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Value creation through marketing data analytics: The distinct contribution of data analytics assets and capabilities to unit and firm performance

Josune Sáenz [a,*], Ana Ortiz de Guinea [b], Carmela Peñalba-Aguirrezabalaga [a]

[a] Deusto Business School, University of Deusto, Camino de Mundaiz 50, San Sebastián 20012, Spain
[b] Department of Information Technologies, HEC Montréal, Chemin de la Côte-Sainte-Catherine 3000, Montréal H3T 2A7, Canada

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ABSTRACT

This study answers research calls regarding data analytics in a specific unit and its impact at the unit and organizational level. In doing so, it takes an information value chain approach to theorize about how quality data and IT-enabled data analytics sensing capability in the marketing unit relate differently to the unit performance as well as to firm-level performance. Results from a survey of 346 firms confirm the hypotheses by showing partially and fully mediated effects for quality data, and direct and partially mediated effects for sensing capability.

1. Introduction

The proliferation and availability of data, as well as the techniques and tools for collecting, processing, and analyzing them, are considered major disruptive forces in the current networked business environment [1]. Not surprisingly, more and more companies are investing in data analytics to generate insights that would translate into performance and competitive position improvements [2]. Practitioners' surveys confirm that such investments have increased among companies over the last few years [3–7]. As a reflection of practitioners' investments in data analytics, the scientific literature has studied and demonstrated positive impacts of data analytics on various firm level capabilities and performance outcomes [8–14].

Several reviews regarding the strategic value of IT and data analytics acknowledge the contribution of past studies regarding the relation between organization-wide data analytics and firm-level performance, while pointing to the need to investigate how data analytics in a given unit might contribute to the unit's performance and overall firm performance [13,15–17]. These current calls for research on data analytics at the unit level fit well with the reality of organizations, which generally deploy and employ data analytics in specific organizational areas or units to minimize associated risks [3,18]. In fact, data analytics leaders warn that all-at-once monolithic efforts on organization-wide data analytics often fail, and thus, they advise to start by targeting data analytics to a specific area or unit to demonstrate its value through an iterative and incremental strategy [19,20]. Even in companies where CEOs foster data analytics adoption throughout the company, the use of data analytics is usually left to the discretion of each business unit leader or functional head [19].

Given that customer loyalty and retention are in decline [21], it is not surprising that most organizations associate data analytics with customer areas, such as marketing [11]. Consistent with this, surveys among practitioners point out that, among all organizational units, marketing is the unit where most data analytics efforts are being applied [5,7]. Four additional insights explain the marketing focus of most data analytics efforts. First, the number of potential touchpoints between consumers and service providers has considerably increased due to the proliferation of mobile and wearable devices [22,23]. Second, marketing data analytics tools are becoming increasingly accessible for all businesses, including those that lacked expertise and resources [24]. Third, customer-centric marketing and integrated marketing communication strategies increase the length and the complexity of customer journeys (i.e., the process or sequence that a customer goes through to access or use an offering of a company; [25]), creating new challenges for marketing effectiveness analysis and data analytics [22]. Finally, the situation generated by Covid-19 has skyrocketed disintermediation to its highest, and investments in marketing data analytics have increased by almost 40% from February 2021 to February 2022, becoming a top priority among firms [7].

As a result, this study answers recent calls for research at the unit level [13,15,17] by investigating how data analytics resources at the marketing unit (i.e., quality data and data analytics sensing capability)

* Corresponding author.
E-mail addresses: josune.saenz@deusto.es (J. Sáenz), ana.ortiz-de-guinea@hec.ca (A. Ortiz de Guinea), carmela.penalba@deusto.es (C. Peñalba-Aguirrezabalaga).

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relate differently to unit-level innovation (i.e., marketing innovation) as well as to firm-level performance (i.e., market performance). To do so, this study takes an information value chain approach [26] and complements it with current theoretical approaches explaining firm-level data analytics relations with performance outcomes as the knowledge-based view of the firm [27]. In contrast to the original value chain model in which information played a supporting role for value creation [28], the information value chain gives information primary value creation potential by explicitly acknowledging that information has value when it leads to change [26]. In other words, by building upon the information value chain perspective, we theorize and test whether and how each specific information resource (i.e., quality data and data analytics sensing capability) adds utility value to the unit (i.e., marketing innovation) and economic value to the firm (i.e., market performance) differently (i.e., direct, partial, or full mediation effects). Overall, the information value chain begins with the provision of quality data and the analysis of information (i.e., data analytics sensing capability) that can then be used to make decisions and implement change (i.e., marketing innovation understood as changes in the marketing mix) [26]. In addition, changes implemented in one place of the firm (i.e., marketing innovation) can but do not always necessarily directly affect subsequent overall outcomes (i.e., firm market performance), which are also dependent upon the relative contribution of the rest of units in the firm [26].

The rest of the paper is organized as follows. We first provide the theoretical background of the article, where we build upon previous literature to conceptualize the two data analytics constructs included in this study, and then introduce the information value chain perspective. Second, we theorize and develop specific hypotheses about the effects of data analytics assets (i.e., quality data) and capabilities (i.e., data analytics sensing) on marketing innovation and market performance. Third, we describe the survey method employed to gather data, as well as the measures utilized to operationalize the different theoretical constructs. Fourth, we explain the analyses that serve to test the hypothesized relations and associated results. Finally, we discuss this study's contributions to both research and practice, acknowledge its limitations, and suggest future opportunities for research.

2. Theoretical background

By building on previous literature, we now conceptualize the two data analytics constructs investigated herein in the marketing unit context and explain how data analytics at the marketing unit can contribute to value creation, which serves to set the theoretical framework that will subsequently guide this study's hypotheses.

2.1. Data analytics at the marketing unit

Data analytics, including that at the marketing unit, is essentially a knowledge resource: it implies coded knowledge such as data as well as the ability to analyze such data to generate business-relevant knowledge, in this case, relevant for decision-making regarding marketing activities [13,16,29]. Thus, consistently with the knowledge-based view of the firm, our umbrella term of data analytics at the marketing unit encompasses both an asset and a capability dimension [16,30–32]. In the context of this paper, quality data (i.e., having data of good quality), constitutes the asset dimension, while IT-enabled data analytics sensing capability represents the capability dimension.

2.1.1. Quality data relevant for the marketing unit

Quality data refers to the extent to which the marketing unit disposes of up-to-date, complete, and readily available relevant knowledge for decision-making about marketing activities and thus, encompasses data regarding best practices, past projects and campaigns, as well as customers, competitors, and current and prospect markets [33]. Such a definition purposely highlights both quality aspects and the object of the knowledge encompassed by the construct. Regarding quality, it includes the intrinsic (e.g., complete) and contextual (e.g., relevancy) attributes of data quality [34], as well as veracity, since firms need to have authentic data that they can trust if they want to derive value from their data analytics efforts [35].

Regarding the object dimension, it is important to note that quality data includes data coming from other organizational areas such as R&D (e.g., information regarding technological market trends) or Accounting & Finance (e.g., product/service performance), besides also encompassing data generated in the marketing unit itself, such as prior marketing-related projects, deals and campaigns, competitors' marketing strategies, and transactional data regarding customers and sales [36]. Furthermore, the object dimension of quality data includes knowledge regarding both the internal and external context of the firm that is relevant to the marketing unit [31,33,35,37–40]. While most of the literature focuses almost exclusively on knowledge regarding the external environment [41–44], which is clearly relevant for the marketing unit's adaptive responses to the market, internal knowledge is also key for reducing uncertainty and gaining insight [35,39]. Thus, quality data includes both internal (i.e., about marketing projects, deals, campaigns, and "who knows what" directory) and external (i.e., about the market, competitors, customers, and influencers) knowledge that is relevant to the marketing unit, resides in artifacts (e.g., databases), and is interpreted through marketing practices [45–47]. In a nutshell, quality data represents up-to-date, accessible, and complete knowledge about the internal and external environments relevant for decision making in the marketing unit.

