

Alma Mater Studiorum Università di Bologna
Archivio istituzionale della ricerca

How to Build an AI Climate-Driven Service Analytics Capability for Innovation and Performance in Industrial Markets?

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:

Akter S., Wamba S.F., Mariani M., Hani U. (2021). How to Build an AI Climate-Driven Service Analytics Capability for Innovation and Performance in Industrial Markets?. INDUSTRIAL MARKETING MANAGEMENT, 97, 258-273 [10.1016/j.indmarman.2021.07.014].

Availability:

This version is available at: <https://hdl.handle.net/11585/858368> since: 2022-03-01

Published:

DOI: <http://doi.org/10.1016/j.indmarman.2021.07.014>

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (<https://cris.unibo.it/>).
When citing, please refer to the published version.

(Article begins on next page)

This is the final peer-reviewed accepted manuscript of:

Akter, S., Wamba, S. F., Mariani, M., & Hani, U. (2021). How to build an AI climate-driven service analytics capability for innovation and performance in industrial markets?. *Industrial Marketing Management*, 97, 258-273.

The final published version is available online at:

<https://doi.org/10.1016/j.indmarman.2021.07.014>

Rights / License:

The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

How to Build an AI Climate-Driven Service Analytics Capability for Innovation and Performance in Industrial Markets?

Abstract

AI climate-driven service analytics capability has been anecdotally argued as a viable strategy to enhance service innovation and market performance in B2B markets. While AI climate refers to the shared perceptions of policies, procedures, and practices to support AI initiatives, cognitive service analytics capability refers to the analytical insights driven by AI climate and augmented by both machines and humans to make marketing decisions. However, there is limited knowledge on the antecedents of such analytics capabilities and their overall effects on service innovation and market performance. Drawing on service analytics literature and the microfoundations of dynamic capability theory, this study fills this research gap using in-depth interviews (n=30) and a survey (n=276) of service analytics managers within the AI climate in Australia. The findings confirm the five microfoundations of cognitive service analytics capabilities (cognitive technology, cognitive information, cognitive problem solving, cognitive knowledge & skills, cognitive training & development). The findings also highlight the significant mediating effect of service innovation in the relationship between analytics climate and market performance and cognitive service analytics capability and market performance.

Keywords AI climate, cognitive service analytics capability, service innovation, market performance, B2B markets.

Paper type: Research paper

1 Introduction

“In customer service, AI is opening entire new frontiers in customer experience and success by applying NLP, sentiment analysis, automation, and personalization to customer relationship management. 90% of organizations are using AI to improve their customer journeys, revolutionize how they interact with customers and deliver them more compelling experiences ” Diorio (2020).

In line with the above news story in Forbes, the AI revolution has sparked research attention to service analytics in industrial marketing due to the higher value deals, complex customer requirements, and close business relationships (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2020; Kotler & Keller 2016; Lytras, Visvizi, Zhang, & Aljohani, 2020). Practitioners and scholars have identified this trend as “the fourth industrial revolution” (Huang & Rust 2018, p.155), “the second machine age” (Brynjolfsson and McAfee 2014, p.1), “ the AI factory” (Iansiti & Lakhani 2020, p.62) or, more specifically, “the game changer for marketing analytics” (Urban et al. 2020, p.71). Indeed, the impact of AI-driven marketing analytics is the most significant development for B2B markets because it requires frequent contact to serve large business customers, which generate data in massive volumes and variety (Davenport, Guha, Grewal, & Bressgott, 2020).

Undoubtedly, the rise of AI has accelerated service interactions through many channels or touchpoints, leading to an explosion of data. B2B marketers leverage this AI-enabled data and analytics for service innovation and firm performance, such as Amazon’s merchant services to facilitate fulfillment and sales, Indigo’s matching platform for linking buyers and sellers and Ant Financial’ screening platform to identify qualified business borrowers (Iansiti & Lakhani, 2020). Superior insights about an industrial market and all its stakeholders (e.g., customers, competitors, and other entities) can enhance innovation and performance (Paschen et al. 2020). A survey conducted by MIT technology review insights (2018) on more than 1400 B2B

marketing executives revealed that AI could play an instrumental role in professional services to adapt to rapidly changing business demands, complex buying decisions, and frequent changes in markets. AI-augmented new services have been considered revolutionary in industrial markets, which have inspired researchers to explore service ecosystems (Vargo, Wieland, & Akaka, 2015), service innovation process (Kindström, Kowalkowski, & Sandberg, 2013), resources and capabilities (Janssen, Castaldi & Alexiev, 2016) and adoption and diffusion (Casidy, Nyadzayo, & Mohan, 2020).

Evidence suggests that AI climate-driven service analytics investment will exceed 11% of overall marketing budgets by 2022. The overall expenditure on AI will exceed \$125B by 2025 (Forbes 2020). The growth of tech-savvy business customers who engage with AI-driven services are dramatically rising all over the world (Hallikainen, Alamäki, & Laukkanen, 2019; Hwang & Oh, 2020; Kurata, 2019) due to the emergence of various service innovations (Hinsch, Felix, & Rauschnabel, 2020; Huang, 2019; Ladhari, Rioux, Souiden, & Chiadmi, 2019; Sebald & Jacob, 2018; Souiden, Chaouali, & Baccouche, 2019). For example, AI enables healthcare service providers to arrange predictive maintenance of their high-value equipment, improve performance, reduce cost and downtime; customers can enjoy a more personalized, consistent and engaging service experience (Marr 2020; Huang & Rust 2018). While AI climate refers to the shared perceptions of policies, procedures, and practices to support AI initiatives (see section 2.1), cognitive service analytics capability refers to the analytical insights driven by AI climate and augmented by both machines and humans to make marketing decisions (see section 2.3). The application of the AI climate is warranting robust analytics capabilities to harness insights to serve complex needs in the B2B markets. Yet AI climate-driven service analytics literature in B2B markets is very sparse (Biemans & Griffin, 2018; Davenport 2018b; Huang & Rust, 2018; Lytras et al. 2020), motivating us to explore the dimensions of cognitive service analytics capability and its effects.

Although service firms are pouring money into developing AI projects, 70 % of them are showing little or no return (Forbes 2020). According to TechRepublic, “Despite increased interest in and adoption of artificial intelligence (AI) in the enterprise, 85% of AI projects ultimately fail to deliver on their intended promises to business”. Interestingly, there is limited understanding of cognitive service analytics capability within the AI climate. As a result, most of the AI initiatives have failed to leverage intuitive (i.e., creative problem-solving capability), empathetic capability (i.e., social/relationship building capability) or, analytical capability (i.e., data-driven decision-making capability) of service managers (Huang & Rust, 2018). For example, an AI climate in the B2B environment can assist service managers with cutting-edge analytics technology and information to explore avenues for service innovation. However, the manager should be able to develop a creative sense of findings and make decisions based on proper knowledge (Huang & Rust, 2020). Although AI climate in B2B markets leverages intelligent machines to perform various B2B services (e.g., portfolio/wealth management recommendations in banks, predictive modeling, answering frequently asked questions), specific capabilities need to be explored from the machine and human perspectives (Davenport & Ronanki, 2018). However, little attention is paid to the role of the emerging AI climate-enabled analytics research (Chiu et al., 2021; Lytras et al., 2020; Sung et al., 2021). As such, drawing on the theories of service analytics capability, resource-based view, and the microfoundations of dynamic capability, this study assesses the impact of cognitive service analytics capability construct on service innovation and market performance. Thus, the study addresses the following research questions (RQs):

RQ1: How does AI climate affect the formation of cognitive service analytics capability?

RQ2: What are the effects of AI climate and cognitive service analytics capability on service innovation and market performance?

Despite the increasing importance of AI in service innovation in B2B markets, literature in this particular stream of knowledge remains fragmented, inadequate, and fails to coalesce into a holistic conceptualization (Lytras et al., 2020; Wang & Wang, 2020). Thus, this study makes several contributions. First, we conceptualize and empirically validate the cognitive service analytics capability construct, combining machine's and marketer's capabilities in digital B2B markets. This represents one of the first attempts to uncover the nuanced application of AI for service analytics in industrial markets: the AI climate can be deployed to augment both machines and marketers rather than displace them. Second, we measure the impact of AI climate on cognitive service analytics capability and model the effects of both these constructs on service innovation and market performance to address the emerging research call for research on AI-based service innovations in industrial markets (Biemans & Griffin, 2018; Davenport et al., 2020; Dwivedi et al., 2021a; Grewal, Hulland, Kopalle, & Karahanna, 2020; Huang & Rust, 2018; Kumar, Ramachandran, & Kumar, 2020). Third, from a practical point of view, our study enables industrial marketers to address challenges they may face when investing in AI climate to develop service analytics capabilities augmented by both machines and marketers. The paper is structured as follows: Section 2 discusses the literature review and theory focusing on AI climate, service analytics, service analytics capability and the microfoundations of DC. Section 3 presents the findings of qualitative research on the dimensions of CSAC using in-depth interviews. Section 4 sheds light on the conceptual model and hypotheses development. Section 5 discusses the rigor and relevance of the empirical research design using survey and analysis techniques. Finally, Section 6 illuminates theoretical and managerial contributions with future research directions.

2 Literature Review

To conduct a literature review on AI climate-driven cognitive service analytics capability, we explored the following major databases: *Emerald Insight*, *EBSCOhost Business Source Complete*, and *ScienceDirect* using the search strings: “AI climate”, “AI-enabled analytics”, “advanced analytics”, “cognitive analytics”, “cognitive service analytics”, “marketing analytics”, “analytics capability” etc. (Borges et al., 2021; Zhang et al., 2021; Hu et al. 2021). From the initial discovery of 233 articles, we selected a total of 49 articles after screening the title, abstract, keywords, and body of the text. To answer the research questions, we have provided our findings in terms of three major themes as follows: AI climate, service analytics, cognitive service analytics capability with its dimensions and effects.

2.1 AI climate

“Organizations that excel at connecting businesses, aggregating the data that flows among them, and extracting its value through analytics and AI will have the upper hand” (Iansiti & Lakhani, 2020, p.65)

AI refers to the science of machines that “behave in ways that would be called intelligent if a human were so behaving” (McCarthy, Minsky, Rochester, & Shannon, 1955), perform “aspects of human intelligence” (Huang & Rust, 2018, p.155), or, “intelligent human behavior” (Syam & Sharma, 2018, p.136). Shankar (2018, p.vi) identifies it as “programs, algorithms, systems and machines that demonstrate intelligence,” while Davenport and Ronanki (2018) and Kaplan and Haenlein (2019) illuminate it as a computer system that is dependent on machine learning, deep learning, physical robots, neural networks, robotic process automation and rule-based expert systems to gather, interpret and learn from data to achieve specific goals through service adaptation. In a similar spirit, SAS (2018) defines it as the science of training machines to act like humans by gathering and processing large amounts of data and identifying patterns using various technologies. Overall, it is evident that AI is reliant on various big data sources that

use analytics approaches (e.g., ML or DL) to identify rules and patterns and learn from the insights without being programmed before. Table 1 provides various definitions of AI, examples of AI climate, and AI applications in B2B services.

AI climate is a natural extension of the basic analytics climate. Davenport (2019) states that it is the aspiration of many service firms to develop an AI climate combining data and analytics, but few are successful in this attempt. Adapting the definition of service climate (Schneider, White, & Paul, 1998; Wilder, Collier, & Barnes, 2014), we define the AI climate in B2B service environment as the service providers' shared perceptions of the procedures, practices, and policies that are expected, supported and rewarded in service provision using AI initiatives. For example, in a successful AI climate, an average service manager can save 5.5 hours per week on data entry using AI automation, which cost firms \$13,200 per manager in a year (AI Multiple 2020). There are many classic stories of failures to develop AI climate. According to Tse, Esposito, Takaaki, and Goh (2020, p.1) *"Companies work closely with a promising technology vendor. They invest the time, money, and effort necessary to achieve resounding success with their proof of concept and demonstrate how the use of artificial intelligence will improve their business. Then everything comes to a screeching halt — the company finds themselves stuck, at a dead end, with their outstanding proof of concept mothballed and their teams frustrated"*. At present, the growth and development of service analytics capability depend on AI applications. AI climate (AICL) can facilitate service analytics by leveraging robust technology and creative marketing capabilities. To build the right AICL, Davenport et al. (2020) report that the goal of AI climate is not to replace marketers rather augment marketing managers' capabilities as expressed by the CEO of IBM, Ginni Rometty, who envisage a man "plus" machine climate rather than a man "versus" machine climate. Tse et al. (2020) highlight that a good AI climate should be conducive to a good platform (i.e.,

dependable, flexible, scalable, extendable, and adaptable service platform) backed by a good management team. The extant literature identifies that an organizational climate for innovation is critical for leveraging innovativeness to ensure firm performance and competitive advantage (Pritchard et al. 1973; Shanker et al. 2017). An investigation of various AI studies discussed in Table 1 shows that there are very few studies that have modelled the impact of AI climate on service analytics capability and its effects on service innovations and market performance.

