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ARTICLE

Data-driven marketing image: scale development and validation

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Abstract

Purpose – This study develops and validates a measurement scale for assessing the corporate image of companies that use data-driven marketing in their decision-making and actions in online retailing.

Theoretical framework – The study is grounded in theories of corporate image and consumer behaviour, integrating concepts of data-driven marketing and privacy to develop the DDMI scale.

Design/methodology/approach – A mixed methods approach is employed, beginning with a deductive literature review and qualitative expert interviews to generate scale items, followed by a pilot study and a large-scale survey of 301 consumers via Amazon MTurk. Exploratory and confirmatory factor analyses are conducted to validate the scale.

Findings – DDM strategies significantly affect how customers perceive a company's image. The DDMI provides a validated scale that measures aspects that are important to customers, such as privacy concerns and personalised customer experience. It reveals that effective communication, efficient payment processes and robust customer support are vital for a positive corporate image.

Practical & social implications of research – The study offers a novel tool to assess corporate image in environments characterised by high data usage. It enables companies to refine their DDM strategies by identifying how specific practices affect consumer perceptions.

Originality/value – This research introduces the first validated scale to measure consumer perceptions of corporate image in DDM contexts. It advances marketing theory by capturing key dimensions of the digital era, personalisation, privacy and support.

Keywords: Data-driven marketing, image, scale development, retail marketing.

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1 Introduction

The current digital era is characterised by the massive production of data from a variety of media, channels, and digital devices, which has led to a profound transformation in business management and marketing in particular. Wedel and Kannan (2016) highlight the emergence of data-rich environments due to the exponential growth of new media, channels, digital devices, and software applications. In the face of this data overload, an innovative working methodology has emerged in marketing that focuses on data collection, analysis, and decision-making, known as data-driven marketing (DDM) (Mulvenna et al., 1998). In the case of constantly evolving markets, this methodology enables companies to be more responsive, agile, and customer-focused in order to meet their needs more effectively. Specifically, DDM assists in evaluating key metrics to select more effective business strategies and tactics (Braverman, 2015). This allows organisations to adapt to the digital economy, maintain competitiveness, and drive growth, thus contributing significantly to economic impact (Borges et al., 2021; Johnson et al., 2019; Saura et al., 2021; Sultana et al., 2022).

Previous research highlights the need to adopt methodologies that collect and analyse data and enable companies to be agile and customer-centred in ever-evolving markets (Rahman et al., 2020). According to De Luca et al. (2021), to reap the benefits of data proliferation, organisations must adopt an approach that masters three key activities: 1) identification of customer behaviour patterns, 2) the ability to respond in real time, and 3) effective exploration and use of DDM. These activities increase value for investors and shareholders by improving profitability, enhancing customer satisfaction, creating competitive advantages, and positioning the company as a leader in innovation and customer orientation (Borges et al., 2021; Grandhi et al., 2020).

However, some experts argue that relying too heavily on data-driven methodologies can lead to the loss of human intuition and creativity in decision-making processes. An over-reliance on data could limit companies' ability to innovate and adapt quickly to market changes, as they may be constrained by the patterns established by historical data. Additionally, the use of data raises concerns about privacy implications and potential ethical issues related to the extensive collection and use of customer data for profit purposes (Jurkiewicz, 2018). There needs to be a stronger link between marketing strategies and user behaviour, so it is important to synchronise the two (Grandhi et al., 2020). Thus, marketing professionals can achieve positive outcomes if they correctly understand the impact of marketing strategies on consumer behaviour patterns through data from different sources (Sheth, 2021). Moreover, with a data-based approach, marketing strategies are not just business choices, but also actions experienced through continuous interactions with brands that influence consumers' perceptions of the company's image (Botezatu, 2019; Braverman, 2015). Specifically, it is recognised that corporate image is the cumulative result of various messages stored in collective memory and is shaped as an integral result of the interaction of all the experiences, beliefs, feelings, knowledge, and impressions that each individual has about the organisation (Bernstein, 1984).

In particular, the use of DDM not only brings benefits in terms of management and profitability, but can also contribute to the development of a favourable image of companies, as employing more effective marketing actions and targeting the right segments will contribute to a positive perception of companies in the market (Vijaya & Rahayu, 2021). In this sense, a strong and positive image can be one of a company's most valuable assets, while a negative image can have significant adverse effects on its success and long-term sustainability (Graciola et al., 2020; Özkan et al., 2020). Previous studies recognise that corporate image, as an essential intangible asset, directly impacts consumers' perceptions and decisions (Sirgy et al., 1997; Spector, 1961). Specifically, the perceived image of the company exerts a significant influence on consumers by guiding their behaviour (Zhang, 2015).

Recent research has highlighted the importance of adapting the way in which corporate image is measured in online contexts with high technology and the evolution of digital marketing (Flavián et al., 2004; Hopkins & Alford, 2006; Tran et al., 2015). Specifically, the measurement of image, including dimensions of online reputation, perceived security, and quality of service received, has been explored.

Previous literature has focused on consumers' ethical perceptions of companies' use of data for decision-making within organisations (Olteanu et al., 2019). However, there is a further gap in explaining how companies are perceived through the use of customer data in their strategies. Despite the importance of measuring image in a dynamic and data-oriented context, the impact of companies employing DDM strategies on the image perceived by consumers has not been discovered. The present work starts from the fact that many executives are making data-based decisions and employing DDM strategies (Grandhi et al., 2020). Thus, strategies and actions based on DDM will impact consumer perceptions, making it crucial to analyse the impact of these actions on consumer perceptions of corporate image. This will make it possible to adjust the perception of the company's image to the realities of the current market and to improve strategies for engaging with consumers.

