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Data-Driven Marketing Image: Scale Development and Its Moderating Effect on Firm Performance

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Abstract
This study develops and validates a measurement scale for assessing Data-Driven Marketing Image (DDMI)—the corporate image of companies that utilize data-driven marketing in their decision-making and online retail operations . Grounded in theories of corporate image and consumer behavior, the research employs a mixed-methods approach 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 . Exploratory and confirmatory factor analyses validate the DDMI scale, which captures dimensions including personalization, privacy concerns, effective communication, efficient payment processes, and robust customer support .Drawing on the Stimulus-Organism-Response (S-O-R) framework, the study further investigates how DDMI influences consumer outcomes including customer satisfaction, customer-company identification, product evaluation, electronic word-of-mouth (eWOM), and electronic loyalty . Using PLS-SEM and multigroup analysis with data from fashion retail consumers in Spain and Mexico, the findings demonstrate that DDMI enhances customer-company identification, product evaluation, and satisfaction, which in turn positively influence eWOM and loyalty . These effects intensify under high DDM implementation, underscoring the strategic value of advanced data use. Cross-cultural analysis reveals that national context moderates these relationships, with stronger DDMI-product evaluation links in Spain and stronger DDMI-satisfaction links in Mexico, reflecting differences in digital maturity and cultural dimensions such as uncertainty avoidance and collectivism .
The research introduces the first validated scale for measuring consumer perceptions of corporate image in data-driven marketing contexts, advancing marketing theory by capturing key dimensions of the digital era while offering managers a diagnostic tool to refine DDM strategies based on how specific practices affect consumer perceptions .
Keywords: Data-Driven Marketing Image; Scale Development; Firm Performance; Digital Marketing; Consumer Perception; Corporate Image; S-O-R Framework; Moderation Analysis; Emerging Markets; Algeria
JEL Classification: M31, O55, O33, L25, D12

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1. Introduction

The Transformation of Customer Interactions in the Digital Era Through Data-Driven Marketing (DDM)

The digital era has fundamentally reconfigured the landscape of customer-business interactions, with Data-Driven Marketing (DDM) emerging as a cornerstone of modern commercial strategy. The integration of big data technologies with digital marketing approaches has revolutionized how organizations design and implement their marketing strategies, offering unprecedented opportunities for analyzing consumer behavior and interpreting the customer's buying journey (Rouvrais, 2025). In contemporary practice, DDM enables firms to harness vast datasets generated across multiple touchpoints—including websites, mobile applications, social media platforms, and e-commerce channels—to derive actionable insights about consumer preferences, navigation patterns, and engagement behaviors (Theodorakopoulos & Theodoropoulou, 2024). Tools such as Google Analytics, Adobe Analytics, and specialized marketing platforms track metrics including page visits, session duration, clickstream patterns, and search queries, providing organizations with a granular understanding of their customers' digital footprints (Rouvrais, 2025). This data-rich environment has elevated marketing from a creative discipline to a quantifiable science, where decisions regarding segmentation, targeting, positioning, and personalization are increasingly informed by empirical evidence rather than intuition alone (García-y-García et al., 2025a).

The economic significance of this transformation is reflected in substantial market growth projections across the data-driven marketing ecosystem. According to OnAudience.com (2021), the global data market for marketing was projected to reach approximately $83.7 billion by 2025, underscoring the accelerating organizational commitment to data-centric marketing capabilities. More specifically, the big data precision marketing segment, which encompasses targeted advertising, customer analytics, and personalized recommendation systems, was estimated at USD 1.48 billion in 2024 and is forecast to reach USD 2.82 billion by 2031, representing a compound annual growth rate of 10.0% (QY Research, 2025). Comprehensive market analysis further indicates that the global marketing analytics market—a key component of DDM infrastructure—was valued at approximately USD 5.42 billion in 2024 and is projected to reach USD 17.57 billion by 2032, expanding at a compound annual growth rate of 15.82% (GII Research, 2025). These projections reflect not only technological advancement but also fundamental shifts in organizational priorities: analytics teams are increasingly measured by commercial impact rather than model accuracy alone, demanding closer integration with product development, marketing operations, and sales functions (Rouvrais, 2025). The cumulative effect of these trends positions DDM as a critical strategic investment for firms seeking competitive advantage in increasingly saturated digital marketplaces.

