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Entrepreneurial performance and marketing analytics: the role of new product innovation

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Entrepreneurial performance and marketing analytics: the role of new product innovation

Abstract

Purpose – Previous studies focus on the direct effects of marketing analytics on entrepreneurial performance, but few explore the underlying mechanisms. Drawing on affordance theory, this study explores pathways through new product innovation (NPI) for the effects of marketing analytics on business performance. NPI is a market-based innovation concept comprising customer- and competitor-driven NPD and incremental innovation.

Design/methodology/approach – Using survey data collected from UK-based entrepreneurial firms operating in the IT and telecoms industries, we apply confirmatory factor analysis and a sequential structural equation model to test the mediating role of NPI in the effect of marketing analytics on market performance and financial performance.

Findings – The results show that marketing analytics enhances business performance through competitor-driven, but not customer-driven NPD. Although using marketing analytics to generate customer knowledge for existing product innovation may enhance market performance, this positive effect becomes negative when competitor-driven NPD is undertaken to improve existing product innovation.

Originality/value - This study makes significant contributions to the innovation and NPD literature. It delves deeper into the existing view on the positive contributions of customer engagement to business value creation, revealing the significance of competitor knowledge to enhance business performance through marketing analytics, particularly in the context of IT and telcoms entrepreneurial firms.

Keywords

Marketing analytics, Customer-driven NPD, Competitor-driven NPD, Incremental innovation, Business performance

Introduction

E-commerce and digital businesses are turning increasingly to big data to better understand customers, competitors and markets for new product development (NPD) (Ciacci and Penco, 2023; Ashrafi and Ravasan, 2018). Firms often employ a wide range of technologies to analyse marketing data to gain market insights for new product innovation (Haug et al., 2023; Germann et al., 2013). Marketing data and analytics are ranked as business priorities in Gartner's chief marketing officer survey (Omale, 2020), and contribute to innovative product development and superior business performance (Xu et al., 2016; Cao and Tian, 2020), yet many businesses struggle to quantify and deliver its value for performance (Cao et al., 2019; Wedel and Kannan, 2016). This is particularly evident in entrepreneurial firms with limited resources that constrain effective deployment of marketing data (Cao et al., 2021). Calls have been made (e.g. Ashrafi and Ravasan, 2018) for more evidence on how entrepreneurial firms maximise marketing analytics for better performance.

Marketing analytics refers to firms' ability to use marketing data and analytics to exploit potential business opportunities and enhance firm performance (van Bruggen et al., 2001; Cao and Tian, 2020). Its pay offs have been described as technological affordances (Dremel et al., 2020). Most scholars contend that it has positive effects on innovation and business performance, but discussion tends to be conceptual (e.g. Sheth, 2021; Branda et al., 2018; Xu et al., 2016; Wedel and Kannan, 2016), with limited empirical evidence of how entrepreneurial firms extract value from marketing data for innovation and business performance (Cao et al., 2021; Rakshit et al., 2022; see Appendix). Underpinned by affordance theory (Gibson, 1979), this study explores marketing analytics' affordances for new product innovation (NPI) and business performance. We aim to answer two research questions: what role does marketing analytics play in supporting business performance; and how does marketing analytics interact with NPI to influence and enhance business performance?

In the context of entrepreneurial firms, which are often constrained by size and resources (Austin et al., 2022), NPI is grounded in firms' ability to collect, analyse and implement market intelligence to create innovative products. We propose two key dimensions of NPI: market-based NPD and incremental innovation. First, NPI is market-based, involving collecting information about customers' needs and feedback and competitors' new product performance (Ramaswami et al., 2009; Narver and Slater, 1990). Market-based NPD can be divided into customer-driven and competitor-driven NPD. Second, entrepreneurial firms' innovation activities are predominantly incremental. They rarely engage in radical product innovation, given their limited resources, knowledge and research and development (R&D) to support fundamental changes (Nieto et al., 2015; Hardwick and Anderson, 2019). For example, in Brown et al.'s (2022) sample, a large number of firms had introduced incremental product innovations in the past three years, and only a small proportion (8.8%) had engaged in radical product innovation. Market-based NPD and incremental innovation are thus essential components of entrepreneurial firms' NPI.

Drawing on affordance theory, this study explores the technological affordances of marketing analytics to support NPI and business performance. We link technologies as possibilities for actualising marketing analytics in the context of NPI, and respond to calls for more research to understand the mechanisms supporting marketing analytics' contribution to firm performance (e.g. Liang et al., 2022; Cao et al., 2022). We explore our research questions in the context of entrepreneurial firms in the IT and telecoms industries. Marketing analytics is crucial for such firms, as their core business is supported by evolving technological advances, which complicate their business offerings and product innovation. For instance, Tableau, a technology company, reports that around 83% of chief executive officers (CEOs) intend to make their companies data-driven to obtain deeper understandings of the market (Longacre, 2021). Marketing analytics is essential in enabling them to stay ahead of the competition. Our

study provides empirical evidence of the importance of marketing analytics in generating positive market performance. We shed new light on the role of competitor-related NPD knowledge in facilitating the effect of marketing analytics on business performance. We also provide insights into entrepreneurial firms' NPI, and offer guidelines for small firms operating in the IT and telecoms industries on effective use of marketing analytics for superior business performance.

The next section presents an overview of our conceptual framework and hypotheses. The research methodology is then explained and the results presented. We conclude by discussing the implications and limitations of our study, and offering suggestions for future research.

Literature review

Affordance theory and research framework

We employ affordance theory as an overarching framework for conceptualising marketing analytics' potential to enhance market-based NPI. This theory was developed in the context of the psychology of perceptions to explain interactions between actors' behaviour (animals or humans) and their environment (Gibson, 1979). It posits that an object's affordances are prerequisites for possible actions (Dremel et al., 2020), and these must be realised and then actualised through actors' perceptions and goals to achieve effects (Norman, 1988). Affordances are dynamic, in that new affordances may emerge and existing ones disappear as the properties of environments, actors and their interactions change over time (Hutchby, 2001; De Luca et al., 2021).

Affordance theory has been employed predominantly in the information systems field to explore the properties and interactions of IT artefacts, employees and organisations (Hutchby, 2001; Dremel et al., 2020). Technological affordances exist at the organisational level, but their

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transition into organisational actions can only be actualised when their potential is exploited through interactions between organisational actors and other properties (De Luca et al., 2021; Strong et al., 2014). Few studies have examined affordance applications in the marketing and NPD domains (De Luca et al., 2021); therefore, more empirical evidence is needed to fully explore the role of technological affordances in business performance (Volkoff and Strong, 2018).