This notion of quality data, as any "asset" conceptualization of data analytics, excludes the resources that "turn data into actionable insight" [16, p. 556]. Thus, a second way of conceptualizing data analytics focuses on its potential to induce change by providing action possibilities, which corresponds to the capability dimension highlighted above. Such data analytics capability is explained next.

2.1.2. IT-enabled data analytics sensing capability for the marketing unit

Data analytics as a capability can focus either on the deployment and management of data and IT assets so that they can be exploited within the organization [13,48,49] or on the ability to generate relevant knowledge by exploiting the deployed data and IT assets for guiding an organization's business decisions and actions [16,29,31,33,50,51]. While the former reflects the capability of deploying assets such as IT and data, the latter, in contrast, focuses on a capability enabled by the use of those IT assets.

In this study, we focus on *IT-enabled data analytics sensing capability* or the ability, enabled by the use of IT, to analyze product/service performance and identify customer behavioral patterns, prospective customers, customers' profitability, customers' groups/segments, market trends, and industry's top insiders and influencers [31,43]. Thus, IT-enabled data analytics sensing capability is the ability to sense the environment for decision-making regarding changes in the marketing mix. This capability is enabled by the use of software in which analytic methods and techniques are embedded [52,53]. For example, in a typical Customer Relationship Management (CRM), the analytical component can serve to analyze the data gathered by the operational one, or it can also include the analysis of data derived from other sources, such as web traffic analysis, sentiment analysis of social media postings, and text analytics of customers' reviews [52,54]. Thus, the use of IT enables learning and generating insights about customers (e.g., profitability, behavioral patterns, groups/segments, identification of prospective customers), the market (e.g., market trends, industry insiders and influencers), and the performance of the firm's products/services [31,33,43]. This sensing regarding customers, the market, and the performance of products and services is an IT-enabled dynamic capability [17] that has been deemed especially important for the marketing unit [41,43,55].

2.2. Data analytics for marketing decision-making and value creation

With its foundations in microeconomics and classical decision sciences, the information value chain approach complements the knowledge-based view of the firm by providing a framework for teasing apart the different benefits of certain information-related assets, capabilities, and activities at a given specific unit and at the overall firm [26, 56]. Given its explicit recognition of information as a key driver of change, and thus, value creation [26], this theoretical perspective has been used to understand the value added potential (and effects) of distinct information-related resources and activities at specific areas/units, organizations, and networks in a wide variety of contexts, such as the assessment of internet of things (IoT) applications [57], patents in SMEs [58], blockchain technology in agri-food [59], and patient self-care [60]. In this study, information value chain theory adds specificity to the knowledge-based perspective regarding the theorization of different value creation effects of data analytics (i.e., quality data and IT-enabled data analytics sensing capability) in the business unit where it is employed (i.e., marketing unit) for decision-making regarding changes in the marketing mix (i.e., marketing innovation), and at the wider organization to which the unit contributes (i.e., firm's market performance). These different effects are explained next.

3. Research model and hypothesis development

From the perspective of the knowledge-based view, what the firm owns (i.e., quality data) and what the firm is capable of doing with what it owns (i.e., IT-enabled sensing) are critical knowledge resources for value creation as they enable changes along the information chain [15, 30]. Knowledge involves being able to gage the impact, relevance, and usefulness of information [61], and it leads to action based on the expected outcome of the intended action [62]. In other words, knowledge implies the capacity to act [15,63]. Thus, quality data is necessary for the application of analytical techniques to sense the environment [15, 30], and in turn, both quality data and IT-enabled data analytics sensing create utility value for the marketing unit by facilitating changes in the marketing mix (i.e., marketing innovation), [15,30]. Ultimately, marketing innovation turns utility into economic value by implementing changes (in communication, product/service design, distribution, and pricing) aimed at customer acquisition and retention, which contribute to the firm's market performance relative to competitors [15,30].

From an information value chain perspective, the specific impacts of quality data and IT-enabled sensing capability are expected to differ depending on their position in the chain, losing strength as they move to more distant elements (see Fig. 1). Proposing each data analytic resource—assets (i.e., quality data) and capabilities (i.e., IT-enabled sensing)—as having different effects (i.e., direct, partial, or fully mediated) on outcomes at the marketing unit and at the firm serves to add precision to our overall understanding of the value creation potential of data analytics.

3.1. Quality data and IT-enabled data analytic sensing

Nowadays, quality data is considered a critical knowledge asset within organizations [64,65]. The general management literature, along with the marketing and information systems (IS) literatures, recognizes the inherent dependency between the quality of information and its use [66–68]. For instance, Wedel and Kannan [54] clearly highlight the criticality of quality data in performing data analytics in the marketing context. The idea of data quality has always been intrinsically associated with the usefulness of data [69,70] and although traditionally data or information quality has been associated with IT quality [71], later investigations indicate that information use is dependent upon information quality but not necessarily upon IT quality [67]. Accordingly, our quality data construct purposely includes quality notions, such as relevancy, completeness, accuracy, and accessibility [72], but excludes IT, which is already embedded in the IT-enabled data analytics sensing capability construct. As a result, quality data at the marketing unit refers to the extent to which key internal and external information relevant for marketing activities is up-to-date, relevant, complete, and easily accessible [33]. In this regard, it is also important to note that although traditionally organizations have primarily relied upon internal structured enterprise-specific data (e.g., data stored in tables like in a relational database) to make business decisions, they currently tend to also include data from other external sources in both structured and unstructured forms (e.g., social media posts) [54]. Data quality is a key antecedent of the capability of sensing the environment through the use of IT analytical tools to provide action possibilities for marketing decision-making [35,73]. The ability to use IT and employ data analytics techniques to generate insights into customer patterns, competitors' performance, and possible prospective customers is preceded by the quality of relevant data on which analytical techniques are going to be performed [54]. To put it differently, for the marketing unit, quality data about the internal and external context [74] is the raw material feeding the IT-enabled analytics that provides the insight for guiding marketing efforts [73,75,76]. Although this is not the only knowledge-based asset that enables the development of IT-enabled sensing capability (e.g., IT infrastructure such as different types of databases, parallel processing, specific analytics, and visualization software could also be considered; [16,48,77]), our focus and scope in this study is on the quality of data relevant for the marketing realm. Thus, to sum up, the idea here is that the insights generated by the application of data analytics tools are dependent upon the quality of the data that feeds those tools [68]. Consequently, we hypothesize the following:

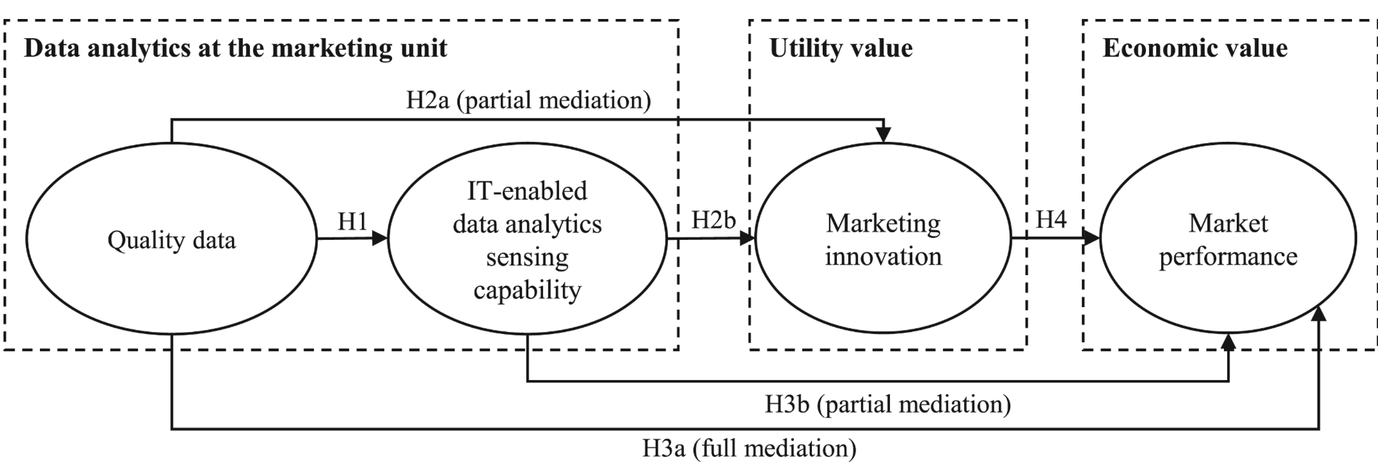

Fig. 1. Research model.

