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Data-driven marketing image: implementation and country of operation moderation effects

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Abstract

Purpose – This study investigates the impact of Data-Driven Marketing Image (DDMI) on consumer outcomes like customer satisfaction, identification, product evaluation, eWOM, and electronic loyalty, using the Stimulus-Organism-Response (S-O-R) framework. It also examines how different Data-Driven Marketing (DDM) implementation levels and cultural differences between Spain and Mexico moderate these effects.

Design/methodology/approach – A quantitative research design was used to distribute an online survey to fashion retail consumers in Spain and Mexico. Relationships were analysed using PLS-SEM, and multigroup analysis assessed the moderating effects of DDM implementation and country.

Findings – The study shows that Data-Driven Marketing Image (DDMI) enhances customer-company identification, product evaluation, and satisfaction, positively influencing eWOM and loyalty. These effects intensify under high DDM implementation, underscoring the strategic value of advanced data use. Cross-cultural results indicate stronger DDMI product evaluation links in Spain and stronger DDMI satisfaction links in Mexico. These patterns reflect differences in digital maturity and cultural dimensions (e.g. uncertainty avoidance, collectivism), highlighting the need to adapt DDM strategies to local contexts.

Originality/value – This research extends data-driven marketing literature by introducing and validating the concept of DDMI within the S-O-R framework. It examines the relationship between DDMI and consumer outcomes across cultures and analyses how varying levels of DDM implementation influence consumer perceptions.

Keywords Data-driven marketing image, Customer-company identification, Product evaluation, Customer satisfaction, Electronic word of mouth, Electronic loyalty, Online fashion retail

Paper type Research paper

1. Introduction

Data-Driven Marketing (DDM) has transformed customer interactions in the digital era, leveraging data to personalise services and enhance decision-making. The global data market for marketing is projected to reach $83.7 billion by 2025 (OnAudience.com, 2021),

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highlighting its growing importance (Cote, 2021). Despite substantial investments in data analytics, a gap persists in understanding its impact on consumer perceptions. Most studies focus on strategy adoption (Holmlund *et al.*, 2020), overlooking their impact on consumer behaviour and well-being.

This study investigates the effects of Data-Driven Marketing Image (DDMI) on satisfaction (CS), identification (CCI), product evaluation (PE), and their influence on eWOM and e-loyalty (eLOY) in the fashion sector. Using the Stimulus-Organism-Response (S-O-R) model (Mehrabian and Russell, 1974), DDMI is the stimulus, CS, CCI, and PE the organism, and eWOM/eLOY the behavioural responses. This model suits the fashion sector, where technology enhances attraction and retention (Jin and Shin, 2020). The study also examines the moderating roles of DDM implementation and country, comparing culturally and technologically distinct markets: Spain and Mexico.

It contributes theoretically by introducing and validating DDMI as a perceptual construct within the S-O-R framework, extending its use to digital marketing and cross-cultural analysis. Empirical evidence confirms DDMI's influence on key outcomes, and the analysis reveals how national context and DDM maturity shape its effects. These findings address the need to understand data strategy effectiveness across market conditions (Holmlund *et al.*, 2020).

2. Theoretical background and hypotheses development

2.1 S-O-R model

The Stimulus-Organism-Response (S-O-R) model explains behaviour as a process where external stimuli (S) affect emotional and cognitive states (O), leading to responses (R) (Mehrabian and Russell, 1974). In this study, the stimulus is a corporate image from DDM strategies (Wang *et al.*, 2022). The organism includes customer-company identification (CCI), product evaluation (PE), and customer satisfaction (CS) (Karim *et al.*, 2021), while responses manifest as electronic loyalty (eLOY) (Taheri *et al.*, 2024) and word of mouth (eWOM) (Errajaa *et al.*, 2022). Widely applied in consumer behaviour research, the S-O-R model is relevant for studying digital marketing strategies (Türkdemir *et al.*, 2023; Zhu *et al.*, 2020).

2.2 Stimulus variable: data-driven marketing image

Although corporate image is widely studied, the Data-Driven Marketing Image (DDMI) concept remains undefined. This study introduces DDMI within the S-O-R framework as stakeholders' perceptions of a company's ability to integrate data into marketing decisions, enabling optimised strategies and stronger customer relationships. Existing studies on corporate image often address online presence (Barreda *et al.*, 2020) or how brand image influences online purchase intention (Savitri *et al.*, 2022). In contrast, this study positions DDMI as a reflection of data-driven strategies, including segmentation, predictive analytics, and personalised communication, to increase customer satisfaction and loyalty (Peltier *et al.*, 2024).

2.3 Organism variables- customer-company identification, product evaluation and customer satisfaction

Customer-Company Identification (CCI) describes the affinity and connection customers feel towards a company (Glaveli, 2021; Raza *et al.*, 2020). According to Social Identity Theory, this identification strengthens social identity when individuals associate with organisations (Tajfel, 1974), often fostered through positive interactions like loyalty programmes (Sriyakula *et al.*, 2019).

