The Future of Marketing Analytics in the Sharing Economy

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Abstract

The rise of sharing economy has accelerated the growth of marketing analytics to match demand and supply in industrial markets. However, the conceptualization of marketing analytics remains unclear in the sharing economy. Theorizing market turbulence as the dark side of the sharing economy, this study presents a marketing analytics capability model using dynamic capabilities and contingency theories to advance thought and practice in industrial marketing research. Using a thematic analysis and a survey-based empirical study on B2B cloud sharing platforms (n=252), the findings present pattern identification, real-time solutions and data governance as the antecedents of marketing analytics capability with its holistic effects on marketing agility and marketing effectiveness. The empirical findings further support the mediating role of marketing agility and the moderating impact of market turbulence on marketing analytics-effectiveness and marketing agility-effectiveness chain. Overall, our results contribute toward a more nuanced understanding of the dark side of market turbulence on marketing analytics capability dynamics in the sharing economy.

Keywords: Marketing analytics capability, sharing economy, marketing agility, marketing effectiveness, market turbulence.

Introduction

"In just a few years, the sharing (or access or gig) economy is already casting a shadow over numerous industries. But while the "sharing" aspect is emphasized, data and analytics is critical to making the sharing actually work. (Ransbotham, 2015 p.1)

The sharing economy is changing the marketing landscape through its scaleable pricing model and on-demand services (Kumar, Lahiri, & Dogan, 2018). The dramatic rise of the sharing economy is fuelled by fast and efficient access to various resources over digital platforms at a reduced cost (Gyana, 2021; Rana et al., 2020). Eckhardt et al. (2019, p. 3) define the sharing economy as "a scalable socio-economic system that employs technology-enabled platforms that provide users with temporary access to tangible and intangible resources that may be crowdsourced." The shared platform revolution has dramatically transformed marketing by enabling the exchange of offerings through temporary access rather than permanent ownership (Eckhardt & Bardhi, 2015; Kumar et al., 2018). Scholars identify marketing analytics at the heart of this transformation (e.g., Chen & Wang) to match demand and supply (e.g., Bardhi and Eckhardt 2012; Zervas, Proserpio, and Byers 2017) across both B2B cloud platforms (e.g., Amazon web services, Google Cloud, Microsoft Azure) and B2C platforms (e.g., Uber, Airbnb, Deliveroo etc.). For example, the global market size of the cloud sharing economy is expected to grow USD 332.3 billion in 2021 at a compound annual growth rate (CAGR) of 20.7% from

2021 to 2026 due to the incessant need for AI and machine learning-based real-time analytics by B2B firms (Gartner 2021a).

Marketing analytics on a B2B cloud sharing platform has emerged as a dominant field due to the rise of sharing economy (Sheth 2021). The growth of marketing analytics on this platform is primarily fuelled by the central role of data to build, test and deploy models regarding customer relationship management (CRM), personalization and service automation in real-time (Chen & Wang, 2019; Wedel & Kannan, 2016). For example, Freshworks, an AWS based B2B customer engagement applications developer, builds and deploys 30,000 models for 11,000 customers within 33 minutes to provide real-time marketing value to customers (Amazon 2020a). A sharing platform is based on five building blocks: temporary access, transfer of economic value, platform mediation, expanded consumer role, and crowdsourced supply (Eckhardt et al. 2019) to create, communicate and deliver value. Although B2B cloud sharing platforms share most of these attributes, the extant literature has failed to articulate the dynamics of marketing analytics capability to match demand and supply under the influence of market turbulence (Chen & Wang 2019). Indeed, most studies have not investigated the contingency effects of technology developments, competitive intensity and changing customer preferences, which are jointly known as market turbulence or the dark side of a sharing economy (Peters et al. 2019).

The Head of AWS, Andy Jassy, stated "Enterprise customers have long overpaid for hardware and software, yet found that infrastructure rarely differentiates their business. By going to the cloud, such customers get cost benefits and agility and don't have to spend their engineering research on their infrastructure" (Miller 2014, p.1). Although cloud sharing platforms have significantly reconfigured marketing agility and scalability (Bardhi and Eckhardt 2012; Zervas, Proserpio, and Byers 2017; Wallenstein and Shelat 2017), the marketing analytics capabilities leveraged by B2B firms and their holistic effects on marketing effectiveness are not explored

(Peters et al., 2019). We refer to marketing effectiveness as mid-range, concurrent market-related performance goals to measure marketing performance (Vorhies, Morgan, Autry, 2009). Since the sharing economy is a subset of the digital economy involving websites, mobile apps, social media and online forums, marketing analytics play a key role in gathering and extracting substantial insights from these data to shape marketing effectiveness (Chen & Wang 2019; Davis, Grewal, & Hamilton 2021). With marketing analytics capability as the critical driver of marketing agility, a sharing platform provides essential insights to meet various real-time needs of an industrial buyer without ownership transfer (Davenport et al., 2020; Fosso Wamba & Akter 2019; Wedel & Kannan 2016). For example, Amazon Web Services (AWS) provide a matching capability for its business customers by accessing millions of usage behavior data points, identifying latent demand through pattern spotting, and efficiently matching real-time needs (Amazon 2020a). Clients on AWS can access customer data, clickstream data, mobile phone-based location data and transaction data to develop and measure various marketing activities. Cloud sharing platforms operate within external environments, and the external forces often influence their opportunities for and constraints on agility (Tidd, 2001). The primary focus of marketing agility is to adapt to market turbulence (Droge, Calantone, & Harmancioglu, 2008) that influences marketing effectiveness (Jansen, Van Den Bosch, & Volberda 2006). This study argues marketing analytics capability of a cloud sharing platform as a dynamic capability, which can explain how, marketing effectiveness can be achieved, especially in highly turbulent market conditions (Eisenhardt and Martin 2000; Helfat and Winter 2011; Teece 2007; Teece et al. 1997).

Whilst a corpus of research has shed light on the B2C sharing platform's marketing activities, insight still remains elusive regarding the marketing analytics capabilities of a B2B sharing platform (Hein et al., 2019). While analytics research has been explored in various B2B domains (Cao et al., 2019; Elia et al., 2020; Gupta et al., 2020; Hajli et al. 2020; Hallikainen et al., 2020), there is a paucity of research on B2B sharing platforms through data & analytics are at the heart of this economy (Ransbotham 2015). Thus, drawing on dynamic capabilities (Teece 2007; Felin 2012) and contingency theory perspectives (Hatch & Cunliffe 2006; Johns 2006; Pfeffer 1997; Tsai & Yang 2013), this study intends to address the following RQs:

RQ1: What are the antecedents of B2B marketing analytics capability on a cloud sharing platform?

RQ2: Is there any impact of overall analytics capabilities on marketing agility and marketing effectiveness under the contingency effects of market turbulence?

In answering these research questions, the study identifies the drivers of marketing analytics capabilities of B2B firms on cloud sharing platforms and model their overall effects on marketing agility and marketing effectiveness using the dynamic capabilities framework (DCF). In exploring this nomological net, the study investigates the moderating effect of market turbulence (i.e., technology turbulence, competitor turbulence and customer turbulence) using contingency theories. As such, the study extends scholarly contribution in several ways. First, extending the extant discourse on B2B analytics research (Akter et al., 2021; Cao et al., 2019; Elia et al., 2020; Gupta et al., 2020; Hajli et al. 2020; Hallikainen et al., 2020), our study is one of the first empirical attempts to identify marketing analytics capabilities of cloud sharing platforms focusing on pattern identification, real-time solutions and data governance. Second, this research sheds light on how marketing analytics capability on cloud sharing platforms help achieve marketing agility by responding rapidly to market turbulence, which advances marketing thoughts in sharing economy research (Dellaert 2019; Eckhardt et al. 2019). Interestingly enough, prior research appears to underestimate the impact of market turbulence on the marketing analytics capability-marketing effectiveness in this context (e.g., Lamberton and Rose 2012; Kumar et al. 2018). As such, this research investigates the impact of market turbulence by taking into account the changes in technology, competitor and customers and modelling their overall effects. As a dark side of sharing economy, the significance of market turbulence appears to be inconclusive in B2B context and has seldom been examined. Overall, the findings of our study illuminate the impact of marketing analytics capability on marketing agility and marketing effectiveness, which varies according to the influence of market turbulence. This is a meaningful extension of the sharing economy literature in marketing by linking analytics with performance variation through a contingency factor (Jiang et al., 2021; Teece et al., 2016). Thus, our research offers significant insights that can transform marketing thoughts and practices across B2B cloud sharing platforms.

2. Literature Review

2.1 Marketing analytics capability on a sharing platform

"What is really new about the sharing economy is the fact that it is built on the digital economy, in which data drive exchange and value creation in an unprecedented manner" (Chen & Wang, 2019 p.1)

We define a sharing platform as an economic platform that facilitates economic activities among a network of economic actors (Perren and Kozinets 2018). Marketing analytics capability (MAAC) on a cloud sharing platform (e.g., AWS, Google Cloud, Microsoft Azure) involves the collection, warehousing, processing and analysis of various data (e.g., app and weblogs, surveys and transactions, sales & revenues and social data) to capture insights on marketing effectiveness using descriptive, diagnostic, predictive and prescriptive tools (Wedel & Kannan 2016). B2B companies on a sharing platform leverage a vast amount of data and analytics to explore customer behaviour. However, the breadth and depth of their marketing activities are driven by the right analytics capabilities provided by the shared platform. For example, the shared data lake architecture capability of AWS has enabled Equinox, Netflix and Zappos to develop personalized customer experiences (Amazon, 2020b). Similarly, the AWS analytics platform has empowered Warner Bros. in capturing, processing and actioning insights for developing games.