In this study, we understand the affordances as possibilities for unstructured data analysis generated by technology and big data. Within marketing analytics affordances, we conceptualise NPI as comprising customer- and competitor-driven NPD and incremental innovation. This is because NPI is market-based, requiring firms to constantly and consistently securitise their external market environment by monitoring customers' needs and demands, competitors' weaknesses and strengths, and behavioural changes (Jaworski and Kohli, 1993; Crick, Karami and Crick, 2022). Market insights effectively support and improve existing product innovation. Previous marketing studies have established a positive relationship between marketing analytics and organisational outcomes such as service innovation (De Luca et al., 2021), marketing decision making (Cao et al., 2019) and capability development to enhance performance (Germann et al., 2013; Liang et al., 2022). However, the gaps between marketing analytics and business performance have not yet been fully explored. In this study, we investigate the underlying mechanisms by proposing the mediating role of NPI in facilitating marketing analytics for superior business performance. Our conceptual framework is outlined in Figure 1.

------------------- Insert Figure 1 Here ----------------

Marketing analytics and market-based NPD

Marketing analytics, a subdomain of business analytics, comprises collecting, analysing, managing, and utilising marketing data to gain market insights for decision making (Wedel and Kannan, 2016; Liang et al., 2022). Research on business analytics has provided ample evidence of its effectiveness for business performance. For example, it can be applied to gain knowledge of customer preferences (Akter et al., 2016) to enhance innovation, marketing and financial performance (Wamba et al., 2017; Ashrafi et al., 2019), and thus achieve competitive advantage (Cao et al., 2019). Marketing analytics has recently attracted scholarly attention, with attempts to examine the interface between marketing analytics and performance (see Appendix). However, more research is needed to understand the mechanisms through which marketing analytics is transformed into business capability, innovation and performance (Ashrafi et al., 2019; Liang et al., 2022).

Marketing analytics provides information on market changes and insights into market data. It resides at the individual level, and requires unlearning, learning and resource reconfiguration to supplement strategic decision making, such as NPD (Akhtar et al., 2019). Marketing analytics skills can be acquired through classroom learning and training, such as marketing models and statistical applications, or through tacit knowledge gained from real-life experiences, such as ability to interpret and communicate data insights (Grant, 1991; Germann et al., 2013). Firms routinely conduct marketing analytics using technology and relevant marketing models to collect, analyse and implement customer, competitor and market intelligence for NPD.

Market-based NPD concerns firms' ability to develop innovative products on the basis of customer and competitor insights (Najafi-Tavani et al., 2016). Customer-driven NPD focuses on gaining a comprehensive understanding of customer needs and market demands (Lynch et al., 2016). Firms involve customers in the NPD process, and use data analytics to determine

patterns of customer behaviour and improve knowledge exchange (Wang et al., 2020; Sánchez-Gutiérrez et al., 2019). This aligns with the concept of customer co-creation, whereby interaction and collaboration with customers in the NPD process raises firms' awareness of what is missing and what is important (Hoyer et al., 2010; Ramaswamy and Ozcan, 2018). Competitor-driven NPD focuses on rivalries between firms and relevant NPD activities. Competitor-driven firms develop good scrutiny systems to assess competitors' NPD strategies and new product strengths and weaknesses, as well as acknowledging internal strengths and weaknesses (Schulze et al., 2022; Wu et al., 2015).

Affordance theory supports this interface of inputs in terms of integrating the technological possibilities of marketing analytics to support market-based development as a mediator in the relationship between marketing analytics and business performance. In other words, marketing analytics aids marketing data analysis, leading to dissemination of intelligence relating to NPD across different organisational functions (Ozkaya et al., 2015). Use of marketing analytics is reflected in firms' analytical ability to learn, filter, shape and sense external information. It enables firms to generate market insights into customer preferences and needs, market trends and competitors' new product features and strategies (Teece, 2007; Günther et al., 2017) to support new product development, manifested in market-based NPD. Overall, effective application of marketing analytics places firms in a better position to realise customer- and competitor-driven NPD, and enables them to leverage data analytics technologies to achieve superior business performance (Sørensen, 2009; Cao and Tian, 2020). Thus, we hypothesise that:

H1: Marketing analytics enables a) customer-driven NPD and b) competitor-driven NPD to achieve superior business performance.

Incremental innovation

Innovation plays a significant role in the NPD process, reflecting firms' ability to use their resources effectively (Sheng and Chien, 2016). It can be categorised, according to the level of newness, as radical or incremental innovation (Foster, 1986; Forés and Camisón, 2016). Radical innovation involves making fundamental changes to the product, knowledge and market (O'Connor, 2008), whereas incremental innovation involves cumulative changes and continuous improvement to existing products, processes or services (Tomás-Miquel et al., 2019). This study focuses on incremental innovation as the key type of innovation driving firms' competitive advantage. It tends to be more practical and common for entrepreneurial firms to engage in incremental innovation, given their inherent lack of resources and R&D to support radical innovation. For entrepreneurial firms, incremental innovation is derived from exploiting existing capabilities to increase operational efficiency and enhance existing value, and hence achieve positive outcomes (Brown et al., 2022; Nieto et al., 2015; Benner and Tushman, 2003). Through fitting, combining and recombining, reapplying and adapting existing knowledge, incremental innovation enhances existing products, directly improves market performance and increases financial returns (Brown et al., 2022; Bhaskaran, 2006; Forés and Camisón, 2016).

Marketing analytics generates potential developments by applying data and technology, and is often conceptualised as an antecedent to capability and performance (Rust and Huang, 2014; Ashrafi and Ravasan, 2018). Its affordances precede innovatory activities, as analytics emerge at the managerial level as internal resources and technologies are integrated into effective outputs (Rust and Huang, 2014; De Luca et al., 2021). Extant studies evidence the contribution of data analysis to innovative performance (Ardito et al., 2019). Specifically, the variety and velocity of data significantly improve the efficacy and efficiency of innovation (Ghasemaghaei and Calic, 2020). We propose that marketing analytics enhances incremental innovation for superior business performance. By analysing marketing data, firms gain

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insightful knowledge about market changes, enabling them to fine-tune existing products and improve their market and financial performance. Thus, we hypothesise that:

H2: Marketing analytics supports incremental innovation to achieve superior business performance.

New product innovation (NPI)

Extant research shows that being market-oriented is positively associated with innovation (e.g. Grinstein 2008; Ngo and O'Cass, 2012; Schulze et al., 2022). For instance, Lukas and Ferrell (2000) find that a customer orientation increases new-to-the-world products, whereas a competitor orientation contributes to me-too products. Schulze et al. (2022) find that proactive exploration of competitor intelligence contributes positively to innovation performance. Thus, customers and competitors play essential roles in supporting NPD. In this study, we propose that NPI is a market-based approach that enhances incremental product innovation. This suggests a positive association between market-based information, such as customers' needs and preferences, competitors' behavioural changes and market demands, and incremental product innovation (Tomás-Miquel et al., 2019).

In the context of entrepreneurial firms, innovation is influenced mainly by factors such as responding to customer needs and feedback, which involve incremental changes to existing products rather than introducing completely new products (Laforet and Tann, 2006). Most entrepreneurial firms are market followers, and their innovation activities are likely to concentrate on improving existing product quality, cutting production costs and modifying product design and functions to boost market share and increase profits (Baregheh et al., 2012; Du, 2021). Thus, by obtaining market information on customers' and competitors' insights into new products, market-based NPD supports changes to existing products.