H1. Quality data has a positive relation with IT-enabled data analytics sensing.

3.2. Quality data, IT-enabled data analytics sensing, and marketing innovation

Data analytics at the marketing unit —quality data and IT-enabled data analytics sensing—provides utility value along the information value chain by generating knowledge to guide marketing decisions and efforts [15,30]. Most marketing data analytics efforts are tailored towards generating insights to guide changes in the marketing mix [54]. Such changes are known as marketing innovation and involve the implementation of new marketing methods. Most specifically, these include "changes in product design and packaging, in product promotion and placement, and in methods for pricing goods and services" [78, p. 17]. Marketing innovation consists of marketing-mix improvements [79] and it is positioned in the literature as a type of incremental innovation [e.g., 80,81].

According to Abernathy and Clark [82] incremental innovations build on and reinforce the applicability of existing knowledge, highlighting the criticality of quality data for innovations in the marketing mix. Because activities regarding marketing-mix processes are usually associated with the marketing function [e.g., 83], knowledge assets such as quality data available in the marketing unit should play a prominent role. As Subramaniam and Youndt [84] point out, quality data involving up-to-date, accessible, complete, and relevant manuals, marketing campaigns, and knowledge directories, along with the establishment of structures, processes, and routines that encourage repeated use of knowledge, boost an organization's incremental innovative capabilities. Likewise, according to Lehrer et al. [53], a firm's capacity to store relevant information about customers and industry provides a critical source for innovation. Additionally, service innovations, such as those implied in the marketing mix, often arise from data on local customer needs and problems early on [85]. In fact, firms often need to access customer data early to involve customers in a more collaborative role, such as in consultations about service changes [37,85]. However, firms not only need to 'look out' to customers, but they also need to 'look in' [74]. Thus, internal data on employees' expertise and past marketing experiences enable ideas to be captured internally [86]. For example, data on past marketing campaigns, deals, and projects, provide insights from experiences about what worked and did not, and thus, it is often used to decide upon marketing innovations [87]. As a result, firms that proactively collect and store quality data are also likely to follow differentiation strategies that often include marketing innovations [41], suggesting a positive relation between marketing-specific data availability and marketing innovation. However, from an information value chain perspective, we would expect such positive relation being partially mediated by IT-enabled data analytics sensing.

Regarding IT-enabled data analytics sensing capability for marketing purposes, a plethora of IT-based solutions (e.g., CRM, customer experience management software, customer journey tracking software, social media management software, marketing intelligence software) have emerged [88,89], which enable companies to generate new knowledge by applying data analytics techniques to marketing relevant data [53]. This IT-enabled analytic capability of identifying potential new customers, customer groups and/or segments, patterns of customer behavior, market trends, and top industry insiders and influencers, as well as analyzing customers' profitability and product/service performance, is critical in guiding marketing innovation decisions [90]. Thus, IT-enabled data analytics sensing yields previously unknown insights regarding customers' behavioral and market trends, which lead to incremental marketing innovations encompassing modifications of current products/services' designs, packaging, pricing, and marketing campaigns [29,53,54,90,91].

Overall, marketing analytics— quality data and IT-enabled data analytics sensing—can generate utility value by providing key knowledge for action down the information value chain, in this case, in the marketing mix [15,30,54]. Thus, firms that dispose of relevant marketing quality data and can generate insights from analyzing such data are in a better position to identify emerging threats and opportunities, so that evolutionary responses to the market through innovations in the marketing mix can take place [92]. Not surprisingly, firms that are leaders in the adoption of data analytics are more likely to produce innovations in their product and service offerings when compared to laggard companies [93]. Based on the above, we hypothesize the following:

H2a. IT-enabled data analytics sensing partially mediates the relation between quality data and marketing innovation.

H2b. IT-enabled data analytics sensing has a positive relation with marketing innovation.

3.3. Quality data, IT-enabled data analytics sensing, and market performance

In general, marketing analytics is expected to also provide economic value through positive impacts on market performance down the information value chain due to customer acquisition and retention [15,29, 30]. Thus, besides the utility value provided through marketing mix innovations, marketing analytics can also enable economic value through improved market performance resulting from such innovations. However, considering the information value chain, we expect that quality data and IT-enabled data analytics sensing influence market performance differently.

More specifically, with respect to quality data, different research traditions point to different possibilities regarding its relation to market performance. On the one hand, research on organizational memory highlights that the reuse of previously stored quality information or quality data is critical to a given firm's economic success [94]. In this regard, the information and data flows that the marketing department analyzes are critical for understanding the complexity of the industry in which a firm operates [95]. On the other hand, taking an information value chain perspective and incorporating a more dynamic view of knowledge, it is likely that an asset like quality data may not have a statistically significant direct effect on firm-level performance but a fully mediated indirect one. Given that market performance is at the opposite end of quality data in the information value chain, it is reasonable to think that the strength of its effects is likely to fade as it travels across the information value chain. Consistent with this idea, meta-analyses or quantitative reviews tackling the IT productivity paradox have shown little support for a direct link between IT assets and firm performance outcomes (i.e., efficiency and profitability), favoring an indirect effect model where the actions enabled by IT assets are included as mediators of the relation between IT-related assets and firm-level outcomes [96]. Hence, quality data reduces current transaction costs by providing information from the past, thus contributing to effective and efficient decision-making and actions regarding the marketing mix, which eventually result in better market performance at the firm level [97,98]. As a result, we expect the relation between quality data and market performance to be fully mediated by marketing innovation.

With respect to the influence of IT-enabled data analytics sensing on market performance, Grover et al. [29] argued that insights about customers, competitors, and markets obtained through marketing analytics enhance market performance by improving customer loyalty and satisfaction. For example, the knowledge generated through such sensing capability regarding potential and existing customers improves the targeting of commercial actions, and thus, the effectiveness of such actions (e.g., selling the right products to the right customers; [89]). Also, although firms have already traditionally performed activities such as monitoring competitors, learning about their customers, and identifying market trends, IT-enabled analytics speed up these activities, reducing their cost and facilitating organizational performance [90]. Consistent with this, research has shown that IT-enabled sensing capability constitutes a major performance differentiator because it enables firms to be more proactive and quicker in identifying and acting upon opportunities and threats, which allows them to reach better market positions [99]. The same research also reports that such sensing capability can lower customer acquisition costs by 47% while enhancing revenues by 8%, directly contributing to market performance [99]. In general, IT-enabled data analytics sensing in the marketing unit appears to be critical for improving firm performance since it leads to better marketing decisions [100] and thus, triggers the implementation of insights that allow a firm to be competitive and profitable [101]. Empirical research also supports this idea since it shows a positive impact of the deployment and use of marketing analytics on firm performance, an impact that is strengthened when competition is more intense and customer preferences change more rapidly [102]. Other research also shows the importance of understanding consumer behavior via, for example, data analytics of browsing activity to enable decision-making [103], with the adoption of website activity dashboards resulting in increases of weekly revenues [104]. Thus, we expect IT-enabled data analytics sensing to have a positive effect on market performance that is partially mediated by marketing innovation. As a result, we posit the following hypotheses:

H3a. Marketing innovation and IT-enabled data analytics sensing fully mediate the relation between quality data and market performance.

H3b. Marketing innovation partially mediates the relation between IT-enabled data analytics sensing and market performance.