These examples indicate how B2B cloud platforms leverage MAAC and unlock the value. Key areas for marketing analytics on a shared platform include data governance (privacy and security), real-time decision making on resource allocations to the marketing mix variables and patterns identification of customer behaviour for personalization and relationship management (Wedel & Kannan 2016; DeLuca et al., 2020). Overall, the objectives of MAAC on a shared platform are to optimize marketing effectiveness, including segmentation and targeting, sales management, customer relationship management (CRM), pricing, branding, promotions, innovations and product portfolio management.

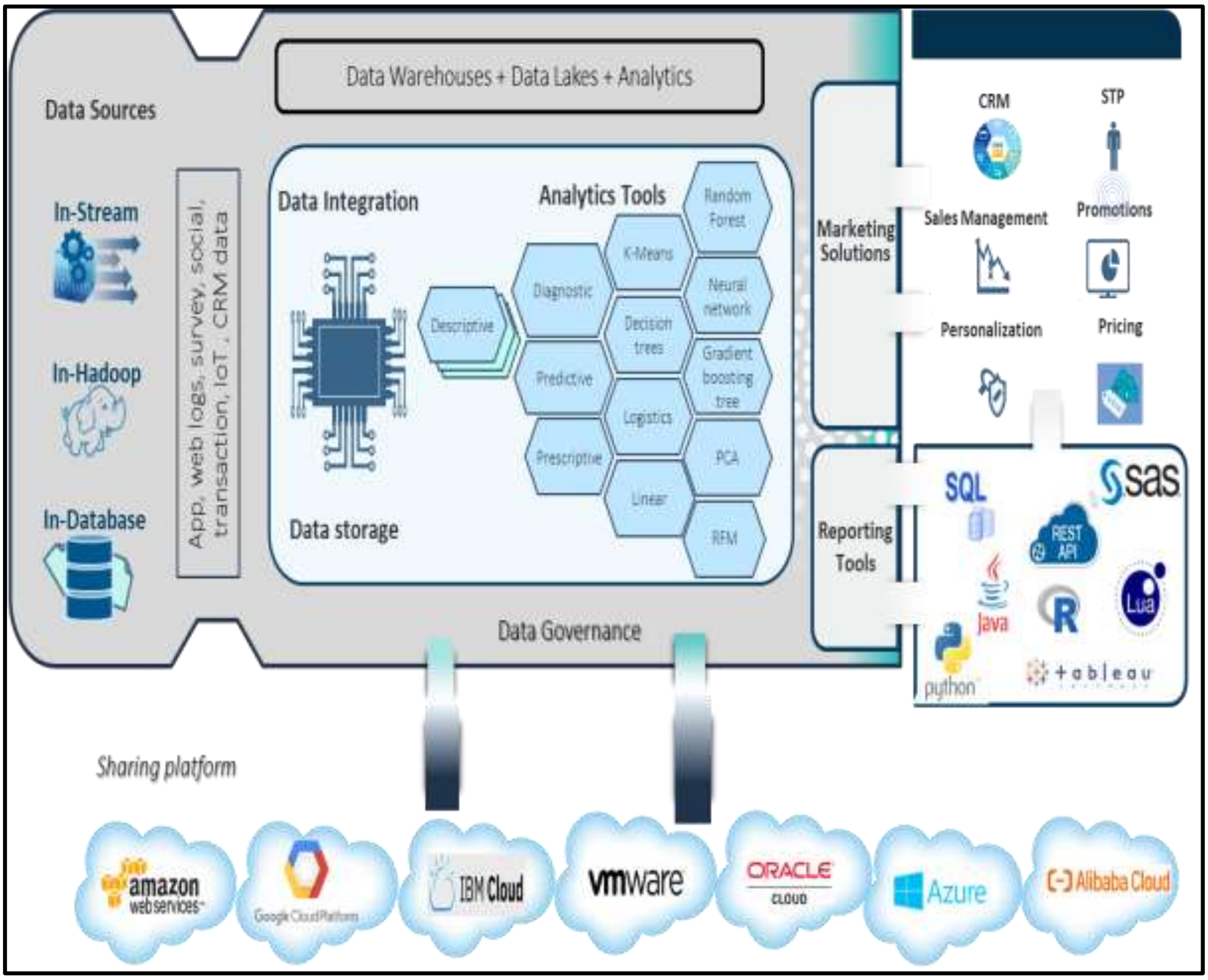

Figure 1: Marketing Analytics on a Cloud Sharing Platform

Figure 1 shows that a cloud sharing platform (e.g., AWS, Google Cloud, Microsoft Azure etc.) can help an organization to collect various types of structured and unstructured data from both organization and external sources, which are then integrated and processed for centralized data storage, access and security. Since all data are in one place, marketing analysts can get quick access to examine, test and review data with the help of a pay as you go service. Using the remote analytics tools embedded in the sharing platform, the marketing team can leverage the benefit of a specialized and well-equipped sharing platform with regard to data governance and data science tools. In addition, a cloud sharing platform provides on-demand comprehensive insights anytime from anywhere to facilitate collaboration, communication and marketing decision making. Since it is managed by sophisticated computer and network systems, data integration and analytics insights happen in real-time.

Despite the importance of data on a cloud sharing platform, there is very limited research on MAAC to enable marketing agility in industrial markets (Chen & Wang, 2019). For example, AWS or Azure analytics provide exceptional insights to small and medium businesses to meet idiosyncratic needs by identifying patterns in consumer usage behaviour data and making real-time decisions. In conceptualizing MAAC of a shared platform, scholars have focused on deeper analysis of data (Kakatkar et al. 2020), decision automation using statistical tools and marketing concepts (Kumar 2020), patter spotting and real-time decisions (DeLuca et al., 2020).

Drawing on the seminal studies on big data analytics (Akter et al., 2016; Wamba et al. 2017), marketing analytics (Wedel & Kannan 2016) and cognitive service analytics (Akter et al. 2021), we define MAAC of a cloud sharing platform as a multidimensional concept consisting of data integration, management, analysis and real time-decision making ability to enhance marketing effectiveness. For example, the extant literature reports that a cloud sharing platform helps B2B firms to increase employee engagement through service automation (Davenport & Ronanki 2018), sales recommendations (Kumar, Ramachandran, and Kumar 2020), smart services like tax preparation (Huang and Rust 2018), business process or security services (Davenport et al., 2020). Although the literature on marketing analytics synthesizes pattern spotting, real-time decisions, data governance as the pillars of the marketing analytics capabilities (De Luca et al. 2020; Hossain et al. 2021), there is a paucity of research in this domain that has identified and tested the analytics capability dimensions and their overall effects on marketing agility and market effectiveness in a sharing economy context.

2.2 Marketing Agility

The concept of agility has received increased attention from researchers in various business domains due to its significant importance in firm performance (Khan, 2020). Agility is identified as a higher-order capability that is built over time (Fosso Wamba & Akter 2019; Doz and Kosonen 2008). Agility "enables firms to acquire, integrate and reconfigure resources and dynamically position themselves competitively" (Vickery, Droge, Setia, & Sambamurthy, 2010, p. 7028). The extant literature has provided few definitions of agility. For instance, Sharifi and Zhang (1999) define agility as taking advantage of opportunities and changes by handling unprecedented threats and challenges in the marketing environment. Others define it as the rapid capability to assemble necessary knowledge, assets, and relationships to seize competitive market opportunities and sense innovation opportunities (Sambamurthy, Bharadwaj, and Grover 2003). Indeed, it is the firm's instant competitive and innovative action level by responding and sensing customer-based opportunities (Roberts and Grover, 2012).

Marketing agility allows firms to respond to market changes quickly by focusing on unpredicted incidences (Osei, Amankwah-Amoah, Khan, Omar, & Gutu, 2019). In conceptualizing marketing agility, Homburg et al. (2020) focused on fast decision making, trial and error learning, whereas Kalaignanam et al. (2021) highlighted sensemaking, iteration, speed and decisions. Zhou et al. (2019) identify marketing agility as a meta dynamic capability representing the novel attributes of market sensing, speed and flexibility to detect opportunities and respond speedily by reconfiguring marketing tactics in a changing environment. However, Khan (2020) extends marketing agility by focusing on under-studied dynamic capabilities, such as proactive market sensing, responsiveness, speed and flexibility. Overall, the extant literature identifies four predominant attributes of marketing agility as outlined by Zhou et al. (2019), which is consistent with Homburg et al. (2020), Khan (2020) and Kalaignanam et al. (2021) to a large extent. First, marketing agility is a higher-order organizational capability, which can adapt to changing market contexts better than rivals (Roberts & Grover, 2012). Second, marketing agility reflects flexibility, speed, responsiveness and proactiveness (Homburg et al. 2020; Sherehiy et al., 2007; Zhang, 2011). Third, marketing agility implies sensemaking and marketing response (Eckstein et al., 2015; Kalaignanam et al., 2021; Roberts & Grover, 2012; Teece 2016) by responding to opportunities and threats and proactively changing the resources and settings (Eckstein et al., 2015; Roberts & Grover, 2012; Teece 2016). Fourth, marketing agility is context-specific (Roberts & Grover, 2012; Zhou et al., 2019).

Researchers identify marketing agility as a critical antecedent of customer satisfaction (Aghina et al. 2020), strategic competitive performance (Sultana et al., 2022) and marketing excellence (Homburg et al., 2020). Despite the growing importance of marketing agility in a sharing economy, its effects have not been clearly studied on marketing effectiveness under the influence of market turbulence (Davenport et al., 2020; Sultana et al., 2022). This sentiment has been echoed by Kalaignanam et al. (2021, p.53) as follows: “Future empirical research, therefore, could investigate the impact of MA (marketing agility) on a multitude of product-market outcomes and the contingencies associated with these relationships.” Since contingency has always been a feature of the industrial marketing environment, thus analytics capability management under deep market turbulence becomes a proactive requirement (Teece et al., 2016). Although marketing analytics is a crucial dynamic capability to know when and how much agility is required, there is scant research on this association in the B2B sharing economy context.