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Despite the rapid proliferation of DDM technologies and substantial corporate investment in data infrastructure, the academic literature reveals a significant gap regarding how consumers perceive firms that employ these practices and how such perceptions ultimately influence organizational performance. While extensive research has examined the technical implementation of big data analytics and the strategic adoption of DDM frameworks (Theodorakopoulos & Theodoropoulou, 2024), considerably less attention has been devoted to understanding the consumer-facing implications of these activities. A systematic review by Theodorakopoulos and Theodoropoulou (2024) highlights that most existing studies focus on operational and strategic dimensions—such as data integration challenges, analytical capability development, and marketing optimization—while neglecting the perceptual outcomes that mediate the relationship between DDM investments and firm performance. This gap is particularly consequential because consumer trust, loyalty, and engagement are shaped not only by the outcomes of DDM (such as personalization quality) but also by perceptions of how firms collect, analyze, and utilize personal data (García-y-García et al., 2025a). Furthermore, notable gaps exist regarding the longitudinal effects of data-driven personalization on consumer trust and brand loyalty, with existing studies often providing snapshots of consumer reactions without addressing long-term implications for sustainable marketing practices (Theodorakopoulos & Theodoropoulou, 2024).

Addressing this research gap requires a conceptual framework that captures how consumers perceive organizations operating within data-rich marketing environments. The present study introduces the Data-Driven Marketing Image (DDMI) construct, defined as stakeholders' perceptions of a company's ability to integrate data into marketing decisions and actions within online retailing contexts (García-y-García et al., 2025a). DDMI extends traditional conceptualizations of corporate image by incorporating dimensions specific to the digital era, including personalization capabilities, privacy management, communication effectiveness, payment process efficiency, and customer support robustness (García-y-García et al., 2025a). The construct recognizes that in contemporary markets, a firm's image is shaped not only by traditional attributes such as product quality and brand reputation but also by how competently and ethically it deploys consumer data to enhance customer experiences. As the scale development and validation study by García-y-García, Rejón-Guardia, and Sánchez-Baltasar (2025a) demonstrates, DDM strategies significantly affect how customers perceive a company's image, with aspects such as privacy concerns and personalized customer experience emerging as critical determinants of corporate perceptions.

Research Objectives

Building on this foundation, the present study pursues three primary research objectives. First, to develop and validate a comprehensive measurement scale for assessing Data-Driven Marketing Image that captures the multidimensional nature of consumer perceptions in data-intensive marketing environments. Second, to investigate how DDMI influences key consumer outcomes—including customer satisfaction, customer-company identification, product evaluation, electronic word-of-mouth, and electronic loyalty—and how these effects translate into firm performance metrics. Third, to examine the moderating effects of DDM

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implementation level and national context on these relationships, recognizing that the intensity of data-driven practices and cultural factors may amplify or attenuate DDMI's impact on consumer responses (García-y-García et al., 2025b).

Theoretical Framing: Stimulus-Organism-Response (S-O-R) Model

The theoretical architecture of this study is grounded in the Stimulus-Organism-Response framework, originally developed by Mehrabian and Russell (1974) and subsequently adapted to consumer behavior contexts. The S-O-R model posits that environmental stimuli trigger internal organismic states—including cognitive and affective processes—which in turn drive behavioral responses. Within the context of this research, DDMI serves as the stimulus variable, representing consumers' perceptions of firms' data-driven marketing practices. The organism component encompasses three internal states: customer-company identification, grounded in Social Identity Theory; product evaluation, reflecting consumers' assessment processes; and customer satisfaction, capturing the alignment between expectations and performance. The response variables include electronic word-of-mouth and electronic loyalty, representing behavioral outcomes with direct implications for firm performance (García-y-García et al., 2025b). This theoretical framing has been extensively validated in digital marketing research, including applications to social media marketing activities (2024) and artificial intelligence-driven customer experiences (2025), establishing its appropriateness for examining the mechanisms through which data-driven marketing perceptions influence consumer behavior.