Therefore, the central purpose of this research is to build a tool that allows the evaluation of the image of a company that implements DDM strategies in its interactions with customers. This work seeks to understand the impact of such strategies on customers' perceptions of the company and to determine how the implementation of DDM strategies modifies the company's image. Moreover, this study contributes to the research on the use of external data by organisations by highlighting the relationship between data-based strategies and their influence on customer perceptions. Specifically, this research is situated within online retailing, a sector that focuses on using customer data to develop strategies (Dekimpe, 2020). It is characterised by high growth and high competitiveness (Verhoef, 2021). This choice is justified because the retail sector, and e-commerce in particular, exhibits a high intensity in the use of DDM strategies, which facilitates the direct observation of their effects on perceived corporate image (Dekimpe, 2020; Verhoef, 2021). The findings of this research can also be applied to other contexts where intensive DDM strategies are implemented, such as the financial, healthcare, or technology sectors.

While DDM strategies enhance decision-making and competitiveness for companies, they also shape how consumers perceive corporate image. The increasing reliance on data-driven strategies influences consumer trust, engagement, and perceptions of brand identity. Given this impact, it is essential to assess how consumers interpret and evaluate the corporate image of companies that implement DDM practices. Therefore, this study examines the consumer perspective on corporate image in DDM environments.

To achieve these objectives, this study focuses on developing a scale to assess perceptions of the image of companies that use data-based decision-making strategies and tactics. This scale has been named the Data-Driven Marketing Image (DDMI). The research began with a thorough review of previous studies to determine the essential dimensions of the scale. Detailed interviews were then conducted with specialists in data-based marketing and corporate image. Next, a preliminary testing phase was developed to allow for adaptation of the scale, followed by exploratory factor analysis to discover the dimensions of the scale. The process culminated in the validation of the scale and its development through its application to a representative sample of consumers in contact with companies that employ DDM in their strategies.

2 Literature review

2.1 Data-driven marketing

The use of data from billions of people worldwide has driven to unprecedented growth in personalised advertising and online services (Jabbar et al., 2020). Continuous data collection through new applications and technologies such as the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) is driving this expansion (Acemoglu et al., 2022).

Data-driven marketing (DDM) is the practice of employing vast amounts of data to make marketing decisions (Mulvenna et al., 1998). It involves gathering offline and online customer data, analysing it to understand consumer psychology and purchasing patterns, and formulating personalised strategies to connect with the target audience (Grandhi et al., 2020). DDM ensures that marketing efforts are focused and relevant to meet customer needs, outpacing the competition in the process (Glass & Callahan, 2015).

The adoption of DDM and digital technologies has transformed the role and scope of marketing. Shah and Murthi (2021) identified five stages in this transformation: 1) Creativity: The traditional role of marketing, focused on developing communication strategies; 2) Relevance: Identifying customers and aligning efforts to meet their needs; 3) Analytical capability: Integrating analytics into marketing to drive growth; 4) Accountability: Demonstrating the financial impact and ROI of marketing efforts; 5) Technology: Adopting digital technologies for marketing purposes.

Crucially, technology is becoming fundamental in establishing customer-centred processes as companies use data to anticipate customer needs (Grandhi et al., 2020). Big data analytics allows organisations to gain insights from customer experiences, enabling actions such as monitoring, prioritising, adapting, and designing the customer journey across touchpoints (Félix et al., 2018; Holmlund et al., 2020).

De Luca et al. (2021) highlight that information technologies open up new marketing opportunities. Key DDM strategies include: 1) Advanced segmentation: Using demographic, behavioural, and preference data for precise market segmentation (Dolnicar et al., 2012; Liu et al., 2019); 2) Personalisation of content and messages: Using data on past customer behaviour to tailor content (Saura et al., 2019). Platforms such as Google Ads and Meta Ads enable the targeting of specific audiences based on interests, online behaviour, and search history (Hao & Yang, 2022; Madadi et al., 2021; Shin & Yu, 2021); 3) Price optimisation: Implementing dynamic pricing strategies based on demand, competition, and other factors (Acemoglu et al., 2022; Ma & Hu, 2020; Mao et al., 2019); 4) Automated marketing campaigns: Sending follow-up emails after shopping cart abandonment, birthday reminders, and personalised offers based on purchase history (Mero et al., 2020, 2022; Silva et al., 2023); 5) Customer experience optimisation: Using data to identify friction points in the customer journey, such as where customers abandon the purchase process, and making improvements to facilitate conversion (Holmlund et al., 2020; Kushwaha et al., 2021; Mishra et al., 2021; Valdez-Mendia & Flores-Cuautle, 2022).

2.2 Company image and data-driven marketing

A company's image is a crucial intangible asset that influences consumer perceptions and decisions (Dichter, 1985). It reflects the overall impression an entity leaves in the minds of others. Historically, the measurement of corporate image has evolved significantly. Spector (1961) initially categorised a company's personality into six distinctive factors, aiming to measure the congruence between the consumer's self-image and the brand image (Sirgy et al., 1997).

Barich and Kotler (1991) introduced a key distinction between marketing image and corporate image, extending the analysis to include specific elements such as product, communication, and distribution channels. Andreassen and Lindestad (1998) proposed three indicators for measuring image, emphasising that reputation, values, and general company behaviour influence corporate image.

Tran et al. (2015) developed a holistic definition of corporate image that includes seven dimensions: 1) visual expression, 2) positive feelings, 3) environmental expression, 4) internet presence, 5) staff appearance, 6) attitude and behaviour, and 7) communications. Notably, the emergence of the internet presence dimension is critical for companies to enhance their image and leave a positive impression on stakeholders (Tran et al., 2015). Burt et al. (2007) used non-traditional techniques to measure store image through customer-generated visual interpretations, focusing on international retailers such as IKEA.