3. Theoretical foundations

3.1 Dynamic capabilities framework and marketing effectiveness

This study is rooted in the dynamic capabilities framework (DCF) (Teece, Pisano and Shuen, 1997), which has gained momentum in recent times in big data analytics research (Fosso Wamba et al. 2017; Akter et al. 2021a; 2021b; Mikalef et al., 2019) due to its ability to sense, seize and respond in volatile markets (Teece 2012; Winter 2003; Fosso Wamba & Akter 2019). The core tenet of DCF is argued as the higher-level capabilities of a firm to integrate, build and transform its internal and external resources to achieve firm performance in the turbulent business environment (Teece and Pisano, 1994). Hence, the DCF focuses on orchestrating or managing a firm's capabilities to adapt and transform rapidly changing business contexts (Teece, 2014).

In a similar spirit, Schilke (2014) clarifies DCF as the mechanism to build and adapt both higher and lower order capabilities to enhance organizational fit within the changing environment. Whereas higher-order DCs focus on direct value creation activities, lower-order capabilities are routines or ordinary resource bases (Akter et al., 2021a; Schilke 2014; Teece 2016). Teece, Peteraf and Leih (2016, p.18) define DCs as " the firm's capacity to innovate, adapt to change, and create change that is favorable to customers and unfavorable to competitors". The DCF identifies agility as the effect of dynamic capabilities to manage uncertainty. The building blocks of agility through DCs depend on management capabilities to quickly transform technologies and infrastructures (Teece et al., 2016). Analytics research has identified marketing analytics capability as a higher-order dynamic capability that allows a firm to collect, integrate, process and analyze data to renew its knowledge base (Côrte-Real, Oliveira, and Ruivo 2017) and learn about customers, competitors, and the broader market environment (Wilden & Gudergan, 2015).

Past analytics capability theories show that market performance can be enhanced through the proper deployment of analytics resources (e.g., Akter et al., 2016; Fosso Wamba et al., 2017). Studies also indicate analytics-driven marketing capabilities can increase overall firm performance through sales growth, market share and market position without sacrificing profitability (De Luca et al. 2020). The sustained market performance can be achieved by using dynamic marketing analytics capability to sense every evolving market opportunity and threat, seize the sensed opportunities of untapped demand and reconfigure new service offerings to meet needs and manage uncertainty (Cao et al. 2019). Using analytics on the sharing platform, marketers assess the value of customers, products and channels using various promotional and pricing scenarios and evaluate effectiveness of their marketing decisions (Farris et al., 2015). We refer marketing effectiveness as the degree to which market related performance goals of an organization is achieved in a sharing economy through dynamic analytics capability. Whereas marketing effectiveness refers to the key performance indicators (KPIs), marketing analytics refers to the data-driven insights in specific marketing contexts (Vorhies et al., 2009). However, few studies have articulated the impact of MAAC on marketing agility and effectiveness by taking into account contingency factors that critically influence the internal operating system of a firm (Teece et al., 2016).

3.2 Contingency theory and market turbulence

The contingency theory is rooted in fitting attributes of an organization, such as its resources to uncertainties that reflect the environment of an organization (Burns and Stalker 1961;

Pennings, 1992). The theory suggests that an organization must have resources to address environmental factors to succeed in a turbulent environment (Tsai & Yang 2013). Since external environments influence market opportunities or challenges, it is critical to give proactive attention to market turbulence factors (Hatch & Cunliffe, 2006). In this context, Penrose (1959) argues that environmental changes "may change the significance of resources to the firm" (p. 79). In a similar spirit, Johns (2006) illuminates the role of situational opportunities and constraints that influence the significance of organizational behaviour and the functional relationships between constructs. Scholars argue that the value creation, value delivery and value communication process of marketing is influenced by exogenous variables (Tsai & Yang 2013). A proper match between internal operations and external influences can enhance firm performance. However, the extent of such a match can moderate internal mechanisms and affect performance indicators (Venkatraman, 1989).

Market turbulence refers to the rate of change in exogenous variables in an industry that influences marketing operations (Jaworski & Kohli, 1993). With greater market turbulence, the extent of unpredictability is more perceived by managers in their external market environment (Eisenhardt and Martin, 2000). The market turbulence concept identifies the distinguishing feature of unpredictability in an external marketing environment, such as technology, customer, and competitor (e.g., Bogner and Barr, 2000; Eisenhardt and Martin, 2000; Helfat and Raubitschek, 2000). The roles of competitor and customer are supported by Grant (2010), who argues that these forces in an industrial environment directly affect firm performance by influencing the strategic choices of a firm. In a similar spirit, Penrose (1959) states that the market environment is "determined by the actions of competitors and by the tastes, or at least the psychology, of consumers (1959, p. 217)." The subsequent literature argues the role of technology (e.g., Eisenhardt and Martin, 2000; Peters et al., 2021) that influences the marketing mechanisms both in creating and capturing value. For example, Baden-Fuller & Teece (2020, p.105) argues that "what was once a valuable resource or market position can become outdated when consumer needs and technology separately or simultaneously change and rivals dream up new ways of identifying and fulfilling wholly new wants in wholly new ways that fundamentally challenge the old order – as vividly illustrated by the demise of Kodak and Nokia". As such, as a component of market turbulence, the degree of change in technology, customer preferences and competitive intensity may alter the effects of a firm's marketing analytics capability on marketing agility and marketing effectiveness. Despite the well-documented impact of market turbulence on the industrial marketing environment, few studies measured its influence on marketing analytics-agility-effectiveness link in a sharing economy context.

4. Qualitative Exploration

In order to answer the research questions on the antecedents of MAAC on a cloud sharing platform (e.g., AWS, Microsoft Azure, Google Cloud etc.), the study conducted a systematic literature review (e.g., Palmatier, Houston, & Hulland, 2018; Tranfield, Denyer, & Smart, 2003; Snyder 2019) and a thematic analysis (e.g., Braun & Clarke, 2006). The study has conducted a thorough review of the following databases: *Business Source Complete (EBSCO),* ABI/Inform Collection (ProQuest), *Wall Street Journal (ProQuest), Emerald Insight* and *ScienceDirect* using the search strings: "sharing platform analytics", "marketing analytics", "cloud analytics", "real-time analytics", "platform analytics", "analytics capability", "marketing analytics capability", "analytics platform" etc. Based on the screening of the title, abstract, keywords, and body of the text, we selected 43 articles from the initial discovery of 277 articles. A check of cross-references added 7 more articles, and a manual inclusion added 5 articles. In total, 55 articles were selected for thematic analysis, which reflected an implicit or explicit indication of MAAC on a cloud sharing platform in the context of industrial markets. Following the guidelines of Braun and Clarke (2006), we applied thematic analysis as it is suitable for identifying repeated patterns in the interview data. We identified three themes as the drivers of MAAC of a cloud sharing platform: pattern identification, real-time solutions and data governance. The reliability of the themes was cross-checked using QSR NVivo 12 software that is suitable for managing and analysing qualitative data and identifying the themes. Furthermore, a panel of four judges (two academics + two practitioners) independent coded four themes against selected articles using a nominal scale (i.e., 1 = pattern identification, 2 = real-time solutions and 3= data governance) using IBM SPSS statistics package (version 26) to assess inter-rater reliability of the themes (Akter & Wamba, 2016; Krippendorff, 2004, 2007). The results provided us with a Kalpha value of 0.84, which exceeds the threshold level of 0.80, confirming substantial evidence of inter-rater reliability of the three themes (De Swert, 2012).

5. Conceptual Model and Hypotheses Development

Drawing on the results of a systematic literature review and thematic analysis, this study conceptualizes MAAC as a higher-order dynamic capability construct, which consists of three, lower-order, operational capabilities including pattern identification, real-time solutions and data governance (see Figure 2). First, *pattern identification* refers to the capability to detect and predict patterns in market demands and buyer behavior on a cloud sharing platform that would not be easily identifiable in an on-premise platform (De Luca et al. 2020). For example, using the Google cloud platform, Airbus provides secure access to satellite imagery and data to enable its business customers to identify patterns (Google 2021). Similarly, AstraZeneca's Genomics Data Processing Solution on AWS runs 51 Billion Tests in 1 Day, which directly contributes to pattern spotting and new drug discovery (Amazon 2021b). Second, r*eal-time solutions* refer to the capability to meet the variety and volume of ever-evolving needs of business customers irrespective of time and location (De Luca et al. 2020). For example, using Oracle cloud applications, IBM, Accenture, Deloitte and PWC provide real-time marketing solutions to its business customers with regard to customer services focusing on consultation, security, technology and strategy (Gartner, 2021b). Finally, we define *data governance* as the capability to access, integrate and process data from all the channels of a firm (e.g., mobile, web, bricks & mortar, social etc.) (Hossain et al. 2020; Mikalef and Krogstie 2020). For example, Salesforce has developed a CRM platform on AWS by processing exabytes of data, integrating various channels and connecting customer identifiers to provide data-driven insights into customer segments and personalized recommendations (Amazon 2021a). Overall, encapsulating pattern identification, real-time solutions and data governance as the antecedents, we propose a higher-order, reflective-formative MAAC construct, which influences marketing agility and market effectiveness on a cloud sharing platform (see Figure 2). We propose market turbulence as the hierarchical moderator consisting of technology turbulence, competitor turbulence and customer turbulence, which influences the nomological chain. We argue that marketing agility mediates the relationship between MAAC and marketing effectiveness.