Table 1: Examples of AI climate in B2B Service innovations

Studies	Definitions of AI	Examples of AI climate	B2B Service innovations
Huang and Rust (2020)	AI refers to the machines that reflect human intelligence (HI), which is distinct from IT as it can learn, connect and adapt.	AI climate is based on mechanical, thinking and feeling AI.	Data and analytics solutions for businesses (e.g., AWS marketplace), financial analysis (e.g., IBM Watson),
Davenport et al. (2020)	AI refers to machines that mimicking intelligent human behaviour using machine learning (ML), deep learning (DL), neural networks, natural language processing (NLP), rule-based expert systems and robotic process automation to interpret, learn and adapt.	The AI climate depends not only on technology but also on its augmentation by a human for various applications, such as insights from data and engagement with employees/customers.	Sales and service (e.g., Conversica), Emotional support to clients (e.g., Replika), Business process service (e.g., IBM Interact), security services (e.g., Knightscope's K5)
Kumar, Ramachandran, and Kumar (2020)	Machines are trained to perform human-like tasks by analyzing large amounts of data and identifying patterns using ML, NLP and others. Machines can learn from experience and adapt to new situations.	The AI climates should be based on the integration of new-age technologies: AI, ML, blockchain and IoT.	Credit rating scores (e.g., FICO), Sales recommendation by Einstein (e.g., Salesforce), Scheduling interactions with potential customers by Genee (e.g., Microsoft) and cross-device advertising by Crosswise (e.g., Oracle)
Grewal et al. (2020) Marr (2020)	AI solutions include both task automation and context-aware activities using combined analyses of numbers, text, voice, faces, and images.	The science of AI and the art of marketing creativity should be combined. A sustainable AI climate should be based on customer satisfaction, employee wellbeing and profitability.	Intelligent design software to design and build (e.g., Autodesk) or transaction processing and data warehousing services (e.g., Oracle's autonomous databases).
Rai (2020)	AI refers to the machines that are used to achieve human objectives.	Ensuring explainability for different types of AI models (ML or DL) to achieve a balance between prediction accuracy and explanation and develop a trustworthy system.	Lead scoring for B2B marketing teams. Introducing trust, fairness, transparency and privacy in AI-based marketing models.
Huang and Rust (2018)	AI refers to the machines that reflect facets of human intelligence.	AI climate consists of mechanical, analytical, intuitive and empathetic.	Service robots (e.g., Amazon), smart services like tax preparation (e.g., H & R block), intuitive (e.g., Google's deepMind AlphaGo) and empathetic (e.g., Replika chatbot).

2.2 *Service Analytics*

AI climate in a service environment can enable and facilitate service analytics process by providing various descriptive (visualization of analytics findings), diagnostic (formulation and validation hypotheses), predictive (prediction of future possibilities) and prescriptive insights (recommendation of possible scenarios) (Kakatkar, Bilgram, & Füller, 2020; Mariani, 2020; Mariani & Nambisan, 2021). Cardoso et al. (2015 p.184-185) define service analytics as “the process of capturing, and analyzing the data generated from the execution of a service system to improve, extend, and personalize a service to create value for both providers and customers”. In conceptualizing analytics, Ransbotham and Kiron (2018) focused on a mix of approaches such as statistical, cognitive, contextual, predictive models to generate insights for decision making. Despite the importance of big data and AI in generating insights, we also highlight the critical role of service managers in making strategic and operational decision making for B2B platforms leveraging data-driven insights, such as service managers of Commonwealth Bank Australia (CBA) triage business customers using AI-based insights to provide repayment holidays to business customers due to pandemic hardship (Eyers 2020). Overall, we define service analytics as data-driven insights using various analytics techniques that help to make critical strategic and operational service decisions. Table 2 presents a review of high-impact studies on big data analytics in B2B service environment. A careful analysis of the following studies in the industrial markets shows a significant research gap in the stream of AI-enabled cognitive service analytics capabilities (see Table 2).

Table 2: Selected studies on service analytics in B2B digital markets

Studies	B2B digital markets	Findings
Gupta et al. (2020)	High tech operations services in India (n=209)	Using resource-based views (RBVs), the findings show that managerial skills and technical skills are the key drivers for big data predictive analytics capabilities that influence market, operational and financial performance.
Hajli, Tajvidi, Gbadamosi, and Nadeem (2020)	Digital service providers in Finland, Canada and the UK using three case studies.	Using DC viewpoint, the findings show the role of customer agility in sensing and responding to develop new products. It also highlights the links among effective use of data aggregation tools, analytics techniques and customer agility.
Mariani and Wamba (2020)	Generation of BDA for multiple international consumer goods companies, using case study.	Leveraging BDA/BDAC conceptualizations and a qualitative research design, the findings describe how BDA companies market their AI-drive insights to large consumer goods companies that need to innovate or launch new products.
Elia, Polimeno, Solazzo, and Passiante (2020)	A systematic literature review of 49 articles in e-commerce, banking and retail.	Using various theories, the findings synthesize five values of big data applications: informational, strategic, transactional, infrastructural and transformational value)
Boldosova (2020)	Smart services (n=32 interviews) in Finland.	Using ethnographic research and storytelling lens, the findings explain the importance of BDA in storytelling that improves customer sense-making of smart services.
Holland, Thornton, and Naudé (2020)	Online travel agents in the US using commercial clickstream dataset.	Using analytics framework viewpoint, the study develops market-level data to investigate the comparative performance of specific companies. It shows that clickstream data is an important source of big data to create a new set of B2B analytical framework.
Jabbar, Akhtar, and Dani (2020)	A systematic literature review of data acquisition tools and techniques, storage facilities, analytical tools and techniques and insights using 3 databases.	Drawing on problematization approach, the findings establish a link between big data, programmatic marketing and real-time processing and relevant decision making for B2B markets.
Kumar, Shankar, and Aljohani (2020)	Big data based demand forecasting framework using fuzzy artificial neural networks (n= 2614 observations and 17 variables).	The findings show the forecast accuracy of fuzzy neural networks and develop marketing plans for products
Sena and Ozdemir (2020)	Importance of big data in measuring the technical efficiency in retail (n=48) in the UK.	Using knowledge spill over theory, the findings show that regional retailers can gain more benefit and can be more efficient than inter-industry upstream by investing in BDA.
Zhang and Xiao (2020)	Customer involvement in big data innovation projects (n=148) in the US.	Using open innovation theory, the findings identify the role of customers as data providers and data analysts in big data innovation projects with customer needs tacitness as a moderator.
Zhang, Wang, Cui, and Han (2020)	Assimilation of big data intelligence to enhance CRM performance (n=147) in China.	Using RBV, the finding shows that big data intelligence assimilation can enhance the mass customization ability of firms in China.

2.3 *Cognitive Service Analytics Capability and its dimensions*

Although the AI climate in B2B digital markets helps to describe, diagnose, predict or prescribe future service situations, it often lacks the required knowledge, skills, or talent to solve service problems for the future (Teece & Leih, 2016). Most firms take a conservative approach to completely rely on cognitive analytics capabilities to make decisions due to their immaturity (Davenport & Ronanki, 2018; Davenport 2018b). As such, drawing on the extant analytics knowledge, service firms are leveraging both AI and human intelligence (HI) to develop CSAC in which machines are taking care of routine/mechanical tasks (e.g., automated account information, reading contracts, billing reports etc.), and both managers and machines are responsible for thinking/feeling services (e.g., price/service negotiation, personalized recommendations etc.) (Huang & Rust, 2020).

In the pursuit of developing CSAC, Kakatkar et al. (2020) highlight the role of cognitive technology in developing service analytics by turning machines into partners of humans to leverage service managers' knowledge and creativity. Cognitive technology should be able to execute deeper analysis of data (e.g., pattern analysis, identifying abnormality in variables, scenarios under uncertainty), and learn over time. In addition to technology, Davenport and Ronanki (2018) suggest that the role of managerial cognitive talent in leveraging knowledge and skills of service managers and data scientists is necessary to learn the bits and pieces of this technology. Acquiring this machine (technology) and creative marketing (talent) capabilities depend on continuous research, training and development capabilities. Data scientists and service managers with their domain knowledge and statistical skills can unlock the potential of innovations using CSAC (Kumar 2020; Mariani & Nambisan, 2021; Mariani & Wamba, 2020; Mikalef & Krogstie 2020).

Based on the above discussions, we defined CSAC in B2B markets as the analytical insights driven by AI climate and propelled by both machines and marketers to describe, diagnose, predict and prescribe industrial marketing situations, understand industrial marketing scenarios and make decisive actions to enhance industrial market performance. Drawing on the seminal studies on analytics (e.g., Davenport 2018a, Davenport & Harris 2017; Wedel & Kannan 2016; Ransbotham & Kiron 2017), service analytics (Akter et al. 2018, 2020ab), cognitive analytics (Davenport 2018b) and the role of AI in services (Brynjolfsson and Mitchell 2017; Davenport & Ronanki 2018; Davenport et al. 2020; Huang & Rust, 2018; Kaplan & Haenlein 2019; Huang & Rust 2020), we identify CSAC as a multidimensional concept. For example, *the sophistication of cognitive technology* as a dimension enables to predict and forecast scenarios, such as ‘what will happen’ and ‘why something can happen’ (Delen & Demirkan, 2013; Gupta et al. 2020; Fosso Wamba et al. 2017). The AI climate in Amazon is an illustration of cognitive technology using an agile, cloud, and open-source platform to provide various services (e.g., video recognition, image recognition, digital assistants, NLP etc.). The quality of *cognitive information* leveraging AI, analytics approaches and various attributes of big data (e.g., volume, variety, velocity, value, veracity, variability, and visualization) play a critical role to provide insights and decision value (Kumar 2020; Mikalef & Krogstie 2020). For example, cognitive insights generated by DBS bank in Singapore help business customers make decisions on wealth management and investment options using market sentiment data, existing portfolio information, news and research reports (Davenport, 2018a). The extant research repeatedly illuminates that cognitive analytics cannot be realized to solve complex service problems without human intervention (Davenport & Ronanki 2018). Thus, *B2B marketers’ problem-solving ability* is a critical element of CSAC, which refers to the ability to address complex service situations and make decisions without algorithmic bias (Huang & Rust, 2018).

In addition, marketing managers' cutting-edge knowledge and skills can help them understand

cognitive technology and insights and tackle non-repetitive problems using creative marketing thinking (Huang & Rust, 2020). For example, knowledge of digital service blueprint, customer experience and interactive analytics applications can help overall marketing management in B2B environment (Kumar et al., 2020). Finally, *training and development* of service managers in AI climate can empower to develop and update various service analytics models by embedding the right attributes and adjusting the right parameters (Davenport, 2018b). AI climate is a natural extension of the basic analytics climate. Since AI-based service analytics models are probabilistic in nature, marketing managers to be trained on new analytics techniques to full deploy AI climate for complex service situations.

Overall, we identify CSAC as a multidimensional concept (Edwards 2001; Law et al. 1998) as such analytics capabilities are based on various machine and marketing capabilities to perform service activities. For example, machine capabilities can perform automated notification services (e.g., Amazon's merchant services) or, provide cognitive insights (e.g., Deloitte's audit practice or GE's data curation services for suppliers), and both machine and marketing capabilities can develop cognitive engagement services (e.g., Vanguard's cognitive help desk engaged with employees) (Davenport & Ronanki 2018). In a similar spirit, we argue that AI-enabled CSAC should be able to support mechanical, thinking and feeling activities in service environment as both machine and marketing are required to develop the algorithms, fix algorithm bias and tailor the right services to the right customers powered by empathy and creativity (Cao et al., 2021; Huang & Rust 2020; Pillai et al., 2021; Dwivedi et al. 2021b). However, there is limited knowledge about the dimensions of machines and marketing capabilities, which could be augmented within an AI climate for service innovation and market performance.

