chapter 9

Impact of AI on Knowledge-based Marketing: A Study of B2B Markets

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Abstract

Knowledge management (KM) is an important topic in the age of big data, and this study adds to the existing body of literature by providing a novel KM perspective on the technological phenomenon of artificial intelligence (AI). This study aims to discover how AI might facilitate knowledge-based business-to-business (B2B) marketing. In this chapter, the authors take a close look at the building blocks of AI and the relationships between them. Future research directions and also the effects of the various market information building components on B2B marketing are discussed. The study's approach is theoretical; it tries to provide a framework for characterising the phenomenon of AI and its constituent parts. Additionally, this chapter provides a methodical analysis of the three categories of market information crucial to B2B marketing: knowledge of customers, knowledge of users, and knowledge of external markets. This research looks at AI through the lens of the conventional data processing framework, analysing the six pillars upon which AI systems are founded. It also explained how the framework's components work together to transform data into actionable information. In this chapter, the authors will look at how AI works and how it can benefit B2B knowledge-based marketing. It's not aimed at AI experts but rather at general marketing managers. In this chapter, the possible effects of AI on B2B marketing are discussed using examples from the real world.

Keywords: AI; B2B marketplaces; machine learning; knowledge-based marketing; data use in marketing

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1. Introduction

Scholars from several fields have noted that firms are transitioning to a more knowledge-based model rather than remaining solely industrial (Grant, 1996, 2006; Spender & Grant, 1996).

Information quantity and quality have made knowledge as valuable to an organisation as physical and financial capital (Archer-Brown & Kietzmann, 2018). Since 1990, marketing practices have shifted to market-oriented approaches. They are supported empirically (Day, 1990, 1994, 2000). Understanding the market helps to create products and services that meet target consumers' needs and build long-term connections with them (Kamal et al., 2022; Kohli & Jaworski, 1990). Digitalisation and new information and communication technology (ICT) impacted B2B value creation, notably in how B2B organisations handle data and knowledge (Khan et al., 2022; Magd et al., 2022; Paschen et al., 2019). This has received a boost during the Covid-19 era (Bocar et al., 2022; Khan et al., 2021). Massive data sets have been accelerated by ICT. Social media and internet of things (IoT) are some examples (Kietzmann et al., 2011). These discoveries are small compared to their collective impact (Pigni et al., 2016).

Big data's volume, velocity, diversity, authenticity, and value give B2B companies market intelligence. With the help of modern information technology, businesses can control, access, and share insights gained from large data sets (Codini et al., 2019). Experts in the field are increasingly drawn to the benefits AI. Several studies (Martnez-López & Casillas, 2013; Singh et al., 2019; Syam & Sharma, 2018) support this theory. AI helps B2B companies use massive data for marketing and sales.

B2B marketers recognise the benefits of AI-enabled information but lack the abilities to use it (Martnez-López & Casillas, 2013; Singh et al., 2019; Syam & Sharma, 2018). In other words, B2B marketers frequently utilise and refer to a number of terminology and concepts when addressing AI, which leads to misunderstandings and ambiguities about what AI can and cannot achieve. B2B executives and managers need to have a firm grasp of what AI is, what the many terms and concepts used to define it entail, and how they interact to provide varying value propositions for B2B marketing.

As an added complication, we cannot yet predict how the rise of AI will alter our views of the B2B industry. In this chapter, we fill in these two gaps. This study addresses the first question, lists popular terminology, and describes AI system components and links. This study also examines how AI might impact market data-driven B2B marketing decisions.

2. Literature Review

Comprehending AI requires an understanding of human intellect is our first step. Russell and Norvig's (2016) technique assesses AI's logic rather than its human-likeness. Any realistic AI will always act according to its knowledge. From a reasonable perspective, AI should produce the best possible or expected result under uncertainty. The contrast between human and rational behaviour shows that people sometimes act in ways that may not achieve their goals (Kahnemann & Tversky, 1979).

As demonstrated (Kahnemann & Tversky, 1979), Herbert Simon (1996) claims that our decisions are influenced by our cognitive capacity, knowledge, and time.