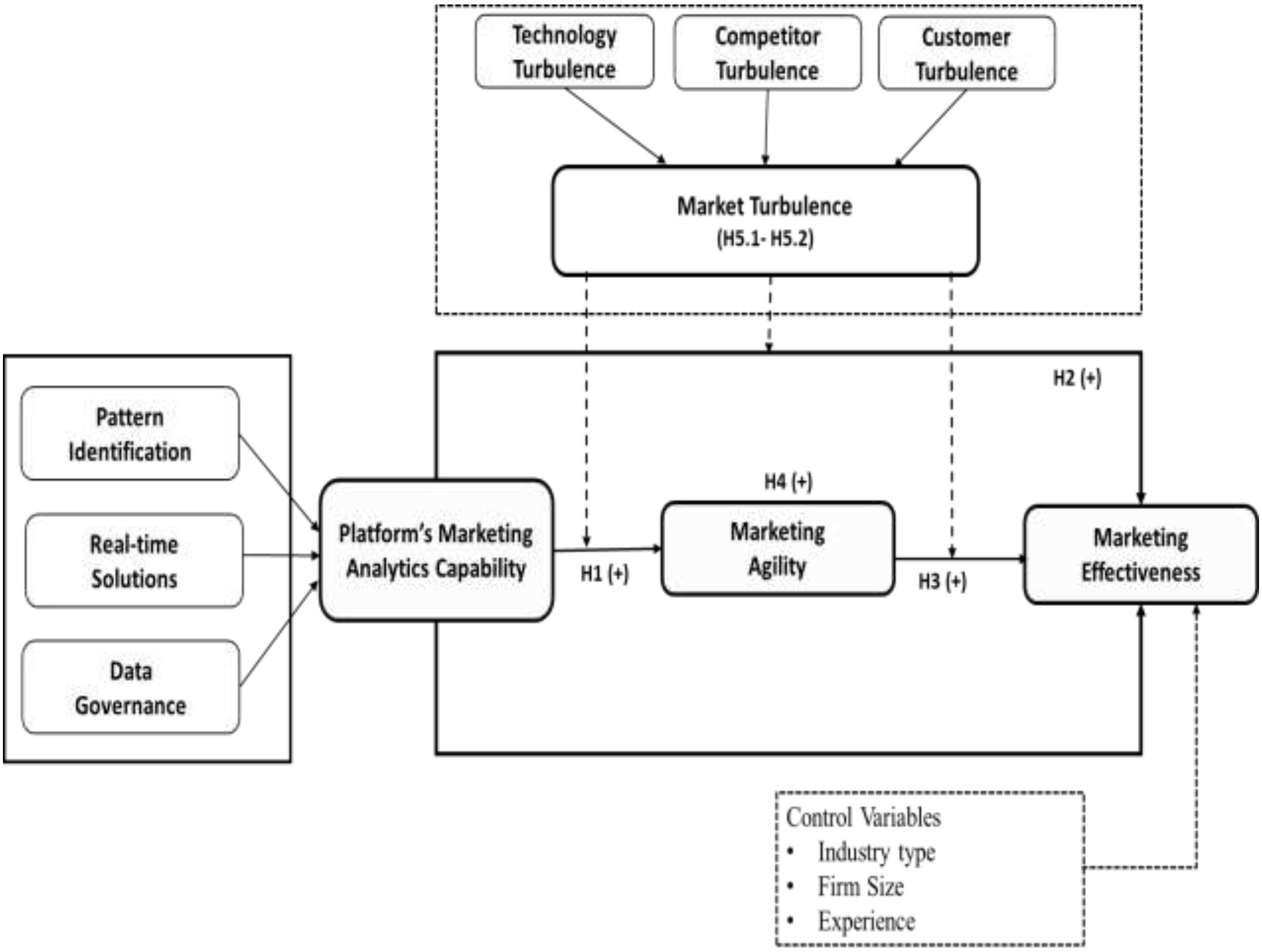

Figure 2: Research Model

5.1 Effects of marketing analytics capability on marketing agility and market performance

Since sharing economy is a subset of the digital economy, the massive amount of data generated by digital platforms (e.g., website, mobile, social media) have advanced the demand for marketing analytics to introduce sophisticated methods, techniques and metrics to harness data, build models and design offerings to customers (Hossain et al. 2020). The growth of marketing analytics in sharing economy has shaped the necessity to embrace marketing agility (Kalaignanam et al., 2021; Lemon and Verhoef 2016; Moorman 2020). For example, using AWS analytics, Moderna achieved the necessary speed and scalability to accelerate new product development and production process through data integration, sophisticated analytics, service automation and regulatory compliance (Amazon 2017). Indeed, MAAC acts as the building block of marketing agility in sharing economy for a nimble and robust deployment of analytics solutions to wide-ranging marketing problems (Wedel & Kannan 2016). The pattern identification, real-time solutions and data governance contribute to marketing agility to establish a flexible process for sensemaking, fast iteration and innovation. The components of MAAC are intertwined and act together to develop agile marketing in sharing platforms so that changing needs of the market can be sensed and matched quickly (Kalaignanam et al., 2021). For example, using AWS, Indigo has developed the sharing platform *Indigo marketplace* to match buyers and sellers in real-time for agricultural commodities, and Ant Financial has developed a borrower screening platform using Alibaba cloud (Akter et al., 2021a; Iansiti & Lakhani, 2020). Since transactions are driven by technology in these sharing platforms, value creation activities are connected in an agile manner by efficiently connecting parties with real-time analytics solutions (Perren and Kozinets, 2018; Eckhardt et al., 2019). Although there is evidence of analytics and agility research in allied disciplines (e.g., Fosso Wamba & Akter 2019; Wamba et al. 2020), the relationship between marketing analytics capability and marketing agility has received limited research attention due to the complexity embedded in sharing platforms concerning the data sources and analytics methods (Hoffman and Novak 2017). As such, proposing MAAC as a higher-order construct combining pattern identification, real-time solutions and data governance, we put forward the following hypothesis:

H1. Marketing analytics capability on a sharing platform has a significant positive impact on marketing agility.

The extant research on big data and MAAC reports increasing ROI, customer retention and market performance (Akter et al. 2016; Davenport & Harris 2017; Wamba et al. 2017; Wedel & Kannan 2016). For example, in the context of B2B marketing, Cao et al. (2019) report that MAAC influences marketing decision making, product development management and sustained competitive advantages. Similarly, Hallikainen et al. (2020) and Zhang et al. (2020)

highlight that big data analytics influence CRM performance and sales growth in the B2B industry. Gupta et al. (2020) extend this line of research by showing how MAAC increases market, operational and financial performance in B2B markets. Hajli et al. (2020) propose a conceptual model on the relationship between MAAC, agility and new product success in industrial markets. Hung et al. (2020) use a case study approach to identify how analytics can enhance marketing and risk management performances in the commercial banking industry. Although a sheer volume of literature identifies a positive relationship between analytics and firm performance, a recent stream of analytics research highlights that the return from MAAC is gradually waning because studies have failed to articulate the right analytics tools/metrics for the right environment (Dekimpe, 2020; KPMG, 2020; Masige, 2020). As a result, Hossain et al. (2021) state that there is pressure on marketers to create value and link customers across channels using analytics to measure marketing effectiveness. Because, understanding a 360-degree view of contextual preferences of buyers is a critical priority in a data-rich sharing economy to measure marketing effectiveness (MSI, 2020). Indeed, prior marketing research urges that marketing activities need to be both efficient and effective in any platform to enhance productivity (Sheth, Sisodia, and Sharma, 2000). In a cloud sharing context, MAAC must increase marketing effectiveness by properly deploying marketing analytics resources. As such, we posit:

H2. Marketing analytics capability on a sharing platform has a significant positive impact on marketing effectiveness.

Marketing agility refers to the higher-order ability of a firm to outperform competitors in any marketplace by realigning resources as required (Accardi-Petersen, 2011). It also highlights proactive marketing strategies to adapt to the emerging needs, changing market conditions and strategic demands to enhance firm performance (Roberts & Grover, 2012; Zhou et al., 2019). The extant literature reports that marketing agility is directly related to innovation capability, marketing revenue (Hern 2014), financial performance (Zhou et al., 2019; Sultana et al., 2022), stock market performance (Schultz 2018) and marketing excellence (Homburg, Theel, and Hohenburg 2020). However, empirical research in the context of a sharing economy has not yet modelled any direct impact of marketing agility on marketing effectiveness (Aghina et al. 2020). This absence of evidence reinforces us to posit:

H3. Marketing agility of a sharing platform has a significant positive impact on marketing effectiveness.

5.2 Mediating effects of marketing agility

Marketing agility is argued to have both a direct and an indirect impact on marketing outcomes (Zhou et al., 2019). Since marketing agility refers to a mechanism to respond to the changing market environment by iterating and reconfiguring analytics capabilities (Fosso Wamba & Akter 2019), it influences marketing effectiveness through its mediating role. For example, companies like Moderna or AstraZeneca use AWS to accelerate marketing agility by combining various types of data and analytics approaches as drivers to gain rapid market performance (Amazon, 2017; 2021b). Although marketing agility is found to influence revenue (Schultz 2018), innovation (Zhou et al. 2019; De Luca et al. 2020) and operational performance (Gupta et al. 2020), these studies did not explore the intermediate processes of marketing agility. Thus, we are intrigued to posit the following hypothesis in the context of a cloud sharing platform:

H4. Marketing agility on a sharing platform mediates the relationship between marketing analytics capability and marketing effectiveness.

5.3 Moderating effects of market turbulence

We identify market turbulence as a contingency factor that influences the nomological relationship between MAAC, marketing agility and market performance. Market turbulence refers to the rate and unpredictability of change in three external forces: technological development, competitive intensity and customer preferences (Tsai & Yang 2013; Peters et al.

2019). In a dynamic or rapidly changing cloud sharing environment, marketing analysts might need a robust analytics platform to be agile or to process high degrees of uncertainty (Chen et al., 2014). Thus, in this environment, MAAC becomes more critical as a dynamic capability to effectively mobilize various analytics resources. MAAC helps to reconfigure various resources to match opportunities/threats in turbulent environments by sharing real-time insights with both internal and external stakeholders (Fosso Wamba & Akter 2019). Hence, greater market turbulence will have more impact on processing marketing insights, thus requires a superior MAAC to enable effective market operations or marketing agility. Thus, identifying technology change, competitors' moves, and shifts in customer demand holistically as market turbulence, we posit:

H5.1 Market turbulence on a sharing platform moderates the relationship between marketing analytics capability and marketing agility.