3. Theory: micro-foundations of dynamic capabilities

Dynamic capabilities (DC) have been first introduced in the second half of the 1990s (Teece, Pisano, & Shuen, 1997; Eisenhardt & Martin, 2000) within the strategy literature and later they have been increasingly adopted in a number of cognate management fields including innovation management, entrepreneurship, management information systems, operations management, and marketing management (Schilke et al., 2018). As suggested by many scholars, the DC framework is currently one of the most prominent theoretical lenses in the wide management field (Cepeda & Vera, 2007; Di Stefano, Peteraf, & Verona, 2014).

While several management scholars (e.g., Helfat & Peteraf, 2003) relate the concept of dynamic capabilities to the resource-based view (RBV) of the firm (Barney, 1991) which aimed at explaining how firms' value and profit are generated based on firms' resources to be conceived as "all assets, capabilities, organizational processes, firms attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness" (Barney, 1991: p. 101), Teece et al. (1997) introduced the concept of DC making a clear distinction from the RBV. More specifically, according to the latter authors, DC should be distinguished from operational capabilities, which relate to the current operations of an organization, and can be defined as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments." (Teece et al., 1997: 516), thus aiming at modifying the enterprise resource base (Helfat et al., 2007).

While the original definition and conceptualization of DCs and the DC framework referred explicitly to the firm, recently management scholars have been increasingly adopting a microfoundations approach (Felin et al., 2015) by unpacking the organizational level concept of DCs to understand how individual-level (e.g., managerial-level) and micro factors impact

those DCs (Argote & Ren, 2012; Helfat & Peteraf, 2015; Hodgkinson & Healey, 2011; Suddaby et al., 2020; Teece, 2007). For instance, Teece (2007) lays out the microfoundations of DCs, by recognizing that cognitive processes of top executives contributes to the microfoundations of dynamic capabilities. Helfat and Peteraf (2015) further develop this line of thought and explain the reasons why several top managers possess more effective capabilities than others when it comes to interpret, anticipate, and respond to the demands of an evolving and uncertain business environment. More specifically, they propose that dynamic capabilities are not only present at the firm level, but that they entail individual managers' capabilities that display and depend on cognitive processes and underpinnings, which are aligned with big data analytics capabilities literature (Akter et al. 2016; Motamarri et al. 2020; Wamba et al. 2017). More specifically, managerial cognitive capabilities such as *perception* and *attention* can be conducive to sensing dynamic managerial capabilities, which in their turn, allow top executives to recognize and create opportunities. Individual managers' cognitive capabilities such as *problem solving* and *reasoning* can translate into seizing dynamic managerial capabilities, which assist top executives to implement strategic investment and carry out business model design (Helfat & Peteraf, 2015; Hodgkinson & Healey, 2011). Last, managerial cognitive capabilities such as *language*, *communication* and *social cognition* can lead managers to reconfigure dynamic managerial capabilities, allowing executives to perform strategic asset alignment and overcome resistance to change. To summarize, sensing, sizing and reconfiguring dynamic managerial capabilities, i.e., dynamic capabilities at the individual managers' level – by assisting executives in recognizing and creating opportunities, implementing strategic investments, carrying out business model design, performing strategic asset alignment, and overcoming resistance to change - are conducive to superior levels of firms' performance (Teece 1997; 2007; 2018; Teece & Leih 2016).

4. Design

We conducted two empirical studies to develop and confirm our research model. In study-1, we conducted 30 in-depth interviews with B2B service analytics professionals in Australia to answer the research question on the dimensionality of CSAC. To confirm the relationships in the proposed conceptual model, we collected survey data from 276 service managers in study-2, who have the experience of working in an AI-enabled analytics climate. Although survey data collection plays a predominant role in this study to validate the research model, we have opted to conduct interviews as it provides rich insights on research questions to gain complementary views and make a complete picture of the research phenomenon (Venkatesh et al. 2013; 2016).

4.1 Exploring cognitive service analytics capabilities (Study 1)

We conducted 30 in-depth interviews in 2019 through face to face/telephone methods using the purposive sampling technique to ensure maximum heterogeneity (Suri 2011; Demlehner et al., 2021). Specifically, we applied both judgmental and snowball sampling techniques, and the sample size was adequate to ensure variety and a thematic saturation (Kuzel 1999; Guest et al. 2006). The selection criteria included service analytics managers working in an AI environment with at least three years of experience. The time session for each interview was between 35-50 minutes, and the interviews were later transcribed to identify latent manifestations of themes. The descriptive analysis of the demographic profile ensured diversity in sample characteristics in terms of gender, age, industry, income, and location. Respondent's demographic profile represents diverse groups, as illustrated in Table 3.

Drawing on Braun and Clarke (2006), we applied a thematic analysis to identify meanings or threads in interview datasets using Nvivo and manual thematic analysis. To establish rigor in

the process, we first highlighted the primary responses; second, we identified the causal statements and, finally, determined the themes after analyzing the excerpts and discussion. Two academics and two industry experts analyzed and scored the excerpts using the Q-sorting method, and the research team calculated the inter-rater reliability score, which equals 0.86, thus exceeding the threshold level of 0.70. The analysis resulted in two overarching themes: machine's capability (consisting of two components/subthemes: cognitive technology & information) and marketer's capability (consisting of three components/subthemes: cognitive problem solving, knowledge & skills, training & development) as recurrent patterns. Overall, the qualitative study findings help us explore the dimensions and subdimensions of CSAC in B2B markets. For example, machine's capability has been reflected by the following comments identifying the roles of technology and information, respectively:

"The analytics platform we have developed at the bank is based on an advanced AI technology, that can match needs and serve our large clients with right time data products." (Participant#3)

"The prepopulated information in the tax forms provided by AI help our business clients to simplify tax filing at the Australian Tax Office." (Participant #9)

Similarly, the marketer's capability has been reflected by the following comments illuminating the importance of problem solving, knowledge & skills and, finally, training & development, respectively:

"Using the insights of AI analytics, human intelligence plays an instrumental role to answer so what questions leveraging past experiences to solve a marketing problem." (Participant #15)

"Since AI-based analytics has a narrow focus, a good dose of human reasoning is critical to understand the wide context of the problem based on marketing knowledge and skills." (Participant #18)

"Training of our marketing analysts on advanced AI analytics makes a difference to correctly interpret the insights from AI systems and identify information that are not relevant." (Participant #23)

Table 3 Respondents' Demographic Profile (in-depth interviews n=30)

Gender		Age		Annual Income (in AUD)	
Male	51.75%	18 - 24	12.91%	Under \$19,999	2.89%
Female	48.25%			\$20,000 – \$39,999	5.19%
		25 - 34	25.58%	\$40,000 – \$59,999	14.23%
		35 - 44	28.28%	\$60,000 – \$79,999	16.58%
		45 - 54	15.23%	\$80,000 – \$99,999	22.91%
		55-64	15.01%	\$100,000-\$149,999	26.25%
		Over 64 years old	2.99%	\$150,000+	11.95%
State				Industry	
New South Wales			31%	Financial & Banking	27.77%
Victoria			26%	Insurance	17.24%
Queensland			16%	Professional services	16.32%
Western Australia			13%	Supply chain & logistics	14.24%
South Australia			11%	Media and advertising	15.11%
Tasmania			2%	Consultancy	7.22%
Northern Territory			1%	Others	2.1%

5. Conceptual Framework and Hypotheses Development

As part of developing the research model, this study identifies that the AI climate is an enabler of CSAC, service innovation and market performance (see Figure 1). Based on the microfoundations of DC (Helfat & Peteraf, 2015; Hodgkinson & Healey, 2011; Teece 2007), service analytics literature in B2B markets (Akter et al. 2020; Motamarri et al. 2020; Wamba et al. 2017) and qualitative findings (n=30), we argue that there are two primary dimensions (machine's and marketer's capabilities) and five dimensions of CSAC (see Figure 1), which work in a synergistic fashion leveraging the attributes of complementarity and co-specialization to influence service innovation and market performance (see Figure 1). We also argue that the CSAC model is multidimensional, hierarchical and contextual in B2B markets. The study discusses the hypothesized relationships in the following section.

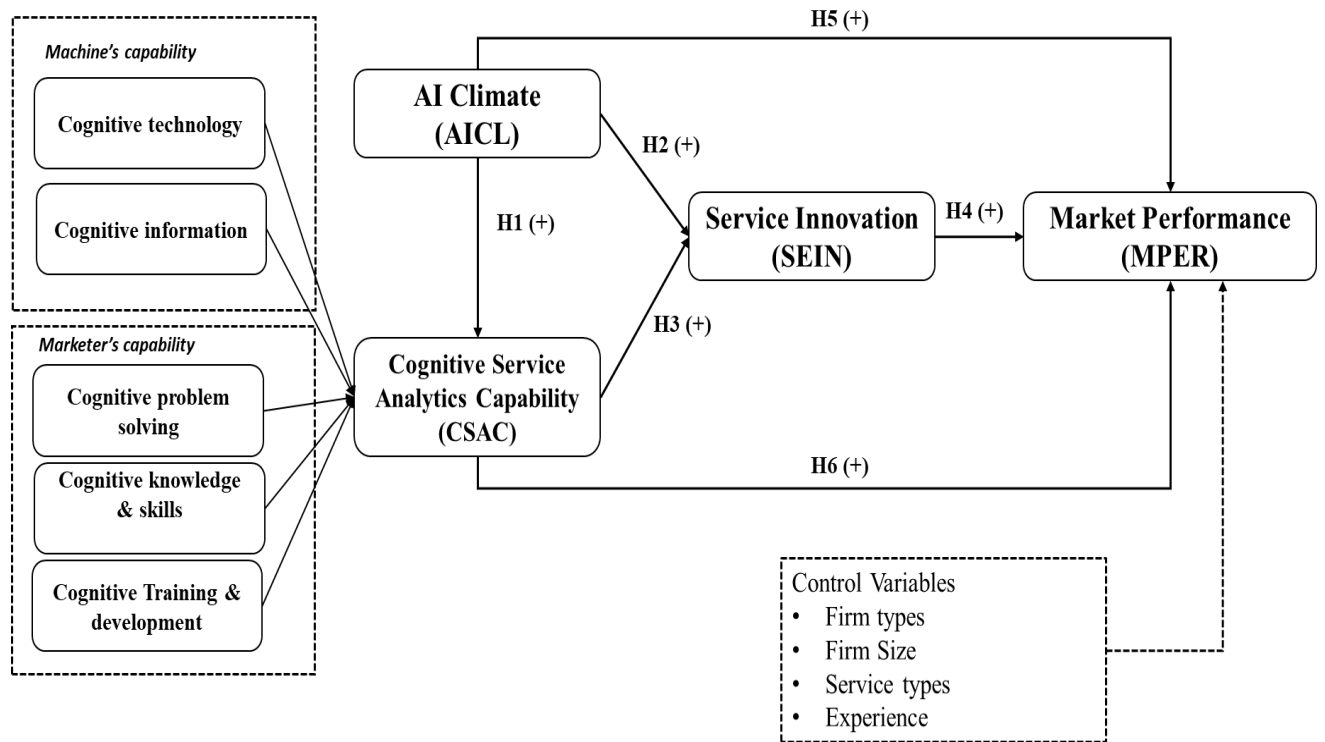


Figure 1 AI climate-driven Service Analytics Capability

5.1 AI climate and cognitive service analytics capabilities

Since AI requires vast data and cutting edge analytics, a well designed AI climate (AICL) in the B2B marketing environment can enable service analytics when the machines and the marketing talent work seamlessly to serve customer needs (Davenport and Ronanki 2018). It is often very difficult to deploy AI models into overall B2B service analytics environment as services require mechanical, analytical, intuitive, and empathetic intelligence to serve customers (Huang & Rust 2018). The missing piece in the puzzle is the development of AICL which influences CSAC by building the right technology to design, architect, integrate, validate, execute and manage the cognitive insights and the right service analytics team with the required knowledge, skills and training (Huang & Rust, 2020). AICL can facilitate CSAC by deriving value from the marketing team's cognitive insights and creative thinking (Davenport, 2018b). This augmentation is necessary to develop a robust CSAC to help develop

an appropriate algorithm for a service problem, avoid bias, flawed models or service failures.

Based on the above discussion, the following hypothesis is postulated:

H1: AI climate has a positive impact on service analytics capability.