With the advent of the digital age, the importance of online image has increased. In the financial sector, Flavián et al. (2004) developed a scale to measure a bank's corporate image on the Internet, taking into account reputation, perceived security, and service quality. In online retailing, Hopkins and Alford (2006) created a scale to assess an e-tailer's image, identifying functional dimensions (price, merchandise, service) and affective dimensions (atmosphere, convenience, self-concept).

In summary, the evolution of corporate image measurement has shifted from traditional methods to incorporate the complexities of the digital environment and evolving consumer expectations. The advent of data-driven marketing (DDM) provides an opportunity to measure a company's image and the impact of DDM strategies on it. Adopting a data-driven strategy offers a new paradigm for understanding and redefining corporate image from a customer experience perspective.

Unlike previous corporate image measurement models that focus on banking services or general perceptions of the environment and communication (Flavián et al., 2004; Tran et al., 2015), this study aims to assess dimensions that are explicitly linked to consumers' concrete experiences in environments where data heavily mediate corporate marketing strategies.

Therefore, it is essential to develop a specific tool to capture the most relevant dimensions as perceived by customers regarding DDM actions. To achieve this, dimensions such as content personalisation, the ethical use of customer information, and the perception of privacy in digital interactions will be considered. This conceptual refinement will allow for a more accurate assessment of the impact of DDM strategies on the construction of perceived corporate image.

Thus, this research paper seeks to address the following research question:

RQ1: How do data-driven marketing (DDM) strategies influence customers' perceptions of a company's corporate image?"

3 Materials and methods

In research, accurate measurement is crucial, which is why the careful development of measurement scales is of great importance (DeVellis & Thorpe, 2021). Specifically, scales can be developed using either a deductive approach, based on the analysis of previous literature as a theoretical basis for defining the constructs to be evaluated, or an inductive approach, which relies on qualitative methods to identify the constructs and the different elements of the scales (Clark & Watson, 1995). The present study adopts a combined deductive-inductive approach for the proposed measurement of consumers' perceived image of companies using data-driven marketing (DDMI – Data-Driven Marketing Image) and follows the steps used in previous work (Aljukhadar et al., 2022; Wang et al., 2024) (see Table 1).

3.1 First phase - Literature review for item collection

This stage aimed to conceptualise the constructs for measuring the projected image of a company employing data-driven marketing (DDM) strategies. Using a deductive approach, a literature review was conducted to identify the most relevant dimensions related to the image perceived by customers when interacting with companies using DDM. The following dimensions were identified:

1. *The customer is at the centre of the organisation.* Companies applying DDM aim to attract and retain the most profitable customers through specific insights (Morgan et al., 2019). They collect data on consumer interests and sentiments (Camilleri, 2020), which allows them to focus on the customer, thereby increasing engagement and sales (Costa et al, 2018; Grandhi et al., 2020). DDM enhances marketing efforts and drives innovation (Woerner & Wixom, 2015; Trabucchi & Buganza, 2019). Putting the consumer at the centre through the use of digital technologies is essential to offer more excellent value (Shah & Murthi, 2021).

2. *Personalised communications.* DDM facilitates the identification of critical buyers based on their history and behaviour (Dremel et al., 2020). This enables the development of relevant communications about products and offers, increasing engagement and sales (Camilleri, 2020). It focuses on tracking users to deliver personalised advertising that is tailored to their preferences and online behaviour (Aiolfi et al., 2021; Boerman et al.,

Table 1
Scale Generation Process

	Action Performed	Description
a.	Literature review for item collection-First phase.	Through the literature review related to the characteristics and attributes observed by customers of companies using DDM, 16 items were obtained.
b.	In-depth interviews with experts for item collection-Second phase and Scale Refinement-First phase.	Subsequently, through content analysis of six in-depth interviews with experts, 12 additional items were generated, and all the generated items were refined. In total, 28 items were refined for scale development.
c.	Scale refinement-Second phase	A questionnaire with 28 items adapted from the previous stages was implemented. A sample of 31 participants was collected through convenience sampling among customers who had made online purchases in the last 12 months to validate the understanding of the questionnaire and its structure.
d.	Exploratory factor analysis	A sample of 100 subjects was subsequently collected through Amazon MTurk, and an exploratory factor analysis (EFA) was carried out. Three dimensions were found. In addition, the instrument's possible Common Method Bias (CMB) was analysed through a single-factor analysis and VIF analysis.
e.	Scale validation and development	Finally, a random sample of 201 subjects was used. A confirmatory factor analysis (CFA) with three dimensions was performed. Analyses of convergent and discriminant validity of the constructs were also conducted, along with an overall model fit assessment and weight and loading assessment.

Source: Own elaboration

2017). Mobile technologies and geolocation allow for personalised ads and coupons based on location (Tong et al., 2020). Companies strive to understand their customers in order to deliver appropriate content and propositions (Grover et al., 2018).

3. *Personalised recommendations.* DDM enables the personalisation of recommendations. Companies analyse behaviours and preferences using recommendation systems with content-based and collaborative filtering (Tripathi et al., 2021). Machine learning algorithms enhance the accuracy of these recommendations (Xiao et al., 2018). Personalised recommendations increase customer satisfaction and engagement (Ettl et al., 2020). Users seek recommendations aligned with their previous purchases and interests (Chinchanachokchai et al., 2021).