We suggest that employing technology-based marketing analytics enhances NPI, which helps to generate insights into customers' needs, competitors' behaviour and market demand for new products (Ashrafi and Ravasan, 2018). Knowledge from both customers and competitors serves as an input into incremental innovation (Takayama and Watanabe, 2002). Theoretically, this should lead to above-average economic rents in terms of superior market and financial performance. Although studies have examined the relationship between marketing analytics and performance outcomes (e.g. Liang et al., 2022), pathways between marketing analytics and business performance have not yet been fully explored. Applying marketing analytics enhances firms' market insights, contributes to market-based NPD, supports and feeds back into incremental innovation and improves business performance. Therefore, we hypothesise that:

H3. The effect of marketing analytics on business performance is sequentially mediated by a) customer-driven NPD and incremental innovation, and b) competitor-driven NPD and incremental innovation.

Methodology and data

The empirical context of this study is UK-based entrepreneurial firms operating in the IT and telecoms industries. Entrepreneurial firms are often small and medium-sized enterprises (SMEs) (Austin et al., 2022) and, following the European Commission's definition, we targeted UK SMEs with fewer than 250 employees. A sampling frame of 5,000 entrepreneurial firms was obtained from a reputable UK-based database company. These firms comprised software developers and distributors, telecoms manufacturers, IT network providers and consultants, telecoms solutions providers, wireless telecommunications activities, and other IT service providers. We approached key informants who held relevant positions (e.g. marketing directors,

senior product development and marketing strategy managers) and/or had strategic responsibility for their businesses (e.g. owners, managing directors, general managers).

A self-administered survey questionnaire was designed for data collection. First, we conducted a pilot test to gain feedback from four academic peers and three representative firms, as a result of which we made minor modifications to the wording and format of the questionnaire. A dedicated research assistant was recruited to conduct the survey online. Emails with a link to the survey were sent to key informants, together with an explanation of the study and an assurance of anonymity. Four follow-up emails were sent at two- to three-week intervals. Non-response bias was tested by comparing early and late responses, and t-tests indicated no significant differences (Armstrong and Overton, 1977).

By the end of the data collection period, 565 companies had attempted the questionnaire and 151 had completed it, resulting in an 11% attempt rate and a 3% full response rate. Incomplete questionnaires were removed from the dataset prior to further analysis. We obtained feedback from some respondents that the low response might be due to unfavourable timing of the survey over the holiday period (between December and early January). Online surveys tend to attract low response rates, and small firms are often less willing to participate in survey research (Manfreda et al., 2008).

The resulting data were screened and cleaned to eliminate incomplete questionnaires and overly rapid completion times (less than five minutes), resulting in a final sample of 138 questionnaires. Figure 2 outlines the research method paradigm. As shown in Table 1, the majority of respondents were in firms with fewer than 250 employees (96.4%) that had been established for over 20 years (53.6%). A large proportion (80%) of respondents' firms had annual sales of less than £10 million, and 71% of firms had market shares of less than 10%.

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Since survey methods are susceptible to common method bias (CMB), we took several steps to mitigate this. Following Podsakoff et al. (2003), we piloted the survey instrument to ensure the clarity of the questions. Respondents were screened based on key target informants and were assured of anonymity. The survey questions were ordered to reduce informed wisdom. For example, performance measures appeared earlier than independent variables. In statistical testing, Harman's single-factor test was performed by uploading all items in the model for exploratory factor analysis. The results showed that the first factor explained 21.83% of the variance, confirming that no single factor accounted for most of the variance (Podsakoff et al., 2003). Furthermore, the results of a correlation matrix of the constructs and Pearson's correlation test revealed that all correlations were well below 0.90, reducing concern for CMB (Johnson and Wichern, 2007).

Measurements

The constructs depicted in Figure 1 were measured using validated scales and items adapted from previous studies. Seven-point Likert scales were used for the measures whenever appropriate, with the wording adapted to each measure, for example from '1 = strongly disagree' to '7 = strongly agree', or from '1 = much worse performance' to '7 = much better performance'.

Dependent variable

The dependent variable, business performance, comprises two components: market performance (*MP*) and financial performance (*FP*). *MP* (Cronbach's alpha = 0.864) concerns performance in the marketplace, such as market share, competitive position, and sales growth. The scale items were derived from Morgan and Turnell (2003). *FP* (Cronbach's alpha = 0.865) has been widely applied to capture performance relative to competitors, based on profit margins, return on assets (ROA) and return on investment (ROI). These perceptual financial indicators have been shown to be reliable measures of firms' financial performance (Reimann et al., 2010).

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We use subjective performance measures because they are commonly adopted in the innovation literature to compensate for the drawbacks of objective performance data. For example, respondents may have inadequate insights into objective performance information, or may be reluctant to share information owing to confidentiality concerns (Blindenbach-Driessen et al., 2010).

Independent variable

The marketing analytics measure (*MA*; Cronbach's alpha = 0.841), adapted from Germann et al. (2013), focuses on applications of marketing analysis in business practice. This three-item measure captures firms' competence in identifying and employing marketing analysis tools appropriate to the problem at hand, knowledge of marketing analysis tools and techniques, and expertise in applying marketing analytics. These scales have been tested in other studies (e.g. Orlandi et al., 2020).

Mediator variables

NPI comprises three first-order constructs: customer-driven NPD (*CUS*; Cronbach's alpha = 0.767), competitor-driven NPD (*COM*; Cronbach's alpha = 0.839) and incremental innovation (*INI*; Cronbach's alpha = 0.801). The *CUS* scale was adapted from Ramaswami et al. (2009), and the *COM* scale was modified from Narver and Slater (1990). *INI* measures firms' ability to implement cumulative innovations and/or improvements to existing products and services. Adapted from Sheng and Chien (2016) and verified by other studies (e.g. Lei et al., 2020), the scale consists of three items relating to refinement, adaptation and efficiency improvements to existing products and services.

Control variables

The control variables are firms' size (number of employees), age (years since establishment), current annual turnover, and the environmental effects of competitive intensity (*CI*) and technological turbulence (*TT*). Previous studies have shown that firms' size and age are crucial internal factors influencing innovatory capability (Kotha et al., 2011). From the resource-based perspective, young and small firms usually have limited resources to support innovation activities, whilst more mature and larger firms are likely to have sufficient resources to invest in innovation development over time (Damanpour, 2010). We also control for firms' current annual turnover, which reflects sales performance in relation to returns on sales and profits, thereby influencing business performance (Storey et al., 2016). The literature also identifies external factors, such as intense market competition and technological changes, that have significant impacts on SMEs' innovation and business performance (Wang et al., 2020). Thus, we adopted *CI* and *TT* from Jaworski and Kohli (1993) as environmental effects. We did not consider R&D expenditure, as previous research suggests that most SMEs have insufficient resources to invest in R&D (Hardwick and Anderson, 2019). Table 2 presents descriptive analyses and a correlation matrix for the constructs.