In the volatile sharing economy, firms need superior dynamic analytics capability to enhance marketing effectiveness. According to Eckhardt et al. (2019, p.18), "Fortunately, sharing platforms are replete with a rich array of digitized transactional data that marketing scholars could potentially use to assess the performance of different pricing strategies across various market conditions and customer segments". In a similar spirit, we argue that sharing platforms are fertile grounds for marketing analytics as they are rich in data. However, the effects of MAAC on marketing effectiveness can be significantly influenced by its technology offerings, such as data aggregation tools and technology platforms (e.g., Hajli et al. 2019), data quality (Bradlow et al., 2017; Rana et al., 2021) and algorithm designs (e.g., Akter et al., 2021). For example, market turbulence in the form of technological developments has urged The Nasdaq Stock Exchange to use AWS cloud-based analytics to match buyers and sellers at high volume and velocity, which is equivalent to 70 billion records a day (Amazon 2020c). However, downtime in these cloud-based solutions due to upgrades or maintenance or a security breach can disrupt the marketing effectiveness of a sharing platform (Gyana 2021). Thus, acknowledging the impact of multidimensional market turbulence on marketing effectiveness, we posit:

H5.2 Market turbulence on a sharing platform moderates the relationship between marketing analytics capability and marketing effectiveness.

Although a firm achieves an optimum level of MAAC on a sharing platform and implements agile marketing, it might not be able to capture value if the industry encounters rapidly changing customer preferences, wide-ranging customer needs and intense interfirm competition in the form of imitation, price competition, promotion competition and value-added services (Li et al., 2008; Tsai & Yang 2013). Indeed, the marketing effectiveness of marketing agility is contingent on both direct and indirect factors (Aghina et al. 2020; Akter et al., 2021). Thus, marketing effectiveness can be influenced by technological, ethical and regulatory limitations on a sharing platform, such as data, methods and applications bias (Akter et al., 2021). These contingencies are paradoxes or the dark side of a sharing economy (Belk et al., 2019), which can cripple the effects of marketing agility on marketing effectiveness (Kalaignanam et al., 2021). However, this investigation seems to be inconclusive in a sharing economy. Thus, we posit that:

H5.3 Market turbulence moderates the relationship between marketing agility and marketing effectiveness.

6. Methods

6.1 Research Setting

The research setting is based on cloud sharing platforms (e.g., AWS, Microsoft Azure, Google Cloud, IBM, Oracle and Alibaba), which enable B2B firms to integrate, process, secure and store data to provide marketing analytics services using “on-demand” and “pay-as-you-go” models (Mgrdechian 2019; Tandon 2018). For example, AWS is the leader in Gartner’s magic quadrant for cloud infrastructure and platform services in 2021, which provide data movement, data storage, data lakes, big data analytics and machine learning services to millions of businesses in 245 countries across the world (Gartner 2021c). This study focuses on Australian B2B firms currently using at least one cloud sharing platform for marketing analytics.

6.2 Scale Development

Scales were adapted from past studies to measure data governance (Mikalef and Krogstie 2020), pattern identification and real-time solutions (De Luca et al. 2020). As part of measuring the outcome constructs, we assessed marketing agility (Tallon 2008; Benzidia & Makaoui 2020) and marketing effectiveness (Vorhies and Morgan, 2005). To estimate the moderating effects of market turbulence, we adapted constructs from (Peters et al., 2019), which is based on Bogner and Barr (2000; Eisenhardt and Martin (2000), Helfat and Raubitschek (2000). Except for control variables, all the constructs were measured using a 7-point Likert scale. The control variables include industry type, firm size and analytics experience using nominal scale. Industry type was controlled to assess differences across a few predominant sectors (e.g., retail, ICT, financial, professional etc.). In addition, firm size may explain variations in analytics practices between small vs big firms, and experience may explain a respondent’s tenure in the industry (Cao et al., 2019). To assess the quality of the questionnaire, we collected data from 35 respondents at the pre-test phase to confirm format, layout, scale structure and items. At the pilot-test phase, we collected data from 55 respondents to confirm the drivers of MAAC and the causal chain. Table 2 shows measurement scales and their definitions.

6.3 Data collection

Using a professional market research firm, we approached a panel of marketing analytics practitioners with at least one year of experience using cloud-based analytics platforms (see Table 1). Using a simple random sampling, the Qualtrics version of the questionnaire was distributed to a panel of 733 respondents who met the screening criteria and were at least 18 years old (see Table 3). In total, 283 respondents filled the survey, and we analyzed the complete responses of 252 respondents after excluding all the spurious responses, such as missing values and flatliners. Table 1 shows diversity in the sample in terms of the industry type, firm size, experience and gender (see Table 1).

Table 1 Respondents' demographic profile (main study n=252)

Gender		**Age**		**Number of employees (Firm Size)**	
Male	51.2%	18-25	10.7%	Less than 20	17.5%
Female	48.8%			20-99	15.9%
		25 - 34	37.7%	101–249	17.1%
		35 - 44	31.7%	250–999	16.3%
		45 +	19.8%	500–999	11.9%
				1,000–2,499	7.5%
				2,500–4,999	1.6%
				5,000+	12.3%
Experience				**Industry type**	
< 5 years			46.0%	Retail	19.4%
5-10 years			38.9%	Media & entertainment	2 %
>10 years			15.1%	ICT	21.4%
				Banking & Finance	14.7%
				Higher education	6.7%
				Professional services	13.1%
				Others	22.6%

Table 2 Operationalization of Constructs

Constructs	Sub-constructs	Definitions	Item labels	Items
Marketing Analytics Capability	Pattern identification	It refers to the ability to detect and predict patterns in market demands and buyer behavior on a sharing platform (De Luca et al. 2020).	PAID1	Analytics at the sharing platform allows me to identify patterns of buyer behavior across our touchpoints.
			PAID2	Analytics at the sharing platform allows me to predict undesirable customer behaviors, such as complaints or churn.
			PAID3	Analytics at the sharing platform allows me to predict desirable customer behaviors, such as propensity to buy or word-of-mouth.
			PAID4	Analytics at the sharing platform allows me to identify patterns of competitive actions affecting our customers.
	Real-time solutions	It refers the ability to meet needs and provide real-time solutions irrespective of time and location (De Luca et al. 2020)	RESO1	Analytics at the sharing platform allows me to perform real-time analyses.
			RESO2	Analytics at the sharing platform allows me to provide real-time marketing solutions.
			RESO3	Analytics at the sharing allows me to implement real-time decision rules.
			RESO4	Analytics at the sharing allows me to identify the best next action in customer interactions.
	Data governance	It refers to the effective management of data on a sharing platform (Mikalef and Krogstie 2020; Ransbotham & Kiron 2017).	DAGO1	Analytics at the sharing platform allows me to access very large, unstructured, or fast-moving data.
			DAGO2	Analytics at the sharing platform allows me to integrate data from multiple sources.
			DAGO3	I feel we provide enough privacy of customer data for analytics purposes.
			DAGO4	I feel the sharing platform provides security for the data.

Market Turbulence	Technology turbulence	The degree to which technology on a sharing platform changes in terms of its prediction, rate and complexity (Peters et al. 2019).	TETO1	It is very difficult to forecast where the technology of a sharing platform will be in two to three years.
			TETO2	The technology of a sharing platform is changing rapidly.
			TETO3	There are many diverse technological events that impact our operations.
	Competitor turbulence	The degree to which competitive intensity on a sharing platform changes in terms of its prediction, rate and complexity (Peters et al. 2019).	COTU1	It is very difficult to predict any changes in who might be our future competitors on a sharing platform
			COTU2	One hears of new competitive moves almost every day on a sharing platform.
			COTU3	There are many, diverse competitor events that impact our business's operations.
	Customer turbulence	The degree to which customer preferences and buying behavior change on a sharing platform in terms of its prediction, rate and complexity (Peters et al. 2019).	CUTU1	It is very difficult to predict any customer changes on a sharing platform.
			CUTU2	Customers' preferences change quite a bit over time.
			CUTU3	There are many, diverse market events that impact our business's operations.
Marketing Agility	NA	It refers to simplified structures, processes and fast decision making to execute growth activities through constant iteration (Homburg et al. 2020; Benzidia & Makaoui 2020)	MAAG1	Analytics on a sharing platform allows us to quickly respond to changes in customer demand.
			MAAG2	Analytics on a sharing platform allows us to change offerings in response to changing market opportunities.
			MAAG3	Analytics allows us to react to new service launches by competitors.
			MAAG4	We can adjust what we offer to match market needs.
Marketing Effectiveness	NA	It refers to the mid-range, concurrent market-related performance goals to measure marketing performance (Vorhies et al., 2009; Vorhies & Morgan 2005)	MAEF1	Market share growth relative to competitors
			MAEF2	Growth in sales revenue
			MAEF3	Acquiring new customers
			MAEF4	Increasing sales to existing customers

6.4 Data Analysis

We used PLS-SEM (Hair et al., 2017) to estimate the overall model due to its soft distributional assumptions and predictive robustness (Chin, 1998; Wold, 1982). Due to the hierarchical nature of the MAAC and market turbulence constructs, we applied a repeated indicator approach to estimate the reflective-formative model (Becker et al., 2012; Sarstedt et al., 2019; Wetzels et al., 2009). Due to the algorithmic benefits of PLS-SEM in assessing latent variable scores (factor determinacy), factor identification and robust prediction, we selected the technique to estimate both the measurement and structural properties of the hierarchical model (Chin 1998; Chin, Peterson, and Brown 2008). Furthermore, PLS-SEM is also suitable for serving the dual objectives of predicting the endogenous constructs and explaining the theoretical relationships (Hair Jr. 2021; Wold 1982). Thus, applying a path weighting scheme for the inside approximation and a nonparametric bootstrapping with 5000 replications, we applied SmartPLS 3.3 to estimate both the measurement and structural model (Ringle et al., 2015).