3.4. Marketing innovation and market performance

Since first addressed in the 1960s, changes in the marketing mix have been consistently researched as providing profit possibilities [105]. According to Medrano-Sáez and colleagues [106], an important part of such literature focuses on the competitive advantages that can be achieved through the implementation of innovations in the marketing mix [e.g., 107–110]. Incremental innovations, such as modifications in the marketing mix, are a critical source of competitive advantage despite managers' tendency to neglect them over more radical innovations, such as the development of entirely new products and/or services [110]. In fact, research has shown that changes in products/services' packaging and design, advertisements, and after-sales services improve a firm's competitive position through an increase in market share [110]. In other words, marketing innovation provides differentiation from competitors and adaptation to markets, thus improving market performance [106, 111]. Because marketing mix innovations focus on better addressing customer needs, newly positioning a firm's offerings in the market, or opening new markets altogether [78], they emphasize shifting consumer demand from elastic to inelastic segments through the delivery of better value [79]. Accordingly, we hypothesize the following:

H4. Marketing innovation is positively related to market performance.

4. Research methodology

A cross-sectional survey of Spanish firms with at least 100 employees was used to collect the necessary data to test the hypotheses. A threshold of a minimum of 100 employees was established to guarantee that companies had a well-established marketing unit. In the following sections, we explain the stratified sampling procedure we followed, the measures used to operationalize the theoretical constructs, and the statistical analyses carried out to test the proposed hypotheses.

4.1. Sampling approach and data collection

We followed a probability sampling approach and, within this approach, a stratified sampling technique [112]. Unlike the non-probability sampling approaches used in most data analytics studies, such as purposive or snowball sampling, our stratified random sampling strategy reduces the potential for human bias in the selection of cases and thus allows us to make generalizations (or statistical inferences) from the sample to the target population with more confidence [112]. In other words, stratified random sampling increases the external validity of the findings [112].

To identify the initial population in which to apply the stratified sampling process, the Sistema de Análisis de Balances Ibéricos (System of Iberian Balance Sheet Analysis; SABI) database was used. This database provided by eInforma (a private company specialized in commercial, financial, sectoral, and marketing information) includes the financial accounts of more than 2.7 million Spanish firms (i.e., all companies that have an obligation to register their accounts in the commercial register), thus being a suitable starting point. The search resulted in 2346 companies with at least 100 employees, which were considered the total population. From this population, we calculated the minimum sample size needed to conduct a representative study [113], which resulted in 342 companies.[1]

This sample size was also large enough to carry out a statistical study based on the partial least squares (PLS) structural equation modeling (SEM) approach. According to the level of complexity of the model to be tested (i.e., considering the number of predictors in the most complex regression of the model, which contained seven independent variables), the minimum R^2 to be expected (10%), a significance level of 5%, and a statistical power (i.e., the probability of finding an effect in the sample if it indeed exists in the population) of 80%, the minimum sample size should be made up of 166 firms [114].

Thus, taking the initial sample size as a reference (i.e., 342 companies), the stratified sampling procedure ensured that different proportions of company types according to size (mid-sized vs. large-sized), industry (manufacturing vs. service), and technology intensity (high-techs vs. low-techs, as established by the OECD and Eurostat) were preserved as they exist in the population, thereby improving the precision and representativeness of the resulting sample. The final sample included 346 companies— 4 over the threshold of 342—that answered the provided questionnaire. Table 1 provides more details about the composition of the sample.

We contacted the target population by phone to obtain the contact details of the person in charge of the marketing function (whether or not it was a separate department) and then invited this person to participate in the survey by sending him or her an email explaining the project and guaranteeing total confidentiality. The possibility was then offered to answer the questionnaire by phone or by filling in a form and then returning it by email, which was the preferred option by almost all participants. Regarding the respondents' profiles, 85.26% held a managerial role in the marketing domain, 6.65% were marketing and sales technicians or assistants, 5.20% were CEOs, 1.45% were salespeople, and the remaining 1.45% did not specify their role.

As data was collected through a single method (i.e., survey), this presented the possibility of the occurrence of what is known as common-method bias [115,116]. To determine the extent of the method variance in the dataset, we used the marker variable approach [117]. To that end,

[1] The following formula was used: $n_{fin} = \frac{n_{inf}}{1+\frac{n_{inf}-1}{N}} = \frac{400}{1+\left(\frac{400-1}{2,346}\right)} = 342$ Where:n_{fin} is the sample size for a statistically finite population.n_{inf} is the sample size for a statistically infinite population.N is the population size.Since the calculation of the sample size for a statistically finite population draws from that of a statistically infinite population, we first calculated such a sample size, which was equal to 400: $n_{inf} = Z^2_{\propto/2} * \frac{PQ}{e^2} = 2^2 * \frac{2.500}{5^2} = 400$ In the previous formula:$Z_{\alpha/2}$ represents the critical value corresponding to the standard normal distribution for the chosen significance level (in our case, 4.5%, which implies a confidence or security level in the inference of results from the sample to the whole population of 95.5%).PQ is the estimate of the population variance under unfavorable sampling conditions (i.e., it is the maximum value that this variance could have).e represents the maximum sampling error acceptable to researchers.

Table 1
Sample composition.

Industry (according to the National Code of Economic Activities—NACE—2009)	*Freq.*	*(%)*
10. Food industry	28	8.09%
11. Manufacture of beverages	2	0.58%
13. Textile industry	3	0.87%
14. Manufacture of clothing	3	0.87%
15. Leather and footwear industry	3	0.87%
16. Wood and cork industry, except furniture: basketry and plaiting	2	0.58%
17. Paper industry	7	2.02%
18. Graphic arts and reproduction of recorded media	4	1.16%
20. Chemical industry	16	4.62%
21. Manufacture of pharmaceutical products	4	1.16%
22. Manufacture of rubber and plastic products	14	4.05%
23. Manufacture of other nonmetallic mineral products	11	3.18%
24. Metallurgy: manufacture of iron, steel, and ferroalloy products	13	3.76%
25. Manufacture of metal products, except machinery and equipment	17	4.91%
26. Manufacture of computer, electronic, and optical products	6	1.73%
27. Manufacture of electrical equipment and material	11	3.18%
28. Manufacture of machinery and equipment	13	3.76%
29. Manufacture of motor vehicles, trailers, and semi-trailers	9	2.60%
30. Manufacture of other transport material	5	1.44%
31. Furniture manufacturing	4	1.16%
32. Other manufacturing industries	3	0.87%
49. Land transport and pipeline	25	7.22%
50. Maritime and inland waterway transport	1	0.29%
55. Accommodation services	16	4.62%
56. Food and beverage services	19	5.49%
58. Edition	5	1.44%
59. Motion picture, video and television program, sound recording, and music editing activities	3	0.87%
60. Programming activities and broadcasting of radio and television	2	0.58%
61. Telecommunications	2	0.58%
62. Programming, consulting, and other activities related to computer science	25	7.22%
63. Information services	4	1.16%
64. Financial services, except insurance and pension funds	5	1.44%
68. Real estate activities	5	1.44%
69. Legal and accounting activities	4	1.16%
70. Activities of head offices, business management consulting activities	11	3.18%
71. Architectural and engineering technical services; technical tests and analyses	18	5.20%
72. Research and development	3	0.87%
73. Advertising and market studies	12	3.47%
74. Other professional, scientific, and technical activities	5	1.44%
79. Activities of travel agencies, tour operators, reservation services, and activities related thereto	3	0.87%
TOTAL	**346**	**100%**

we included a two-item scale regarding competition intensity,[2] based on Jaworski and Kohli [118]. Subsequent correlation analysis revealed that correlations between the marker variable and independent, mediating, and dependent variables were very low, the largest one being 0.191. Thus, it could be concluded that common method variance was not a likely problem in our dataset. Also, a full collinearity test specially conceived for PLS-SEM [119] was carried out. The above test includes both vertical (predictor–predictor) and lateral (predictor–criterion) collinearity analyses. According to Kock [119], if all the variance inflation factors (VIFs) resulting from a full collinearity test are equal to or lower than 3.3, the model can be considered free of common-method bias. The highest VIF in our model (see Table 2) was 2.023, well below the 3.3 threshold. Therefore, this provides further evidence for ruling out the potential for common-method bias.