4. *Customer experience.* Customer experience (CX) is a fundamental reason for using DDM (Bashar et al., 2022). CX refers to the customer's internal response to any contact with the company (Meyer & Schwager, 2007), including cognitive and emotional aspects (Gentile et al., 2007; Tyrväinen et al., 2020). DDM creates personalised experiences based on income and purchases (Grandhi et al., 2020). Data enhances personalised interactions and optimises design and functionality (Dremel et al., 2020; Zhang et al., 2020). Companies can personalise every aspect of the user experience (Grover et al., 2018). Technologies such as IoT, augmented reality, virtual reality, and chatbots transform the customer experience (Hoyer et al., 2020).

5. *Data use and security.* Privacy and regulatory compliance are essential in data usage (Miklosik & Evans, 2020). Companies employing DDM must ensure data security, obtain informed consent, and guarantee transparency (Ivanov et al., 2022). Failure to do so can violate privacy and damage corporate image (Camilleri, 2020). Adherence to regulations and consideration of social impact are critical for ethical DDM practices (Nassar & Kamal, 2021). Based on the above reviews, the items listed in Appendix A were proposed.

The existing body of research on corporate image (Flavián et al., 2004; Tran et al., 2015; Hopkins & Alford, 2006) highlights the importance of multiple dimensions, but none specifically addresses the impact of DDM strategies. To bridge this gap, this study integrates insights from marketing analytics (Saura et al., 2021), customer experience (Grandhi et al., 2020; Holmlund et al., 2020), and privacy concerns (Nassar & Kamal, 2021) to define a relevant set of dimensions.

The five dimensions – customer centricity, personalised communications, personalised recommendations, customer experience, and data use and security – capture the essential aspects of corporate image formation in a data-driven environment. These dimensions are consistent with previous studies on customer engagement and brand perception in digital settings (Camilleri, 2020; Hoyer et al., 2020). While alternative dimensions such as "brand trust" and "corporate social responsibility" were considered, they were ultimately excluded due to their indirect relationship with the immediate customer experience of DDM practices. The five dimensions selected represent the core areas where consumers interact with data-driven strategies, ensuring the validity of the scale in measuring DDMI. This selection also accounts for increasing consumer concerns about data security, transparency, and the balance between personalisation and privacy (Bandara et al., 2017). By focusing on these dimensions, this research provides a targeted approach that reflects the reality of digital marketing environments where consumer perceptions are shaped by data-driven interactions (Acemoglu et al., 2022). These dimensions will be further operationalised in the next section and form the basis for the scale development.

3.2 Second phase - In-depth interviews with experts for item collection

With the aim of supplementing the scale based on the items selected in the literature review, a qualitative study was conducted to integrate the scale. Qualitative data collection began with an exploratory approach based on in-depth interviews. A sample of academic researchers and marketing experts was selected to ensure the diversity and representativeness of opinions. A screening question was included at the beginning of the interview process to ensure that expert participants had engaged in transactions with companies implementing DDM in the past 12 months. Participants were asked to confirm their recent interactions with companies using DDM strategies by providing examples of specific transactions or experiences.

They were also asked to describe how these companies implemented data-driven strategies in their marketing approaches. This verification process helped to ensure that the selected experts had direct and relevant exposure to DDM practices, thereby enhancing the validity of their insights. Six in-depth interviews were conducted, each lasting an average of forty minutes. These interviews were carried out face-to-face to facilitate understanding and capture of essential details in the perception of DDMI. The interviews began by sharing the items generated in phase one through the literature review to gather observations on the clarity or meaning of the items. Once the interviews were completed, a content analysis helped to identify new ideas, themes, and categories that were important for supplementing the proposed scale. At the end of this phase, 28 items for the DDMI scale were generated to ensure the face validity, content analysis, and inter-rater reliability of the scale. These items were implemented in the questionnaire design and are presented in Supplementary Data 3 – Appendix A. All items were rated on a 7-point Likert scale where 1 = strongly disagree and 7 = strongly agree (Supplementary Data 2 – DDMI Scale Questionnaire).

3.3 Third phase - Scale refinement

At this stage, the design and implementation of the questionnaire began, and its development took place in two phases. The first was a convenience sampling pilot study (Stratton, 2021) in June 2023. The questionnaire was administered via Google Forms in random blocks of questions, collecting 39 responses, of which eight had to be discarded due to incomplete questionnaires. During the pilot application, participants were consulted about their understanding of the items and the visual structure of the questionnaire. Ultimately, based on participant feedback, no changes were necessary, and the questionnaire remained unchanged.

The second phase began in July 2023, with the distribution and administration of the questionnaire to consumers recruited via Amazon MTurk. The study implemented several control strategies recommended in the literature were implemented to ensure the quality of the data collected through Amazon MTurk (Dennis et al., 2020; Wessling et al., 2017) (Supplementary Data 1 – DDMI Scale Dataset and Codebook).

Firstly, an alphanumeric verification code was provided exclusively to participants who completed the questionnaire. This code had to be entered on the platform to confirm legitimate completion and to prevent automated or fraudulent responses. Secondly, three reverse-coded questions were included to mitigate the risk of convenience responses and bot participation. These questions were designed to identify inconsistencies in responses and eliminate those that exhibited systematic response patterns without a conscious evaluation of content (see Supplementary Data 4 – Appendix B). Additionally, the questionnaire was structured into six blocks of questions which were presented to participants in random order. This technique reduced the impact of order bias and helped to prevent mechanical responses due to fatigue effects or a tendency to answer uniformly based on the questionnaire structure (Dennis et al., 2020; Wessling et al., 2017).