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Measurement validity

Following Hair et al. (2010), we conducted confirmatory factor analysis (CFA) by applying the maximum likelihood estimation procedure to assess the structure of the constructs and examine the fit of the measurement model. Construct validity was tested, and items with less than 0.6 factor loadings or high cross-loadings were removed. The final confirmatory model had eight factors: marketing analytics (*MA*), customer-driven NPD (*CUS*), competitor-driven

NPD (*COM*), incremental innovation (*INI*), market performance (*MP*), financial performance

(*FP*), competitive intensity (*CI*) and technological turbulence (*TT*). The results showed that the

confirmatory model fitted the data satisfactorily (see Table 3).

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In addition, the focal constructs were examined in a six-factor confirmatory measurement

model to assess convergent validity. All six latent variables were loaded significantly (p <

0.001). Each measurement item was loaded in the first-order factor. The latent constructs may

be correlated, but we constrained the measurement items and de-correlated their error items.

The model suggested uni-dimensionality of the measures, with a satisfactory fit with the data

(χ^2 = 298.340; df = 223; p < 0.01; CMIN/DF = 1.338; goodness-of-fix index [GFI] = 0.861;

incremental fit index [IFI] = 0.952; confirmatory fit index [CFI] = 0.951; root mean square

error of approximation [RMSEA] = 0.050) (Anderson and Gerbing, 1988). The composite

reliabilities of all constructs exceeded the threshold of 0.70 (Nunnally, 1978). In tests for

multicollinearity, tolerance values ranged between 0.617 and 0.891, and variance inflation

factor (VIF) scores were between 1.123 and 1.520, below the threshold of 2 for confirming

data reliability (Hair et al., 2010). The findings indicated that the measures had adequate

convergent validity and reliability.

Discriminant validity was examined through two approaches. First, chi-square difference

tests were computed. We loaded all items from the CFA onto a common latent factor (CLF),

and compared the chi-square difference between the constrained and unconstrained models.

The results showed significance ($\Delta\chi^2$ = 56.027, Δdf = 23, p < 0.001), supporting discriminant

validity (Anderson and Gerbing, 1988). Second, we computed the common variance of

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available pairs of attributes and the average variance extracted (AVE). The findings showed that the AVE value was greater than its highest shared variance with other variables, also supporting discriminant validity (see Table 2). Thus, the results confirmed adequate reliability and validity of our measures.

Hypothesis testing and results

To test our hypotheses, we employed structural equation modeling (SEM) software, AMOS v. 23, and the maximum likelihood estimation method, based on the framework shown in Figure 1. We first tested the direct effects of the control variables on *MP* and *FP*. The results show that only competitive intensity (*CI*) has a significant negative impact on *MP* (β = -0.291, t = - 4.233 at $p < 0.001$), while the other interactions are all insignificant. Second, we tested the direct effect of *MA* on *MP* and *FP*. The results show that *MA* significantly and positively affects *MP* (β = 0.281, t = 4.224 at $p < 0.001$), with an R-squared value of 0.253; In contrast, *MA* does not affect *FP* (β = 0.034, t = 0.576 at $p > 0.05$). The control variable *CI* remains significant and negative for *MP* (β = -0.332, t = -5.076 at $p < 0.001$), and size has a significant negative effect on *FP* (β = -0.162, t = -2.154 at $p < 0.05$). The remaining control variables are insignificant.

Figure 3 shows the results for the pathways in the model. We examine first the direct effect of *MA* on *CUS* and *COM*, and then their effect on *MP* and *FP*. Figure 3 indicates positive and significant relationships between *MA* and both *CUS* and *COM* (β = 0.195, t = 2.556 at $p < 0.05$, and β = 0.549, t = 6.115 at $p < 0.001$, respectively). In the effect of *CUS* and *COM* on *MP* and *FP*, *CUS* positively and significantly affects *FP* (β = 0.287, t = 5.171 at $p < 0.001$) but not *MP* (β = -0.096, t = -1.495 at $p > 0.05$). In contrast, *COM* positively and significantly affects *MP* (β = 0.248, t = 5.855 at $p < 0.001$), but not *FP* (β = -0.017, t = 5.855 at $p > 0.05$).

To test for mediation effects, we employed user-defined causal steps by bootstrapping 10,000 samples at the 95% confidence interval (Preacher and Hayes, 2008). As shown in Table 4, the results indicate that *CUS* does not mediate the effects of *MA* on either *MP* (SIE1: β = -

0.019 at $p > 0.05$) or *FP* (SIE6: $\beta = 0.041$ at $p > 0.05$). However, *COM* has a strong mediating

effect on the effects of *MA* on both *MP* (SIE2: $\beta = 0.164$ at $p < 0.001$) and *FP* (SIE7: $\beta = 0.120$

at $p < 0.01$). Therefore, H1a is rejected and H1b is supported.

Table 4 also shows the results for the mediating role of *INI*, and the sequential mediation

effects. First, *INI* significantly mediates the effect of *MA* on *MP* (SIE3: $\beta = 0.041$ at $p < 0.05$),

but not on *FP* (SIE8: $\beta = 0.017$ at $p > 0.05$). Thus, H2 is partially supported. Second, the results

for sequential mediation effects show that the sequential pathway of *CUS* to *INI* positively and

significantly mediates the effect of *MA* on *MP* (SIE4: $\beta = 0.031$ at $p < 0.05$), whereas the

pathway from *COM* to *INI* has a negative but significant effect (SIE5: $\beta = -0.027$ at $p < 0.01$).

No sequential mediation effect is found for *FP*. Therefore, H3a and H3b are partially supported.

All control variables were tested against *MP* and *FP*, including age, size, annual turnover

(*AT*), technological turbulence (*TT*) and competitive intensity (*CI*). The results show that *CI*

has a strong negative effect on *MP* ($\beta = -0.368$, t = -6.054 at $p < 0.001$) but a positive effect on

FP ($\beta = 0.126$, t = 2.170 at $p < 0.05$). Interestingly, size is found to be negatively and

significantly linked with *FP* ($\beta = -0.167$, t = -2.374 at $p < 0.05$). The other control variables

produce insignificant results. The final model (see Figure 2) shows an overall good model fit:

$\chi^2 = 41.290$ (df = 18, p < 0.01); CMIN/DF = 2.294; GFI = 0.951; IFI = 0.957; CFI = 0.953; and

RMSEA = 0.097. Table 5 summarises the outcomes of our hypothesis testing.