Understanding "computational agents" is our second AI education foundation. Russell and Norvig's (2016) information system agent constantly consumes data and adjusts its behaviour. Humans utilise their hands, feet, vocal chords, and other senses to gather information and respond. Based on sensor data from cameras or keyboards, computer agents can write files, modify objects, or show results. This chapter argues that computational agents can help AI go from theory to problem-solving.

Information systems include hardware, software, data, people, and procedures. Computers and servers are hardware. Algorithms are software. Facts and statistics are data. An information systems' interaction with its organisational and social surrounding is governed by the fundamental input–process–output paradigm, which describes the systems' flow of data. This concept considers the system to be independent from its surrounding environment.

Consequently, in order for systems to function, data must first be gathered from the surrounding environment (referred to as inputs). These data must then be processed in order to produce something of value (referred to as processes) (outputs). Raw facts are referred to as data in the context of information systems. The surrounding information makes it much simpler to understand these specifics. We may have a better understanding of, and control over, our surroundings if we analyse data in a variety of different ways (Ackoff, 1989).

3. Need for the Study

AI-enabled data must be understood by academics and professionals. Depending on these criteria, a B2B corporation may utilise AI to develop, organise, and share knowledge and other intangible resources to gain a competitive edge or improve organisational performance (Grant, 1996, 2006; North & Maier, 2018).

4. Methodology and Purpose of the Study

This study sought to better understand AI and B2B marketing. The study seeks to understand AI system components. This research discusses B2B marketing's several components' effects on market intelligence and alternative research methods. For this purpose, the researchers selected few literatures to understand the components of AI in context of B2B marketing. The methodology adopted thus is 'review of literature', for this purpose, the relevant literatures were extracted from the sources like google scholar, Scopus, Ebsco, and other databases.

5. Conceptual Development and Findings

Earlier literature provided definitions for information systems and AI. After defining AI and information systems, we can explore AI systems. It is possible to break down AI systems into six basic components if we assume that AI is the theory and practice of designing systems that operate to achieve the optimal intended outcome. Then, we'll define each building block and discuss its significance in AI systems. In order to perform input–process–output transformation, any information system needs to gather data from its environment. An AI's inputs can be categorised as either structured data or unstructured data.

5.1. Element One of AI: Structured Data

Structured data (also known as foundation of AI) is standardised and organised. Business analytics relies on quantitative analysis of organised data. Customer profiles, web-browsing behaviours, and purchase history are internally structured data. External structured data include stock transactions and social media reviews. AI can now calculate structured data in real time thanks to faster processors and more advanced machine learning (ML) algorithms.

5.2. Element Two of AI: Unstructured Data

Unstructured data are not standardised or organised. Unstructured data can overwhelm conventional information systems, but AI can process it. IoT and mobile devices generate infinite unstructured data. This can be human-generated text (blogs, posts, reviews, comments, or tweets), voice (podcasts), or photos of real-world stuff. Customers can submit structured data using web forms. For extra comments or queries, a comment box (unstructured data) may be provided.

5.3. Element Three of AI: Pre-processing

Before being used, all unstructured data must be cleansed, normalised, transformed, feature extracted, and selected.

5.3.1. Ability to Comprehend Spoken Language

Natural language understanding (NLU), that is, words and sounds produce language (spoken language) and teaches AI language. AIs type via voice recognition. Voice recognition identifies speakers and words. Text-to-speech AI just understands words. NLU seeks text meaning. Context, linguistic preferences, and conversation evolution obscure spoken language, making this challenging. AI must distinguish homophones, homographs, and homonyms. Slang, jargon, and dialects misinterpret. Thus, understanding natural language (words and phrases in context) requires syntax, semantics, and pragmatics (Gill, 2019). Modern systems analyse text using ML instead of hard-coded rules like early NLU implementations (explained in AI's element four below). A lexicon and grammar rules (vocabulary) are standard components of NLU application approaches (vocabulary). These programmes use these factors, statistical models, and ML to determine the most likely interpretation of spoken text. Words with many inflections, such as 'fishing and 'fisher', can be 'stemmed' using a NLU tool.