The data collection process was carried out in a single phase, obtaining responses from consumers who interact with companies implementing DDM strategies. In order to define this target group, a list of companies with different levels of adoption of data-driven strategies was compiled, allowing for a more precise segmentation of participants. Furthermore, to ensure a homogeneous understanding of the research context, a clear definition of DDM was provided, along with a practical example of its application. This ensured that respondents had an appropriate frame of reference before completing the questionnaire. Taken together, these strategies enhance the reliability of the data collected and ensure the validity of the results obtained in this study. After applying data quality control measures, a total of 301 fully completed and valid responses were included in the final analysis (35% of the total obtained). Responses that were incomplete or failed attention checks were excluded to ensure the reliability of the dataset. Table 2 presents the descriptive data of the final sample. Specifically, the study consisted of 61.92% women, 66.8% were individuals aged between 26 and 45 years, 56.10% reported having a Bachelor's degree, with the majority coming from the USA (71.43%), followed by India (9.30%) and Mexico (8.97%). The majority of the participants reported earning an annual income of between US$10,000 and US$60,000 (51.8%).

3.4 Exploratory factor analysis

For this analysis phase, a random subsample of 100 participants was selected. These data were subjected to exploratory factor analysis (EFA) with varimax rotation and

Table 2
Respondent profile

Demographic characteristics (n = 301)	Measures	Frequency	Valid percentage
Biological gender	Female	187	61.92
	Male	112	37.09
	Other	3	0.99
Age	15-25	27	9.00
	26-35	105	34.90
	36-45	96	31.90
	46-55	47	15.60
	Above 56	26	8.60
Level of Education	Less than a high school diploma	1	0.30
	High school degree or equivalent	65	21.60
	Bachelor's degree (e.g., BA, BS)	169	56.10
	Master's decree (e.g., MA, MS, MEd)	47	15.60
	Doctorate (e.g., PhD, EdD)	8	2.70
	Other	11	3.70
Country	Brazil	4	1.33
	Canada	6	1.99
	Greece	1	0.33
	India	28	9.30
	Italy	6	1.99
	Kenya	1	0.33
	Mexico	27	8.97
	Slovenia	1	0.33
	Spain	6	1.99
	United Kingdom	4	1.33
	USA	215	71.43
	Other	2	0.66
Annual Household in US dollars	Below $10k	34	11.30
	$10k- $30k	81	26.90
	$30k- $60k	75	24.90
	$60k - $90k	49	16.30
	Over $90k	62	20.60

Source: Own elaboration.

extraction of eigenvalues greater than one. Two tests were performed to assess the suitability of the data for EFA. The first was the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, which yielded a value of 0.891, indicating that the data were highly suitable for factor analysis (Williams et al., 2010). The second, using Bartlett's test of sphericity, yielded a chi-square of 1871.857 with 276 degrees of freedom ($p < 0.001$), demonstrating the suitability of the data for factor analysis (Jackson, 1993). In this phase, three factors were identified that together explained 64.73% of the total variance and varimax rotation was employed to improve the interpretation of these factors. This process reduced the number of items from 28 to 24 and the dimensions to three (see Appendix B, Supplementary Material). Specifically, the identified factors were named as follows:

- Factor 1. Customer experience: This factor includes questions that focus on the customer's shopping experience, from the payment process to personalised suggestions based on previous purchases and searches. It also includes aspects such as ease of making returns and product availability;
- Factor 2. Communication and privacy: This factor includes items related to the company's communication

with the customer, offers and promotions, transparency in the use of information, and protection of customer privacy. It also includes the company's use of decision-making to personalise the customer experience;

- Factor 3. Support and payments: This factor focuses on questions about how the company responds to customer issues in real-time, interactive support, and flexible payment options.

Harman's single factor test procedure was applied to assess the presence of common method bias (CMB), a technique recommended by Podsakoff et al. (2003) that allows for the control of the influence of variance attributable to the data collection method. The resulting factor solution, without rotation, revealed that this single factor explained a percentage of 46.291% of the total variance. This percentage is below the 50% threshold generally accepted as indicative of the absence of CMB, as detailed in Table 3. Furthermore, this approach was complemented by an analysis of the variance inflation factor (VIF), following the methodology proposed by Kock (2015). Specifically, all VIFs resulting from a collinearity test were equal to or below 3.3. Additionally, we examined the correlation matrix and found no extremely high correlations (the highest correlation was $r = 0.769$). In contrast, CMB should have resulted in extremely high correlations ($r > 0.90$). This additional analysis corroborated the previous results and strengthened the evidence that CMB was not a significant concern in the current study.

3.5 Scale validation and development

At this stage, confirmatory factor analysis (CFA) was conducted and applied to a subsample of 201 individuals. Having identified three factors through principal component analysis (PCA), the next step was to confirm the factorial structure. For this purpose, structural equation modelling was used to carry out CFA on the proposed model. Thus,

Table 3
Common method bias analysis (Herman single factor test output)

Total Variance Explained						
Components	Inicial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	11.110	46.291	46.291	11.110	46.291	46.291
2	2.705	11.271	57.562			
3	1.722	7.176	64.737			
4	1.001	4.171	68.909			
5	.891	3.712	72.621			
6	.789	3.287	75.908			
7	.757	3.156	79.064			
8	.680	2.835	81.899			
9	.557	2.320	84.219			
10	.501	2.086	86.305			
11	.438	1.824	88.130			
12	.422	1.760	89.889			
13	.380	1.582	91.471			
14	.358	1.491	92.962			
15	.294	1.226	94.188			
16	.246	1.024	95.212			
17	.220	.916	96.128			
18	.197	.822	96.950			
19	.166	.691	97.641			
20	.144	.600	98.241			
21	.136	.565	98.806			
22	.127	.531	99.337			
23	.105	.438	99.776			
24	.054	.224	100.000			

Note 1: Extraction method: Principal component analysis.
Source: Own elaboration.

the model consists of three first-order factors, which contain three first-order latent variables named "customer experience", "communication and privacy", and "support and payments". The analysis first examines measurement of each construct individually to assess the validity of the measurement model. Secondly, all measures are evaluated together, following the methodology proposed by Cheng (2001) (see Table 4).