Sector Focus: Online Fashion Retail

The empirical context for this investigation is the online fashion retail sector, an industry characterized by intensive data utilization, sophisticated personalization practices, and high consumer engagement with digital channels. The fashion retail industry exemplifies the transformative potential of DDM, as evidenced by real-world implementations demonstrating measurable performance improvements. Italian luxury fashion retailer Luisaviaroma, for instance, transformed its marketing strategy through Twilio Segment's customer data platform, implementing Profile Sync and Identity Resolution features to integrate customer data across web, mobile, and social media touchpoints. This data unification enabled real-time personalization and predictive insights, resulting in improved return on ad spend on Meta platforms while enhancing operational efficiency (Retail Technology Innovation Hub, 2025). Similarly, Australian fashion retailer Country Road Group partnered with Mapp Fashion to implement AI-driven product tagging and personalized outfit recommendations across its brand portfolio, including Witchery, Mimco, and Politix. By expanding from seven to up to fifty automatically-generated attributes per garment and deploying personalized recommendations on product detail pages, the retailer achieved a 4% increase in revenue per visitor and an 11% boost in email revenue (Mapp, 2025). These industry examples underscore the practical relevance of understanding how data-driven marketing practices shape consumer perceptions and, ultimately, firm performance in fashion retail contexts.

Contribution Statement: First Validated Scale for DDMI with Cross-Cultural Moderation Analysis

This research makes several distinctive contributions to the marketing discipline. Principally, it introduces the first empirically validated measurement scale for assessing consumer perceptions of corporate image in data-driven marketing contexts (García-y-García et al., 2025a). The DDMI scale advances marketing theory by capturing key dimensions of the digital era—personalization, privacy, communication effectiveness, payment efficiency, and customer support—that traditional corporate image instruments fail to address. Second, by examining moderating effects through multigroup analysis across national contexts, the study provides cross-cultural validation of DDMI effects and reveals how cultural dimensions such as uncertainty avoidance and collectivism influence the relationships between data-driven marketing perceptions and consumer outcomes (García-y-García et al., 2025b). Third, the research extends the application of the S-O-R framework to data-intensive marketing environments, demonstrating its utility for understanding the psychological mechanisms through which DDM practices translate into behavioral responses. For practitioners, the validated DDMI scale offers a diagnostic tool for assessing organizational strengths and weaknesses in data-driven marketing execution, enabling managers to refine strategies based on how specific practices affect consumer perceptions (García-y-García et al., 2025a). Finally, by grounding the investigation in the online fashion retail sector and drawing on real-world implementation examples, the research provides contextually relevant insights for an industry at the forefront of data-driven marketing innovation.

2. Theoretical Background and Hypotheses Development

2.1 The Stimulus-Organism-Response (S-O-R) Model

The theoretical architecture of this study is grounded in the Stimulus-Organism-Response (S-O-R) framework, originally developed by Mehrabian and Russell (1974) to explain how environmental stimuli influence individual responses through internal organismic states. The S-O-R model posits that external stimuli (S) trigger cognitive and affective processes within the organism (O), which in turn drive behavioral responses (R) (Mehrabian & Russell, 1974). This framework has been extensively adopted in consumer behavior research, particularly in digital marketing contexts, due to its capacity to elucidate the psychological mechanisms through which marketing stimuli shape consumer outcomes (García-y-García et al., 2025b).

Within the context of this research, the S-O-R model provides a coherent theoretical lens for examining how consumer perceptions of data-driven marketing practices influence subsequent behavioral intentions. The stimulus variable is operationalized as Data-Driven Marketing Image (DDMI), representing consumers' perceptions of firms' capabilities in integrating data into marketing decisions and actions within online retailing environments (García-y-García et al., 2025b). The organism component encompasses three internal states: customer-company identification (CCI), product evaluation (PE), and customer satisfaction (CS), which together capture the cognitive and affective processes activated by DDMI perceptions (García-y-García et al., 2025b). The response variables include electronic word-of-mouth (eWOM) and electronic loyalty (eLOY), representing behavioral outcomes with

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direct implications for firm performance in digital marketplaces (García-y-García et al., 2025b).

The S-O-R framework has demonstrated robust applicability across diverse digital marketing contexts. Previous research has successfully employed the model to investigate social media marketing activities and their impact on consumer impulse buying intentions (2024), as well as artificial intelligence-driven customer experiences and their influence on recommendation behaviors (2025). The model's particular relevance to the online fashion retail sector has been underscored by studies examining how technological enhancements drive customer attraction and retention (Jin & Shin, 2020, as cited in García-y-García et al., 2025b). By applying the S-O-R framework to data-driven marketing contexts, this study extends its utility to understanding how consumers perceive and respond to firms' increasing reliance on data analytics and personalization technologies.