5.3.2. Computer-vision Processing

An AI system must translate visual data into internal world representations. The application determines how well computers can distinguish objects, sceneries, events, borders, surfaces, and volumes (Forsyth & Ponce, 2011). Cloverleaf, a retail technology business, uses in-store screens to detect shoppers' moods in real time to price and promote products. Output-dependent AI systems struggle with visual processing, which humans do intuitively.

ML provides the algorithmic foundation for picture data pattern recognition and significance. Computer vision and ML are interconnected. Modern object categorisation algorithms outperform human recognition rates, unlike early computer vision systems that used human-designed attributes.

5.4. Element Four of AI: Main Processing

Primary processing is the fourth key component of AI. Intelligent people are characterised by their capacity to reason their way through difficult problems and unfamiliar situations. To learn is to acquire new knowledge or modify one's perspective in order to better carry out one's intended actions. The fourth facet of AI is ML, and it is this facet that is responsible for the three hallmarks of intelligent behaviour.

5.4.1. Problem-solving

One must choose the best action from plausible options to address a problem. Like humans, AI solves issues in two ways. AI systems rank problem solutions during divergent problem-solving. This shows that numerous tactics may produce comparable outcomes rather than a single best one. Convergent problem-solving narrows down solutions until one is optimal, if not unique, to the situation. We can exploit AI systems' vast data processing capabilities. AI problem-solving decisions don't always consider all options before choosing the optimal one. AI uses heuristics to find solutions that fit the present problem (Tecuci, 2012).

5.4.2. Reasoning

Reasoning using facts leads to a conclusion. Computers draw inferences from data using logic. Classical reasoning machines are different from AI systems that can reason under uncertainty. Inference engines are AI systems that draw conclusions from data. Applying laws to publicly available data yields information (Wilson & Keil, 2001). Reasoning explains why something works, while problem-solving solves difficulties. This situation has two main schools of thinking. Deductive reasoning uses presumptions to derive new conclusions. Science uses top-down thinking. Thus, if the premises are correct, then is the conclusion. Hypotheses and facts yield new findings. After collecting a vast protein training data set, IBM Watson Health employed deductive reasoning to identify proteins associated with cardiovascular disease. Inductive reasoning, or bottom-up thinking, draws generalisations from specific evidence. AI systems analyse internal business data to predict future regulatory obligations.

5.4.3. Machine Learning

ML allows computers 'learn from experience' and improve without programming (ML). Machines learned from supervision. Effective systems inferred from massive data sets and learned from prior mistakes without explicit coding. ML and statistics reveal insights. Massive data, deep learning, and Graphics Processing Unit (GPU) technology enable algorithms automatically analyse complicated data components and perform optimally. AI uses ML in this process.

Unsupervised, supervised, and reinforcement learning are frequent. Speech and object detection require supervision. Labelled training data teach machines patterns and rules. Unsupervised learning helps clustering and dimensionality reduction grasp data structure (e.g. clustering and dimensionality reduction). Repetition teaches complicated behaviours. Experts, AIs, and data train them. ML enhances reasoning, problem-solving, and improves the workflow.

Modern AI learns. It predicts using massive data sets gathered from multiple sources (Kietzmann et al., 2019). The cascaded network can compute complex mappings from nonlinear calculations (Knight, 2017). A neural network trained to recognise objects in pictures may scan pixels for straight lines in its initial layer. The second layer recognises complex patterns (curves, crosses, etc.) using oriented lines instead of pixels (curves, crosses, etc.).

Deeper network units are conceptualised by complex geometries. The network's output layer determines image classification confidence. Data and GPU power hamper the creation of millions-of-parameter artificial neural network. Deep neural networks are gaining prominence (Yao, 2017). These networks learn any input–output relationship and other non-visual inputs such as website clicks, medical laser scans, temperature sensor data, and movie soundwaves are.

5.4.4. Information Storage

Memory, the repository of facts, information, and knowledge, allow intelligent beings to be moulded by their past experiences. AI systems are able to store and retrieve massive amounts of data in real time and archives to reason, learn from experience, and solve problems.