The fit of the proposed model was examined by assessing several indices: the relative chi-square index (CMIN/DF), the comparative fit index (CFI), the goodness of fit index (GFI), the adjusted goodness of fit index (AGFI), and the root mean square error of approximation (RMSEA) (see Table 5). These indices were used to calculate the model fit estimates and to determine their suitability for measuring the overall DDMI, which includes the three constructs studied. In relation to the initial estimation of the measurement model for these three constructs, the results obtained were optimised using the covariance modification indices and the regression weights suggested by IBM SPSS Amos 28. This optimisation allowed the model to achieve satisfactory levels of fit, indicating that the results obtained were within the recommended tolerance levels (GFI = 0.887, RMSEA = 0.077, AGFI = 0.847, TLI = 0.927, CFI = 0.940, CMIM/df = 2.768). The revised graphical model is shown in Figure 1 and Table 5.

Table 6 provides a detailed analysis of the reliability and validity of each of the constructs included in the study, using data from Gaskin's (2021) Validity Master statistical tool package. The Cronbach's alpha reliability coefficients for the "support and payments", "customer experience", and "communication and privacy" constructs are 0.784, 0.940, and 0.875, respectively, indicating a satisfactory level of reliability. The composite reliability (CR) and average variance extracted (AVE) for these constructs also reflect adequate internal consistency and convergent validity, with the AVE of each construct exceeding the recommended threshold of 0.5. Interestingly, customer experience has the highest AVE (0.639), suggesting convergent solid validity for this construct. Furthermore, the values of the square root of the AVE, shown on the main diagonal of the correlation matrix, exceed all corresponding inter-construct correlations, supporting the discriminant validity of the constructs. The HTMT values above the main diagonal also confirm the clear

Table 4
Model fit indices for individual constructs

	Customer Experience	**Communication and Privacy**	**Support and Payments**
CFI	0.926	0.862	0.999
GFI	0.865	0.870	0.996
AGFI	0.775	0.698	0.981
TLI	0.902	0.770	0.997
CMIM/DF	6.969	14.653	1.162
P-VALUE	0.000	0.000	0.313
RMSEA	0.141	0.213	0.023

Source: Own elaboration.

Table 5
Overall measurement model fit indices

	Recommended value	**Initial model fit indices**	**Revised fit indices**
CFI	≧0.90	0.872	0.940
GFI	≧0.90	0.807	0.887
AGFI	≧0.80	0.749	0.847
TLI	≧0.90	0.850	0.927
CMIM/DF	< 3.00	4.644	2.768
RMSEA	≤0.05	0.110	0.077
p - value	≤0.05	0.000	0.000

Source: IBM SPSS Amos output.