5.2 AI climate, cognitive service analytics capability and service innovation

AI climate that facilitates the development of dynamic machine and marketing capabilities to learn, connect, and adapt is a major source of service innovation and revolution (Rust & Huang, 2014). With AI and humans' help, service innovation occurs as the firm captures, processes, analyses relevant data and automates routine decisions to cut costs and improve efficiency (Davenport & Kudyba, 2016; Stone & Wang, 2014). It is important to develop a meaningful and novel service offerings to satisfy customers and enhance market performance. Examples of AI climate-driven service innovations for B2B markets include the collaborative filtering engine for Amazon merchants (Xiao, Wang, Jiang, & Li, 2018), search behaviour analytics for Google advertisers (Bharat et al. 2016) and recommendation engines for eBay dealers (Trotman, Kallumadi, & Dagenhardt, 2020). Service innovations help firms adapt to a dynamic environment. In this regard, Harald Rudolph, head of Daimler strategy, states that “the key lever to implement AI technologies to improve existing processes along the entire value chain as well as developing new products and services to delight our customers. For us, this is of utmost importance” (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018,p.10). However, despite the shift towards AI initiatives in service innovation in B2B markets, it is surprising that only a few studies have explored the impact of AI climate on service innovations in industrial markets. Thus, we hypothesize that:

H2: AI climate has a positive impact on service innovation.

The service innovation process is powered by analytics, as it is embedded in every phase of the digital innovation process to develop innovative service offerings (George & Lin, 2017; Mikalef & Krogstie 2020). CSAC influences service innovations by “defining and training models, engineering features or variables, tweaking parameters, rebuilding models, and retraining and updating models” (Davenport 2018, p. 78). Equipped with cutting-edge machine capabilities (i.e., cognitive technology and insights) and human capabilities (i.e., problem solving, knowledge & skills, training & development), industrial marketers in digital markets gather cognitive insights to identify patterns and offer innovative services (Lytras et al., 2020). Thus, we posit that:

H3: Cognitive service analytics capability positively influences service innovation.

The innovation literature identifies innovative service offerings as both meaningful and novel (Nakata et al., 2018). Whereas meaningfulness indicates to what extent the service offering is appropriate and useful relative to competitors’, novelty measures the uniqueness of service offerings relative to the competitors’ (Amabile, 1983; Nakata et al., 2018). All these industrial service offerings are developed and tested in a digital environment to pursue new markets, foster new service development and enhance market performance (Akter, Motamarri, Hani, Shams, Fernando, Babu, et al., 2020). However, this process raises a fundamental question of how these capabilities in the digital frontier create novel and meaningful service offerings (Biemans & Griffin, 2018) and market performance. Thus, we hypothesize that:

H4: Service innovation has a positive effect on market performance.

5.3 AI climate and market performance

AI climate focuses not only on the right hardware and software but also on skills and knowledge of the team to integrate AI into the industrial marketing processes and systems (Tse

et al., 2020). A perfect AI climate should embrace both AI and HI (human intelligence) to augment decision making in industrial markets (Davenport, 2018a; Huang & Rust, 2020). It is important to transform the holistic AI climate into innovative services offerings that can enhance market performance and competitiveness. Based on the microfoundations of DC, we argue that AI climate can help an industrial marketing system enhance market performance by constantly updating and improving its analytics capabilities (Kumar et al., 2020). To achieve higher market performance, industrial marketers can use AI for mechanical, thinking and intuitive activities (Huang & Rust, 2020). For example, Amazon has successfully built an AI climate in the last twenty years which has resulted into a robust cloud service platform, Amazon web services (AWS), serving millions of B2B customers (e.g., Netflix, Twitch, LinkedIn, Facebook, Apple etc.) with a dramatic rise in its market performance (Saunders 2020). Although the relationship between AI climate and market performance has been discussed in an anecdotal manner in recent studies (Davenport, Guha, Grewal, & Bressgott, 2019; Davenport et al., 2020; Davenport & Ronanki, 2018; Huang & Rust, 2018; Kumar et al., 2020), few studies have tested the empirical relationship between these two constructs. Thus, from the above discussions, this research posits:

H5: AI climate positively influences market performance.

5.4 Cognitive service analytics capability and market performance

We refer to CSAC as the analytical insights driven by AI climate and generated by both machines and marketers to develop innovative service offerings (e.g., service and deal recommendations, demand forecasting, service placements, fraud detection) for both routine and complex situations that eventually increase market performance. For example, B2B data analytics companies, such as Amazon Web Services (AWS) provide a real-time matching capability for platform service providers (e.g., Netflix, Airbnb or Uber) (Amazon 2020). Using

both the machines and industrial marketing talent, the CSAC developed by AWS can access millions of usage behavior data points, identifying latent demand through pattern spotting, and efficiently matching real-time needs (Davenport, 2018a). According to Huang and Rust (2020p.8), “In terms of AI applications, predictive analytics can be used to predict customer preferences, computing creativity can be used to develop new service, and data mining (or any other types of pattern mining) can be used to identify like-minded customers for creating personalized service”. Although studies have reported various benefits of CSAC on market performance, there is limited empirical evidence in B2B markets. Based on the aforementioned discussion, we posit that:

H6: Cognitive service analytics capability positively affects market performance.

5.5 The mediating role of service innovation

Service innovation refers to “service offerings that directly or indirectly result in value for the firms and its customers/clients” (Salunke et al., 2019, p.147). Recent studies have illuminated a conceptual relationship between AI and service innovation in B2B markets (Grewal et al., 2020; Huang & Rust, 2018, 2020) and between analytics and service innovation (Akter, Motamarri, Hani, Shams, Fernando, Mohiuddin Babu, et al., 2020; Ransbotham & Kiron, 2017). In addition, the B2B marketing literature has frequently identified service innovation as a critical antecedent of sustained competitive advantage (Casidy et al., 2020; Den Hertog, Van der Aa, & De Jong, 2010; Salunke, Weerawardena, & McColl-Kennedy, 2019). However, there is limited understanding of how service innovation mediates between AICL and market performance and CSAC and market performance. Thus, we posit that

H7a: Service innovation mediates the relationship between AI climate and market performance.

H7b: Service innovation mediates the relationship between cognitive service analytics capability and market performance.

6. Survey research method (Study 2)

6.1 Scale

Qualitative findings were used to reflect the context of the study, and all the scales were adapted from past studies (see Table 4) to measure the analytics climate (Wilder et al., 2014), cognitive analytics technology (Aguinis & Kraiger, 2009; Bowen, 2016; Bowen & Lawler, 1992; Motamarri, Akter, & Yanamandram, 2020; Teece, 2007), cognitive analytics information (Motamarri et al., 2020), cognitive problem solving (Kiron, Prentice, & Ferguson, 2014; Melhem, 2004; Motamarri et al., 2020; Wilder et al., 2014), cognitive knowledge & skills (Bowen & Lawler, 1992; Melhem, 2004; Motamarri et al., 2020; Spreitzer, 1995), cognitive training & development (Aguinis & Kraiger, 2009; Bowen, 2016; Bowen & Lawler, 1992; Motamarri et al., 2020; Teece, 2007). We also adapted the outcome constructs using past studies, that is, hierarchical service innovation construct, including meaningfulness & novelty (Nakata et al., 2018) and market performance (Wamba et al., 2017). We used a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7) to measure each construct. We conducted a pre-test with 33 respondents to confirm format, wording, screening questions, scale points and overall instructions.

6.2 Sampling

Survey data were collected between September-December 2019 using a professional market research company in Australia, which holds a panel of 369,000 respondents with various demographic profiles (Pureprofile AU, 2020). Using a simple random sampling, the survey questionnaire was distributed to service analytics managers in B2B markets for pilot testing. With the screening criteria of working experience in AI and data scientists-enabled service analytics climate for at least three years, the questionnaire was distributed to a potential sample

of 523 respondents of 18+ years old for a pilot study using Qualtrics. Data were analyzed for 61 qualified cases in this phase to check dimensionality of the constructs, reliability, convergent validity, discriminant validity and overall nomological validity (MacKenzie, Podsakoff, & Podsakoff, 2011; Straub, 1989). All the constructs were confirmed satisfactory after dropping a few items that did not meet the measurement model's threshold. Table 4 presents all the constructs' operationalization with definitions, items, and sources, which were used for the main study.

Table 4 Operationalization of Constructs

Constructs	Sub-constructs	Definitions		Items	Studies
	AI climate (ANCL)	The degree to which perceptions of the policies, practices, and procedures within service operations are supported and expected with AI initiatives.	ANCL1 ANCL2 ANCL3 ANCL4	My organization relies on AI for providing services. My organization invests in AI to deliver services. My organization promotes best practices to deliver services using AI. My organization makes decisions regarding services using AI.	(Wilder et al., 2014)
Cognitive service analytics capabilities (CSAC)	Cognitive analytics technologies (CATE)	The degree to which cognitive analytics technologies empower service analytics processes.	CATE1 CATE2 CATE3	My organization provides me with cognitive analytics technologies to deliver services. My organization regularly invests in upgrading cognitive analytics technologies to provide services. My organization provides cognitive analytics technologies that are equal to or better than other organizations to provide services.	(Aguinis & Kraiger, 2009; Bowen, 2016; Bowen & Lawler, 1992; Motamarri et al., 2020; David J. Teece, 2007)
	Cognitive analytics information (CAIN)	The degree to which service managers have access to cognitive information about various service situations and changing conditions.	CAIN1 CAIN2 CAIN3	I have access to cognitive analytics information about the services. I have access to cognitive analytics information about related service processes and procedures. I have access to cognitive analytics information about what services are in demand.	(Motamarri et al., 2020)
	Cognitive knowledge & Skills (COKS)	The degree to which service managers can interpret cognitive analytics, apply in the processes and evaluate outcomes.	COKS1 COKS2 COKS3	I have the necessary analytics skills to best serve customers in a cognitive environment. I have the necessary analytics knowledge to serve customers in a cognitive environment. I have mastered the analytics skills necessary to serve customers in a cognitive environment.	(Bowen & Lawler, 1992; Melhem, 2004; Motamarri et al., 2020; Spreitzer, 1995)
	Cognitive Training & development (COTD)	The degree to which service operations managers are equipped with cutting-edge cognitive skillsets to tackle service situations.	COTD1 COTD2 COTD3	My organization provides regular analytics training on the tools I am expected to use in a cognitive environment. My organization invests in my analytics skill development to serve customers in cognitive environment. My organization regularly communicates about the changes in the analytics skill in cognitive environment.	(Aguinis & Kraiger, 2009; Bowen, 2016; Bowen & Lawler, 1992; Motamarri et al., 2020; David J. Teece, 2007)

	Cognitive problem solving (COPS)	The degree to which service managers can solve problems and make decisions with cognitive analytics insights.	COPS1 COPS2 COPS3	The cognitive analytics environment in my organization allows me to correct problems when they occur. The cognitive analytics environment in my organization allows me to rely on data over experience in making service decisions. The cognitive analytics environment in my organization allows me to be creative in dealing with service problems.	(Kiron et al., 2014; Melhem, 2004; Motamarri et al., 2020; Wilder et al., 2014)
Service Innovation	Meaningfulness	The degree to which a new service is appropriate and useful relative to competitors’.	MEAN1 MEAN2 MEAN3 MEAN4	Compared to your competitors, the service innovation you developed using AI-enabled CSAC- Is relevant to customers’ needs and expectations. Is considered suitable for customers’ desires. Is appropriate for customers’ needs and expectations. Is useful for customers.	(Nakata et al., 2018)
	Novelty	The degree to which a new service is unique relative to competitors’.	NOVE1 NOVE2 NOVE3 NOVE4	Compared to your competitors, the service innovation you developed using AI-enabled CSAC- Is really “out of the ordinary”. Can be considered as revolutionary. Is stimulating. Shows an unconventional way of solving problems.	
Market performance		The degree to which AI-enabled CSAC enhances market performance in B2B markets.	MPER1 MPER2 MPER3 MPER4	Using AI-enabled CSAC during the last 3 years relative to competitors- We have entered new markets more quickly than our competitors We have introduced new services to the market faster than our competitors. Our success rate of new services has been higher than our competitors. Our market share has exceeded that of our competitors.	(Wamba et al., 2017)

6.3 Main Study

We obtained 397 responses in total out of 4123 attempts from the panel of B2B service analytics managers. After checking the data quality criteria carefully (e.g., screening questions, attention checking questions, missing values, speeders and flatliners), we analyzed 276 valid responses of service managers who have experience working in AI-enabled analytics climate. The demographic profile of the respondents predominantly represents financial & banking services (21%), ICT services (23%), professional services (19%), supply chain and logistics (12%), media and advertising (10%) and insurance services (8%). Table 5 represents the demographic profile of service analytics managers with diverse backgrounds.