5.5. Element Fifth of AI: Knowledge

These representations are built on databased digital reproductions of the original physical artefacts for future use. Structured data warehouses were developed in the 1970s using relational or hierarchical databases. They encoded, decoded, stored, and retrieved calculated values like modern AI systems. In AI, these representations may be structured data, pre-processed data, or system-generated data. These models demonstrate AI's three main abilities: issue-solving, ML, and problem-solving.

5.6. Element Sixth of AI: Information

Organisations use AI to enhance Search Engine Optimization (SEO). The approach is similar to SEO keyword research, but by translating keywords into semantic concepts, it can think about a wider range of difficulties, more deeply than people can.

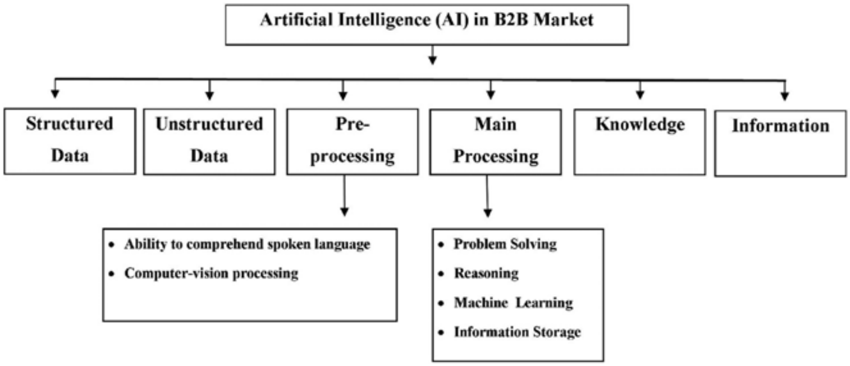

Fig. 9.1. AI and its Elements in Context of B2B Market.

'Emotion AI' and other sentiment analysis tools can help marketers understand and quantify customers' emotions and affective states to make better marketing decisions. Advertising and media companies use cameras, computer vision, and ML to evaluate commercials. Marketers can decide whether to pull a commercial from broadcast by altering media material and testing advertising (e.g. by testing advertisements beforehand). Many business apps leverage AI-generated data for automation and decision-making.

5.7. Conceptual Framework

Based on the discussion above, the graphical representation of the AI and its six elements is drawn in Fig. 9.1.

6. Practical Implications

National language generation (NLG) writes and NLU interprets conversational narratives. Natural Language Processing (NLP) is when an AI system reads and interprets human language (NLU), makes decisions, and reacts in natural language. NLG may give reports and business information to internal and external customers using big data sets or other internal resources. AI can be utilised with NLG to create journalistic or commercial content at scale.

Recent AI programmes have learned to identify sounds in text and modelled human speech patterns, allowing them to accurately duplicate it. Google Assistant's latest deep learning-based voice recognition, reasoning, and speech production engine can initiate calls to businesses, engage in two-way conversations, and schedule appointments. If it enables machine translation, then technology may soon recognise, translate, and produce spoken words in another language.

6.1. Image Creation

An AI system that can create images can do so without a training set, unlike image recognition. This function, although in its infancy, can complete photos with missing background information, change images to look like they were painted by a famous artist, and make portraits of imaginary persons. Image creation can help photographers improve their editing skills and graphic designers who need advertising stock photos. AI-driven picture synthesis can create animated films and building designs.

6.2. Robotics

Robotics applies information to devices that physically affect their surroundings. In emergencies, intelligent robots' capacity to traverse the physical world is vital. Robots can now pick up unique products in warehouses with human precision and skill. Chatbots and other conversational AIs could use it. Chatbots can answer simple enquiries and make complex reservations for customers. Hubspot's chatbot attracts and engages site visitors. It also generates leads and educates consumers.