Product Evaluation (PE) involves assessing or rating a product based on perceived quality, features, and benefits influenced by preferences, past experiences, and marketing communications (Wang *et al.*, 2019). Consumers compare alternatives and rely on sources such as reviews and recommendations to make decisions (Guo *et al.*, 2020).

Customer Satisfaction (CS) represents customers' evaluation of their experiences, determined by aligning expectations and performance (Goić *et al.*, 2021). CS drives improvement in responsiveness and reliability while positively impacting financial outcomes such as profitability and cash flow, highlighting its role as a success indicator (AbuRaya *et al.*, 2023).

This study posited that a company's corporate image significantly affects CCI (Mukonza and Swarts, 2020; Waris *et al.*, 2024). Several studies have demonstrated that a robust corporate image strengthens the bond between the customer and the company (Waris *et al.*, 2024). For instance, Cheng *et al.* (2021) argue that an innovative image reinforces identification with the company. Similarly, Mukonza and Swarts (2020) found that how a company communicates its brand and social responsibility activities positively affects CCI. Since corporate image affects CCI in other contexts, it is reasonable to expect that companies that develop an image based on data-driven marketing strategies will similarly influence CCI. Building on this evidence, the following hypothesis is proposed:

H1. The image of a company employing Data-Driven Marketing strategies directly and positively influences Customer-Company Identification.

A positive corporate image can signal product quality and impact firm value by improving product market perception, particularly for standardised goods and competitive industries (Bardos *et al.*, 2020). Additionally, the image of prototypical brands strongly associated with a country, such as Samsung for South Korea, shapes the country's micro image, influencing consumer perceptions (Jin *et al.*, 2020). These findings suggest that a company's image, including its DDMI, directly impacts PE. Based on this, the following hypothesis is proposed:

H2. The image of a company employing Data-Driven Marketing strategies directly and positively influences Product Evaluation.

Various studies have shown that corporate image influences CS directly (Xi, 2022). Mohammed and Rashid (2018) point out that brand image plays a crucial role in CS, as positive perceptions of the brand contribute to a favourable view of the company's operations and communications, directly impacting CS. A strong, positive corporate image can shape perceptions, generate trust, and enhance customer experience, which in turn increases CS (Özkan *et al.*, 2020). Based on these findings, the following hypothesis is proposed:

H3. The image of a company employing Data-Driven Marketing strategies directly and positively influences Customer Satisfaction.

CCI influences PE, as customers who identify with a company tend to evaluate products favourably, viewing such evaluation as an extension of their self-expression (Chae *et al.*, 2020). For instance, Kassemeier *et al.* (2022) demonstrated that CCI is influenced by various functional characteristics of the company, such as perceived quality and innovation capacity. These findings suggest that customers who perceive high quality or innovation in a company tend to identify more with it. Based on this, the following hypothesis is proposed:

H4. Customer-Company Identification directly and positively influences Product Evaluation.

Kassemeier *et al.* (2022) suggest that when the customer's need for self-definition aligns with the company's functional characteristics, such as quality or innovation, the symbolic value of these characteristics is reinforced, strengthening CCI and, consequently, CS. Raza *et al.* (2020) also indicate that CCI plays a crucial role in fostering a strong emotional bond between the customer and the company, affecting customer satisfaction. This bond strengthens trust and loyalty, generating positive perceptions of the company's offerings. Based on this evidence, we propose the following hypothesis:

H5. Customer-Company Identification directly and positively influences Customer Satisfaction.

Customers evaluate products based on innovation, quality, and value-added services, directly impacting their satisfaction levels (Pan and Nguyen, 2015). Positive product evaluations lead not only to higher satisfaction levels but also to increased customer loyalty and retention. Fitrianis *et al.* (2022) emphasise that PE is key in determining CS, as it influences product quality and value perception. Evaluations that meet or exceed expectations increase the likelihood of repurchase and loyalty. Consequently, the following hypothesis is proposed:

H6. Product Evaluation directly and positively influences Customer Satisfaction.

2.4 Response variables – eWOM and eLoyalty

This study explores two response variables, electronic word of mouth (eWOM) and electronic loyalty (eLOY), critical for understanding consumer behaviour in digital contexts. eWOM, akin to traditional word-of-mouth, entails consumers sharing opinions online, thereby shaping brand reputation and fostering business growth through credible experiences (Marcos and Coelho, 2022).

eLoyalty reflects digital loyalty behaviours, such as repeat purchases and brand advocacy, driven by trust and satisfaction, evident in reviews and recommendations (Ng *et al.*, 2023).