Table 5 Respondents' demographic profile (main study n=276)

Gender		Age		Annual Income (in AUD)	
Male	52.33%	18 - 24	09.25%	Under \$19,999	1.78%
Female	47.67%			\$20,000 – \$39,999	1.44%
		25 - 34	27.11%	\$40,000 – \$59,999	3.55%
		35 - 44	31.44%	\$60,000 – \$79,999	21.66%
		45 - 54	17.23%	\$80,000 – \$99,999	25.47%
		55-64	12.02%	\$100,000-\$149,999	28.85%
		Over 64 years old	2.95%	\$150,000+	17.25%
State				Industry	
New South Wales			33%	Financial and banking services	21.21%
Victoria			23%	ICT services	23.44%
Queensland			15%	Professional services	19.32%
Western Australia			17%	Supply chain & logistics	12.24%
South Australia			7%	Media and advertising	10.44%
Tasmania			4%	Insurance	08.22%
Northern Territory			1%	Others	5.13%

6.4 Data Analysis

Data were analyzed using the partial least squares (PLS) structural equation modeling (SEM) as it supports estimating complex, hierarchical models (Wetzels et al. 2009; Becker et al. 2012) using a robust bootstrapping feature to arrive at the significance of parameter estimates (Streukens & Leroi-Werelds, 2016). Also, PLS-SEM is suitable for testing nomological models as it assures factor determinacy, factor identification, and robust prediction due to its soft modeling assumptions (Chin, 2010; Hair Jr, Hult, Ringle, & Sarstedt, 2017).

Using the guidelines of the repeated indicator approach by Becker, Klein, and Wetzels (2012), the study measured two hierarchical constructs: CSAC and SEIN. As such, all the items of the five subdimensions of CSAC and two subdimensions of SEIN were used repeatedly to estimate the latent scores of higher-order constructs. The study applied SmartPLS software package v3 (Ringle, Wende, & Becker, 2015) with a non-parametric bootstrapping with 5000 replications to estimate the path coefficient and their corresponding significance (Joseph F. Hair, Sarstedt, & Ringle, 2019).

Finally, as part of addressing the common method variance (CMV), we followed Hulland, Baumgartner, and Smith (2018)'s guidelines to tackle CMV before and after data collection. For example, during the questionnaire design, we separated antecedents (e.g., analytics climate, CSAC) from outcome variables (e.g., service innovation, market performance) to test causality. We also addressed social desirability bias issues by introducing attention checkers and introducing various words and formats of the scales. After data collection, first, we confirmed that there is no evidence of non-response bias by testing the first and last 20% responses using a paired t-test (Stanko, Molina-Castillo, & Munuera-Aleman, 2012). Second, the marker variable analysis reported a non-significant correlation ($r=0.034-0.047$, $p>0.05$) between the marker variables and key outcome constructs (Lindell & Whitney, 2001).

7. Analysis and Results

7.1 Measurement Model

Table 6 shows the reliability and validity of the first-order measurement model including AI climate, cognitive analytics technology, cognitive analytics information, cognitive problem solving, cognitive knowledge & skills, cognitive training & development, service innovation and market performance. Since all the item loadings exceed 0.70 ($p < 0.001$), thus, items adequately reflected respective constructs confirming the reliability of the measurement model (Hair Jr et al., 2017). Then we checked internal consistency among the items using composite reliability (CR), which evidence adequacy as all the scores exceed 0.80. We also confirmed the convergent validity of all the constructs using the average variance extracted (AVE). All the AVE scores exceed the 0.50 threshold confirming that all the constructs explain an adequate amount of variance against measurement errors (Chin, 2010). We also assessed the measurement properties of control variables by estimating the variance inflation factor (VIF), which are satisfactory as all the scores vary between 1.017 to 1.217 (≤ 5).

As part of checking discriminant validity, Table 7 shows inter-construct correlations, mean and standard deviations of the first-order constructs. The square root of AVE in the diagonal confirms discriminant validity of each scale as it satisfies the Fornell-Larcker criterion (1981). An assessment of the heterotrait-monotrait (HTMT) scores further confirm discriminant validity as all the scores were less than 0.90 (Henseler et al., 2015). Finally, the discriminant validity was evidenced by an examination of the indicator cross-loadings matrix, showing that items had higher loadings to their respective constructs than other constructs (Chin, 2010).

Table 6: Assessment of First-Order Measurement Model

Reflective Constructs		Items	Loadings	CR	AVE
Analytics climate (ANCL)		ANCL1 ANCL2 ANCL3 ANCL4	0.895 0.927 0.920 0.800	0.936	0.786
Cognitive service analytics capability (CSAC)	Cognitive analytics technologies (CATE)	CATE1 CATE2 CATE3	0.869 0.935 0.773	0.896	0.742
	Cognitive analytics information (CAIN)	CAIN1 CAIN2 CAIN3	0.863 0.918 0.844	0.908	0.767
	Cognitive problem solving (COPS)	COPS1 COPS2 COPS3	0.880 0.906 0.817	0.902	0.754
	Cognitive knowledge & Skills (COKS)	COKS1 COKS2 COKS3	0.903 0.932 0.804	0.912	0.777
	Cognitive training & development (COTD)	COTD1 COTD2 COTD3	0.881 0.937 0.800	0.907	0.764
Service Innovation (SEIN)	Meaningfulness (MEAN)	MEAN1 MEAN2 MEAN3 MEAN4	0.858 0.902 0.917 0.726	0.915	0.729
	Novelty (NOVE)	NOVE1 NOVE2 NOVE3 NOVE4	0.847 0.902 0.891 0.801	0.920	0.741
Market performance (MPER)		MPER1 MPER2 MPER3 MPER4	0.821 0.870 0.845 0.723	0.889	0.667
Formative construct		Items	Weights	t-value	VIF
Control variables (COVR)		Firm size Firm type Service type Experience	0.284 0.781 0.290 0.055	0.637 1.574 0.605 0.132	1.217 1.017 1.062 1.178

Table 7: Correlations and AVEs*

	ANCL	CATE	CAIN	COPS	COKS	COTD	MEAN	NOVE	MPER	COVR
ANCL	0.887									
CATE	0.396	0.862								
CAIN	0.384	0.436	0.876							
COPS	0.364	0.494	0.394	0.869						
COKS	0.369	0.486	0.481	0.341	0.881					
COTD	0.460	0.463	0.117	0.462	0.399	0.874				
MEAN	0.433	0.483	0.327	0.329	0.370	0.476	0.854			
NOVE	0.491	0.441	0.413	0.393	0.418	0.446	0.484	0.861		
MPER	0.485	0.446	0.428	0.414	0.404	0.307	0.494	0.387	0.816	
COVR	0.060	0.212	0.168	0.154	0.204	0.116	0.130	0.012	0.066	N/A

**Square root of AVE on the diagonals.*

To estimate the measurement properties of the higher-order, reflective-formative CSAC, and SEIN constructs, we calculated path coefficients across various orders to test the significance of relationships (see Table 9). For example, the degree of variance of the third-order CSAC construct (3+3+3+3+3=15 items) is explained by the two second-order constructs, that is, machine's capability ($\beta=0.441$) and marketer's capability ($\beta=0.597$). Similarly, the second-order machine's capability (3+3=6 items) is explained by CATE ($\beta=0.529$) and CAIN ($\beta=0.544$). And, marketer's capability (3+3+3=9 items) is explained by COPS ($\beta=0.388$), COKS ($\beta=0.406$) and COTD ($\beta=0.376$). The third-order CSAC construct shows $R^2=1.0$ because the second-order machine's and marketer's capabilities, containing the first-order CATE, CAIN, COPS, COKS and COTD, explain all of the variances. All the path coefficients are significant at $p < 0.001$. Similarly, the second-order SEIN construct is explained by the first-

order meaningfulness ($\beta=0.576$) and novelty ($\beta=0.585$), which are significant at $p < 0.001$ and resulted in $R^2=1.0$ (see Table 8).

Table 8 Higher-order relationships in the Measurement model

3 rd order construct	2 nd to 3 rd order formative relationships	1 st -2 nd order formative relationships	β	Standard deviation	t-value
Cognitive service analytics capability (CSAC)	Machine’s capability (β=0.441, t=32.197)	Cognitive analytics technologies (CATE)	0.529	0.012	44.083
		Cognitive analytics information (CAIN)	0.544	0.013	41.846
	Marketer’s capability (β=0.597, t=19.467)	Cognitive problem solving (COPS)	0.388	0.014	27.714
		Cognitive knowledge & Skills (COKS)	0.406	0.015	27.066
		Cognitive training & development (COTD)	0.376	0.015	25.066
	2 nd order construct		1 st -2 nd order formative relationship		
Service Innovation (SEIN)	Meaningfulness (MEAN)	0.576	0.019	30.568	
	Novelty (NOVE)	0.585	0.024	24.474	

Note: Third-order CSAC ($5 \times 3=15$ items) and second-order service innovation ($2 \times 4=8$ items).

7.2 Structural Model

As part of testing the nomological relationships and corresponding hypotheses, the study calculates path-coefficients (β), coefficient of determination (R^2), effect size (f^2), predictive validity (Q^2) and PLSpredict values. Table 9 and Figure 2 reveal that the AICL-CSAC link is significant ($\beta=0.513$, $p<0.000$), thus we support H1. Similarly, the relationships between AICL-SEIN ($\beta=0.222$, $p<0.000$) and CSAC-SEIN are significant ($\beta=0.633$, $p<0.000$). Thus, we support H2 and H3, respectively. Furthermore, the findings support AICL, CSAC and

SEIN's effects on the ultimate outcome construct, market performance. As such, SEIN-MPER ($\beta=0.363$), AICL-MPER ($\beta=0.264$), and CSAC-MPER ($\beta=0.239$) links are significant ($p<0.000$), which support H4, H5 and H6.

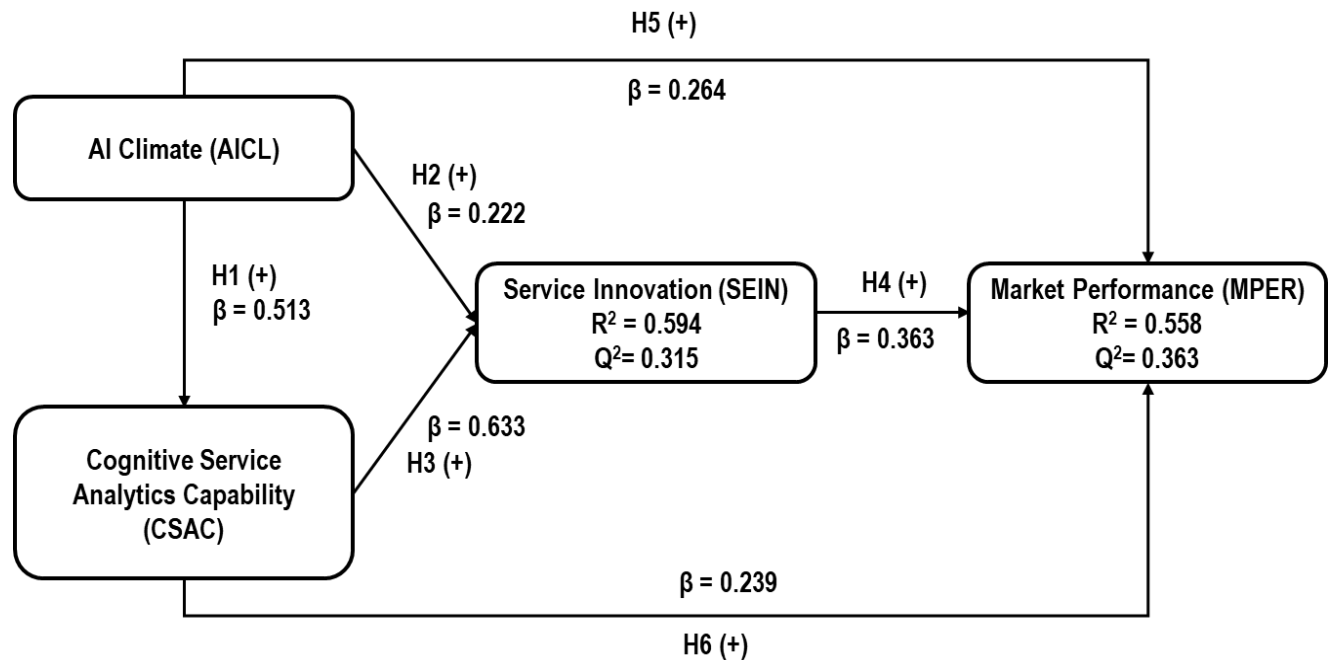


Figure 2: Structural Model

Table 9 Results of Structural Model

Hypotheses	Direct Paths	β /Path Coefficients	Standard Error	T-Statistics	P-Value
H1	AICL-CSAC	0.513	0.050	10.215	0.000
H2	AICL-SEIN	0.222	0.053	4.130	0.000
H3	CSAC-SEIN	0.633	0.047	13.438	0.000
H4	SEIN-MPER	0.363	0.105	3.473	0.010
H5	AICL-MPER	0.264	0.063	4.190	0.000
H6	CSAC-MPER	0.239	0.073	3.277	0.000
<i>Control Model</i>	<i>COVR-MPER</i>	<i>0.030</i>	<i>0.051</i>	<i>0.598</i>	<i>0.550</i>

Based on the guidelines of Preacher and Hayes (2008), Hayes, Preacher, and Myers (2011), we tested the mediating effects of service innovation. Using a 95% confidence interval, we bootstrapped the sampling distribution to estimate the mediating effects of ANCL-SEIN-MPER and CSAC-SEIN-MPER relationships, which were respectively 0.081 and 0.229 and significant at $p < 0.05$ (Table 10). As such, the findings confirm SEIN as a partial mediator between ANCL-MPER and CSAC-MPER relationships, supporting H7a and H7b (Joseph F Hair, Hult, Ringle, Sarstedt, & Thiele, 2017). The findings on 4 control variables (firm size, firm type, service type and experience) show that they have an insignificant impact on MPER ($p > 0.05$).