7. AI's Impact on B2B Marketers' Market Understanding

AI, an intelligent system, can be connected with any of the above components to help B2B marketers strategise, organise, and execute their marketing initiatives. This study proposes that the inputs–processes–outputs framework and AI building blocks can assist B2B marketers turn raw data into useable information and expertise. Diversity in construction can be used to study theoretical concepts and AI breakthroughs. AI can aid user, customer, and external market knowledge (Kohli & Jaworski, 1990).

8. Discussion and Future Research Directions

8.1. Understanding of the Customer

B2B companies must know their customers because this affects product or service performance. AI can build client profiles. AI analyses the customer's recent purchases (size, frequency, and type), online activity (pages seen), personality (demographics and psychographics), and corporate interactions to develop this profile (Khan & Magd, 2021; Magd & Khan, 2022). ML and prediction algorithms can analyse client profiles to improve relationships and find new consumers. AI can improve B2B sales marketing by identifying potential leads (Järvinen & Taiminen, 2016). AI can automate time-consuming operations like meeting scheduling and chatbot responses to frequently requested questions during approach and pre-approach. Salespeople can use AI presentation bots to produce compelling presentations during presentation and closing. AI can alleviate customer difficulties by interpreting real-time consumer input. Automated order processing and chatbot follow-up can improve order fulfilment with AI.

8.1.1. Future Research Directions

The above discussion provides further research directions. For instance, if AI complements or replaces human-performed tasks in B2B sales, it's important to examine how this would affect sales professionals' employment. How does AI affect salespeople's knowledge and effectiveness? How will salespeople act when AI formalises their tacit knowledge? How much and what kind of sales work might AI do? How might AI help salesmen communicate client needs? AI's impact on B2B clients' value generation processes may be worth studying. How can AI be used in marketing and sales to create, organise, and use client data?

8.2. Understanding of the User

User knowledge encompasses users' desires, goals, and expectations (Abrell et al., 2016). According to the research, user knowledge helps B2B organisations meet long-term consumer demand and develop products and services (Abrell et al., 2016). User input enhances products and processes. AI enhances learning. AI can process massive data faster and more accurately thanks to social media. B2B marketers can learn about customers' wants, attitudes, and actions by analysing social media content (Martínez et al., 2016). IBM Watson recognises text tone, emotions, attitudes, and values (Biondi et al., 2017; IBM, 2018). B2B marketers may use these psychographic traits to develop products. AI can analyse user feedback and suggest product improvements. AI-enabled users may disclose new ways consumers change existing items, which is useful for product development and innovation.

8.2.1. Future Research Directions

Consumer knowledge research may inform user knowledge and AI studies. How will AI aid B2B knowledge sharing? How does AI help B2B advertisers' transfer and store knowledge? Future study may examine how AI affects customers and users differently and how to optimise their interactions as users are lower on the value chain than consumers.

8.3. Understanding of the Market

The market orientation paradigm suggests that B2B companies obtain and apply more external market intelligence since external factors may influence user or consumer preferences and behaviours. 'External forces' include competitors, politicians, and news outlets (Kohli & Jaworski, 1990). AI can analyse massive amounts of internet content and therefore can comprehend the external market. For instance, natural language-researching AI algorithms detect bogus news. Marketers must understand how fake news can hurt a brand's reputation and success (Berthon & Pitt, 2018). Marketers should monitor how their brands are associated with incorrect information to respond properly. These insights can promote B2B sales, positioning, and product development.

8.3.1. Future Research Directions

Discussion suggests several new research avenues. First, user, customer, and market data can be used to analyse research topics. Exploring how AI can improve market sensing and how it can change the way users and consumers produce value in reaction to other market knowledge are all potential future fields of study.

9. Conclusion

In this age of digitisation, ICT, the ability of AI's ability to gradually understand massive amounts of data, will have the greatest impact. As with many developing technologies, B2B managers need to understand how these technologies work and how they may affect KM methods.

This study aims to teach B2B marketing managers and executives about AI systems and their interdependencies. This research suggests a six-part AI framework, analyses how those parts relate, and provides real-world examples of how each building block affects B2B marketing.