Customer satisfaction (CS) significantly drives eWOM and eLOY. Satisfied customers are more likely to recommend services (Khoo, 2022), and satisfaction enhances loyalty (Mai and Cuong, 2021). Beyond quality, overall experience fosters loyalty, emphasising customer-centric strategies and satisfaction (Mainardes and Freitas, 2023). Based on this evidence, the following hypotheses are proposed:

H7. Customer satisfaction directly and positively influences the eWOM generated by the customer about the company.

H8. Customer satisfaction directly and positively influences the eLoyalty developed by customers towards the company.

2.5 Moderating effects level of data-driven marketing implementation and country of operation

The proposed model considers the moderating role of DDM implementation levels on customer responses. Johnson *et al.* (2019) identify five DDM adoption stages: Emergence, Recognition, Engagement, Cultural Change, and Data-Driven Marketing, each reflecting varying analytical capacities. Not all companies reach advanced DDM maturity, affecting their strategies and outcomes.

Technology significantly influences consumer perceptions. For instance, ICT impacts perceived quality and loyalty through brand image (Šeric *et al.*, 2016), while Artificial Intelligence, Big Data, and the Internet of Things enable personalised solutions, fostering loyalty and enhancing experiences (Jorzik *et al.*, 2024). Based on this, the following hypothesis is proposed:

H9. The level of DDM implementation positively moderates the relationships in the theoretical model regarding consumer response in retail.

Culture, defined as collective mental programming (Hofstede *et al.*, 2010), also shapes consumer behaviour, affecting product evaluations and loyalty programme responses (Wang *et al.*, 2019). This study examines cultural and technological contrasts between Mexico and Spain, where Spain boasts advanced digital infrastructure (Lorente-Martínez *et al.*, 2020), and Mexico faces digital challenges (Casalet and Stezano, 2020). These differences inform effective marketing strategies. The research question is:

RQ1. How does the country context moderate the relationships in the theoretical model of consumer response to Data-Driven Marketing Image in online retail?

3. Methods

3.1 Research design – selection of companies for the study

This study examines DDM strategies in the fashion retail sector in Spain and Mexico, two markets with differing levels of digital maturity (Passport, 2022a, b). With higher digital development (International Telecommunication Union, 2024), Spain contrasts with Mexico's growing adoption amid infrastructural and socio-economic challenges (Martínez-Domínguez and Mora-Rivera, 2020). Despite shared language and historical ties, cultural differences in uncertainty avoidance and collectivism (Culture Factor Group, 2025) may shape consumer responses to data-driven initiatives (Balabanis *et al.*, 2025), justifying their inclusion in a comparative design.

The level of DDM implementation was assessed using five variables based on Johnson *et al.* (2019): 1) Recognition of the value of big data; 2) Investment in DDM tools; 3) Organisational commitment; 4) Data-driven cultural transformation; 5) Use of data in marketing strategies.

These variables were measured on an ordinal scale with three levels (low, medium, and high), facilitating the collection of qualitative judgements by providing a practical framework for classifying companies' progress (Verhulst and Neale, 2021). Each of these variables contributes to a comprehensive view of the company's maturity in using DDM, evaluating everything from investment in tools to cultural change towards a more data-centric approach. To assess the level of DDM implementation, multiple sources of information were used, including corporate websites, annual reports, interviews with executives, industry reports, and analyses from specialised media such as "Mundo de la Empresa" and "Fashion Network" in Spain, and "Forbes" and "Expansión" in Mexico. These sources provided detailed data and diverse perspectives, enabling a comprehensive evaluation of the DDM status in each company.

Furthermore, a panel of six experts, composed of professionals from both countries, evaluated the companies. This panel used the variables defined by Johnson *et al.* (2019) and performance indicators such as global sales and the percentage of online sales. Additionally, web and mobile app performance metrics were analysed using Similarweb (https://www.similarweb.com, accessed August 2023). The consensus process among the experts involved a series of iterative discussions to ensure the accuracy and reliability of the evaluations (Beiderbeck *et al.*, 2021).

This study simplified the five levels of DDM implementation proposed by Johnson *et al.* (2019) into three: high, medium and low, to facilitate statistical analysis and ensure clarity in the results. This reduction allowed for a manageable classification and direct company comparisons without compromising representativeness (Becker *et al.*, 2023). According to these three levels, the companies' classification is presented in Table 1, reflecting the consensus reached by the six experts.

3.2 Research design – measurements and sample

Data were collected via a self-administered online survey using purposive sampling. The target population comprises adults in Spain and Mexico with prior experience purchasing from international online fashion retailers using DDM. Participants received a brief explanation of DDM before completing the questionnaire. A non-probabilistic purposive sampling strategy was employed. Participants were recruited through professional online panels to ensure diversity in age, gender, and shopping frequency. Screening questions confirmed recent purchase experience. Screening questions confirmed at least one purchase in the past six months.