[2] The two items composing the measure are the following: *competition in our industry is cutthroat*, and *one hears about one competitive move almost every day*.

Table 2
Full collinearity analysis.

Constructs	*VIFs*
Size	1.037
Year of foundation	1.102
Industry (manufacturing vs. service)	1.134
Technology intensity (high-techs vs. low-techs)	1.030
Customer type (B2B vs. B2C)	1.105
Quality data	2.023
IT-enabled data analytics sensing	2.019
Marketing innovation	1.898
Market performance	1.537

4.2. Measures

Our research model included one independent variable (quality data), two mediating variables (IT-enabled data analytics sensing and marketing innovation), one dependent variable (market performance), and five control variables: size, (i.e., the natural logarithm of the number of employees), age (i.e., the year of the foundation of the company), industry (manufacturing vs. service), technology intensity (high-techs vs. low-techs), and customer type (B2B vs. B2C). We employed previously developed and validated measures by Peñalba-Aguirrezabalaga et al. [47] for the quality data and IT-enabled data analytics sensing constructs (seven items each), and by Liozu [120] for market performance (two items); while the measure capturing marketing innovation (four items) was based on traditional marketing mix components. All measures employ 7-point Likert scales and are shown in Table 3.

Quality data, IT-enabled data analytics sensing, marketing innovation, and market performance constitute formative variables [121]. In this case, the items describe and define the construct, rather than cause it [121]. For instance, different bits of computer-generated knowledge "form" or "shape" IT-enabled data analytics sensing, while different kinds of preserved knowledge that do not involve data processing "form" or "shape" quality data. Likewise, marketing innovation consists of different subtypes of innovation in marketing methods, while market performance is conceived as a combination of customer acquisition and retention.

Under these circumstances, a composite measurement model applies [122,123]. According to Sarstedt et al. [124], composite measurement constitutes a variant of formative measurement, in which the distinction should be made between causal and composite indicators. In composite measurement, the indicators or observable variables define or build up the conceptual variable; they do not cause it, but they make it up. In other words, it is a definitorial relationship [125]. In such a measurement model, constructs are obtained as a linear combination of their indicators without an error term, and each indicator enters the linear combination with a specific weight. To calculate such weights, correlations (mode "A" composites) or multiple regression (mode "B" composites) could be used [124]. The latter involves a multiple ordinary least squares (OLS) regression of the construct on its associated indicators. Due to the definitional nature of indicators vis-à-vis designed conceptual variables, this is the "natural" way of posing the relationships between indicators and constructs in composite measurement: even though indicators do not cause the conceptual variable, they contribute to defining it and, thus, the relationships should go from the indicators to the construct [124].

Finally, several control variables were included (see Table 3). Company size and year of foundation were included as prior studies have demonstrated that size and age influence performance outcomes [126–129]. Moreover, taking into consideration that prior studies have also reported direct impacts of the environment on performance outcomes [130–132], two additional variables regarding the environment were also included as controls: industry type and technology intensity. Finally, customer type was also included because of the important differences that exist between business-to-business (B2B) and

Table 3
Measurement model evaluation.

Constructs and measures	*Item wording*	*VIFs*	*Weights*	*Loadings*
Quality data Mode "B" composite Convergency: 0.856	To what extent do the following statements apply to your company? (1 = completely disagree, 7 = completely agree)			
QD1	We have well-established marketing routines and procedures	2.038	0.180*	0.754***
QD2	We have an updated and easily accessible record (in whatever format: written, video, or podcast) of sales and marketing best practices and lessons learned	2.471	0.187*	0.807***
QD3	We have updated and easily accessible information records on key projects, deals, and/or campaigns so that employees can reuse them when needed	2.129	0.177*	0.785***
QD4	We have a complete and updated "who knows what" directory so that employees can easily find the right expert to take advice from when needed	2.040	0.115†	0.746***
QD5	We have updated, relevant, and easily accessible information records about customers	1.761	0.092	0.668***
QD6	We have updated, relevant, and easily accessible information records about competitors	2.677	0.253*	0.851***
QD7	We have updated and easily accessible information about relevant trends in our markets (e.g., technological trends, regulations, social, political, and economic situation)	2.405	0.251**	0.842***
QD8+	Overall, our company has relevant documented knowledge to support its marketing and sales function	N/A	N/A	N/A
IT-enabled data analytics sensing capability Mode "B" composite Convergency: 0.735	Rate the extent to which data processed by your company's marketing related IT tools allow you to (1 = not at all, 7 = very satisfactorily):			
ITEDAS01	Identify new customers	2.275	0.116†	0.788***
ITEDAS02	Identify patterns of customer behavior	2.294	0.272***	0.831***
ITEDAS03	Analyze customers' profitability	1.653	0.063	0.588***
ITEDAS04	Identify customers' groups and/or segments	2.810	0.113	0.817***
ITEDAS05	Identify top industry insiders and influencers	2.082	0.308***	0.812***
ITEDAS06	Identify market trends	2.687	0.045	0.798***
ITEDAS07	Analyze product and/or service performance	2.690	0.312***	0.854***
ITEDAS08+	Overall, our marketing-related IT tools generate very useful and relevant knowledge	N/A	N/A	N/A
Marketing innovation Mode "B" composite Convergency: 0.883	Compare your company performance vis-à-vis competitors in the following innovation domains (1 = much worse than competitors, 7 = much better than competitors):			
MI01	Innovation in pricing	1.681	0.410***	0.838***
MI02	Innovation in product/service presentation (design, image, packaging)	2.452	0.166†	0.812***
MI03	Innovation in product/service distribution	2.327	0.294**	0.861***
MI04	Innovation in communication	2.198	0.323**	0.829***
MI05+	Innovation in marketing methods as a whole	N/A	N/A	N/A
Market performance Mode "B" composite Convergency: 0.692	Rate your company performance relative to its major competitors in the following areas (1 = much worse than competitors, 7 = much better than competitors):			
MP01	Acquisition of new customers	1.254	0.749***	0.932***
MP02	Customer retention	1.254	0.406***	0.743***
MP03+	Overall market performance	N/A	N/A	N/A
Control variables				
Company size (SIZE)	Natural logarithm of the number of employees	N/A	N/A	N/A
Year of found. (YEARF)	Year in which the company was founded	N/A	N/A	N/A
Industry (IND)	1 = manufacturing; 0 = services	N/A	N/A	N/A
Technology intensity (TI)	1 = high-tech; 0 = low-tech	N/A	N/A	N/A
Customer type (CT)	1 = B2B; 0 = B2C	N/A	N/A	N/A

+ Summary indicator for convergent validity assessment. †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, one-tailed test.

business-to-consumer (B2C) firms regarding their marketing and selling processes [e.g., 133].

4.3. Statistical analyses

The proposed research model was analyzed with SEM based on PLS using SmartPLS 3.2.8 software [134]. Unlike covariance-based SEM, which adopts a common factor approach, PLS-based SEM relies only on composites [135], as is the case with the variables under study. There are two stages in PLS-based SEM: (1) assessment of the measurement model and (2) assessment of the structural model. Conducting assessments in this order ensures that the constructs' measures are valid and reliable before attempting to draw conclusions about the relationships among the constructs [136]. Within the assessment of the structural model, considering the mediating effects explicitly defined in our hypotheses (in order to reflect how the effects of data analytics diffuse over the different elements along the information value chain), we report direct, indirect, and total effects (i.e., the sum of direct and indirect effects), whose significance was tested with bootstrapping [137].