Table 10: Results of the mediation testing

Hypotheses	Mediating paths	Direct effect	t-value	Significance ($p < 0.05$)	Indirect effect	t-value	Significance ($p < 0.05$)
H7a	ANCL-MPER	0.264	4.190	0.000	0.081	2.500	0.012
H7b	CSAC-MPER	0.239	3.277	0.000	0.229	3.338	0.000

Overall, the R^2 show that AICL and COSAC explain 59.4% of the variance in SEIN and 55.8% of the variance in MPER. These are strong effect sizes (> 0.350) according to the goodness of fit (Cohen, 1988) guidelines by Cohen (1988). The results also report the Q^2 values of 0.315 for SEIN and 0.363 for MPER, suggesting an out-of-sample predictive power of the model, according to Stone (1974) and Geisser (1974).

7.3 Robustness analysis

The R^2 and Q^2 have some inherent limitations because the first is based on an in-sample model-fit and the latter one is a blindfolding procedure based “on single omitted and imputed data points” (Shmueli et al., 2019 p.2324). Indeed, from mere testing of the model for significance

(beta coefficients, t-stats, and p-values), it is critical to ascertain its out-of-sample predictive validity. Thus, we applied PLS-predict following the guidelines of Shmueli et al. (2019). As such, we calculated the root mean squared error (RMSE) and residuals histograms by partitioning the main sample (n=276) into 10 with 10 repetitions with the training sample (n=248) and a holdout sample (n=28). The findings confirm the adequate predictive power of the AICL and COSAC constructs on SEIN and MPER.

8. Discussion and Conclusions

The findings of our study highlight the importance of AI climate and CSAC in B2B digital markets and, thus, answer the two research questions that the study pursued in this study. Our findings clearly demonstrate the critical role of AI climate in industrial markets, enhancing CSAC ($\beta=0.513$), SEIN ($\beta=0.222$) and MPER ($\beta=0.870$). These findings contribute to the ongoing and increasing scholarly enthusiasm about AI climate in industrial marketing research and how to utilize it (Campbell, Sands, Ferraro, Tsao, & Mavrommatis, 2020; Paschen, Wilson, & Ferreira, 2020). In addition to the relationship between AI climate and CSAC, our findings confirm the significant roles of the cutting-edge machine ($\beta=0.441$) and creative marketing ($\beta=0.597$) to build cognitive service analytics capabilities. This finding is consistent with the recent insights by Huang and Rust (2020, p.5), who state that “Thinking tasks should be performed by both thinking AI and HI. This is the type of task where augmentation (skilled service employees augmented by thinking AI) is most likely to occur”. To build machine capability, the findings suggest relatively the equal importance of cognitive analytics technology ($\beta=0.529$) and cognitive analytics information ($\beta=0.544$), whereas to build marketer’s capability, the findings highlight the roles of cognitive problem solving ($\beta=0.388$), cognitive knowledge & skills ($\beta=0.406$) and cognitive training & development ($\beta=0.376$). This finding is consistent with the recent industry report by Everstring (2018) which indicates that

63% marketers in industrial markets are not using AI because they are quite confused about what and how to use AI in B2B digital markets.

Finally, our findings confirm the role of AI climate and CSAC in enhancing SEIN ($R^2=0.594$) and MPER ($R^2=0.558$). With regard to SEIN, we refer to the significantly meaningful ($\beta=0.576$) and novel ($\beta=0.585$) service offerings, such as Amazon's fulfillment services (Huang & Rust, 2020), DBS bank's portfolio management (Davenport, 2018a), IBM Watson's COVID-19 vaccine discovery (Fortune, 2020) or, Amex's AI-powered risk management models to reduce fraud by 50% (Forbes 2020). Our findings also confirm the critical mediating role of SEIN to enhance MPER. This finding clarifies that it is difficult to achieve higher MPER without robust innovations like those made by Amazon or Amex.

8.1 Theoretical implications

“Most people still believe that no machine could ever be conscious, or feed ambition, jealousy, humor, or have any other mental life experience. But this only means that we need better theories about how thinking works.” Minsky (1986, p.19)

In a similar spirit with AI pioneer Marvin Minsky, this research extends theoretical contributions in B2B digital marketing by linking AI initiatives with service analytics capabilities, framing and testing their joint effects on service innovation and market performance. Specifically, this is a major shift from past analytics research in B2B marketing (Balakrishnan & Dwivedi, 2021a,b; Cao, Duan, & El Banna, 2019; Elia et al., 2020; Elia et al., 2021; Gupta et al., 2020; Hajli et al., 2020; Hallikainen, Savimäki, & Laukkanen, 2020; Zhang et al., 2020) by highlighting the role of AI climate in influencing cognitive service analytics capabilities. First, the findings on AI climate suggest that when firms create a clear understanding of AI initiatives and expectations to develop new services, it facilitates building

robust analytics capabilities that continuously adapt and excel in the market. Aligned with our finding on the role of AI climate, Tse et al. (2020, p.5) mention, “For any business wanting to leverage on the benefits of AI, what truly matters is not the AI models themselves; rather, it’s the well-oiled machine, powered by AI, that takes the company from where it’s today to where it wants to be in the future. Ideals and one-time projects don’t.” Second, since the emergence of AI has seriously challenged the growth of traditional analytics in B2B marketing, the empirical findings illuminate the microfoundations of both machine (i.e., cognitive technology & information) and marketer’s capabilities (i.e., cognitive problem solving, knowledge & skills, and training & development) in developing dynamic service analytics capabilities. The specific role of each micro foundation extends DC research in B2B marketing by combining the complementary and cospecialization attributes of each capability in building the synergistic effects on innovation and performance (Felin & Powell, 2016; Helfat & Peteraf, 2015; Teece, 2007; Teece, 2018). More specifically, in line with Teece (2007), it seems that marketing managers’ cognitive processes – which in this study are embedded in marketers’ capabilities - play a crucial role in determining CASC and influencing firm performance. We also extend Helfat and Peteraf (2015) work, as it seems that those marketing managers possessing more effective capabilities can better interpret, anticipate, and respond to the demands of fast-paced B2B digital markets. Third, the findings of our study on AI and CSAC contribute to the development of service innovation research by developing innovative service offerings focusing on meaningfulness and novelty. Fourth, our findings have novel implications for addressing the dark side of AI in marketing through better augmentation of decision making using both machines and marketers (Rana et al. 2021). Unpacking technology and human components in the emerging AI climate can extend industrial marketing research and the emerging discourse to build fair, transparent and accountable analytics in marketing. Overall, we augment the previous analytics research in B2B markets (Gupta et al., 2020; Kumar 2020);

however, we extend the relationship by highlighting the role of AI climate in building CSAC with machine and marketing capabilities to foster new service offerings and enhance market performance.

8.2 Practical implications

Our findings highlight the role played by AI climate in relation to analytics capability, service innovations and market performance. The practical findings directly contribute to the gap in managerial practice, as hinted by Davenport (2019), “Many organizations aspire to have cultures that embrace data, analytics and AI, and other new technologies, but few make specific attempts to create such cultures”. For example, our findings show how to enhance market outcomes by building the right AI climate of adhocracy, combining machine capability and marketers’ creativity to facilitate service innovations. According to Huang and Rust (2018), “Artificial intelligence (AI), manifested by machines that exhibit aspects of human intelligence (HI), is increasingly utilized in service and today is a major source of innovation”. For example, AWS has reported a 36% growth in their net income in the last quarter of 2019 to \$11.6 billion through a robust growth of its cloud service innovations powered by AI and HI. However, it is vital to develop an AI climate that can build robust CSAC that can develop innovative service offerings, such as the recent creations of Salesforce’s Einstein, Oracle’s Crosswise and Microsoft’s Genee for industrial markets. For example, using both marketing talent and machine capabilities, CSAC in the form of predictive modeling, demand forecasting and recommendation engines can help gain a competitive edge in B2B markets. Our findings highlight the specific roles of three HI capabilities: *problem-solving*, *knowledge & skills* and *training & development*, which are aligned with the extant literature (Canhoto & Clear 2020; Kaplan & Haenlein, 2019; Paschen et al. 2020). Since AI-enabled analytics has a narrow focus, our findings show that marketers should be ready to solve problems by answering “so what”

questions, they should have adequate knowledge & skills to make proper reasoning, and they should be equipped with proper training to interpret AI-based output. AI climate can supercharge CSAC in a range of marketing areas, such as predictive modeling, new market development, new service development and cost-effectiveness with a direct impact on market performance (Everstring 2020).

8.3 Limitations & Future Research Directions

There are several limitations to our study. First, data were collected from Australia using a cross-sectional design, which has some inherent limitations. For example, first, a single time data collection from a single country inhibits generalizability of the overall findings in a new context. Second, data from the Australian service industry may not reflect AI climate, cognitive analytics and corresponding outcomes in a new setting. Thus, future research can design and investigate research questions specific to a particular industry. Although few studies have focused on new AI climate, new innovations, sales in B2B markets, there is very limited research on the dynamics of AI climate enabled service analytics and their effects on innovation and performance. Future research can collect data from multiple countries and test the model across various settings using situational factors as moderators, such as market turbulence, and technology turbulence, customer heterogeneity etc. Future research can also develop scales to measure intelligent machine capabilities and marketing capabilities in AI-driven climates, such as manufacturing, supply chain, retailing, banking, healthcare etc. In addition, it is important to establish fairness in AI models (i.e., race, gender, demographic and socioeconomic variables), the privacy of business units, high levels of transparency and explanation to the users (Akter et al., 2021; Collins et al. 2021; Kumar et al., 2021; Rai, 2020; Rana et al., 2021; Vimalkumar et al., 2021), and strike a balance between long term profitability and sustainability (Sivarajah, Irani, Gupta, & Mahroof, 2020).

9. Conclusion

The findings of the study confirm the impact of AI climate on cognitive service analytics capabilities in B2B markets. The findings also support the significant effects of both these constructs on new service offerings and market performance. The results on the microfoundations of analytics capabilities can help managers design a blueprint of AI-powered service analytics capabilities as part of developing and deploying AI climate in B2B markets. Our research provides the initial foundation in investigating the antecedents and effects of CSAC in industrial markets. We hope our findings will inspire more research on this critical interface between AI climate & analytics, service innovation and market performance.