The questionnaire measured respondents' perceptions of the image of companies implementing DDM strategies (DDMI, CCI, PE, and CS) and the dependent variables (eWOM and eLOY). Responses were recorded using a seven-point Likert scale (1 = "completely disagree", 7 = "completely agree"). Further details are presented in Table 2. The Data-Driven Marketing Image (DDMI) scale was developed in three phases. In phase one, a literature review and six in-depth interviews with marketing and e-commerce experts were conducted. The interviews evaluated item relevance, representativeness, and clarity to ensure content validity and contextual appropriateness. In phase two, a pre-test with

Table 1. Assessment of the level of DDM implementation

Indicator	Gpo. Inditex	H&M	Shein	Liverpool	El Corte Inglés	Mango	Levi Strauss & Co.	C&A México	Primark	Springfield/ Tendam
Awareness and recognition of the value of BD	*H*	*H*	*H*	*H*	*H*	*H*	*H*	*H*	M	*H*
Investment in DDM tools	*H*	*H*	*H*	M	M	M	M	L	L	L
Commitment to DDM initiatives	*H*	*H*	*H*	*H*	*H*	M	M	M	M	M
Cultural transformation towards data-driven decision-making	M	M	*H*	M	M	M	M	M	M	M
Data-driven marketing strategies	*H*	*H*	*H*	*H*	*H*	*H*	*H*	*H*	M	M
Global sales 2022 (USD, in billions)	35	20	30	10	15	3	6	1	10	1
% of online sales	24%	30%	100%	23%	15%	36%	8%	3%	N/A	19%
Average monthly app downloads (thousands)	1,850	1,100	16,600	518	85	196	64	135	0.64	13
Average monthly website visits (millions)	158	101	245	18	32	29	12	0.7	10	0.0002
DDM implementation level	*H*	*H*	*H*	*H*	*H*	L	L	L	L	L

Note(s): H: High (Italic), M: Medium (Regular), L: Low (Underline).
Source(s): Own elaboration

Table 2. Descriptive statistics

Data set complete (all countries combined) $n = 328$	FL	M	SD
Data-Driven Marketing Image (DDMI) (developed by the authors for this study)			
$\alpha = 0.698$; CR = 0.702; AVE = 0.527			
DDMI1– It is very easy to place an order with the company	0.653	6.329	1.034
DDMI2 – The payment process works very well	0.736	6.235	1.017
DDMI3 – The company offers an increasingly personalized experience	0.791	5.741	1.380
DDMI4 – The company responds appropriately to my difficulties in real time	0.716	5.018	1.498
Customer-Company Identification (CCI) (Bergami and Bagozzi, 2000; Glaveli, 2021)			
$\alpha = 0.920$; CR = 0.934; AVE = 0.713			
CCI1 – I strongly identify with the selected company and its online store	0.884	4.982	1.686
CCI2 – This company and its online store match my personality	0.800	5.329	1.494
CCI3 – I feel good about being a customer of this company and its online store	0.840	5.372	1.451
CCI4 – I like to say that I am a customer of this company and its online store	0.837	5.098	1.715
CCI5 – I feel closely connected to this company and its online store	0.861	4.543	1.784
CCI6 – I have a strong sense of belonging to this company and its online store	0.837	4.271	1.855
Product evaluation (PE) (Dose *et al.*, 2019)			
$\alpha = 0.931$; CR = 0.931; AVE = 0.879			
PE1 – I am satisfied with the product I last purchased from the selected online provider	0.940	6.113	1.108
PE2 – Overall, I am pleased with the product I last purchased from the selected online provider	0.928	6.149	1.139
PE3 – Overall, my experience with the most recent product I purchased was positive	0.945	6.168	1.047
Customer Satisfaction (CS) (Li *et al.*, 2015)			
$\alpha = 0.917$; CR = 0.918; AVE = 0.802			
CS1 – Overall, this online provider meets my expectations	0.889	5.933	1.040
CS2 – My overall experience with this online provider is satisfactory	0.902	6.070	0.943
CS3 – Overall, this company is a capable and competent service provider	0.884	5.997	1.072
CS4 – The online service provided is satisfactory	0.906	6.015	1.058
eWOM (Goyette *et al.*, 2010)			
$\alpha = 0.924$; CR = 0.931; AVE = 0.867			
eWOM1 – I talk about this company more often than any other online retailer	0.943	4.540	1.916
eWOM2 – I talk about this company more often than companies of any other type	0.930	4.491	1.821
eWOM3 – I talk about this company to many people	0.921	4.558	1.907
eLoyalty (eLOY) (Li *et al.*, 2015)			
$\alpha = 0.831$; CR = 0.868; AVE = 0.662			
eLOY1 – I usually visit the website of the selected online provider first when I need to shop online	0.735	5.354	1.674
eLOY2 – I intend to continue buying from the selected online provider	0.873	5.921	1.254
eLOY3 – I often recommend this online provider to others	0.795	4.991	1.810
eLOY4 – I am a regular customer of this online provider	0.845	5.113	1.572

Note(s): All items are measured with a seven-point Likert scale anchoring strongly disagree (1) and strongly agree (7); FL = Factor loading; M = Mean; SD = Standard deviation. The DDMI scale was developed by the authors and validated in this study through a three-phase process, including literature review, expert consultation, and confirmatory factor analysis.
Source(s): Own elaboration

31 participants and an exploratory factor analysis (sample of 100 respondents) refined the scale. In phase three, the scale was validated with a sample of 201 subjects through confirmatory factor analysis, ensuring convergent and discriminant validity and good model fit.