5. Results

5.1. Measurement model evaluation

In composite measurement, researchers need to analyze convergent validity to determine the extent to which the indicators that make up a construct capture the essence of the conceptual variable they are intended to represent. According to Hair et al. [137], this requires redundancy analysis. To perform this analysis, the survey included one indicator that summarized each conceptual variable under study to calculate the correlation between the composite and this summary indicator. Appropriate convergent validity requires a correlation of 0.707 or higher, which translates into 50% of the variance explained by the summary indicator [137]. Good correlations were found for all the constructs in the research but one: market performance. As the correlation obtained in this case was very close to the established limit (0.692), no changes were made in the model (see Table 3).

Potential problems in the estimation of indicators' weights due to collinearity issues is another aspect that must be considered [138]. Ideally, VIF values should be lower than 3 [139], which is the case for all indicators used in the model. Finally, the significance and relevance of indicators should be assessed [138]. For indicators with nonsignificant weight estimates, researchers should investigate whether composite loading estimates are statistically significant and consider dropping any indicator with nonsignificant weight and loading estimates [122].

Significance levels were tested by means of a one-tailed 5000 subsample bias-corrected and accelerated (BCA) bootstrap [137]. While indicators' weights show the relative contribution of each indicator to its construct, indicators' loadings show their absolute contribution [122]. As can be observed in Table 3, although not all indicators' weights are statistically significant, all indicators' loadings are statistically relevant. Therefore, the decision has been made to keep all the indicators in the model, as their absolute contribution is at least statistically significant. Detailed comments regarding indicators' weights will be provided in the next section once the overall role of each independent and mediating variable is clarified.

5.2. Structural model evaluation

Once the quality of the measurement model was guaranteed and before evaluating the structural model, a collinearity test was carried out. This collinearity test was performed to rule out any potential bias in path coefficients due to critical levels of collinearity among the predictor constructs [137]. Analogous to the assessment of composite measurement models, VIF values should be lower than 3. Table 4 shows the results obtained. As can be observed, all VIFs are well below the established threshold, the highest one being 2.121. Therefore, collinearity in the structural model is not a problem in this research.

Table 4
Inner VIF values.

Predictor constructs	*IT-enabled data analytics sensing capability*	*Marketing innovation*	*Market performance*
Size	N.A.	1.038	1.024
Year of foundation	N.A.	1.090	1.018
Industry (manufacturing vs. service)	N.A.	1.136	N.A.
Technology intensity (high-techs vs. low-techs)	N.A.	1.034	N.A.
Customer type (B2B vs. B2C)	N.A.	1.096	N.A.
Quality data	1.000	1.954	2.121
IT-enabled data analytics sensing capability	N.A.	1.929	2.077
Marketing innovation	N.A.	N.A.	1.614

To test the significance and strength of the proposed relations, we used a one-tailed 5000 subsample BCA bootstrap [137]. Fig. 2 and Table 5 show the results obtained. As can be observed, quality data shows a very strong and positive relationship with IT-enabled data analytics sensing (β = 0.689). Thus, hypothesis H1 is supported. Moreover, both quality data (β = 0.340) and IT-enabled data analytics sensing (β = 0.317) are positively and significantly related to marketing innovation. As the indirect effect of quality data on marketing innovation via IT-enabled data analytics sensing is positive and significant (β1 × β2 = 0.219), partial mediation applies. Hence, hypotheses H2a and H2b are supported.

Moving on now to the direct and indirect effects of quality data on market performance, while the direct effect is nonsignificant (β = 0.050), all indirect effects (i.e., via IT-enabled data analytics sensing, 0.125; via marketing innovation, 0.144; and via both IT-enabled data analytics sensing and marketing innovation, 0.093) are positive and statistically significant. Hence, full mediation applies, and thus hypothesis H3a is supported. In the case of marketing-specific IT-enabled data analytics sensing, both its direct effect (β = 0.181) and indirect effect on performance via marketing innovation (β1 × β2 = 0.135) are positive and statistically significant. Therefore, partial mediation applies, and thus hypothesis H3b is supported. Finally, regarding the direct linkage between marketing innovation and market performance, this is positive and significant (β = 0.425). Hence, hypothesis H4 is supported.

Once the significance of the established relationships has been tested, the relative relevance of each of the items making up each construct when it comes to maximizing the amount of variance explained by the dependent variables will be explained. Such relevance depends on the indicators' weights (see Table 3) [137]. In the case of quality data, having updated, relevant, and easily accessible information records about competitors (γ = 0.253) and about relevant trends in the market (γ = 0.251) constitute the most relevant items within this construct, followed by having an updated and easily accessible record of sales and marketing best practices and lessons learned (γ = 0.187), well-established routines and procedures (γ = 0.180), and also about key projects, deals, and/or campaigns so that employees can reuse them when needed (γ = 0.177). Conversely, having a "who knows what" directory is barely relevant (γ = 0.115), while having updated, relevant, and easily information records about customers is totally nonsignificant. Overall, the results support the importance of quality data of both the external and internal environments to derive value along the information value chain.

In the case of IT-enabled data analytics sensing, analyzing product and/or service performance (γ = 0.312) and identifying top industry insiders and influencers (γ = 0.308) constitute the most relevant functionalities provided by marketing-related IT solutions, followed by the identification of patterns of customer behavior (γ = 0.272) and the identification of new customers (γ = 0.116). However, identifying customers' groups and/or segments (γ = 0.113) is not statistically relevant, the same as analyzing customer profitability and identifying market trends, whose specific weights are very close to 0. These results confirm that the use of marketing-oriented IT can be effective in sensing the marketing environment and generating specific knowledge about customers, the market, and products and/or services for guiding companies' decisions and strategies.

Finally, although all dimensions within marketing innovation are statistically relevant to improve market performance, innovation in pricing shows the highest weight (γ = 0.410), followed by innovation in communication (γ = 0.324) and by innovation in product/service distribution (γ = 0.294). Thus, innovation in product/service design, image, and/or packaging is the least relevant, although still significant (γ = 0.166). These findings support the significance of marketing innovation, and in particular changes in pricing, to adapt to customer needs, leading to improvements in market performance.

The coefficient of determination (R^2 value) of the mediating and dependent variables was also examined, which represents a measure of

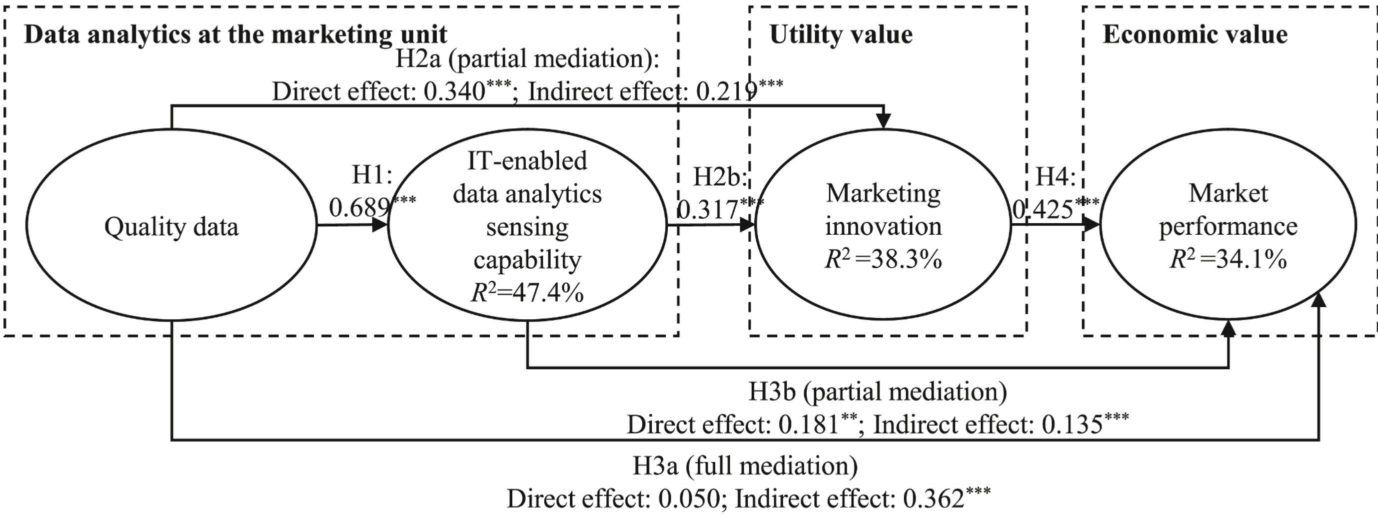

Fig. 2. Direct and indirect influences on market performance †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, one-tailed test.

in-sample predictive power that also indicates explanatory power [122, 137]. As can be observed in Table 6, the amount of variance explained for IT-enabled data analytics sensing reached 47.4%, while for marketing innovation, it scored 38.3% and for market performance 34.1%. Moreover, changes in R^2 when a specified exogenous construct is omitted from the model were analyzed by means of the so-called "f^2 effect size" [137]. According to Hair et al. [137], for a construct to be relevant when explaining another variable, its effect size should reach the minimum threshold of 0.02. This was the case for both the independent and mediating variables, except for quality data vis-à-vis market performance.