------------------- Insert Figure 3 Here ----------------

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Further analysis

To fully explore the possible interactions of NPI, we investigated whether *INI* also plays a

moderating role in the mediating effects of marketing analytics, market-based NPD and

business performance. The results show that none of the interaction effects is significant. This

includes the moderating role of *INI* on the effect of *CUS* on *MP* (β = 0.056 at *p* >0.05) and on

the effect of *COM* on *MP* (β = -0.097 at *p* >0.05). *INI* also plays no moderating role in the

effect of *CUS* on *FP* (β = 0.035 at *p* >0.05), nor in the effect of *COM* on *FP* (β = 0.022 at

p >0.05). We further tested the interaction between *INI* and *MA* and their effect on business

performance. The results are insignificant, with β = -0.028 at *p* >0.05 for the effect on *MP*, and

β = 0.001 at *p* >0.05 for the effect on *FP*. Overall, no moderating effect of *INI* is established in

this study.

Conclusions and implications

This paper explores mechanisms underlying the effects of marketing analytics on NPI and

business performance. NPI is conceptualised as market-based NPD, which comprises

customer- and competitor-driven NPD, to support incremental innovation. Survey data were

collected from UK entrepreneurial firms in the IT and telecoms sectors. We find that customers

and competitors play different roles in influencing the effects of marketing analytics on

business performance. Applying technology to analyse competitor NPD information enhances

entrepreneurial firms' market performance and financial returns. However, to support

innovation for better market performance, firms should collaborate with customers to generate

innovative product ideas, rather than collecting data and learning from their competitors. Our

study makes significant contributions to the innovation and NPD literature, indicating that

entrepreneurial firms should consider different mechanisms when using technology to analyse

market data to support NPD and business performance.

Theoretical implications

This study makes several theoretical contributions. First, we provide empirical evidence to

support the application of affordance theory to using technological applications for marketing

data to exploit new possibilities. Affordance theory complements the resource-based view of the firm, in terms of entrepreneurial possibilities created through technology-enabled marketing analytics when firms use their resources and capabilities for innovation. Affordance theory frames marketing analytics as an antecedent that offers technological affordances by integrating marketing data, technologies and analytical skills to enhance performance (Marinova et al., 2017; Mikalef et al., 2019). Our study reveals a positive and direct association between marketing analytics and innovative products and their effects on market performance, supplementing the currently limited understanding of applications of IT for innovation (Haug et al., 2023).

In addition, our study reveals the mechanisms through which marketing analytics leads to successful business performance, in which NPI plays an essential mediating role. Our results show that entrepreneurial firms' use of marketing analytics to process competitors' NPD information can significantly enhance their market and financial performance, but using customers' NPD information does not have the same effect. This finding challenges previous results on the importance of customers in supporting performance (e.g. Fuchs and Schreier, 2011; Cao and Tian, 2020). A possible explanation is that the sampled IT and telecoms industries deal with technological activities and services to transmit messages through electronic systems (Bigliardi et al., 2012). They are technology-driven and highly professional, but face intense competition in a high-velocity market environment. Their competitors are key industrial-level players, and understanding their NPD information determines firms' competitiveness (Colombo et al., 2014; Kelley and Rice, 2002). Thus, unlike previous findings of the importance of engaging with customers for market performance (Fuchs and Schreier, 2011; Cao and Tian, 2020), customer-driven NPD plays a limited role in this specific research context. In contrast, using technology to analyse competitor information to develop new products has a significant effect on both market and financial performance.

However, when entrepreneurial firms use customer and competitor NPD knowledge to improve their innovation, the outcomes differ. We find that firms that innovate by collaborating and co-creating with customers on NPD experience positive market performance. This finding supports the customer co-creation concept (Hoyer et al., 2010), highlighting the importance of involving customers in the NPD process to gain deep insights into their needs to support new product innovation (Roberts and Darler, 2017; Sánchez-Gutiérrez et al., 2019). However, unlike existing understanding of a positive association between a competitor orientation and innovation (Grinstein, 2008), we find that their interaction negatively affects market performance. We argue that in highly competitive IT environments, entrepreneurial firms that are constrained by their resources may use shortcuts and directly apply competitors' NPD information to their product innovation, resulting in 'me-too' products (Lukas and Ferrel, 2000). When superior market performance is defined by market share and leadership position, producing new but similar products is unlikely to enhance firms' market growth and competitive position.

Practical implications

This study has several significant managerial implications. Our study extends extant research on marketing analytics by linking analytics relating to data, processes and technology to support NPI. It will inform managers on the importance of obtaining marketing analytics skills to improve market performance. We find that entrepreneurial performance can be supported by marketing analytics. Entrepreneurial firms should therefore develop marketing skills through training, while capitalising on their technology as an integrating mechanism to gain insights into customers and competitors.

We also suggest that entrepreneurial firms should develop a competitor monitoring system, routinely examining competitors' NPD behaviour by using marketing analytics tools effectively. Understanding competitors' NPD performance and responding rapidly to any

potential threats can ensure that firms retain a competitive edge. However, firms are discouraged from using competitor NPD information to supplement innovation, as this will not aid their competitive market position. Therefore, while it is important for firms to monitor competitors' NPD information, we recommend that when engaging in product innovation, they should actively explore customers' needs and demands. This might be accompanied by a thorough review of the customer journey to gain a better understanding of customers' processes and perceptions. This will help firms to obtain innovative ideas directly from customers, and will support their market positioning.

In addition, in examining the context of entrepreneurial firms in IT and telecoms industries, our findings have significant socioeconomic implications. Entrepreneurial firms are often the backbone of social and economic progress in affluent nations like the UK. Current literature on entrepreneurial organisations lacks empirical investigations into applications of marketing analytics for competitive advantage (Cao et al., 2021). Our study highlights that it is crucial for entrepreneurial firms to combine marketing analytics with customer insights in their pursuit of product innovation. This has socioeconomic implications in terms of focusing on fulfilling societal needs in the marketplace and creating positive economic impacts. With the growing complexity associated with technology adoption, our findings will serve as a guide for entrepreneurs and SMEs, aiding them in effective development of IT professionals to support socioeconomic development. Overall, by leveraging affordance theory, this study has significant socioeconomic implications in exploring the potential to augment industry innovation through the dynamic interplay of marketing analytics, new product innovation and overall performance.

Limitations and future research

This study explores the effect of marketing analytics on business performance, but does not provide a full picture of marketing analytics' implementation within organisations. Future

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research might consider adopting other analytics-related variables to investigate intra-organisational aspects of applying marketing analytics, such as an analytics culture, top management involvement, prior knowledge and learning capabilities (Germann et al., 2013). Furthermore, we examine market-based NPD and incremental innovation as mediators, whereas future research might consider other types of market-based capabilities, such as customer value creation (Ramaswami et al., 2009), and their effects on different types of innovation, including radical innovation and process innovation. Second, this study examines two performance indicators: market performance and financial performance. Other performance measures, such as new product success, might also be explored. Moreover, our research focuses on entrepreneurial firms, and particularly SMEs, whereas future studies might compare the performance implications of marketing analytics between SMEs and larger firms. Finally, this study was based on cross-sectional survey data from 138 completed questionnaires. The sample size may be too small to adequately reflect the population, and the cross-sectional nature of the study may give rise to debate about CMB and causal inference (Rindfleisch et al., 2008). Future research might obtain a large sample size and/or longitudinal data, such as financial data from secondary sources, to track changes in marketing analytics adoption, and define how these affect firms' innovation, and thus business performance, over time.