This study also details how AI technology is changing how B2B marketers view the industry. B2Bmarketers may be able to use AI to turn raw data into actionable insights about their target audience, products, and market. These steps will help B2B organisations acquire, organise, and use customer, user, and market force data. We suggest future research directions for each of these areas to encourage management and marketing researchers to examine AI in business.

References

Abrell, T., Pihlajamaa, M., Kanto, L., Vom Brocke, J., & Uebernickel, F. (2016). The role of users and customers in digital innovation: Insights from B2B manufacturing firms. *Information & Management*, *53*(3), 324–335.

Ackoff, R. L. (1989). From data to wisdom. *Journal of Applied Systems Analysis*, *16*(1), 3–9.

Archer-Brown, C., & Kietzmann, J. (2018). Strategic knowledge management and enterprise social media. *Journal of Knowledge Management*, *22*(6), 1288–1309.

Berthon, P. R., & Pitt, L. F. (2018). Brands, truthiness and post-fact: Managing brands in a post-rational world. *Journal of Macromarketing*, *38*(2), 218–227.

Biondi, G., Franzoni, V., & Poggioni, V. (2017). A deep learning semantic approach to emotion recognition using the IBM Watson Bluemix alchemy language. In O. Gervasi, B. Murgante, S. Misra, G. Borruso, C. M. Torre, A. Maria, A. C. Rocha, D. Taniar, O. Apduhan, E. Stankova & A. Cuzzocrea (Eds.), *Lecture notes in computer science, computational science and its applications – ICCSA 2017* (Vol. 10406, pp. 718–729). Springer.

Bocar, A. C., Khan, S. A., & Epoc, F. (2022). COVID-19 work from home stressors and the degree of its impact: Employers and employees actions. *International Journal of Technology Transfer and Commercialisation. Inderscience*, *19*(2), 270–291.

Codini, A., Abbate, T., & Aquilani, B. (2019). Knowledge cocreation in open innovation digital platforms: Processes, tools and services abstract. *Journal of Business & Industrial Marketing*, *34*(7), 1434–1447. https://doi.org/10.1108/JBIM-09-2018-0276

Day, G. S. (1990). *Market-driven strategy: Processes for creating value*. The Free Press.

Day, G. S. (1994). The capabilities of market-driven organizations. *Journal of Marketing*, *58*(4), 37–52.

Day, G. S. (2000). Managing market relationships. *Journal of the Academy of Marketing Science*, *28*(1), 24–30.

Forsyth, D., & Ponce, J. (2011). *Computer vision: A modern approach*. Prentice Hall.

Gill, N. S. (2019). *Overview of artificial intelligence and natural language processing*. Retrieved January 2023 from www.upwork.com/hiring/forclients/artificial-intelligence-and-natural-language-processing-inbig-data/

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109–122.

Grant, R. M. (2006). The knowledge-based view of the firm. In D. O. Faulkner & A. Campbell (Eds.), *The strategic management of intellectual capital and organizational knowledge* (pp. 133–148). Oxford University Press.

IBM. (2018). *IBM clouds/natural language understanding*. https://console.bluemix.net/docs/services/naturallanguage-understanding/getting-started.html#analyze-phrase

Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management*, *54*, 164–175.

Kahnemann, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Kamal, S., Naim, A., Magd, H., Khan, S. A., & Khan, F. M. (2022). The relationship between e-service quality, ease of use, and E-CRM performance referred by brand image. In A. Naim & S. Kautish (Eds.), *Building a brand image through electronic customer relationship management* (pp. 84–108). IGI Global.

Khan, S. A, Epoc, F., Gangwar, V. P., Ligori, T. A. A., Ansari, Z. A. (2021). Will online banking sustain in Bhutan post Covid-19? A quantitative analysis of the customer e-satisfaction and e-loyalty in the Kingdom of Bhutan. *Transnational Marketing Journal*, *9*(3), 607–624. https://doi.org/10.33182/tmj.v9i3.1288

Khan, S. A., & Magd, H. (2021, December). Empirical examination of MS teams in conducting webinar: Evidence from international online program conducted in Oman. *Journal of Content, Community and Communication*, *14*(7). https://doi.org/10.31620/JCCC.12.21/13

Khan, S. A., Magd, H., & Epoc, F. (2022). Application of data management system in business to business electronic commerce. In A. Naim & P. K. Malik (Eds.), *Competitive trends and technologies in business management* (pp. 109–124). Nova Science Publishers, USA.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251.