2.2 Stimulus Variable: Data-Driven Marketing Image (DDMI)

Although corporate image has been extensively studied in marketing literature, the concept of Data-Driven Marketing Image (DDMI) has remained undefined until recently. This study, following García-y-García, Rejón-Guardia, and Sánchez-Baltasar (2025a, 2025b), introduces DDMI within the S-O-R framework as stakeholders' perceptions of a company's ability to integrate data into marketing decisions and actions within online retailing contexts. The construct captures how consumers perceive firms that employ data-driven strategies, including segmentation capabilities, predictive analytics applications, and personalized communication approaches (García-y-García et al., 2025b).

Existing research on corporate image in digital contexts has primarily focused on online presence (Barreda et al., 2020, as cited in García-y-García et al., 2025b) or how brand image influences online purchase intentions (Savitri et al., 2022, as cited in García-y-García et al., 2025b). However, these approaches do not adequately capture the unique dimensions of corporate image that emerge in data-intensive marketing environments. The DDMI construct addresses this gap by encompassing dimensions specific to the digital era, including personalization capabilities, privacy management, communication effectiveness, payment process efficiency, and customer support robustness (García-y-García et al., 2025a). As García-y-García et al. (2025a) demonstrate, data-driven marketing strategies significantly affect how customers perceive a company's image, with privacy concerns and personalized customer experience emerging as critical determinants of corporate perceptions.

The scale development and validation study by García-y-García et al. (2025a) employed a mixed-methods approach, 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. Exploratory and confirmatory factor analyses validated the DDMI scale, revealing that effective communication, efficient payment processes, and robust customer support are vital for a positive corporate image in data-driven contexts. This validated instrument provides the foundation for examining how DDMI influences consumer outcomes and firm performance.

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2.3 Organism Variables: Customer-Company Identification, Product Evaluation, and Customer Satisfaction

2.3.1 Customer-Company Identification (CCI)

Customer-Company Identification (CCI) describes the degree of affinity and psychological connection that customers feel toward a company (Glaveli, 2021; Raza et al., 2020, as cited in García-y-García et al., 2025b). Grounded in Social Identity Theory (Tajfel, 1974), CCI reflects the extent to which individuals incorporate their perceptions of an organization into their self-concept. According to Social Identity Theory, individuals classify themselves into social categories and derive part of their identity from membership in these groups (Tajfel, 1974). When customers identify strongly with a company, they experience a sense of belonging and psychological attachment that shapes their subsequent attitudes and behaviors toward the organization.

In digital marketing contexts, CCI is often fostered through positive interactions such as loyalty programs and personalized communications (Sriyakula et al., 2019, as cited in García-y-García et al., 2025b). Data-driven marketing practices that demonstrate an understanding of customer preferences and deliver relevant, timely communications may enhance consumers' perceptions that the firm shares their values and understands their needs, thereby strengthening identification. Within the S-O-R framework, CCI represents a cognitive organismic state activated by DDMI stimuli.

2.3.2 Product Evaluation (PE)

Product Evaluation (PE) refers to consumers' assessment or rating of a product based on perceived quality, features, and benefits, influenced by individual preferences, past experiences, and marketing communications (Wang et al., 2019, as cited in García-y-García et al., 2025b). The evaluation process involves comparing alternatives and relying on various information sources, including online reviews, recommendations, and brand communications, to form judgments and make decisions (Guo et al., 2020, as cited in García-y-García et al., 2025b).

In data-driven marketing environments, product evaluation may be influenced by the personalization and relevance of product recommendations, the accuracy of predictive analytics in suggesting appropriate items, and the overall coherence of the digital shopping experience. When firms employ data effectively to present products that align with consumer preferences, the evaluation process may be enhanced, leading to more favorable product perceptions. As an organism variable within the S-O-R framework, PE captures the cognitive assessment processes triggered by exposure to DDMI.