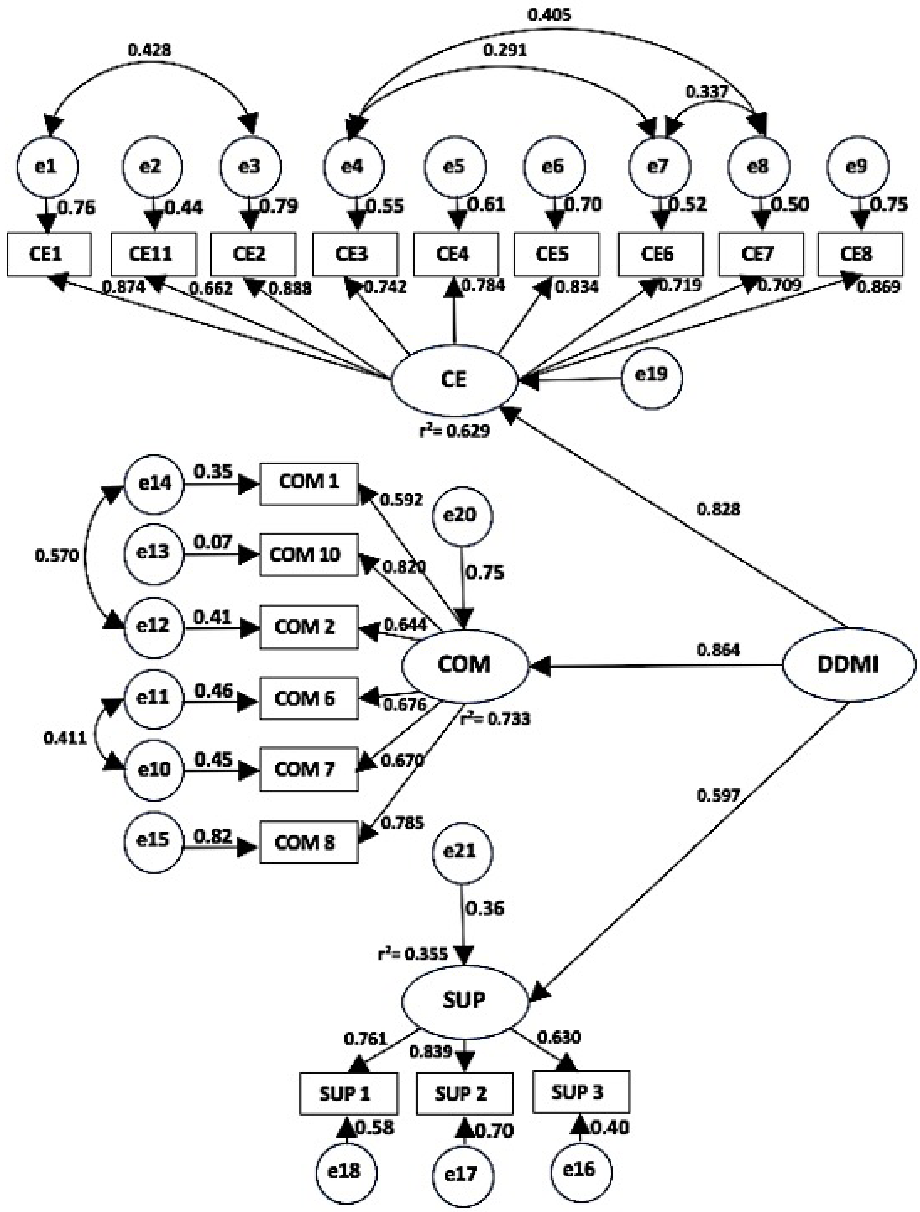

Figure 1. Revised measurement model with IBM SPSS Amos.

Note: CE = Experience Communication; COM = Customer and Privacy; SUP = Support and Payments; DDMI = Data-Driven Marketing Image

Source: Own elaboration

Table 6

Reliability and validity for individual constructs

Constructs	Cronbach's α	CR	AVE	MSV	MaxR (H)	Matrix of Correlations Above the Main Diagonal – Square Root of AVE (On the Diagonal) HTMT Above the Main Diagonal		
						Support and Payments	Customer Experience	Communication and Privacy
Support and Payments	0.784	0.790	0.560	0.223	0.814	0.748	0.519	0.433
Customer Experience	0.940	0.940	0.639	0.399	0.953	0.472	0.799	0.662
Communication and Privacy	0.875	0.874	0.537	0.399	0.877	0.460	0.632	0.732

Note 1: CR = Composite Reliability; AVE = Average Variance Extracted, MSV = Maximum Shared Variance, MaxR (H) = Maximum Reliability H. Source: Stats Tools Package – Validity Master (Gaskin, 2021).

distinction between the constructs. This comprehensive analysis demonstrates the methodological robustness of the study in terms of the reliability and validity of the constructs analysed.

4 Discussion

The study contributes to the field of data-driven marketing (DDM) by developing a scale to measure the image perceived by customers of companies that adopt DDM strategies. Specifically, this work addresses the research question: How do DDM strategies influence perceptions of companies' corporate image? This scale, consisting of the constructs "communication and privacy", "customer experience", and "support and payments", provides a tool to evaluate the impact of interactions with companies that use marketing data in their decision-making processes to shape corporate image.

The refinement of the scale from its initial development (Appendix A) to its final version following the EFA (Appendix B, Supplementary Material) was based on theoretical considerations and empirical validation. Items were either removed or modified based on their factor loadings, cross-loadings, and theoretical alignment with previous studies on corporate image and DDM (Flavián et al., 2004; Hopkins & Alford, 2006; Tran et al., 2015). Specifically, items with low communalities or those that did not load significantly onto a single factor were eliminated to enhance construct validity (DeVellis & Thorpe, 2021). Additionally, modifications were made to refine the conceptual clarity of certain dimensions to ensure consistency with existing literature on consumer perceptions of digital marketing practices (Grandhi et al., 2020; Camilleri, 2020). In particular, the removal of certain items related to "perceived security" is consistent with previous findings suggesting that privacy concerns may be more relevant in specific contexts, such as financial services, than in online retailing (Flavián et al., 2004). These adjustments ensure a balance between empirical robustness and theoretical coherence, guaranteeing that the validated scale captures the most relevant aspects of corporate image in DDM.

Specifically, the "communication and privacy" dimension was the most significant in shaping the image. The personalisation of marketing communications is confirmed as a crucial element within this dimension, in line with previous literature highlighting the value of personalised communications as a basis for engagement and consumer satisfaction (Aiolfi et al., 2021; Grover et al., 2018; Tong et al., 2020; Varnali, 2021). Data privacy also emerges as an influential element, associated with mistrust and the potential to diminish the company's positive image when excessive personalisation of marketing actions is perceived as intrusive (Bandara et al., 2017). This reflects the delicate balance that companies must maintain between personalising communications and protecting privacy, a topic that is still under debate in the literature (Nassar & Kamal, 2021; Pantano, 2019). Therefore, companies must carefully manage data in the eyes of consumers in order to strengthen their image (Acemoglu et al., 2022).

Regarding the "customer experience" dimension, the results highlight the importance of the interaction between the user and the company. Specifically, each element identified in the scale, from the ease of placing an order to the constant availability of stock, underscores the importance for companies to have a frictionless design to support a positive user experience (Dremel et al., 2020; Hoyer et al., 2020).

The third dimension, named "Support and Payments", highlights the importance of real-time assistance and financing options as a key part of the overall digital customer experience, a finding supported by previous research (Grover et al., 2018; Hoyer et al., 2020). These results suggest that customer support and online payment options should be considered as essential to completing the image of a company committed to supporting its customers in a comprehensive way (Ngai et al., 2021).