Kietzmann, T. C., McClure, P., McCarthy, I. P., & Kriegeskorte, N. (2019). Deep neural networks in computational neuroscience. In *Oxford research encyclopedia of neuroscience*. Oxford University Press.

Knight, W. (2017). The dark secret at the heart of AI. *MIT Technology Review*. www.technologyreview.com/s/604087/the-dark-secret-at-the-heart-of-ai/

Kohli, A. K., & Jaworski, B. J. (1990). Market orientation: The construct, research propositions, and managerial implications. *Journal of Marketing*, *54*(2), 1–18.

Lytics | Source Media. (2019). *Lytics customer stories*. Retrieved January 2023 from www.lytics.com/assets/documents/SourceMedia-CaseStudy.pdf

Magd, H., Jonathan, H., Khan, S. A., & El Geddawy, M. (2022). Artificial intelligence – The driving force of Industry 4.0. In J. M. Chatterjee, H. Garg & R. N. Thakur (Eds.), *A roadmap for enabling Industry 4.0 by artificial intelligence* (pp. 1–15). Wiley.

Magd, H., & Khan, S. A. (2022). Effectiveness of using online teaching platforms as communication tools in higher education institutions in Oman: Stakeholders perspectives. *Journal of Content, Community and Communication*, *16*(8), 148–160. https://doi.org/10.31620/JCCC.12.22/13

Martínez, P., Martínez, J. L., Segura-Bedmar, I., MorenoSchneider, J., Luna, A., & Revert, R. (2016). Turning user generated health-related content into actionable knowledge through text analytics services. *Computers in Industry*, *78*, 43–56.

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.

North, K., Maier, R., & Haas, O. (2018). Value creation in the digitally enabled knowledge economy. *Knowledge Management in Digital Change: New Findings and Practical Cases*, 1–29.

Paschen, J., Pitt, L. F., & Kietzmann, J. H. (2019). Emerging technologies and value creation in business and industrial marketing. *Journal of Business & Industrial Marketing*, 34(7), 1401–1402. https://doi.org/10.1108/JBIM-08-2019-416

Pigni, F., Piccoli, G., & Watson, R. (2016). Digital data streams: Creating value from the real-time flow of big data. *California Management Review*, *58*(3), 5–25.

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Pearson Education.

Simon, H. (1996). *Models of my life*. MIT Press.

Singh, J., Flaherty, K., Sohi, R. S., Deeter-Schmelz, D., Habel, J., Le Meunier-FitzHugh, K., ... & Onyemah, V. (2019). Sales profession and professionals in the age of digitization and artificial intelligence technologies: concepts, priorities, and questions. *Journal of Personal Selling & Sales Management*, *39*(1), 2–22.

Spender, J.-C., & Grant, R. M. (1996). Knowledge and the firm: Overview. *Strategic Management Journal*, *17*, 5–9.

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, *69*, 135–146.

Tecuci, G. (2012). Artificial intelligence. *Wiley Interdisciplinary Reviews: Computational Statistics*, *4*(2), 168–180. https://doi.org/10.1002/wics.200

Turunen, T., Eloranta, V., & Hakanen, E. (2018). Contemporary perspectives on the strategic role of information in internet of things-driven industrial services. *Journal of Business & Industrial Marketing*, *33*(6), 837–845.

Wilson, M. (2016). When creative consumers go green: Understanding consumer upcycling. *Journal of Product & Brand Management*, *25*(4), 394–399.

Wilson, R. A., & Keil, F. C. (2001). *The MIT encyclopedia of the cognitive sciences (MITECS)*. MIT Press.

Yao, M. (2017). *Understanding the limits of deep learning*. Retrieved January 2023 from www.topbots.com/understanding-limits-deeplearning-artificial-intelligence/