Data were collected using a self-administered online questionnaire. Respondents accessed the survey via an anonymous link and completed it in their own time. This format ensured standardisation of item presentation and minimised interviewer bias. To enhance validity, a pre-test was conducted with 30 users in each country to confirm item clarity and functionality of the online system. Of the total responses, 328 complete surveys were retained (86.58%), demonstrating sufficient statistical power as verified using G*Power and heuristic methods (Hair *et al.*, 2017). Of the respondents, 52.7% ($n = 173$) were from Mexico and 47.3% ($n = 155$) from Spain. The sample was predominantly female (63.5%, $n = 209$), with an average age of 30.43 years (SD = 12.23). Most had a bachelor's degree (69.9%) or higher education (17%). Regarding online fashion purchases, respondents typically bought every two to three months (37.2%) or monthly (25.6%). In Spain, Grupo Inditex was the most frequented retailer (54.19%), followed by Shein (30.77%), while in Mexico, Liverpool ranked first (36.99%), followed by Grupo Inditex (30.06%).

3.3 Measurement model assessment: common method bias, validity and reliability

To ensure methodological integrity, common method bias (CMB) was mitigated through participant confidentiality and clear instructions (Podsakoff *et al.*, 2024). CMB tests—Harman's single-factor test (<40.5%), inter-construct correlations (r < 0.703), and collinearity analysis (VIF <4.1) (Kock, 2015) indicated minimal impact. Partial least squares structural equation modelling (PLS-SEM) using Smart PLS 4.1.0.3 (Sarstedt *et al.*, 2024) employed the consistent PLS algorithm for precision (Dijkstra and Henseler, 2015). Reliability (Cronbach's alpha, composite reliability >0.68) and validity (AVE >0.50) were confirmed (Fornell and Larcker, 1981). Table 3 validates the model's robustness.

Regarding discriminant validity, it was analysed using the heterotrait-monotrait ratio (HTMT) between any two reflective constructs, which was found to be below 0.90 (Henseler *et al.*, 2015), and all values were consistent with the recommended thresholds (Table 4). Therefore, the measurement model has discriminant validity. Finally, the standardised root mean square residual (SRMR) was calculated to indicate the overall model fit. The SRMR for the research model is 0.067, indicating a good fit since it is below the threshold of 0.08. The research model's normed fit index (NFI) is also 0.85, close to the recommended threshold of 0.90 (Cho *et al.*, 2020).

3.4 Structural model assessment and hypotheses testing

The structural model was evaluated using path coefficients, effect size coefficients (f^2), and determination coefficients (R^2) to predict relationships between constructs. Effect sizes were classified as strong ($f^2 > 0.35$), moderate ($f^2 > 0.15$), or weak ($f^2 > 0.02$). Results revealed moderate to strong effect sizes across supported relationships. Customer Satisfaction (CS) explained 75.3% of electronic loyalty (eLOY) and 14% of electronic word-of-mouth

Table 3. Convergent validity and reliability

	Complete ($n = 328$)			Spain ($n = 155$)			Mexico ($n = 173$)		
Items	CA	CR	AVE	CA	CR	AVE	CA	CR	AVE
DDMI	0.698	0.702	0.527	0.687	0.707	0.526	0.712	0.718	0.537
CCI	0.920	0.934	0.713	0.913	0.926	0.696	0.924	0.939	0.722
PE	0.931	0.931	0.879	0.925	0.925	0.869	0.937	0.937	0.888
CS	0.917	0.918	0.802	0.883	0.884	0.740	0.941	0.942	0.850
eWOM	0.924	0.931	0.867	0.911	0.913	0.849	0.933	0.953	0.881
eLOY	0.831	0.868	0.662	0.818	0.864	0.647	0.842	0.875	0.677

Note(s): CA: Cronbach's alpha. CR: Composite reliability; AVE: average variance extracted.
Source(s): Own elaboration