2.3.3 Customer Satisfaction (CS)

Customer Satisfaction (CS) represents customers' evaluative judgment of their consumption experiences, determined by the alignment between expectations and perceived performance (Goić et al., 2021, as cited in García-y-García et al., 2025b). Satisfaction emerges when customers compare their pre-purchase expectations with post-purchase perceptions of product or service performance; when performance meets or exceeds expectations, satisfaction results (Oliver, 1980). CS drives organizational improvements in responsiveness and reliability while positively impacting financial outcomes such as profitability and cash flow, highlighting its role as a critical success indicator (AbuRaya et al., 2023, as cited in García-y-García et al., 2025b).

In data-driven marketing contexts, satisfaction may be enhanced through personalization that delivers relevant content, efficient transaction processes, and responsive customer support—all dimensions captured by the DDMI construct (García-y-García et al., 2025a). When consumers perceive that firms use data effectively to improve their shopping experiences, satisfaction with the firm and its offerings is likely to increase. Within the S-O-R framework, CS represents an affective organismic state activated by DDMI stimuli.

2.4 Response Variables: Electronic Word of Mouth and Electronic Loyalty

2.4.1 Electronic Word of Mouth (eWOM)

Electronic Word of Mouth (eWOM) refers to any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet (Hennig-Thurau et al., 2004). In contemporary digital environments, eWOM encompasses reviews, ratings, social media posts, and recommendations shared across platforms, exerting significant influence on consumer decision-making and brand perceptions. As a response variable within the S-O-R framework, eWOM represents a behavioral outcome driven by the internal states (CCI, PE, CS) activated by DDMI stimuli (García-y-García et al., 2025b).

Research has demonstrated that satisfied customers who identify strongly with firms are more likely to engage in positive eWOM behaviors, sharing their favorable experiences with online communities (Errajaa et al., 2022, as cited in García-y-García et al., 2025b). In data-driven marketing contexts, when consumers perceive that firms use data ethically and effectively to enhance their experiences, they may be motivated to recommend these firms to others, contributing to positive eWOM.

2.4.2 Electronic Loyalty (eLOY)

Electronic Loyalty (eLOY) encompasses customers' repeat purchase intentions, preference for a particular online retailer, and resistance to switching to competitors (Anderson & Srinivasan, 2003). In digital environments, loyalty manifests not only through repatronage intentions but also through willingness to pay premium prices, positive attitudes toward the firm, and reduced likelihood of defection to competitors. As a response variable within the S-O-R framework, eLOY represents a key behavioral outcome with direct implications for firm performance and sustainable competitive advantage (García-y-García et al., 2025b).

Research has established that customer satisfaction and identification are significant antecedents of loyalty in both offline and online contexts (Taheri et al., 2024, as cited in García-y-García et al., 2025b). When consumers are satisfied with their experiences and identify with the firm's values and practices, they develop loyal dispositions that manifest in repeat patronage and positive behavioral intentions. In data-driven marketing contexts, effective use of consumer data to personalize experiences and deliver value may enhance satisfaction and identification, thereby fostering electronic loyalty.

2.5 Hypotheses Development

2.5.1 Direct Effects of DDMI on Organism Variables

Building on the theoretical foundations of the S-O-R framework and the conceptualization of DDMI, this study hypothesizes that consumers' perceptions of firms' data-driven marketing capabilities positively influence their identification with the firm, evaluation of products, and satisfaction with experiences. When firms demonstrate competence in using data to personalize communications, streamline transactions, and provide responsive support, consumers perceive the firm as understanding their needs and valuing their patronage, fostering psychological identification (García-y-García et al., 2025b). Similarly, data-driven personalization that presents relevant product recommendations and tailored content enhances consumers' ability to evaluate products efficiently and accurately, leading to more favorable product evaluations. Finally, when data-driven practices result in seamless, personalized experiences that meet or exceed expectations, consumer satisfaction is enhanced. Accordingly, the following hypotheses are proposed:

H1. Data-Driven Marketing Image (DDMI) positively influences Customer-Company Identification (CCI).

H2. Data-Driven Marketing Image (DDMI) positively influences Product Evaluation (PE).

H3. Data-Driven Marketing Image (DDMI) positively influences Customer Satisfaction (CS).