6. Discussion

This research takes an information value chain perspective and builds upon the knowledge-based view of the firm to theorize about the different value-generating potential of the marketing unit's data analytics assets and capabilities for performance outcomes at the marketing unit and the firm. Such results shed light on the relative importance of quality data and IT-enabled data analytics sensing capability in the marketing unit for utility value through innovations in the marketing mix and for economic value through improved firm performance. In doing so, this research contributes to theory and practice in several meaningful ways, which are explained next.

6.1. Theoretical contributions

By answering recent calls for research regarding data analytics in a given unit (or area) [13] and its relation with unit-level and firm-level outcomes [17], this study makes several contributions that come to light when situating this research within the literature on data analytics. Data analytics is a broadly used concept within the IS discipline encompassing multiple elements including data and technological infrastructure [e.g., 140,141], the use of data and data analytics tools [e.g., 142,143], domain knowledge [50], technical skills [e.g., 38], management skills [144], organizational learning [13], and data culture [141]. As such, it is often conceptualized as a multidimensional (or second-order) construct that integrates a wide variety of disparate assets and capabilities. In this sense, data analytics represents a "domain concept" that can take on multiple meanings [145], where much specificity and precision can be gained by unpacking it into more concrete concepts [146]. Thus, conceptualizing data analytics into the two specific constructs of quality data as an asset and IT-enabled data analytics sensing as a capability represents a contribution to specificity, also demanded in recent IT research [132].

Such a concrete conceptualization allows us to add precision in theorization efforts by specifying how each specific data analytics construct (i.e., quality data and IT-enabled data analytics sensing capability) relates differently to outcomes at the unit- and firm-levels. In doing so, this study also contributes by answering calls for research into how different concrete IT-related assets (such as quality data) and capabilities relate differently to change and performance outcomes [17]. First, we theoretically explain and empirically support the idea that quality data and IT-enabled data analytics sensing have different potential for enabling changes in marketing actions, and as such, have distinct effects (i.e., direct, partially, or fully mediated) on subsequent variables along the information value chain. Thus, quality data contributes to value creation (i.e., marketing innovation through changes in the marketing mix) directly and indirectly through IT-enabled data analytics sensing, while its positive influence on firm market performance is fully mediated by IT-enabled data analytics sensing and marketing innovation. In other words, quality data provides utility value, but its effects on economic value are fully mediated by both the capability that it enables and the utility value that it partially provides. On the other hand, IT-enabled data analytics sensing capability creates utility value by directly enabling changes in the marketing mix (i.e., marketing innovation), and it also creates economic value (i.e., firm market performance) directly as well as indirectly via marketing innovation. Overall, defining data analytics constructs concretely by separating them into an asset and a capability, as well as adopting an information value chain perspective allows us to explain how each construct relates in a distinct way to different elements in the chain.

Second, the fact that our two concrete data analytics constructs are operationalized as composites also contributes to gain specificity about which particular aspects of quality data and IT-enabled data analytics sensing capability contribute more or less to utility and economic value creation. Regarding quality data, the findings obtained show that, in relative terms (i.e., according to indicators' weights), all knowledge stocks included within this construct are relevant but one whose absolute contribution (i.e., indicator loading) is nevertheless significant [122]. This seems logical, considering that quality data contributes simultaneously to the remaining three variables in the information value chain, namely, IT-enabled data analytics sensing, marketing innovation, and market performance. Thus, if one specific knowledge item is not particularly relevant for one of the dependent variables, it may be important for the other, which means that, in the end, all of them are relevant to support the entire information value chain.

The statistical significance of all the items making up the quality data

Table 5
Structural model evaluation, Part I.

	Effects	*STDEV*	*t statist.*	*p-values*	*5%*	*95%*
Direct effects on IT-enabled data analytics sensing						
Quality data	**0.689**	**0.033**	**20.821**	**0.000**	**0.061**	**0.298**
Direct effects on marketing innovation						
Size	0.039	0.040	0.983	0.163	−0.024	0.108
Year of foundation	0.033	0.044	0.765	0.222	−0.040	0.103
Industry (manufacturing vs. service)	−0.016	0.046	0.347	0.364	−0.091	0.059
Technology intensity (high-techs vs. low-techs)	−0.020	0.044	0.459	0.323	−0.094	0.053
Customer type (B2B vs. B2C)	−0.035	0.046	0.758	0.224	−0.109	0.040
Quality data	**0.340**	**0.073**	**4.670**	**0.000**	**0.217**	**0.457**
IT-enabled data analytics sensing	**0.317**	**0.069**	**4.577**	**0.000**	**0.190**	**0.420**
Direct effects on market performance						
Size	−0.028	0.043	0.642	0.260	−0.097	0.045
Year of foundation	0.046	0.047	0.985	0.162	−0.024	0.133
Quality data	0.050	0.077	0.645	0.259	−0.079	0.173
IT-enabled data analytics sensing	**0.181**	**0.072**	**2.505**	**0.006**	**0.061**	**0.298**
Marketing innovation	**0.425**	**0.062**	**6.863**	**0.000**	**0.314**	**0.519**
Indirect and total effects of quality data on marketing innovation						
Indirect effect via IT-enabled data analytics sensing	**0.219**	**0.049**	**4.420**	**0.000**	**0.130**	**0.294**
Total effect (direct + indirect)	**0.559**	**0.046**	**12.171**	**0.000**	**0.470**	**0.623**
Indirect and total effects of quality data on market performance						
Indirect effect via IT-enabled data analytics sensing	**0.125**	**0.050**	**2.500**	**0.006**	**0.041**	**0.204**
Indirect effect via marketing innovation	**0.144**	**0.039**	**3.708**	**0.000**	**0.085**	**0.214**
Indirect effect via IT-enabled data analytics sensing and marketing innovation	**0.093**	**0.025**	**3.644**	**0.000**	**0.053**	**0.135**
Total indirect effect	**0.361**	**0.056**	**6.469**	**0.000**	**0.265**	**0.449**
Total effect (direct + indirect)	**0.412**	**0.049**	**8.397**	**0.000**	**0.319**	**0.479**
Indirect and total effects of IT-enabled data analytics sensing on market performance						
Indirect effect via marketing innovation	**0.135**	**0.036**	**3.736**	**0.000**	**0.079**	**0.196**
Total effect (direct + indirect)	**0.316**	**0.077**	**4.115**	**0.000**	**0.182**	**0.435**

Table 6
Structural model evaluation, Part II.