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Tables and Figures

Table 1. Sample description

Characteristics	Count	%	Characteristics	Count	%
Size (no. of employees)			*Age (year of establishment)*		
> 250	5	3.6%	40 years or more	8	5.8%
50–250	40	29%	20–39 years	66	47.8%
< 50	93	67.4%	11–19 years	51	37.0%
			5–10 years	13	9.4%
Total	*138*	*100%*	*Total*	*138*	*100%*
Annual sales (GBP)			*Market share (percentage)*		
> 50 million	6	4.4%	> 50	13	9.4%
10–49.9 million	22	15.9%	10–49.9	27	19.6%
2–9.9 million	71	51.4%	1–10	67	48.5%
< 2 million	39	28.3%	< 1	31	22.5%
Total	*138*	*100%*	*Total*	*138*	*100%*

Table 2. Descriptive analyses and correlation matrix

	Mean	SD	1	2	3	4	5	6	7	8
Firm size	1.71	1.384								
Firm age	3.78	1.153								
Annual turnover	2.07	1.062								
1. CI	3.669	1.159	**0.802**							
2. CUS	5.099	0.943	0.028	**0.729**						
3. COM	4.766	1.223	0.238	0.238	**0.807**					
4. INI	4.690	0.624	0.097	0.480	-0.004	**0.773**				
5. MA	3.267	1.032	0.221	0.179	0.411	0.160	**0.807**			
6. MP	4.194	0.883	-0.302	0.101	0.240	0.142	0.219	**0.828**		
7. FP	4.423	0.930	-0.083	0.315	0.272	0.194	0.234	0.627	**0.864**	
8. TT	5.703	1.077	0.426	0.202	0.147	0.270	0.230	-0.052	0.054	**0.761**

Notes: SD = standard deviation; bold values on the diagonal are AVEs.

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Table 3. Item loading, scale reliability and validity results

Variables and items	Cronbach's alpha	CR	AVE	Loading
Customer-driven NPD (*CUS*)	**0.767**	**0.772**	**0.531**	
- We typically co-design our products with our customers				0.737
- We typically rely on users to help us define and clarify their needs in developing our new products				0.784
- We typically try to put working prototypes in users' hands as early as possible in our development efforts				0.660
Competitor-driven NPD (*COM*)	**0.839**	**0.848**	**0.651**	
- We closely monitor and report on competitors' activities in new product development				0.895
- We respond rapidly to competitors' actions in new product development				0.772
- We frequently collect competitors' information to help direct our new product plans				0.746
Marketing analytics (*MA*)	**0.841**	**0.847**	**0.651**	
- Our people are very good at identifying and employing marketing analysis tools appropriate to the problem at hand				0.696
- Our people master many different quantitative marketing analysis tools and techniques				0.854
- Our people can be considered experts in marketing analytics				0.860
Incremental innovation (*INI*)	**0.801**	**0.814**	**0.598**	
- We frequently refine the provision of existing products and services				0.661
- We regularly implement small adaptations to existing products and services				0.915
- We improve the efficiency of our existing products and services				0.720
Market performance (*MP*)	**0.864**	**0.867**	**0.685**	
- Market share				0.788
- Competitive market position				0.829
- Sales growth				0.865
Financial performance (*FP*)	**0.865**	**0.898**	**0.746**	
- Profit margins				0.785
- Return on assets (ROA): a financial percentage of profit in overall resources, commonly defined as net income divided by total assets				0.871
- Return on investment (ROI): used to evaluate the efficiency of an investment, measuring the amount of return on an investment				0.929
Technological turbulence (*TT*)	**0.801**	**0.805**	**0.580**	
- The technology in our industry is changing rapidly				0.824
- Technological changes provide big opportunities in our industry				0.699
- A large number of new product ideas have been made possible through technological breakthroughs in our industry				0.756
Competitive intensity (*CI*)	**0.831**	**0.841**	**0.643**	
- Competition in our industry is cut-throat				0.870
- There are many 'promotion wars' in our industry				0.882
- Price competition is a hallmark of our industry				0.629

Notes: CR = composite reliability; AVE = average variance extracted; model fit statistics: $\chi^2 = 298.340$ (df = 223, p < 0.01), CMIN/DF = 1.338, GFI = 0.861, IFI = 0.952, CFI = 0.951 and RMSEA = 0.050.
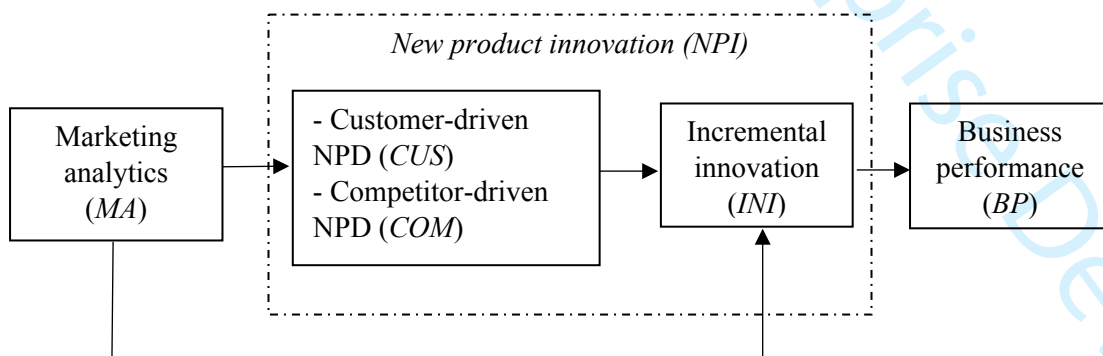
Table 4. Indirect effects

Effect on		Parameter	Estimate	Lower	Upper	P
MP	SIE1	MA→CUS→MP	-0.019	-0.060	0.011	n.s
	SIE2	MA→COM→MP	0.164	0.097	0.241	***
	SIE3	MA→INI→MP	0.041	0.005	0.094	*
	SIE4	MA→CUS→INI→MP	0.031	0.007	0.064	*
	SIE5	MA→COM→INI→MP	-0.027	-0.056	-0.006	*
FP	SIE6	MA→CUS→FP	0.041	0.002	0.092	n.s
	SIE7	MA→COM→FP	0.120	0.050	0.199	**
	SIE8	MA→IC→FP	0.017	-0.003	0.056	n.s
	SIE9	MA→CUS→INI→FP	0.013	-0.003	0.038	n.s
	SIE10	MA→COM→INI→FP	-0.011	-0.034	0.003	n.s

Notes: SIE= specific indirect effect; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; n.s = not significant.