References

- Aggarwal, V.A. Posen, H.E. and Workiewicz, M. (2017). Adaptive capacity to technological change: A microfoundational approach”, *Strategic Management Journal*, 38 (6), 1212-1231.
- Aguinis, H., & Kraiger, K. (2009). Benefits of Training and Development for Individuals and Teams, Organizations, and Society. *Annual Review of Psychology*, 60(1), 451-474. doi: 10.1146/annurev.psych.60.110707.163505
- AI Multiple (2020). Artificial Intelligence is transforming B2B Sales! Retrieved on January 02, 2021 from <https://research.aimultiple.com/b2b-sales/>
- Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y. K., D'Ambra, J., & Shen, K. N. (2021). Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management*, DoI: <https://doi.org/10.1016/j.ijinfomgt.2021.102387>
- Akter, S., Fosso Wamba, S., & Dewan, S. (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. *Production Planning & Control*, 28(11-12), 1011-1021.
- Akter, S., Motamarri, S., Hani, U., Shams, R., Fernando, M., Babu, M. M., & Shen, K. N. (2020). Building dynamic service analytics capabilities for the digital marketplace. *Journal of Business Research*, 118, 177-188.
- Akter, S., Motamarri, S., Hani, U., Shams, R., Fernando, M., Mohiuddin Babu, M., & Ning Shen, K. (2020). Building dynamic service analytics capabilities for the digital marketplace. *Journal of Business Research*, 118, 177-188. doi: <https://doi.org/10.1016/j.jbusres.2020.06.016>
- Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *Journal of personality and social psychology*, 45(2), 357.
- Argote, L., & Ren, Y. (2012). Transactive memory systems: A microfoundation of dynamic capabilities. *Journal of Management Studies*, 49, 1375–1382.
- Balakrishnan, J., & Dwivedi, Y. K. (2021a), “Role of cognitive absorption in building user trust and experience”, *Psychology & Marketing*, Vol. 38 No. 4, pp. 643-668

- Balakrishnan, J., & Dwivedi, Y. K. (2021b). Conversational commerce: entering the next stage of AI-powered digital assistants. *Annals of Operations Research*, 1-35, doi: <https://doi.org/10.1007/s10479-021-04049-5>
- Becker, J.-M., Klein, K., & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models. *Long Range Planning*, 45(5-6), 359-394.
- Biemans, W., & Griffin, A. J. I. M. M. (2018). Innovation practices of B2B manufacturers and service providers: Are they really different? , 75, 112-124.
- Boldosova, V. (2020). Telling stories that sell: The role of storytelling and big data analytics in smart service sales. *Industrial Marketing Management*, 86, 122-134. doi: <https://doi.org/10.1016/j.indmarman.2019.12.004>
- Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, 57, 102225.
- Bowen, D. E. (2016). The changing role of employees in service theory and practice: An interdisciplinary view. *Human Resource Management Review*, 26(1), 4-13. doi: 10.1016/j.hrmr.2015.09.002
- Bowen, D. E., & Lawler, E. E. I. (1992). The empowerment of service workers: what, why, how, and when. *Sloan management review*, 33(3), 31-39.
- Brynjolfsson, E. and McAfee, A., 2014. The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.
- Brynjolfsson, Erik, Xiang Hui, and Meng Liu (2019). Does Machine Translation Affect International Trade? Evidence from a Large Digital Platform, *Management Science*, 65 (12), 5449–60.
- Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. J., & Mavrommatis, A. J. B. H. (2020). From data to action: How marketers can leverage AI. 63(2), 227-243.
- Canhoto, A.I. and Clear, F., 2020. Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. *Business Horizons*, 63(2), pp.183-193.
- Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, 106, 102312.
- Cao, G., Duan, Y., & El Banna, A. (2019). A dynamic capability view of marketing analytics: Evidence from UK firms. *Industrial Marketing Management*, 76, 72-83. doi: <https://doi.org/10.1016/j.indmarman.2018.08.002>
- Cardoso, J., Hoxha, J., & Fromm, H. (2015). Service Analytics. In J. Cardoso, H. Fromm, S. Nickel, G. Satzger, R. Studer & C. Weinhardt (Eds.), *Fundamentals of Service Systems* (pp. 179-215). Cham: Springer International Publishing.
- Casidy, R., Nyadzayo, M., & Mohan, M. J. (2020). Service innovation and adoption in industrial markets: An SME perspective. *Industrial Marketing Management*, 89, 157-170.
- Chin, W. W. (2010). How to write up and report PLS analyses *Handbook of partial least squares* (pp. 655-690): Springer.
- Chiu, Y. T., Zhu, Y. Q., & Corbett, J. (2021). In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations. *International Journal of Information Management*, 60, 102379.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*: Routledge Academic.

- Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, 60, 102383.
- Conboy, K., Mikalef, P., Dennehy, D. and Krogstie, J., (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research*, 281(3), pp.656-672.
- Davenport, T. H. (2018a). *The AI advantage: How to put the artificial intelligence revolution to work*: MIT Press.
- Davenport, T. H. (2018b). From analytics to artificial intelligence. *Journal of Business Analytics*, 1(2), 73-80.
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 1-19.
- Davenport, T. and Harris, J., 2017. Competing on analytics: Updated, with a new introduction: The new science of winning. Harvard Business Press.
- Davenport, T. H., & Kudyba, S. (2016). Designing and Developing Analytics-Based Data Products. *MIT Sloan Management Review*, 58(1), 83-89.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116.
- Davenport, T.H. (2019). Building a culture that embraces data and analytics. Retrieved from <https://hbr.org/2019/10/building-a-culture-that-embraces-data-and-ai?registration=success>
- Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. *Decision Support Systems*, 55(1), 359-363.
- Demlehner, Q., Schoemer, D., & Laumer, S. (2021). How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. *International Journal of Information Management*, 58, 102317.
- Den Hertog, P., Van der Aa, W., & De Jong, M. J. (2010). Capabilities for managing service innovation: towards a conceptual framework. *Journal of Service Management*, 21(4), 490-514.
- Diorio, S. (2020). Realizing the Growth Potential of AI. Retrieved on January 14, 2020 from: <https://www.forbes.com/sites/forbesinsights/2020/05/08/realizing-the-growth-potential-of-ai/?sh=41cec74333f3>
- Di Stefano, G., Peteraf, M., & Verona, G. 2014. The organizational drivetrain: A road to integration of dynamic capabilities research. *Academy of Management Perspectives*, 28(4): 307–327.
- Dubey, R., Gunasekaran, A., Childe, S.J., Blome, C. and Papadopoulos, T., 2019. Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, 30(2), pp.341-361.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., . . . Eirug, A. (2021a). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 101994.
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ... & Wang, Y. (2021b). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59 102168, doi: <https://doi.org/10.1016/j.ijinfomgt.2020.102168>
- Edwards, J. R. (2001). Multidimensional constructs in organizational behavior research: An integrative analytical framework. *Organizational Research Methods*, 4(2), 144-192.

- Eisenhardt, K. M., & Martin, J. A. 2000. Dynamic capabilities: What are they? *Strategic Management Journal*, 21(10/11): 1105–1121.
- Elia, S., Giuffrida, M., Mariani, M., & Bresciani, S. (2021). Resources and digital export: An RBV perspective on the role of digital technologies and capabilities in cross- border e-commerce. *Journal of Business Research*, 132, 158–169.
- Elia, G., Polimeno, G., Solazzo, G., & Passiante, G. (2020). A multi-dimension framework for value creation through Big Data. *Industrial Marketing Management*, 90, 617-632. doi: <https://doi.org/10.1016/j.indmarman.2020.03.015>
- Endres, A. M. (1999), “Utility Theory,” in *The Elgar Companion to Consumer Research and Economic Psychology*, Peter E. Earl and Simon Kemp, eds. Cheltenham, UK: Edward Elgar, 599-604.
- EverString. (2018). The state of artificial intelligence in B2B marketing. Retrieved on January 08, 2021 from: <https://www.everstring.com/blog/the-state-of-artificial-intelligence-in-b2b-marketing/>
- Eyers (2020). CommBank using AI to help triage loan deferral customers. Retrieved on January 14, 2021 from <https://www.afr.com/companies/financial-services/commbank-using-ai-to-help-triage-loan-deferral-customers-20200629-p5578e>
- Eisenhardt, K.M. and Martin, J.A. (2000). Dynamic capabilities: what are they?, *Strategic management journal*, 21(10-11), 1105-1121.
- Felin, T. Foss, N.J. Heimeriks, K.H. and Madsen, T.L. (2012). Microfoundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies*, 49 (8), 1351-1374.
- Felin, T., & Powell, T. C. (2016). Designing Organizations for Dynamic Capabilities. [Article]. *California Management Review*, 58(4), 78-96. doi: 10.1525/cmr.2016.58.4.78
- Felin, T., Foss, N. J., & Ployhart, R. E. (2015). The microfoundations movement in strategy and organization theory. *Academy of Management Annals*, 9(1), 575-632.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 39-50.
- Forbes (2020). How Amex Uses AI To Automate 8 Billion Risk Decisions (And Achieve 50% Less Fraud), Retrieved on January 08, 2021 from <https://www.forbes.com/sites/johnkoetsier/2020/09/21/50-less-fraud-how-amex-uses-ai-to-automate-8-billion-risk-decisions/?sh=1668d4b11a97>
- Fortune (2020). How IBM Watson supercomputers are speeding up the search for a COVID-19 vaccine, Retrieved on January 08, 2021 from: <https://fortune.com/2020/07/07/covid-19-coronavirus-vaccine-ibm-watson/>
- Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, 61(1), 101-107.
- George, G., & Lin, Y. J. (2017). Analytics, innovation, and organizational adaptation. *Innovation* 19(1), 16-22.
- Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: a multidisciplinary perspective: Springer.
- Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E. (2020). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management*, 90, 581-592. doi: <https://doi.org/10.1016/j.indmarman.2019.11.009>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, 45(5), 616-632.

- Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. [JOURNAL]. *European Journal of Marketing* (4), 566. doi: 10.1108/EJM-10-2018-0665
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. S. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)*: Sage Publications.
- Hajli, N., Tajvidi, M., Gbadamosi, A., & Nadeem, W. (2020). Understanding market agility for new product success with big data analytics. *Industrial Marketing Management*, 86, 135-143. doi: <https://doi.org/10.1016/j.indmarman.2019.09.010>
- Hallikainen, H., Savimäki, E., & Laukkanen, T. (2020). Fostering B2B sales with customer big data analytics. *Industrial Marketing Management*, 86, 90-98. doi: <https://doi.org/10.1016/j.indmarman.2019.12.005>
- Hayes, A. F., Preacher, K. J., & Myers, T. A. (2011). Mediation and the estimation of indirect effects in political communication research. *Sourcebook for political communication research: Methods, measures, and analytical techniques*, 23, 434-465.
- Helfat, C. E., & Peteraf, M. A. J. (2015). Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management Journal* 36(6), 831-850.
- Helfat, C. E., & Peteraf, M. A. 2003. The dynamic resource-based view: Capability lifecycles. *Strategic Management Journal*, 24(10): 997–1010.
- Helfat C, Finkelstein S, Mitchell W, Peteraf MA, Singh H, Teece DJ, Winter SG. 2007. *Dynamic Capabilities: Understanding Strategic Change in Organizations*. Blackwell: Oxford, U.K.
- Hodgkinson, G. P., & Healey, M. P. (2011). Psychological foundations of dynamic capabilities: Reflexion and reflection in strategic management. *Strategic Management Journal*, 32, 1500–1516.
- Holland, C. P., Thornton, S. C., & Naudé, P. (2020). B2B analytics in the airline market: Harnessing the power of consumer big data. *Industrial Marketing Management*, 86, 52-64. DOI: <https://doi.org/10.1016/j.indmarman.2019.11.002>
- Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management*, 56, 102250.
- Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155-172.
- Huang, M.-H., & Rust, R. T. (2020). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, 24 (1), 30-41.
- Hulland, J., Baumgartner, H., & Smith, K. M. (2018). Marketing survey research best practices: evidence and recommendations from a review of JAMS articles. *Journal of the Academy of Marketing Science*, 46(1), 92-108.
- Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI. *Harvard Business Review*, 98(1), 60-67.
- Insights, SAS (2018). Artificial Intelligence: What it is and why it matters. Retrieved from https://www.sas.com/en_us/insights/analytics/what-is-artificial-intelligence.html.)
- Jabbar, A., Akhtar, P., & Dani, S. (2020). Real-time big data processing for instantaneous marketing decisions: A problematization approach. *Industrial Marketing Management*, 90, 558-569. doi: <https://doi.org/10.1016/j.indmarman.2019.09.001>
- Janssen, M. J., Castaldi, C., Alexiev, A. J. (2016). Dynamic capabilities for service innovation: conceptualization and measurement. *R&D Management*, 46(4), 797-811.