6.5 Measurement Model

The study estimates the latent construct scores of all the first-order constructs: data governance, pattern identification, real-time solutions, marketing agility, marketing effectiveness, technology turbulence, competitor turbulence, customer turbulence. Table 3 shows loadings, composite reliability (CR) and average variance extracted (Hair Jr et al., 2017a). All loadings are greater than 0.70 and significant at $p<0.001$, indicating the reliability of each item. All the CR scores exceed 0.80, the minimum threshold level, confirming the convergent validity (Fornell and Larcker, 1981). In addition, all the AVE values meet the minimum cut-off value of 0.50, indicating convergent validity of each construct since an adequate amount of variance against measurement errors were explained (Chin, 2010). We measured three formative control variables (i.e., firm size, industry type and experience) using weights and variance inflation factors (VIF). The VIFs indicate no collinearity among the control variables as they vary between 1.062 to 1.278 (≤ 5).

Table 3: Assessment of First-Order, Reflective Model

Dimensions	Reflective Constructs	Items	Loadings	CR	AVE
Marketing analytics cpability (MAAC)	Pattern identification (PAID)	PAID1 PAID2 PAID3 PAID4	0.816 0.849 0.821 0.815	0.895	0.681
	Real-time solutions (RESO)	RESO1 RESO2 RESO3 RESO4	0.914 0.891 0.922 0.882	0.946	0.814
	Data governance (DAGO)	DAGO1 DAGO2 DAGO3 DAGO4	0.792 0.840 0.780 0.745	0.869	0.624
Market Turbulence (MATU)-Moderator	Technology turbulence (TETU)	TETO1 TETO2 TETO3	0.749 0.898 0.851	0.873	0.698
	Competitor turbulence (COTU)	COTU1 COTU2 COTU3	0.808 0.860 0.858	0.879	0.709
	Customer turbulence (CUTU)	CUTU1 CUTU2 CUTU3	0.816 0.829 0.803	0.857	0.666
Outcome constructs	Marketing agility (MAAG)	MAAG1 MAAG2 MAAG3 MAAG4	0.873 0.829 0.848 0.872	0.916	0.732
	Marketing effectiveness (MAEF)	MAEF1 MAEF2 MAEF3 MAEF4	0.852 0.862 0.891 0.883	0.927	0.760
Formative construct		Items	Weights	t-value	VIF
Control variables (COVA)		Industry Firm size Experience	0.414 0003 0.904	0.805 0.009 0.158	1.001 1.006 1.005

Table 4: Correlations of LVs, AVEs and Descriptive Statistics*

Construct	Mean	Standard deviation	DAGO	PAID	RESO	TETU	COTU	CUTU	MAAG	MAEF	COVA
Data governance (DAGO)	5.150	1.412	0.790								
Pattern identification (PAID)	5.225	1.447	0.488	0.825							
Real-time solutions (RESO)	5.223	1.430	0.472	0.471	0.902						
Technology turbulence (TETU)	5.120	1.390	0.451	0.412	0.551	0.835					
Competitor turbulence (COTU)	5.080	1.323	0.494	0.562	0.532	0.446	0.842				
Customer turbulence (CUTU)	5.050	1.403	0.471	0.523	0.487	0.531	0.464	0.816			
Marketing Agility (MAAG)	5.300	1.352	0.416	0.441	0.462	0.466	0.531	0.510	0.856		
Marketing Effectiveness (MAEF)	5.378	1.312	0.426	0.495	0.491	0.487	0.538	0.451	0.411	0.872	
Control Variables (COVA)	n.a.	n.a.	0.034	0.026	-0.040	0.071	0.032	0.091	-0.018	-0.118	n.a.

*square root of AVE on the diagonal

Table 4 shows the discriminant validity of the first-order model as the square root of the AVEs in the diagonals are higher than correlation coefficients across the correlation matrix (Fornell & Larcker, 1981). An assessment of the cross-loading also confirms that each item has a higher loading on its own construct than other constructs (Chin 2010; Hair Jr. et al., 2017a). Finally, an examination of the heterotrait-monotrait (HTMT) criterion confirms additional discriminant validity as all the values are less than 0.90 (Henseler, Ringle, and Sarstedt, 2015).

Table 5 shows the path coefficients (or weights) of the hierarchical, reflective-formative measurement model. Following the guidelines of Sarstedt et al. (2019), first, the redundancy analysis confirms the formative nature of both MAAC and MATU constructs as the path co-efficient linking each construct with a global item exceeds 0.70. Second, the collinearity index confirms that the first-order constructs of both MAAC and MATU are not correlated as the variance inflation factor (VIF) values are less than 3. Finally, we check the significance of path coefficients (or weights) between the lower-order and the higher-order constructs. MAAC consists of 12 items (4+4+4) representing PAID, RESO and DAGO whereas the moderating construct MATU consists of 9 items representing TETU, COTU and CUTU. Table 5 shows that PAID (β=0.370), RESO (β=0.435) and DAGO (β=0.302) are significant antecedents of MAAC ($p<0.001$). On the other hand, TETU (β=0.403), COTU (β=0.381) and CUTU (β=0.362) are significant antecedents of MATU ($p<0.001$). Overall, following Becker et al. (2012)'s type-B (reflective-formative) modelling, the study confirms the robustness of the hierarchical model through the significance of the path coefficients between first-order to second-order constructs as follows in Table 5.

Table 5: Assessment of the higher-order model

Model	Second-order	First-order	β	*t*-statistic
Hierarchical, Reflective-formative	Marketing Analytics Capability (MAAC)	Pattern identification (PAID)	0.370	19.759
		Real-time solutions (RESO)	0.435	25.211
		Data governance (DAGO)	0.302	17.656
	Market Turbulence (MATU)	Technology turbulence (TETU)	0.403	18.809
		Competitor turbulence (COTU)	0.381	19.959
		Customer turbulence (CUTU)	0.362	16.547

6.6 Structural Model

The study uses path-coefficients (β), coefficient of determination (R^2) and the effect size (f^2) to test the proposed hypothetical relationships of the research model (Table 6). The results show the MAAC has a significant, positive impact on MAAG (β=0.886, p<0.001). Similarly, the findings confirm the positive, significant influence of MAAC on MAEF (β=0.452, p<0.001) and MAAG on MAEF (β=0.314, p<0.001). Hence, we confirm H1, H2 and H3. The findings also confirm MAAG as a significant partial mediator (β=0.279, p<0.001) (Hayes et al., 2011; Preacher and Hayes 2008). In establishing mediation chain, we argue that MAAC (the predictor) has a significant impact on MAAG; second, MAAG has a significant impact on MAEF (the criterion variable), and finally, the predictor MAAC has a significant impact on the criterion variable (i.e., MAEF) without the influence of the mediator (Barron & Kenny 1986). Thus, we confirm H4. The findings on R^2 confirm that MAAC explains 79% of the variance in MAAG and 56% of the variance in MAEF.

The findings of our research model show that the hierarchical moderating construct, MATU, does not have a significant impact on the MAAC-MAAG relationship (β= 0.019, p>0.05).

Thus, we reject H5.1. However, MATU has a significant, negative impact on the relationship between MAAC and MAEF (β= -0.135, $p<0.001$) and MAAG and MAEF (β= -0.115, $p<0.001$). The evidence of moderation is also reflected by the degree of incremental variance in the criterion variable, MAEF, due to the effects of both MAAC* MATU ($\Delta R^2= R^2_{interaction} - R^2_{main}= 0.638 - 0.555 = 0.083$) and MAAG*MATU ($\Delta R^2= R^2_{interaction} - R^2_{main}= 0.631 - 0.555 = 0.076$) (Cohen & Cohen 1983). The findings show that the R^2 values of MAEF increase significantly with the incorporation of MATU as a moderator in MAAC-MAEF and MAAG-MAEF relationships. The f^2 effect size indicates how much the moderating effect contributes to the explanation of the MAEF (Hair, Jr. et al., 2017). In measuring effect sizes, Cohen (1988) recommends f^2 of small (0.02), medium (0.15) and large sizes, whereas Kenny (2015) identifies f^2 of 0.005, 0.01, and 0.025 as small, medium and large effect sizes. our findings show that both MAAC*MATU (f^2 =0.077) and MAAG*MATU (f^2 =0.055) have large effects on MAEF, according to Kenny (2015). Hence, our results support H5.2 and H5.3. We also estimated the non-significant effects of control variables, that is, industry type, firm size and analytics experience, on marketing effectiveness.

6.7 Robustness analysis

As part of robustness testing, first, we addressed non-response bias by comparing the responses of the first 25% with the last 25% using a paired t-test (Stanko et al., 2012). The findings did not provide any evidence of a significant difference between the two sets of responses. We also confirmed that there is no over-representation of any particular sample unit, which is evidenced by industry types in Table 1. Second, we checked common method variance (CMV) using a marker variable technique (Lindell & Whitney, 2001; Williams et al., 2010). The results did not show any significant correlation between the marker variable and our target variable ($r=0.033$, $p>0.05$). At the instrument development stage, the study also exercised due caution in designing the questionnaire by establishing a psychological separation between antecedents

(MAAC) and endogenous constructs (MAAG and MAEF) to reduce a systematic covariation and causality (MacKenzie and Podsakoff 2012). Third, we tested the predictive validity of the nomological net using PLSpredict (Shmueli et al., 2019). As part of this, we applied PLSpredict on MAEF (i.e., criterion variable) using both a training sample (n=225) and a holdout sample (n=25). The findings confirm the predictive validity of the MAAC construct on MAEF as it provided lower prediction errors when the results of PLS-SEM based root mean squared error (RMSE) was compared with Linear Regression Model-based RMSE. Finally, we tested non-linear relationships, and the findings show that there is no quadratic association between $MAAC^2$-MAAC (β=-0.023, P>0.05) and $MAAC^2$-MAEF (β=0.018, P>0.05). Thus, we retain the significant, positive linear relationship between MAAC-MAAG and MAAC-MAEF.