Table 4. Discriminant validity

Data set	Construct	DDMI	eLOY	eWOM	CCI	PE	CS
Complete	DDMI		0.422	0.263	0.420	0.542	0.658
$n = 328$	eLOY	0.541		0.671	0.612	0.502	0.576
	eWOM	0.330	0.785		0.638	0.270	0.347
	CCI	0.511	0.696	0.696		0.392	0.437
	PE	0.670	0.553	0.290	0.406		0.703
	CS	0.821	0.639	0.374	0.454	0.760	
Spain	DDMI		0.493	0.301	0.446	0.644	0.648
$n = 155$	eLOY	0.617		0.694	0.577	0.519	0.591
	eWOM	0.382	0.816		0.701	0.312	0.378
	CCI	0.559	0.672	0.766		0.450	0.401
	PE	0.805	0.570	0.340	0.475		0.680
	CS	0.824	0.669	0.419	0.431	0.754	
Mexico	DDMI		0.375	0.238	0.421	0.474	0.673
$n = 173$	eLOY	0.485		0.651	0.676	0.497	0.571
	eWOM	0.291	0.759		0.622	0.242	0.330
	CCI	0.500	0.761	0.685		0.357	0.474
	PE	0.578	0.546	0.256	0.360		0.721
	CS	0.818	0.623	0.347	0.482	0.767	

Note(s): The HTMT results fall below the diagonal value, while the above result belongs to inter-construct correlations.
Source(s): Own elaboration

(eWOM), while Customer-Company Identification (CCI) and Product Evaluation (PE) were explained by Data-Driven Marketing Image (DDMI) at 26.9% and 45.7%, respectively. Predictive relevance (Q^2), assessed using PLSpredict, confirmed strong predictive validity (Shmueli *et al.*, 2019).

Table 5 presents the results of hypothesis testing. All proposed relationships were supported with statistically significant path coefficients. DDMI had strong and positive effects on product evaluation (PE) ($\beta 2 = 0.459$, $p < 0.001$), customer-company identification (CI) ($\beta 1 = 0.420$, $p < 0.001$), and customer satisfaction (CS) ($\beta 5 = 0.102$, $p < 0.001$), confirming its central role in shaping consumer perceptions. CCI positively influenced both PE ($\beta 4 = 0.200$, $p < 0.001$) and CS ($\beta 5 = 0.102$, $p < 0.001$), while PE had a substantial effect on CS ($\beta 6 = 0.467$, $p < 0.001$). In turn, CS emerged as the strongest predictor of both eLoyalty ($\beta 7 = 0.576$, $p < 0.001$) and eWOM ($\beta 8 = 0.347$, $p < 0.001$), confirming its mediating role between cognitive evaluations and behavioural responses. Control analyses showed no significant additional effects, supporting the robustness of the model. Further details are presented in Table 5 and Figure 1.

3.5 Multigroup análisis

This study used Partial Least Squares Multigroup Analysis (PLS-MGA) to test the moderating effects of DDM implementation (H9) and country (RQ1). The sample was segmented by high/low DDM levels and country (Mexico vs. Spain). Although DDM implementation was initially measured in three levels (low, medium, high), these were recoded into two (high vs. low) to ensure adequate group sizes and clearer interpretation, following methodological guidelines (e.g. Becker *et al.*, 2023). Table 1 retains the original classification for transparency based on expert ratings using five indicators (Johnson *et al.*, 2019). MICOM analysis confirmed factorial invariance through high correlations and non-significant *p*-values, validating group comparisons (Table 5). In the high-DDM group, most relationships were significant, except for CCI→CS. In the low-DDM group, links between CCI → PE and CCI → CS were not significant. A stronger CCI→PE link in high-DDM contexts suggests that

Table 5. Results of hypothesis testing and moderation effects (DDM level and country)

Hypothesis	Relationships	β	f^2	*t*-value	CI [2.5%; 97.5%]	Result
H1	DDMI → CCI	0.420	0.367	9.195*	[0.333; 0.511]	Supported
H2	DDMI → PE	0.459	0.517	7.316*	[0.328; 0.576]	Supported
H3	DDMI → CS	0.362	0.593	5.499*	[0.234; 0.491]	Supported
H4	CCI → PE	0.200	0.013	3.806*	[0.101; 0.306]	Supported
H5	CCI → CS	0.102	0.002	2.336*	[0.019; 0.188]	Supported
H6	PE → CS	0.467	0.315	7.845*	[0.344; 0.580]	Supported
H7	CS → eLOY	0.576	0.727	12.560*	[0.485; 0.665]	Supported
H8	CS → eWOM	0.347	0.162	6.879*	[0.248; 0.447]	Supported
Control Relationships	Gender → eWOM	0.012	0.002	0.947		ns
	Gender → eLOY	0.001	0.000	0.989		ns
	Age → eWOM	0.022	0.007	0.817		ns
	Age → eLOY	−0.042	0.026	0.817		ns
	Incomes → eWOM	0.000	0.000	0.005		ns
	Incomes → eLOY	0.032	0.001	0.780		ns
	Monthly expenditure → eWOM	−0.159	0.000	0.178		ns
	Monthly expenditure → eLOY	−0.010	0.001	0.586		ns
		R^2		Q^2		
	CCI	0.269		0.168		
	PE	0.457		0.283		
	CS	0.753		0.422		
	eWOM	0.191		0.066		
	eLOY	0.467		0.171		