	IT-enabled data analytics sensing	*Marketing innovation*	*Market performance*
R^2	47.4%	38.3%	34.1%
Effect sizes (f^2)			
Size	N.A.	0.002	0.001
Year of foundation	N.A.	0.002	0.003
Industry (manufacturing vs. service)	N.A.	0.000	N.A.
Technology intensity (high-techs vs. low-techs)	N.A.	0.001	N.A.
Customer type (B2B vs. B2C)	N.A.	0.002	N.A.
Quality data	**0.902**	**0.096**	0.002
IT-enabled data analytics sensing	N.A.	**0.085**	**0.024**
Marketing innovation	N.A.	N.A.	**0.170**

construct also provides empirical support for the relevance of preserving and storing data from both the external and internal environment, as was already suggested by Cao et al. [33], Mikalef et al. [38], and Torres et al. [31]. Likewise, "knowing about" or explicit knowledge [147]—that is, knowledge about competitors and markets; about best practices and lessons learned; about key projects, deals, and/or campaigns; and about "who knows what"—as well as "knowing how" or tacit knowledge [62,148]—that is, marketing routines and procedures—prove to be equally relevant to develop IT-enabled sensing capability, outperform competitors in marketing innovation, and enhance market performance. In other words, the "concrete representation" (i.e., know-what) and the "concrete interpretation" (i.e., know-how) of knowledge [149–152] are equally important.

The fact that having updated, relevant, and easily accessible records about customers is the only indicator whose weight is not statistically significant within the quality data construct may be apparently surprising. However, this may just tell us that having quality information records about customers is the minimum expected thing within the marketing unit [153,154]. As a result, the mere fact of having such information does not make the difference among firms when it comes to promoting successful marketing innovation and subsequent market performance. What really makes the difference is being able to identify patterns of customer behavior from such data by using data analytics techniques [155,156].

Regarding the IT-enabled data analytics sensing capability variable, three first-order capabilities appear to be the most important in promoting marketing innovation and market performance: being able to identify patterns of customer behavior, being able to analyze product/service performance, and being able to identify top industry insiders and influencers. Thus, beyond the relevance traditionally awarded in the marketing literature to customer knowledge [e.g., 157-160] and product knowledge [e.g., 106, 111, 161,162], top industry insiders and influencers emerge as a key ingredient to increase the chances of successful marketing innovation and market performance. Today, insiders and influencers are the ones dictating the directions of the different industries: they have built a sizable social network of people following them, and due to their high authenticity and credibility, marketers can get better market acceptance and increase market performance if they collaborate with them [163].

Moreover, it is interesting to note that analyzing product/service performance is much more relevant than analyzing customers' profitability and identifying customers' groups and/or segments (the weights of these last two indicators are insignificant). The lack of relevance of identifying customers' groups/segments may be related to the fact that today marketing analytics enables a fully individualized approach to marketing [e.g., 22] On the other hand, the lack of relevance of analyzing customers' profitability may be related to the type of firm performance we are focusing on (market performance: i.e., acquiring new customers and retaining existing ones). In this case, knowledge about existing customers' profitability is not a key issue, but being aware of product/service performance (i.e., knowing what products/services are most successful in the market) certainly is.

6.2. Practical implications

From a practical viewpoint, this research provides a more fine-grained picture about the specific knowledge resources in the marketing context that need to be considered to promote marketing innovation and enhance market performance, providing managers with more concrete information to guide their knowledge management efforts [e.g., 47,164]. According to the results obtained, data analytics efforts at the marketing unit should be targeted to developing analytic capabilities regarding the identification of patterns of customer behavior, the detection of top industry insiders and influencers, and the analysis of product and/or service performance. Moreover, it should be noted that relatively "cheap" information strategies, such as keeping track of best practices and lessons learned, as well as of past projects, deals, and/or campaigns, and developing marketing routines and procedures prove to be very rewarding [e.g., 165]. Indeed, they enable the development of more effective marketing mix strategies based on past experiences on what has worked and not. Additionally, keeping abreast of competitors' marketing strategies and market trends is of utmost importance.

Finally, this study also reveals which of the marketing mix components are the most important for innovating and enhancing market performance. In this vein, innovation in pricing seems to be the most effective component, followed by innovation in communication, distribution, and product/service presentation. This finding supports the idea that the pricing capability of a firm constitutes a key antecedent of firm performance [83]. Innovation in pricing is a complex and difficult-to-imitate process. It encompasses not only the price-setting capability within the firm (identification of competitor prices, setting pricing strategy, and translation from pricing strategy to price) but also the price-setting capability vis-à-vis customers (convincing customers on the price change logic and negotiating price changes with major customers) [120]. Pricing is unique for each organization, and it has a direct and substantial effect on firm performance, being the most effective strategy to differentiate and improve organizations' market performance [166]. Therefore, being aware of customers' behavior when faced with price changes and different discount policies is a key aspect to which IT-enabled sensing capability could contribute when it comes to shaping the firm's pricing innovation strategy.

6.3. Limitations and future research

This study has several limitations that provide future opportunities for research. For example, this investigation, like others taking an information value perspective [e.g., 57,60], could not investigate all the resources, activities, and outcomes associated with the information value chain of the whole organization. Thus, future research could incorporate additional chain elements to further explain the value creation potential of concrete data analytics assets, capabilities, and processes. In addition, although the variance approach that we took allowed us to evaluate the distinct and net effects of quality data and IT-enabled data analytics sensing on marketing unit innovation and market performance, a future contribution would be to take a process approach to investigate the value creation potential of different stages and activities involved in data analytics, hence adding time ordering as well as analyzing the information value chain longitudinally [167].

An additional limitation arises from the sample of companies, as it included merely Spanish organizations and thus, findings may have been influenced by the national and cultural context. Given that the implementation, adoption, and use of data analytics vary significantly across countries [e.g., 168,169], future research should test the developed model in other geographical settings for generalizability purposes or to theorize about cultural or geographical differences.

Finally, although we looked at how data analytics at the marketing unit enabled marketing innovation in terms of changes in the marketing mix (a form of incremental innovation), future research could be aimed at studying the possibility of data analytics' contributions spanning the marketing unit's boundaries and enabling radical innovations. Therefore, future research could investigate the potential of marketing data analytics for fostering innovation in other areas of the organization, such as new product or service design and development.

Besides the above opportunities stemming from this study's limitations, future research could focus on the role that data analytics culture plays for a given unit's data analytics resources and performance at the rest of the firm.[3] Given that organizations with a strong analytic culture invest more on data analytics capabilities (i.e., tools, methods, and people), and tend to rely more on the usage of analytics to support their decisions [170], future research could investigate the potential positive moderating effect of data analytics culture in the relation between data analytics resources and performance.

6.4. Conclusion

In summary, this research investigates the impact of data analytics assets and capabilities on the marketing function and the market performance of the firm. Building upon the knowledge-based view of the firm and from an information value chain viewpoint, this study shows that both quality data (i.e., assets) and IT-enabled data analytics sensing capability have utility value by facilitating marketing innovation at the marketing unit. Additionally, while IT-enabled data analytics sensing capability has direct economic value through its direct effect on firm market performance, the effects of quality data on market performance are fully mediated, thus showing how data assets lose direct influence as they travel through the information value chain. Therefore, this research clarifies the link between data analytics in the marketing unit and performance by disaggregating data analytics into assets and capabilities, as well as by including both marketing unit- and firm-level performance.

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All co-authors contributed equally to the development of this article.

Declaration of Competing Interest

None.

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Josune Sáenz is an Associate Professor and Vice Dean for Research and Transfer at Deusto Business School (University of Deusto, Spain). She also chairs the Academic Committee of the joint Doctorate Program on Business and Territorial Competitiveness, Innovation and Sustainability offered by the University of Deusto, the Pontifical University of Comillas, and the Ramon Llull University. Her research focuses on intellectual capital, knowledge management, and innovation.

Ana Ortiz de Guinea is a Computer Engineer from the University of Deusto and holds a PhD in Management from Queen's University. She is a Professor in Strategy and Management Information Systems at HEC Montréal. Her research focuses on emotional and cognitive processes during interactions with information systems, organizational- and individual-level perceptions of information systems, and quantitative methods and their application in Information systems research.

Carmela Peñalba-Aguirrezabalaga holds a PhD in Business and Territorial Competitiveness, Innovation, and Sustainability from the University of Deusto (Spain) and a PhD in Business and Management from Lappeenranta University of Technology (Finland). She is an Assistant Professor at the Marketing Department of Deusto Business School, and her research focuses on marketing and intellectual capital.