Table 6: Results of the structural model

Hypotheses	**Main Model**	**Path coefficients**	**Stand. error**	***t*-stat.**	R^2	f^2
H1	MAAC → MAAG	0.886	0.017	53.409	0.786	*n.a.*
H2	MAAC → MAEF	0.452	0.117	3.871	0.555	*n.a.*
H3	MAAG → MAEF	0.314	0.114	2.754		
H4	MAAC → MAAG → MAEF	0.279	0.102	2.737		
Hypotheses	**Interaction Model**	**Path coefficients**	**Stand. error**	***t*-stat.**	R^2	f^2
H5.1	MAAC * MATU → MAAG	0.019	0.036	0.531	0.787	0.003
H5.2	MAAC * MATU → MAEF	-0.135	0.015	4.666	0.638	0.055
H5.3	MAAG * MATU → MAEF	-0.115	0.043	2.679	0.631	0.077

7. Discussion

7.1 Summary of findings

The findings confirm that marketing analytics capability on a sharing platform is a second-order construct, which represents three first-order components: pattern identification, real-time solutions and data governance. Among these three components, the results identify real-time marketing solutions (β=0.435) as the most important dimension on a sharing platform, followed by pattern identification (β=0.370) and data governance (β=0.302). The findings also confirm that marketing analytics capability positively influences marketing agility (β=0.886) and marketing effectiveness (β=0.452). In this nomological relationship, marketing agility plays a partial mediating role as it explains 38% of the overall variance using the VAF (Variance Accounted For) criterion (Hair Jr. et al., 2017).

The findings identify that technology turbulence (β=0.403) contributes most to the market turbulence in a sharing economy, followed by competitor turbulence (β=0.381) and customer turbulence (β=0.362). The results show that the moderating effect of hierarchical market turbulence on the relationship between marketing analytics capability and marketing agility is not significant (β=-0.019). This non-significant impact may be caused by the presence of strong dynamic capability (i.e., marketing analytics capability) on a cloud sharing platform which is helping B2B firms to perform well in any type of turbulence without making costly reconfiguration investments in marketing agility (Teece et al. 2016). The strength of dynamic capability is also evidenced by the impact of MAAC on MAAG (β=0.886) in the main model (see Table 6).

However, the findings confirm the significant, moderating impact of the market turbulence construct on the relationship between marketing analytics capability and marketing effectiveness (β= -0.135, p<0.001). Since the moderating term is negative, the linear relationship between marketing analytics capability and marketing effectiveness decreases by 0.135 units if the value of the market turbulence increases by one unit of standard deviation (see Figure 3A). Figure 3A shows, for higher levels of market turbulence, the relationship between marketing analytics capability and marketing effectiveness reduces by the interaction term (i.e., 0.452-0.135=0.317). On the other hand, for lower levels of market turbulence, the relationship between marketing analytics capability and marketing effectiveness becomes more robust (i.e., 0.452+0.135=0.587) (Hair Jr. et al., 2017b).

Similarly, the hierarchical market turbulence construct has a significant, moderating impact on marketing agility-marketing effectiveness link (β= -0.115, p<0.001). Due to the negative interaction term, the effect of marketing agility on marketing effectiveness declines, with one unit of standard deviation increase in market turbulence. Figure 3B shows, for higher levels of market turbulence, the link between marketing agility and marketing effectiveness weakens (i.e., 0.314-0.115=0.199). On the contrary, when there is low market turbulence, the relationship between marketing agility and marketing effectiveness becomes stronger (i.e., 0.314+0.115=0.429).

Overall, the findings in Figures 3A and 3B show that that the positive relationships between marketing analytics capability (MAAC) and marketing effectiveness as well as marketing agility (MAAG) and marketing effectiveness are more likely to be observed in firms facing lower levels of market turbulence (MATU) on a sharing platform.

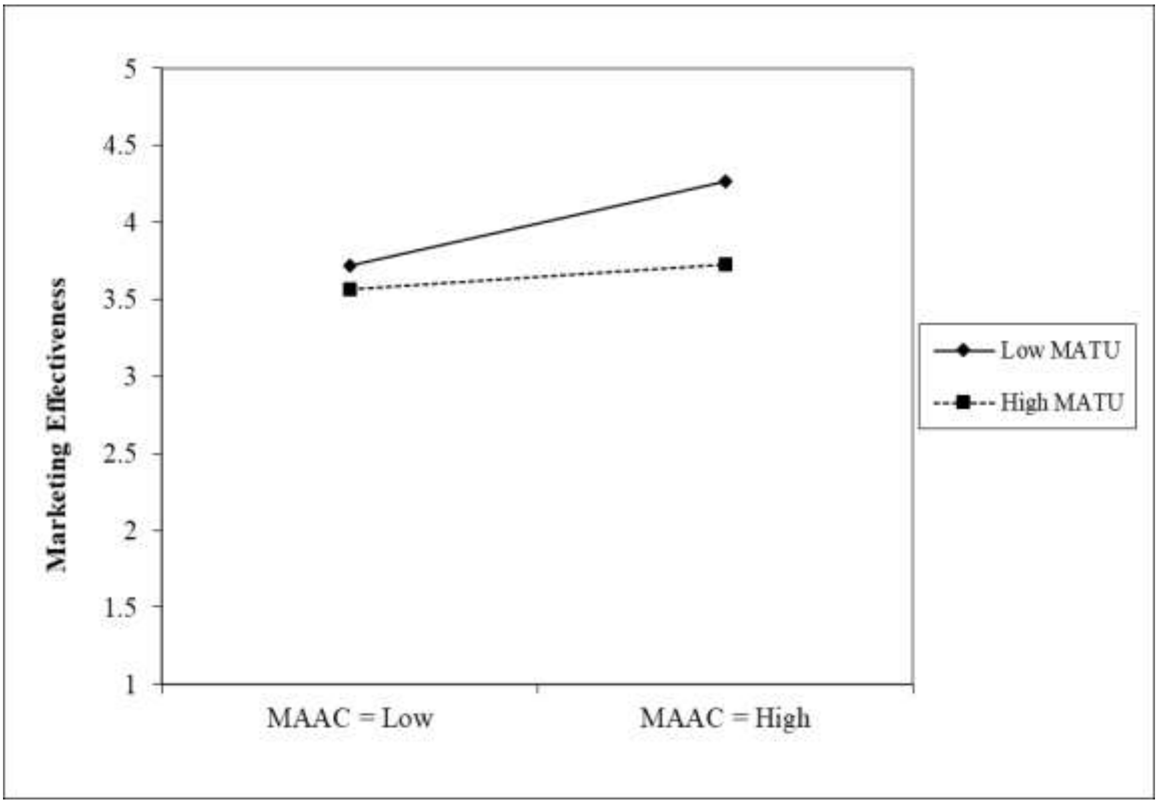

Figure 3A: Moderating Effects of MAAC*MATU on Marketing effectiveness

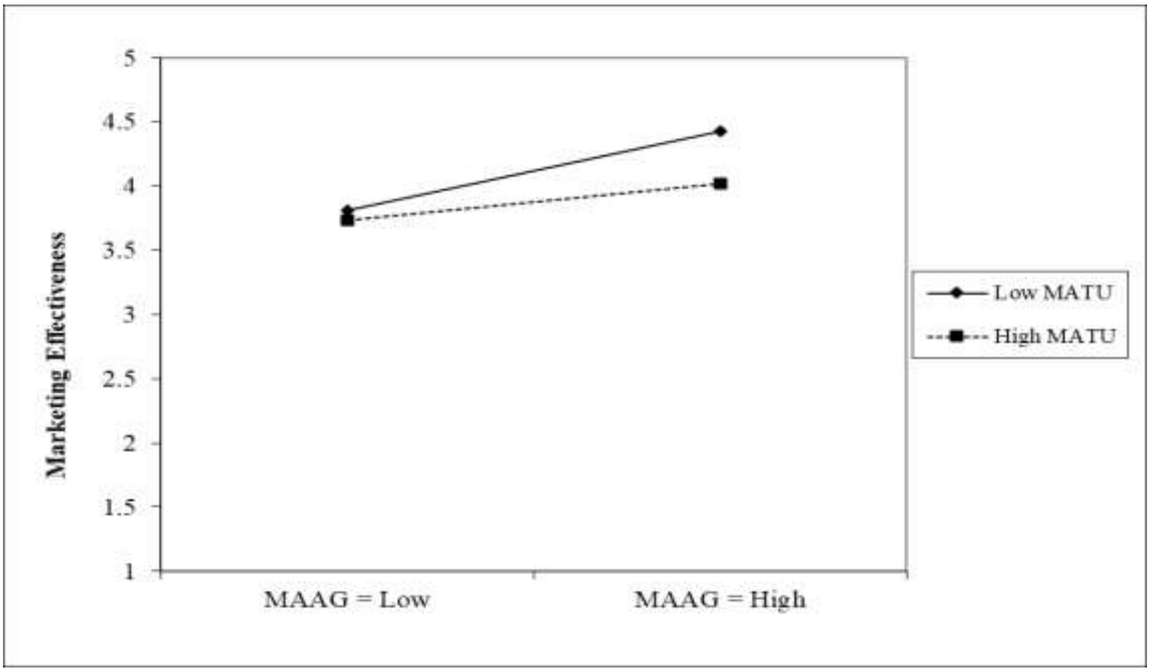

Figure 3B: Moderating Effects of MAAG*MATU on Marketing effectiveness

7.2 Theoretical Implications

Due to the rise of sharing economy, marketing analytics has emerged as a dominant force in marketing science since its early development time (e.g., Magee, 1954; Bass et al. 1961; Buzzell 1964, Kuehn, and Massy 1962; Day and Parsons 1970; Montgomery and Urban 1969; Massy, Montgomery, and Morrison 1970; Kotler 1971) to the present day data-rich environment (Wedel & Kannan 2016). In a sharing economy context, our research answers the research questions on marketing analytics capabilities and their overall effects on marketing agility and marketing effectiveness with contingency effects. The findings of our study extend theoretical contributions to several areas.