Table 5. Summary of hypothesis tests

Parameters and relationships		β	p-value	*Result*
H1a	MA→CUS→MP	-0.019	ns	Reject
	MA→CUS→FP	0.041	ns	
H1b	MA→COM→MP	0.164	***	Accept
	MA→COM→FP	0.120	**	
H2	MA→INI→MP	0.041	*	Partially accept
	MA→INI→FP	0.017	ns	
H3a	MA→CUS→INI→MP	0.031	*	Accept
	MA→COM→INI→MP	-0.027	*	
H3b	MA→CUS→INI→FP	0.013	ns	Reject
	MA→COM→INI→FP	-0.011	ns	

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; ns = not significant.

Figure 1. Conceptual model

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| Survey method | Self-administered online questionnaire |

| Sample design | UK-based entrepreneurial firms in the IT and telecoms industries |

| Questionnaire design | Questionnaire designed based on the conceptual framework in Figure 1. Pilot test conducted with four academic peers and three sample firms. Questionnaire then finalised. |

| Data collection | Dataset obtained containing 5,000 UK entrepreneurial firms. Research assistant recruited to send invitation email with survey link. Four follow-up emails sent at two- to three-week intervals. |

| Data analysis and hypothesis tests | From 565 attempted and 151 completed questionnaires, after data screening and cleaning, 138 remained for data analysis. The analytical approach included descriptive analysis (see Table 1), reliability and validity tests (Cronbach's alpha, CFA, AVE, CR, and correlation matrix, see Tables 2 and 3). Hypothesis testing applied an SEM approach. |

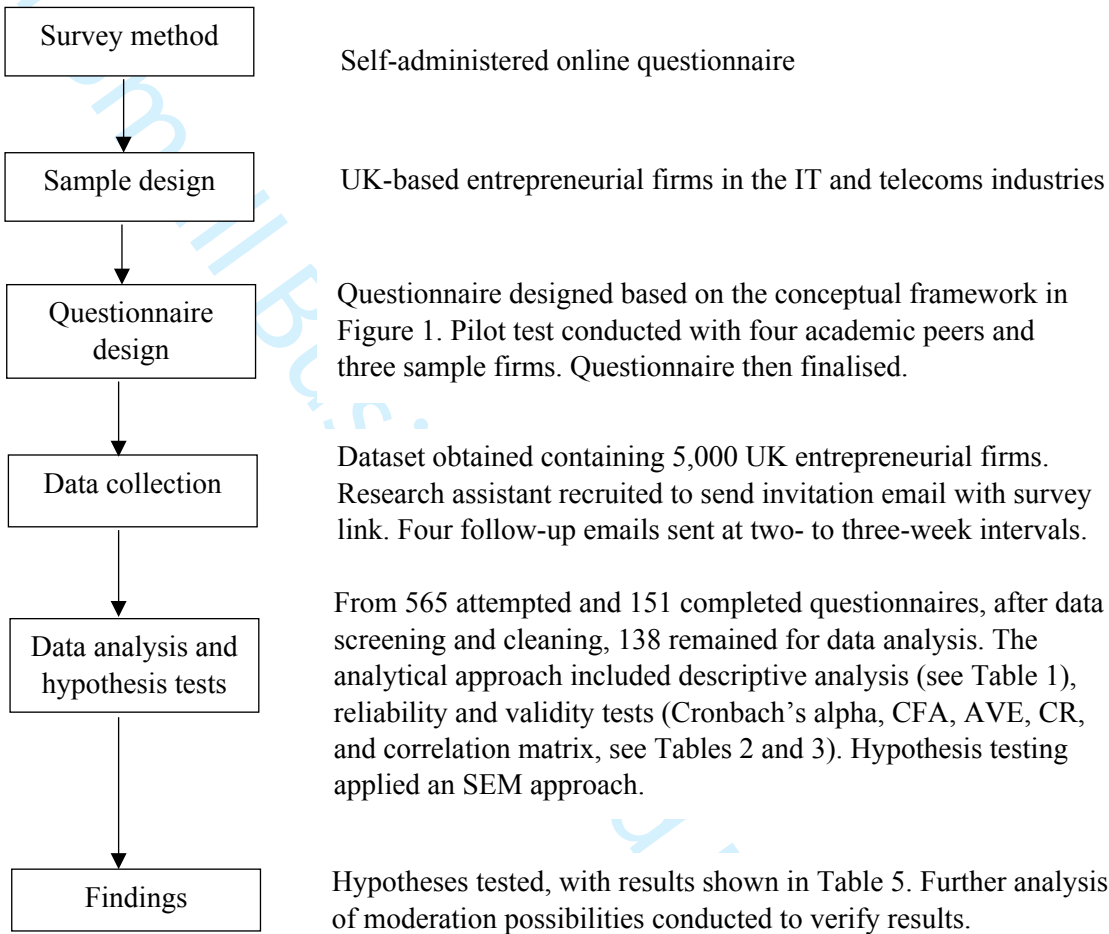| Findings | Hypotheses tested, with results shown in Table 5. Further analysis of moderation possibilities conducted to verify results. |

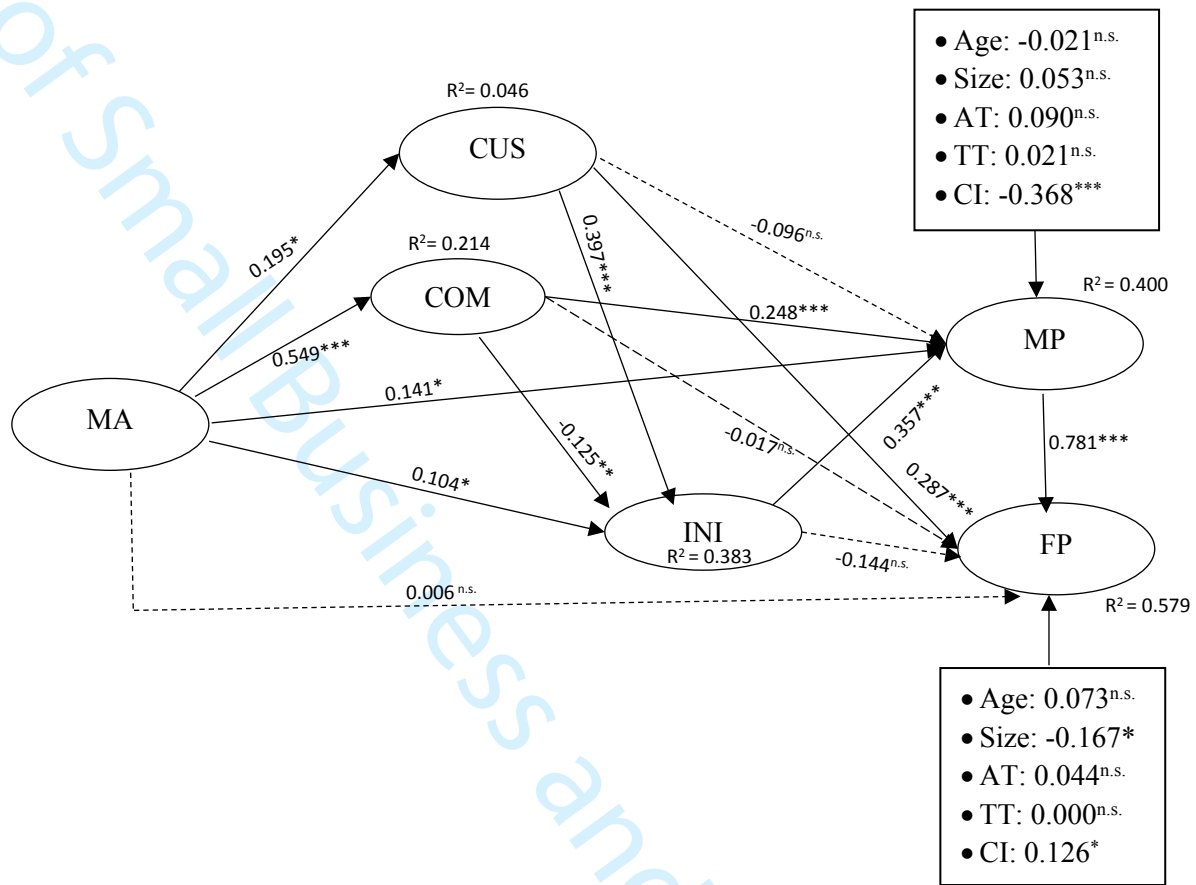**Figure 2.** An overview of the research process