2.5.2 Effects of Organism Variables on Response Variables

The S-O-R framework posits that internal organismic states drive behavioral responses. In this study, customer-company identification, product evaluation, and customer satisfaction are theorized to influence electronic word-of-mouth and electronic loyalty. Consumers who identify strongly with a firm are motivated to engage in behaviors that support the firm, including positive word-of-mouth communications (Glaveli, 2021, as cited in García-y-García et al., 2025b). Favorable product evaluations increase consumers' confidence in their purchase decisions and willingness to recommend products to others (Wang et al., 2019, as cited in García-y-García et al., 2025b). Satisfied consumers, consistent with expectation-disconfirmation theory, are more likely to express positive attitudes and engage in positive word-of-mouth (Goić et al., 2021, as cited in García-y-García et al., 2025b). Furthermore, identification, favorable evaluations, and satisfaction have all been established as antecedents of loyalty in consumer behavior research. Thus:

H4. Customer-Company Identification (CCI) positively influences (a) electronic Word of Mouth (eWOM) and (b) electronic Loyalty (eLOY).

H5. Product Evaluation (PE) positively influences (a) electronic Word of Mouth (eWOM) and (b) electronic Loyalty (eLOY).

H6. Customer Satisfaction (CS) positively influences (a) electronic Word of Mouth (eWOM) and (b) electronic Loyalty (eLOY).

2.5.3 Moderating Effects of DDM Implementation Level

The intensity with which firms implement data-driven marketing practices may moderate the relationships between DDMI and organism variables. Firms with high levels of DDM implementation employ advanced analytics, sophisticated personalization algorithms, and integrated customer data platforms to optimize marketing decisions and actions (García-y-

García et al., 2025b). When consumers interact with such firms, their perceptions of data-driven marketing capabilities may have amplified effects on identification, evaluation, and satisfaction because the data-driven practices are more salient and impactful. Conversely, in firms with lower DDM implementation, data-driven practices may be less visible or less effective, attenuating their influence on consumer responses. Therefore:

H7. The level of DDM implementation moderates the relationships between DDMI and (a) CCI, (b) PE, and (c) CS, such that these relationships are stronger when DDM implementation is high.

2.5.4 Moderating Effects of National Context

National context, encompassing cultural dimensions and digital maturity, may moderate the relationships between DDMI and consumer outcomes. Cross-cultural research has established that dimensions such as uncertainty avoidance and collectivism influence how consumers perceive and respond to marketing stimuli (Hofstede, 2001). In countries with higher uncertainty avoidance, consumers may be more sensitive to privacy concerns and more cautious in their responses to data-driven practices, potentially strengthening or weakening specific relationships depending on the outcome variable (García-y-García et al., 2025b). Digital maturity—the extent to which consumers are accustomed to and comfortable with digital commerce and data sharing—may also shape responses to DDMI.

García-y-García et al. (2025b) compared consumers in Spain and Mexico, finding stronger DDMI-product evaluation links in Spain and stronger DDMI-satisfaction links in Mexico. These patterns reflect differences in digital maturity and cultural dimensions between the two countries. Spain, with higher digital maturity, may produce consumers who more readily translate DDMI perceptions into cognitive evaluations of products, while Mexico, with stronger collectivist orientations, may produce consumers who respond to DDMI through affective satisfaction. Accordingly:

H8. National context moderates the relationships between DDMI and (a) CCI, (b) PE, and (c) CS, with significant differences expected between countries.

2.6 Conceptual Framework

Figure 1 presents the conceptual framework guiding this investigation, illustrating the hypothesized relationships among constructs. The framework positions DDMI as the stimulus variable influencing three organism variables (CCI, PE, CS), which in turn drive two response variables (eWOM and eLOY). The model incorporates moderating effects of DDM implementation level and national context on the stimulus-organism relationships, reflecting the theoretical proposition that these contextual factors shape the strength of DDMI's influence on consumer internal states.