First, our research shows that marketing analytics capability on a cloud sharing platform represents three crucial antecedents: pattern identification, real-time solutions and data governance. These findings are consistent with the extant research on marketing analytics (e.g., De Luca et al. 2020; Hossain et al. 2021). However, our findings extend this line of research in the sharing economy context by incorporating data governance and highlighting the roles of data integration, processing, security and privacy issues in marketing analytics (Rana et al. 2021; Ransbotham & Kiron 2017; Tallon 2016). Theoretically, our findings identify marketing analytics as a second-order, dynamic capability that includes three first-order capabilities. In addition to *data governance*, our findings provide a more nuanced understanding of *pattern identification* and *real-time solutions* to form marketing capability as a dynamic capability to manage the uncertainty of on a cloud sharing platform, which are at the core of DC viewpoints (e.g., Teece 2007; Teece et al. 2016).

Second, our findings extend marketing analytics capability research by linking it with marketing agility. The Marketing Science Institute (MSI) identifies marketing agility as a key research priority (MSI 2020) due to the need for agile marketing (Moorman 2020) and marketing excellence (Homburg et al. 2020). Marketing agility is a higher-order capability, and our findings clarify the processes or routines that enable marketing agility to achieve marketing effectiveness better than others. This finding extends the existing literature on marketing agility by identifying three analytics drivers as a dynamic capability to enhance marketing excellence through marketing agility (e.g., Kalaignanam et al., 2021). For example, Salesforce pursues marketing agility in new service development (e.g., Salesforce customer 360- a CRM solution) by securely connecting data and workflows using AWS analytics (Amazon 2021a). Thus, our findings extend the literature in sharing economy by identifying marketing agility as a specialized capability to influence the overall discovery and delivery processes. Both the dynamic capability and agility literature identify that marketing agility is needed to manage uncertainty and the contingencies of marketing outcomes (Teece et al., 2016; Kalaignanam et al., 2021). Thus, our research extends marketing analytics capability and marketing agility chain in the context of market turbulence.

Finally, a comprehensive understanding of the impact of market turbulence on the marketing analytics-agility-effectiveness chain addresses the emerging debate of the dark side of sharing economy. Using both DCV and contingency theories, we provide a compatible and complementary viewpoint to extend marketing analytics-agility-effectiveness literature by modelling the holistic impact of market turbulence. Our findings show that marketing analytics as a strong dynamic capability plays a crucial role in low to moderate market turbulence situations to enhance marketing effectiveness (see Figures 3A and 3B) (Zahra et al., 2006; Zhou et al., 2019). Our findings on moderation (i.e., H5.1) show that when marketing analytics capabilities are nurtured well to be agile as dynamic capabilities, "firms may perform well in stable or even predictably volatile (i.e., risky) environments without having made costly investments in agility" (Teece et al., 2016, p.31). Overall, our findings extend the dynamic capability, market performance and contingency literature (e.g., Schilke, 2014; Wilden, Gudergan, Nielsen, & Lings, 2013; Karna, Richter, & Riesenkampff, 2016; Peters et al., 2019) by modelling the holistic impact of the hierarchical market turbulence construct on the nomological net in a sharing economy context.

7.3 Managerial Implications

While managing marketing analytics on a cloud sharing platform involves pattern identification, real-time solutions and data governance, the ultimate success depends on establishing the marketing analytics-marketing agility-marketing effectiveness chain under various market turbulence conditions. Thus, our research has several managerial implications, which are of specific interest to industrial marketers in sharing economy contexts.

First, marketing in the sharing economy enables exchanges of offerings through temporary access than permanent ownership (Eckhardt et al., 2019; Kumar et al., 2018). Our findings illuminate how the marketing analytics capability (i.e., data governance, pattern identification and real-time solutions) can match buyers and sellers on a sharing platform to engage customers, reduce churn and execute personalized communication campaigns. Aligned with our findings, a recent salesforce report (2021) indicates that 84% of business buyers expect vendors to understand their business needs, and 83% want engagement with them in real-time. This highlights the importance of investment in developing a superior marketing analytics capability to thrive on a cloud sharing platform. As such, our findings recommend building this emerging cloud analytics climate by focusing on problem-solving, knowledge & skills and training & development of internal marketing resources (Akter et al., 2021a).

Second, our findings reflect that marketing effectiveness using analytics largely depends on how agile a firm is in meeting customer needs. The success of the marketing analytics-agility-effectiveness chain is largely reflected by customer segmentation and targeting programs, customized offerings, unique contents and relevant marketing metrics. Thus, proper development and deployment of marketing analytics capability are necessary to sense, seize and transform opportunities through marketing agility (Teece et al., 2016). Since efficient matching between buyers and sellers on a cloud sharing platform is scaled through agile marketing, agility plays a key role in offering on-demand services through scalable pricing models. For example, B2B customers use various functionalities of AWS analytics to develop marketing agility, such as Amazon Kinesis enables sensing by processing streaming data, Amazon QuickSight empowers seizing by acting on deep insights using machine learning, and Amazon Redshift reconfigures data-driven insights by connecting the operational database, data warehouse and data lake (Amazon 2021a). Hence, the marketing excellence a firm can achieve through marketing effectiveness depends significantly on how analytics capabilities are leveraged to improve or enable marketing agility.

Third, our results show the critical role of market turbulence as a contingency factor in a sharing economy. Although technological developments, competitive intensity and customer behaviour are often difficult to control due to their external nature, a nuanced understanding can inform practitioners' decisions. The findings suggest managers build robust marketing agility to manage market turbulence. For instance, when competitive intensity is high among B2B firms, superior marketing analytics capability can improve marketing agility, which in turn enhances marketing effectiveness through increased market share, sales growth, customer acquisition and retention. The findings of our study can help guide marketing managers when and how to manage market turbulence by investing in a dynamic analytics-agility framework to sense, seize and transform offerings. Since the market environment of a cloud sharing platform is saturated with rapid turbulence, marketing agility needs to be aligned with the overall corporate strategy.According to Teece et al. (2016.p. 32). "…agility may sometimes be a fool's errand; enterprise death may in fact be the best solution if squandering resources to transform would leave stakeholders worse off". Thus, marketing analytics capability as a higher-order dynamic capability requires a strategic alignment with marketing agility to create and capture value in a volatile environment.

Overall, the findings of our study show that using cloud sharing platforms, B2B marketers can achieve agility by leveraging data lakes, customer analytics, personalization, relationship management, promotion analytics, messaging, channel analytics and digital customer experience. As such, we recommend empowering the internal marketing department to avail these benefits of emerging cloud analytics to enhance customer satisfaction, marketing effectiveness and firm performance.

7.4 Limitations and future research directions

Our study has several limitations. First, the constructs and their respective instruments studied are assessed at a relatively high level of abstraction. Future studies could develop more refined measures to enhance our knowledge, focusing on the marketing analytics process of a specific cloud sharing platform. Second, data were collected using a cross-sectional study from a single country, which has limitations concerning CMV. Although we undertook various steps to reduce CMV, a longitudinal, multi-country might address the limitations. Although few studies have focused on a sharing economy, there is very limited research on cloud sharing platforms. Thus, future research can also explore cloud-based marketing analytics across various marketing contexts, such as marketing mix, retail, social media, AI and services and nonprofit sectors (Davis et al., 2021). For example, marketing mix analytics can yield insights on marketing programs (i.e., product, brand, price, channel and promotions) and marketing strategies (i.e., segmentation, targeting and positioning). In a similar spirit, retail analytics can investigate customer engagement across channels, product mixes, location and times (Bradlow et al., 2017). An exciting new area is social media analytics involving real-time market insights from Facebook, YouTube, Instagram, Pinterest, Twitter, TikTok, Weixin/WeChat and

WhatsApp (Grewal et al., 2020). Furthermore, the rise of AI in services can contribute to future research on service innovations, customer welfare, privacy and security (Akter et al., 2021a). With regard to analytics capabilities, our study sheds light on the core marketing analytics dimensions, and it does not discuss how marketing managers can develop, deploy and nurture higher-order marketing analytics capability. Future research can explore this gap with analytics empowerment capability theory (Motamarri et al., 2020) and organizational learning theory (Dickson, Farris, and Verbeke 2001). Analytics bias is another area that has gained attention in recent times (Akter et al. 2021d). Algorithmic bias in the form of data, model or method bias can produce unfair outcomes and put a business in advantage or disadvantage situations. Thus, we suggest following both a priori and post-hoc approaches (Akter et al. 2021c) in addressing algorithmic failures on sharing platforms. In addition, future studies can consult dynamic managerial capabilities to predict, detect, mitigate potential biases on a cloud sharing platform to ensure fairness to customers.

8. Conclusions

Market turbulence and associated uncertainties are the dark side of a sharing economy "where existing "rules" are being changed and entirely new "rules" invented" (Teece et al. 2016, p.16). In this study, harnessing B2B cloud sharing platform concepts and tools, along with dynamic capability and contingency theories, we identify the role of marketing analytics as a superior dynamic capability to enhance marketing agility and effectiveness. While the marketing analytics-agility-effectiveness relationship should be embraced by B2B marketers on a cloud sharing platform, firms with superior dynamic capabilities must know how to navigate market turbulence and manage deep uncertainty. It is worth noting that the greater the market turbulence in a sharing economy, the greater the need for dynamic analytics capabilities to enhance marketing agility for marketing effectiveness.

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