Propositions	Paths	High DDM level	Low DDM level	Comparison	Significant difference
$P9_1$	DDMI → CCI	0.453*	0.368*	0.085 ns	–
$P9_2$	DDMI → PE	0.385*	0.613*	−0.229 ns	–
$P9_3$	DDMI → CS	0.343*	0.360*	−0.017 ns	–
$P9_4$	CCI → PE	0.281*	0.031 ns	0.250	Yes
$P9_5$	CCI → CS	0.060 ns	0.096 ns	−0.037 ns	–
$P9_6$	PE → CS	0.469*	0.516*	−0.047 ns	–
$P9_7$	CS → eWOM	0.361*	0.328*	−0.060 ns	–
$P9_8$	CS → eLOY	0.554*	0.614*	0.034 ns	–

Propositions	Paths	Mexico	Spain	Comparison	Significant difference
$RQ1_1$	DDMI → CCI	0.421*	0.446*	0.025 ns	–
$RQ1_2$	DDMI → PE	0.393*	0.553*	0.160 ns	–
$RQ1_3$	DDMI → CS	0.382*	0.346*	−0.036 ns	–
$RQ1_4$	CCI → PE	0.192*	0.195*	0.011 ns	–

(*continued*)

Table 5. Continued

Propositions	Paths	Mexico	Spain	Comparison	Significant difference
RQ1$_5$	CCI → CS	0.138*	0.138 ns	−0.087 ns	–
RQ1$_6$	PE → CS	0.490*	0.434*	−0.056 ns	–
RQ1$_7$	CS → eWOM	0.330*	0.378*	0.019 ns	–
RQ1$_8$	CS → eLOY	0.571*	0.591*	0.048 ns	–

Note(s): $n = 5000$ subsamples; 95% confidence level – two tailed; *p < 0.001; ns: not significant. "Comparison" refers to the t-value testing coefficient differences between groups.
Source(s): Own elaboration

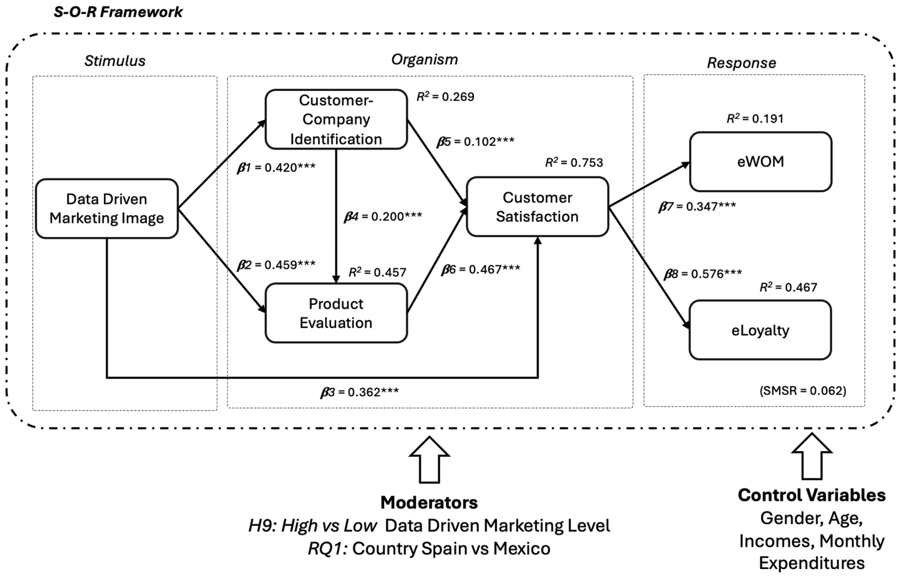

Figure 1. Results of the structural model assessment. Source: Own elaboration

advanced DDM strategies enhance customer identification, which improves product evaluation.

At the country level, all relationships were significant in Mexico. In Spain, the CCI→CS link was not significant. However, cross-country comparisons revealed no statistically significant differences, indicating structural consistency across markets. Hence, H9 was partially supported, as DDM implementation moderated specific paths. Regarding RQ1, cultural variation was observed, but the country did not moderate all model relationships significantly.