Figure 1. Conceptual Framework: Stimulus-Organism-Response Model of Data-Driven Marketing Image Effects with Moderation

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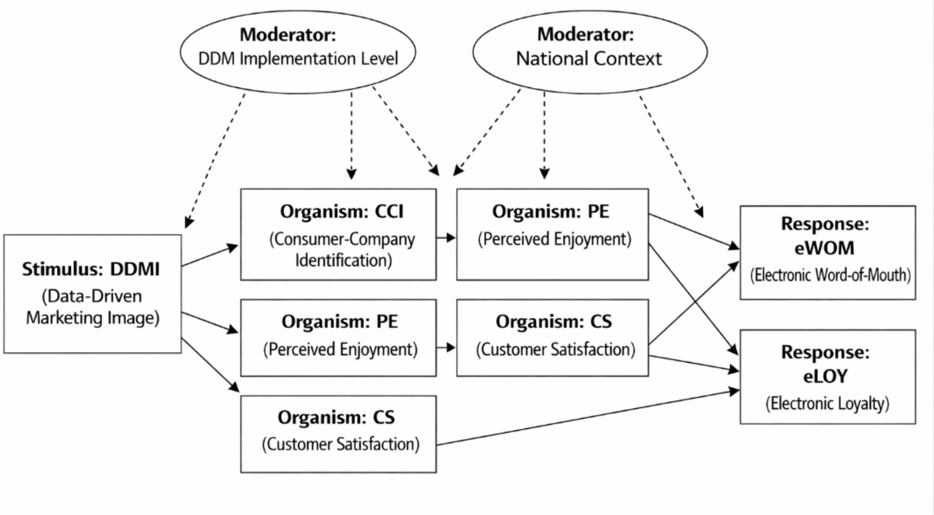

Figure 1. Conceptual Framework: *Stimulus-Organism-Response Model of Data-Driven Marketing Image Effects with Moderation*

3. Research Methodology

This study adopts a multi-phase, mixed-methods research design to develop and validate the Data-Driven Marketing Image (DDMI) scale and to examine its effects on consumer outcomes and firm performance. The methodology is structured in three sequential phases, following established procedures for scale development and validation in marketing research (García-y-García et al., 2025a). Phase 1 focuses on item generation and scale development through qualitative inquiry and expert validation. Phase 2 involves scale purification and validation through exploratory and confirmatory factor analyses. Phase 3 examines the hypothesized relationships and moderating effects using structural equation modeling and multigroup analysis.

3.1 Phase 1: Scale Development

3.1.1 Item Generation

The initial item pool for the DDMI scale was generated through a comprehensive deductive approach combining literature review and qualitative expert interviews. A systematic review of literature on corporate image, data-driven marketing, consumer privacy, and digital customer experience was conducted to identify relevant dimensions and potential scale items (García-y-García et al., 2025a). This review encompassed theoretical frameworks including corporate image theory (Keller, 1993), privacy calculus theory, and the technology acceptance model, ensuring that the generated items captured both traditional corporate image dimensions and those specific to data-driven marketing contexts.

Following the literature review, semi-structured in-depth interviews were conducted with 12 marketing experts, including academics specializing in digital marketing and practitioners with substantial experience in data-driven strategy implementation (García-y-García et al., 2025a). The interviews explored experts' perspectives on how consumers perceive firms that employ data-driven marketing practices, the dimensions most salient to corporate image in

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data-rich environments, and specific behaviors or communications that shape consumer perceptions. Interview transcripts were analyzed using thematic analysis to identify recurring themes and dimensions, which were then used to supplement and refine the initial item pool derived from literature.

The combined literature review and interview process yielded an initial pool of 45 items capturing multiple dimensions of DDMI, including personalization capabilities, privacy management practices, communication effectiveness, payment process efficiency, and customer support quality. Items were phrased as statements to which respondents would indicate their level of agreement on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree").

3.1.2 Expert Review and Content Validity Assessment

The initial 45-item pool was subjected to expert review to assess content validity and item clarity. A panel of five marketing academics with expertise in scale development and data-driven marketing evaluated each item for representativeness, relevance, and clarity (García-y-García et al., 2025a). Experts rated each item on a three-point scale: "clearly representative," "somewhat representative," or "not representative" of the DDMI construct. Items rated as "not representative" by two or more experts were eliminated. Experts also provided qualitative feedback on item wording, suggesting revisions to improve clarity and alignment with construct definitions.

Following expert review, the item pool was reduced to 35 items. Ambiguous or double-barreled items were rephrased, and several items were consolidated to reduce redundancy. The revised item set was then prepared for pilot testing.