- Kakatkar, C., Bilgram, V., & Fuller, J. (2020). Innovation analytics: Leveraging artificial intelligence in the innovation process. *Business Horizon*, 63(2), 171-181.
- Kaplan, A., & Haenlein, M. J. B. H. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. 62(1), 15-25.
- Kindström, D., Kowalkowski, C., & Sandberg, E. J. (2013). Enabling service innovation: A dynamic capabilities approach. *Journal of Business Research*, 66(8), 1063-1073.
- Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). The analytics mandate. *MIT Sloan Management Review*, 55(4), 1-25.
- Kotler, P. and Keller, K.L., 2015. Marketing Management, Global edition. Pearson Education UK.
- Kumar, P., Dwivedi, Y. K., & Anand, A. (2021). Responsible Artificial Intelligence (AI) for Value Formation and Market Performance in Healthcare: the Mediating Role of Patient's Cognitive Engagement. *Information Systems Frontiers*, 1-24, doi: <https://doi.org/10.1007/s10796-021-10136-6>
- Kumar, A., Shankar, R., & Aljohani, N. R. (2020). A big data driven framework for demand-driven forecasting with effects of marketing-mix variables. *Industrial Marketing Management*, 90, 493-507. doi: <https://doi.org/10.1016/j.indmarman.2019.05.003>
- Kumar, V., Ramachandran, D., & Kumar, B. (2020). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*. doi: <https://doi.org/10.1016/j.jbusres.2020.01.007>
- Law, K. S., Wong, C. S., Mobley, W. M. (1998). Toward a taxonomy of multidimensional constructs. *Academy of Management Review*, 23(4), 741-755.
- Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of applied psychology*, 86(1), 114.
- Lytras, M., Visvizi, A., Zhang, X., & Aljohani, N. R. (2020). Cognitive computing, Big Data Analytics and data driven industrial marketing. *Industrial Marketing Management*, 90, 663-666. doi: <https://doi.org/10.1016/j.indmarman.2020.03.024>
- MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS quarterly*, 35(2), 293-334.
- Makkonen, H. Pohjola, M. Olkkonen, R. and Koponen, A. (2014). Dynamic capabilities and firm performance in a financial crisis", *Journal of Business Research*, 67 (1), 2707-2719.
- Mariani, M. (2020). Big data and analytics in tourism and hospitality: a perspective article. *Tourism Review*, 75(1), 299–303.
- Mariani, M., & Nambisan, S. (2021). Innovation analytics and digital innovation experimentation: the rise of research-driven online review platforms. *Technological Forecasting and Social Change*, 172, Article 121009
- Mariani, M., & Wamba, S. F. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, 121, 338–352.
- Marr, B. (2020). How Is Artificial Intelligence Used In B2B Companies: Here Are Powerful Examples. *Forbes*. Available at: <https://www.forbes.com/sites/bernardmarr/2020/10/02/how-is-artificial-intelligence-used-in-b2b-companies-here-are-powerful-examples/?sh=31eeb8be3ca4>
- McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). A proposal for the Dartmouth summer research project on artificial intelligence. Available at [http:// www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html](http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html)

- Melhem, Y. (2004). The antecedents of customer-contact employees' empowerment. *Employee Relations*, 26(1), 72-93. doi: doi:10.1108/01425450410506913
- Mikalef, P. and Krogstie, J., (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, 29 (3), 260-287.
- MIT Technology Review Insights. (2018, November 2). Professionalservices firms see huge potential in machine learning. Available at: <https://www.technologyreview.com/2018/11/02/139216/professional-services-firms-see-huge-potential-in-machine-learning/>
- Motamarri, S., Akter, S., & Yanamandram, V. (2020). Frontline employee empowerment: Scale development and validation using Confirmatory Composite Analysis. *International Journal of Information Management*, 54, 102177. doi: <https://doi.org/10.1016/j.ijinfomgt.2020.102177>
- Muninger, M.I. Hammedi, W. and Mahr, D. (2019). The value of social media for innovation: A capability perspective, *Journal of Business Research*, Vol. 95, pp.116-127.
- Nakata, C., Rubera, G., Im, S., Pae, J. H., Lee, H. J., Onzo, N., & Park, H. (2018). New Product Creativity Antecedents and Consequences: Evidence from South Korea, Japan, and China. *Journal of Product Innovation Management*, 35(6), 939-959. doi: doi:10.1111/jpim.12436
- Paschen, J., Wilson, M. and Ferreira, J.J., 2020. Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. *Business Horizons*, 63(3), pp.403-414.
- Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control*, 1-17, doi: <https://doi.org/10.1080/09537287.2021.1882689>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods*, 40(3), 879-891.
- Pritchard, R.D. and Karasick, B.W., (1973). The effects of organizational climate on managerial job performance and job satisfaction. *Organizational behavior and human performance*, 9(1), pp.126-146.
- Pureprofile AU. (2020). Pureprofile Australia Consumer Panel Book. Accessed on January 17, 2021: <https://business.pureprofile.com/lp-panel-book/>
- Rai, A. (2020). Explainable AI: from black box to glass box. *Journal of the Academy of Marketing Science*, 48(1), 137-141. DOI: 10.1007/s11747-019-00710-5
- Rana, N.P., Chatterjee, S., Dwivedi, Y.K., and Akter, S. (2021). Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firms' operational inefficiency and competitive disadvantage, *European Journal of Information Systems* (in press), DOI: <https://doi.org/10.1080/0960085X.2021.1955628>
- Randhawa, K. Wilden, R. and Gudergan, S. (2018), "Open service innovation: the role of intermediary capabilities", *Journal of Product Innovation Management*, 35(5), 808-838.
- Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial intelligence in business gets real. *MIT Sloan Management Review and The Boston Consulting Group*.
- Ransbotham, S., & Kiron, D. (2017). Analytics as a Source of Business Innovation. *MIT Sloan Management Review*, 58(3), n/a-0.
- Ransbotham, S., & Kiron, D. (2018). Using Analytics to Improve Customer Engagement. *MIT Sloan Management Review*, January-2018.

- Ringle, C., Wende, S., & Becker, J. (2015). SmartPLS 3. SmartPLS GmbH: Boenningstedt. *Google Scholar*.
- Rust, R. T., & Huang, M.-H. (2014). The service revolution and the transformation of marketing science. *Marketing Science*, 33(2), 206-221.
- Salvato, C. and Vassolo, R. (2018), The sources of dynamism in dynamic capabilities, *Strategic Management Journal*, Vol. 39 No. 6, pp.1728-1752.
- Salunke, S., Weerawardena, J., & McColl-Kennedy, J. R. J. I. M. M. (2019). The central role of knowledge integration capability in service innovation-based competitive strategy. 76, 144-156.
- Saunders, B. (2020). Who's Using Amazon Web Services? [2020 Update] . Retrieved on January 02, 2021 from: <https://www.contino.io/insights/whos-using-aws>
- Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals*, 12(1), 390-439.
- Schneider, B., White, S. S., & Paul, M. C. (1998). Linking service climate and customer perceptions of service quality: Test of a causal model. [Article]. *Journal of Applied Psychology*, 83(2), 150-163.
- Sena, V., & Ozdemir, S. (2020). Spillover effects of investment in big data analytics in B2B relationships: What is the role of human capital? *Industrial Marketing Management*, 86, 77-89. doi: <https://doi.org/10.1016/j.indmarman.2019.05.016>
- Shankar, V. J. J. o. r. (2018). How artificial intelligence (AI) is reshaping retailing. 94(4), vi-xi.
- Shanker, R., Bhanugopan, R., Van der Heijden, B.I. and Farrell, M., (2017). Organizational climate for innovation and organizational performance: The mediating effect of innovative work behavior. *Journal of vocational behavior*, 100, pp.67-77.
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*.
- Sivarajah, U., Irani, Z., Gupta, S., & Mahroof, K. (2020). Role of big data and social media analytics for business to business sustainability: A participatory web context. *Industrial Marketing Management*, 86, 163-179. doi: <https://doi.org/10.1016/j.indmarman.2019.04.005>
- Spreitzer, G. M. J. A. o. m. J. (1995). Psychological empowerment in the workplace: Dimensions, measurement, and validation. 38(5), 1442-1465.
- Stanko, M. A., Molina-Castillo, F. J., & Munuera-Aleman, J. L. (2012). Speed to market for innovative products: blessing or curse? *Journal of Product Innovation Management*, 29(5), 751-765.
- Stone, D., & Wang, R. (2014). Deciding with data—How data-driven innovation is fuelling Australia's economic growth: PricewaterhouseCoopers (PwC). <http://www.pwc.com.au/consulting/assets/publications/Data-drive-innovation-Sep14.pdf>.
- Stone, M. (1974). Cross-validated choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 111-133.
- Storbacka, K., Brodie, R.J., Böhmann, T., Maglio, P.P. and Nenonen, S., 2016. Actor engagement as a microfoundation for value co-creation. *Journal of Business Research*, 69(8), pp.3008-3017.
- Straub, D. W. (1989). Validating instruments in MIS research. *MIS quarterly*, 147-169.
- Streukens, S., & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. [Article]. *European Management Journal*, 34(6), 618-632. doi: 10.1016/j.emj.2016.06.003

- Suddaby, R., Coraiola, D., Harvey, C., & Foster, W. (2020). History and the micro-foundations of dynamic capabilities. *Strategic Management Journal*, 41(3), 530-556.
- Sung, E. C., Bae, S., Han, D. I. D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management*, 60, 102382.
- Suri, H., 2011. Purposeful sampling in qualitative research synthesis. *Qualitative research journal*.
- 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. doi: <https://doi.org/10.1016/j.indmarman.2017.12.019>
- Teece, D., & Leih, S. (2016). Uncertainty, Innovation, and Dynamic Capabilities: An Introduction. [Article]. *California Management Review*, 58(4), 5-12. doi: 10.1525/cmr.2016.58.4.5
- Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350. doi: 10.1002/smj.640
- Teece, D. J. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems Reply: Elsevier Science Bv Po Box 211, 1000 Ae Amsterdam, Netherlands.
- Teece, D. J., Pisano, G., & Shuen, A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7): 509–533.
- Trotman, A., Kallumadi, S., & Dagenhardt, J. (2020). Introduction to special issue on eCommerce search and recommendation. *Information Retrieval Journal*, 1-2.
- Tse, T., Esposito, M., Takaaki, M., & Goh, D. (2020). The Dumb Reason Your AI Project Will Fail. [Article]. *Harvard Business Review Digital Articles*, 2-5.
- Vargo, S. L., Wieland, H., & Akaka, M. A. J. I. M. M. (2015). Innovation through institutionalization: A service ecosystems perspective. 44, 63-72.
- Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly* (37:1), 21-54.
- Venkatesh, V., Brown, S. A., & Sullivan, Y. W. (2016). Guidelines for conducting mixed-methods research: An extension and illustration. *Journal of the Association for Information Systems*, (17:7), 435-494.
- Vimalkumar, M., Gupta, A., Sharma, D., & Dwivedi, Y. (2021). Understanding the Effect that Task Complexity has on Automation Potential and Opacity: Implications for Algorithmic Fairness. *AIS Transactions on Human-Computer Interactions*, 13(1), 104.
- Wedel, M. and Kannan, P.K., 2016. Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), pp.97-121.
- Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS quarterly*, 177-195.
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356-365.
- Wang, W. Y. C., & Wang, Y. (2020). Analytics in the era of big data: The digital transformations and value creation in industrial marketing. *Industrial Marketing Management*, 86, 12-15. doi: <https://doi.org/10.1016/j.indmarman.2020.01.005>

- Wilder, K. M., Collier, J. E., & Barnes, D. C. (2014). Tailoring to Customers' Needs: Understanding How to Promote an Adaptive Service Experience With Frontline Employees. *Journal of Service Research*, 17(4), 446-459 417)444). doi: 10.1177/1094670514530043
- Xiao, J., Wang, M., Jiang, B., & Li, J. (2018). A personalized recommendation system with combinational algorithm for online learning. *Journal of Ambient Intelligence and Humanized Computing*, 9(3), 667-677.
- Zhang, D., Pee, L. G., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management*, 57, 102304.
- Zhang, C., Wang, X., Cui, A. P., & Han, S. (2020). Linking big data analytical intelligence to customer relationship management performance. *Industrial Marketing Management*, 91, 483-494. doi: <https://doi.org/10.1016/j.indmarman.2020.10.012>
- Zhang, H., & Xiao, Y. (2020). Customer involvement in big data analytics and its impact on B2B innovation. *Industrial Marketing Management*, 86, 99-108. doi: <https://doi.org/10.1016/j.indmarman.2019.02.020>