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Figure 3. Final model output

Notes: Dotted lines indicate insignificant relationships; Model fit statistics: χ^2 = 37.247 (df = 16, p < 0.01), CMIN/DF = 2.328, GFI = 0.956, IFI = 0.933, CFI = 0.957, and RMSEA = 0.098.

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Appendix: Recent empirical studies of marketing analytics (MA) and performance

Study	Research aims/ Questions	Theory/Concept	Method/Sample	Main findings	Future research directions
Cheng and Shiu (2023)	To determine whether big data analytics (BDA) or traditional marketing analytics (TMA) has a stronger effect on the NPD performance, and the potential moderating effects of innovation strategies on the roles of BDA/TMA in NPD performance	Integrates the strategic information technology alignment (SITA) perspective with innovation ambidexterity theory	Survey conducted through on-site interviews; sample of 1,000 firms drawn from the China Credit Information Service in Taiwan; NPD managers contacted by phone, resulting in 238 firms; longitudinal data collected from 2018 to 2021	Both BDA and TMA have positive and significant effects on NPD performance, and BDA has a more significant effect on NPD than TMA; both exploratory and exploitative innovation have positive moderating effects; an exploitative innovation strategy has a stronger impact on the relationship between TMA and NPD performance	Supplement BDA with TMA information, along with exploratory innovation strategy to support innovation development
Hossain et al. (2022)	How does the MA capability of an export-oriented manufacturing firm assure sustained competitive advantage?	Resource-based view and dynamic capabilities	Multi-phase research design; sample from the export-oriented ready-made garment (RMG) manufacturing industry	Marketing analytics capability leads to sustainable competitive advantage through sensing, seizing and reconfiguring the market	Test the model in different industries using a longitudinal or experimental approach; extend studies of MA capability in B2B manufacturing settings
Akter et al (2022)	To investigate the antecedents of B2B MA capability on a cloud-sharing platform, and its effect on marketing agility and marketing effectiveness while affected by market turbulence	Dynamic capability and contingency theory	Systematic literature review and survey method based on cloud-sharing platforms, focusing on Australian B2B firms	MA capability is a second-order construct that includes pattern identification, real-time solutions and data governance; it positively influences marketing agility and marketing effectiveness; these relationships interact with market turbulence	Develop more refined measures that focus on the MA processes of a specific cloud-sharing platform; explore cloud-based MA in different marketing contexts; extend exploration of the dynamics of MA capability for better performance while considering market changes
Liang et al (2022)	To understand how and under what conditions MA benefit business performance	Contingency theory	Survey data collected from senior marketing managers in Chinese firms	Market agility mediates the effect of MA on firm performance; inter-departmental coordination and market turbulence both enhance the effect of MA on market agility; success traps play a negative moderating role in the effect of MA on market agility	Understand how MA relates to other types of dynamic capabilities (DC); explore the complementary resources needed for MA, and how MA and DC affect performance; explore other theories to enhance understanding of the MA–firm performance relationship

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Cao et al (2022)	To explore mechanisms of big data and MA that can be applied to enhance marketing capability	Dynamic capability	Survey to collect data from Chinese firms through a Chinese marketing research firm	Use of big data positively affects use of MA; use of MA positively affects marketing capabilities for planning, implementation, brand management, customer relationship management and product development management	Explore different research contexts and approaches, and how the impact of big data and MA on capabilities may lead to competitive advantage
Cao and Tian (2020)	To explore the mechanisms that enable firms to apply MA to improve marketing capabilities, and thus marketing performance	Absorptive capacity	Survey to collect data from Chinese companies through a Chinese market research firm.	MA use relates positively to CRM capability and brand management, and both lead to positive marketing performance; CRM and brand management both play mediating roles in the MA–marketing performance relationship	Use different research methods and contexts, and more relevant variables relating to market-sensing and customer management capabilities
Kakatka and Spann (2019)	How can retailers make use of anonymised and fragmented event-based (AFE) tracking data for MA?	N/A	Experiment using AFE tracking data on consumer behaviour collected in the store of a large European university	The presence of a sweatshirt and self-interactivity leads to touch interaction; time of day is a significant predictor, with more interactions in the morning	Use different methods to identify more accurate individual-level heterogeneity; explore alternatives to the network representation of AFE data; validate the AFE data application in different settings
Cao et al (2019)	To explore mechanisms to achieve competitiveness through MA, and how antecedents affect MA use, and marketing decision making and product development management.	Dynamic capability view	Survey questionnaire to collect data from UK firms	Use of MA relates positively to marketing decision making and product development management; MA mediates the effect of data availability on marketing decision making and product development management, the effect of managerial perceptions on product development management, and the effect of managerial support on marketing decision making	Consider other conditional variables, such as environmental dynamism in the effects of MA on competitive advantage
Germann et al. (2013)	To explore whether widespread deployment of MA within a firm leads to improved firm performance, and if so, what leads to widespread deployment of MA within firms?	Resource-based view and upper echelons theory	Mail survey to executives of Fortune 1000 firms	Deployment of MA leads to better performance; interactions between deployment of MA, competition and changing customer preferences have positive effects on firm performance, but the prevalence of analytics interacts negatively with deployment of MA to affect firm performance	Employ longitudinal data to explore the effect of MA deployment on firm performance; explore the implications of different types of analytics effects for performance, and various aspects of analytics implementations for decisions and actions

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