4. General discussion

This study underscores the impact of Data-Driven Marketing Image (DDMI) on consumer behaviour, particularly customer-company identification (CCI), product evaluation (PE), and customer satisfaction (CS) in the fashion sector. These results contribute to ongoing debates about the effectiveness of DDM by confirming that perceived strategic use of data (i.e. DDMI) shapes key emotional and cognitive reactions in consumers. This aligns with prior conceptual models on personalisation and customer experience (Holmlund *et al.*, 2020; Hoyer *et al.*, 2020) and offers empirical support for their assumptions in a cross-cultural fashion retail context. Advanced DDM strengthens CCI, improving product perception and satisfaction, consistent with prior findings on emotional customer-company connections (Raza *et al.*, 2020). Moreover, the findings show that DDM effectiveness depends not only on the presence of data strategies but also on their level of sophistication. Often overlooked in S-O-R studies, this insight shows that analytics maturity shapes consumer responses to data-driven marketing.

The results show that higher DDM levels enhance the CCI→PE link, supporting previous research on advanced DDM's role in precise segmentation and personalised marketing (Johnson *et al.*, 2019). However, our findings further nuance this relationship by showing that the CCI→PE effect is significantly amplified in high-DDM contexts, suggesting that the sophistication of data strategies plays a crucial role that has not been previously explored in detail within this specific link.

Cultural differences reveal that CCI is a stronger determinant of satisfaction in Mexico than in Spain, aligning with research on cross-cultural variations in marketing strategy effectiveness (Hoppner *et al.*, 2015; Wang *et al.*, 2019). Additionally, CS strongly predicts eWOM and eLOY, reinforcing findings that satisfaction drives brand loyalty and recommendations (Goyette *et al.*, 2010). Companies should prioritise CCI in high-DDM markets and adapt strategies to cultural contexts to maximise satisfaction and loyalty.

This study reinforces the idea that firms must not only do DDM but also signal and communicate it effectively to consumers. DDMI acts as a perceptual mechanism that bridges technological capability with consumer experience, offering scholars and practitioners a measurable construct for assessing digital trust and value creation.

4.1 Theoretical and managerial contributions

This study advances the theoretical understanding of DDM by examining how the perceived data-driven image (DDMI) affects customer-company identification (CCI), product evaluation (PE), and satisfaction (CS) in the competitive fashion sector (Jin and Shin, 2020). It also shows that advanced DDM implementation enhances CCI and PE, contributing to theories of personalisation and customer experience (Holmlund *et al.*, 2020; Hoyer *et al.*, 2020).

Findings enrich the intercultural analysis of DDM, revealing distinct patterns regarding CCI's influence on satisfaction in Spain and Mexico, reinforcing the need for culturally tailored strategies (Messner, 2022).

The study extends the Stimulus-Organism-Response (S-O-R) framework by introducing DDMI as a construct that captures the perceived effectiveness of data strategies. Unlike prior research on operational metrics, DDMI reflects consumer value perceptions, bridging technical implementation and experiential outcomes. This conceptual advancement connects firms' technological capabilities with consumer responses. By combining cross-cultural comparison and implementation levels, the study supports the contextualisation of DDM effects and addresses calls for more nuanced digital marketing research (Holmlund *et al.*, 2020; Peltier *et al.*, 2024). It also positions DDMI as a potential mediator or moderator in broader engagement models.

From a managerial standpoint, high-DDM contexts benefit from personalised loyalty schemes and sustainability messaging to reinforce CCI (Sriyakula *et al.*, 2019; Kassemeier *et al.*, 2022). Omnichannel strategies and CRM systems support consistent, personalised interactions. Trust-based approaches such as tailored loyalty programmes are more effective in Mexico, while product quality and customer service take precedence in Spain. Globally, adapting DDM strategies to digital maturity is essential: advanced analytics and personalisation may drive value in mature markets like Spain, whereas in emerging ones like Mexico, transparency and responsiveness build satisfaction.

Integrating technologies such as AI, Big Data, and Machine Learning further enhances DDM's strategic impact by enabling precise, personalised experiences (Peltier *et al.*, 2024).

Managers should align their strategies with DDM maturity and market characteristics: large, data-intensive firms should invest in advanced analytics, while those in early stages should prioritise trust, clear value communication, and tangible benefits. CCI should be monitored as an intermediate alignment signal between brand and consumer expectations.

4.2 Limitations and directions for future research

This study has limitations that open avenues for future research. First, it focuses on consumers from Spain and Mexico in online fashion retail. Despite these countries' cultural and technological differences, the findings may not be generalised to other contexts. Replication in other cultural settings (e.g. Asia or Nordic countries) or sectors (e.g. finance, hospitality, healthcare) would test applicability where customer expectations differ. Second, the cross-sectional design allows robust comparisons but cannot track changes over time. Longitudinal studies could examine how perceptions of DDMI evolve as consumers gain experience or firms adjust their data-driven practices. Third, although DDMI provides a valuable perceptual indicator, future work could include constructs like trust in technology, perceived intrusiveness, or digital literacy, which may mediate or moderate observed effects. This would enrich the understanding of how data strategies influence engagement. Finally, DDMI could be explored as a dynamic key performance indicator (KPI) for managers, assessing its responsiveness to strategic communication and brand positioning in practice.

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