Unlike previous studies on corporate image (Flavián et al., 2004; Tran et al., 2015), which have approached this concept from general perspectives or within specific sectors, this study develops a scale specifically designed to measure corporate image in data-driven marketing contexts. While prior models focus on traditional dimensions such as reputation, trust, and communication, the DDMI scale incorporates key factors in digital environments, including the personalisation of interactions, privacy perceptions, and the impact of user experience on corporate image. By integrating these dimensions into a structured model, this study provides a more precise and contextualised understanding of how DDM strategies shape consumer perceptions, offering a tool that is aligned with the evolution of digital marketing. The dimensions identified provide a novel perspective on the impact of firm-customer interactions in shaping corporate image within the context of DDM. In particular, inadequate implementation of DDM strategies may lead to negative perceptions (Gawankar et al., 2020), highlighting the need for a strategic and ethical approach to data management.

5 Conclusion

This study contributes to the field of data-driven marketing (DDM) by developing a scale for evaluating the image of companies that employ DDM strategies (DDMI). This research highlights how DDM strategies affect the image of companies in the eyes of their customers, particularly in the retail sector, where data exchange is increasingly intensive. The work offers a validated scale that allows companies to measure aspects that customers consider important and to capture their concerns about the use of their data online, with particular focus on privacy issues and the personalisation of the customer experience by companies.

From a theoretical perspective, this research is one of the first studies to measure the data-driven marketing image. The scale was constructed through a literature review and was empirically validated through consultations with experts and customers using mixed methods. The proposed scale complements the understanding of DDM practices, as most studies in the area aim to analyse concepts related to the implementation of DDM activities rather than their effect on customers. Moreover, the instrument enhances existing DDM research and lays the groundwork for future studies and suggests, for example, the use of the DDMI scale in sectors other than retail, such as travel and tourism, financial services, media and entertainment, and health and wellness, since these industries are characterised by their digitalisation and significant use of data (Bhavnani et al., 2016; Abou-foul et al., 2021; Waldfogel, 2017; Xiang, 2018).

These industries share the need to build trust in the handling of personal data, ensure effective personalisation without being perceived as intrusive, and optimise the customer experience through data-driven strategies. Applying the DDMI in these sectors would allow companies to measure how their DDM practices influence consumer perceptions and adjust their strategies accordingly. Moreover, given the global expansion of DDM strategies, future studies could employ the DDMI in different cultural contexts to analyse how consumer perceptions vary across regions and market segments. Cross-cultural comparisons would provide valuable insights into differences in data trust, personalisation expectations, and privacy concerns, enabling businesses to tailor their strategies to the sensitivities and regulatory frameworks of each market.

From a practical perspective, the DDMI scale developed in this study provides marketing managers with a comprehensive tool for assessing and optimising consumer perceptions of DDM strategies. Its application enables companies to identify the key factors that influence their corporate image, particularly trust, personalisation, and data privacy. By leveraging this information, marketing professionals can refine their communication strategies to ensure that customer experience personalisation is perceived as a benefit rather than an intrusion. Additionally, the scale facilitates strategic decision-making when implementing technologies such as artificial intelligence and automation, ensuring that these initiatives enhance accessibility, efficiency, and perceived transparency.

For instance, in the retail sector, the DDMI can be used to monitor the impact of personalised offers and the integration of virtual assistants on consumer trust. Furthermore, its application in longitudinal studies makes it possible to analyse how corporate perceptions evolve over time and to assess the effects of regulatory changes on data privacy, helping businesses to adapt their corporate strategies accordingly. Specifically, the findings of this study support the fundamental role of communications in shaping the DDMI, highlighting the importance of delivering relevant information, personalised promotions, and messages that are aligned with consumers' interests without compromising privacy. For example, one well-known retailer implemented a data management strategy that included transparent communication about data usage and customer-controlled privacy settings, which significantly improved customer trust and the company's overall image.

Regarding customer experience, factors such as ease of purchase, efficiency of the payment process, and a company's commitment to customer satisfaction emerge as key determinants. To maintain a positive corporate image, managers must ensure that these processes are intuitive and frictionless. Additionally, the availability of real-time interactive support and flexible payment options can improve perceptions of a company's accessibility and efficiency. For instance, the implementation of AI-powered chatbots that provide immediate assistance can optimise the customer experience and enhance the corporate image. Thus, companies that achieve a positive and efficient user experience will improve their image among consumers. For instance, a leading electronics retailer redesigned its website to streamline the checkout process, which reduced cart abandonment rates and increased customer satisfaction scores. Similarly, a prominent online grocer implemented a real-time inventory management system that accurately reflects stock levels on its website, ensuring that customers always find the products they need available, thereby increasing trust and satisfaction. In this way, continuously adapting digital interfaces will enhance the customer experience (Hoyer et al., 2020). In another example, a major online fashion retailer introduced a highly intuitive and user-friendly mobile app that features augmented reality to try on clothes virtually, significantly improving the shopping experience and boosting company image. Each of these initiatives demonstrates how adept handling of support and payment options can positively impact a company's reputation and customer relationships, ultimately strengthening its overall image.

Despite the findings and contributions of this study, there are some limitations. The nature of our study suggests that extending the research to different regions and cultural contexts could enrich the generalisability of the findings. Furthermore, subsequent studies could explore the relationship between DDMI and other relevant constructs, such as customer loyalty, customer satisfaction, and perceived value. Future research could take a longitudinal approach, analysing the evolution of the image over time based on its response to DDM strategies. It may also be important to analyse the contribution of different industries.

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Supplementary Material

Supplementary material accompanies this paper.
Supplementary Data 1 – DDMI Scale Dataset and Codebook
Supplementary Data 2 – DDMI Scale Questionnaire
Supplementary Data 3 – Appendix A
Supplementary Data 4 – Appendix B
Supplementary data to this article can be found online at https://doi.org/10.7910/DVN/HLKEQZ

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