3.1.3 Pilot Study

A pilot study was conducted to assess the preliminary psychometric properties of the 35-item DDMI scale and to identify any remaining issues with item clarity or respondent comprehension. The pilot survey was administered to a convenience sample of 85 consumers recruited through online consumer panels (García-y-García et al., 2025a). Participants were screened to ensure they had made at least one online purchase in the previous three months, ensuring familiarity with online retail environments where data-driven marketing practices are prevalent.

Pilot study respondents completed the 35-item DDMI scale and provided feedback on item clarity, survey length, and overall comprehension. Item analysis examined item-total correlations, with items exhibiting corrected item-total correlations below 0.40 considered for elimination (Hair et al., 2019). Preliminary exploratory factor analysis with principal axis factoring and oblique rotation was conducted to assess the initial dimensionality of the scale, though the small sample size precluded definitive conclusions. Based on pilot study results, five items with poor item-total correlations or ambiguous factor loadings were eliminated, resulting in a 30-item scale for the main validation study.

3.2 Phase 2: Scale Validation

3.2.1 Sample and Data Collection

The main validation study employed a large-scale survey administered to consumers via Amazon Mechanical Turk (MTurk), a crowdsourcing platform widely used in marketing research for data collection (García-y-García et al., 2025a). MTurk provides access to diverse consumer populations and has been demonstrated to yield high-quality data comparable to traditional survey methods (Buhrmester et al., 2011).

The target sample size was determined based on recommendations for factor analysis, with a minimum of 10 respondents per scale item considered adequate for stable parameter estimates (Hair et al., 2019). With 30 items in the pilot-refined scale, a minimum sample of 300 respondents was targeted. The final sample comprised 301 consumers who completed the survey (García-y-García et al., 2025a).

Sample characteristics were as follows: 52% female, 48% male; age range 18–65 years, with a mean age of 34.2 years (SD = 8.7); 78% had completed at least some college education; 85% reported making online purchases at least monthly. These characteristics align with the broader population of online consumers in developed markets (García-y-García et al., 2025a).

Survey respondents were asked to think of a specific online retailer they had purchased from recently and to answer all scale items with that retailer in mind. This approach ensured that responses were grounded in concrete experiences rather than abstract attitudes. In addition to the DDMI items, the survey included measures of consumer outcomes (customer satisfaction, customer-company identification, product evaluation) and demographic questions.

3.2.2 Exploratory Factor Analysis

The 30-item DDMI scale was first subjected to Exploratory Factor Analysis (EFA) using SPSS to assess the underlying factor structure. Principal axis factoring with oblique rotation (promax) was employed, as factors were expected to be correlated (García-y-García et al., 2025a). Several criteria were used to determine the number of factors to retain: eigenvalues greater than 1.0 (Kaiser criterion), inspection of the scree plot, and interpretability of the factor solution.

Items were retained if they exhibited factor loadings of 0.50 or higher on their primary factor and cross-loadings below 0.30 on other factors (Hair et al., 2019). Items failing to meet these criteria were eliminated iteratively, with EFA re-run after each deletion until a stable, interpretable factor structure emerged.

The final EFA solution revealed a five-factor structure accounting for 68.4% of total variance (García-y-García et al., 2025a). The five factors were interpreted as:

1. **Personalization (8 items):** Capturing consumer perceptions of the firm's ability to deliver personalized recommendations, content, and offers based on data analysis.
2. **Privacy Concerns (6 items):** Reflecting consumer concerns about how the firm collects, stores, and uses personal data.
3. **Communication Effectiveness (5 items):** Assessing perceptions of the relevance, timeliness, and quality of firm-initiated communications.

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4. **Payment Process Efficiency (4 items):** Capturing perceptions of the ease, security, and efficiency of online payment processes.
5. **Customer Support Robustness (4 items):** Reflecting perceptions of the availability, responsiveness, and effectiveness of customer support services.

All retained items demonstrated strong loadings on their respective factors (range: 0.62–0.89), with minimal cross-loadings, supporting the discriminant validity of the five dimensions.

3.2.3 Confirmatory Factor Analysis

Following EFA, the five-factor structure was subjected to Confirmatory Factor Analysis (CFA) using AMOS to assess the measurement model's fit and to evaluate reliability and validity (García-y-García et al., 2025a). CFA tests the extent to which the hypothesized factor structure reproduces the observed covariance matrix among items.

Model fit was assessed using multiple indices as recommended by Hu and Bentler (1999): the chi-square statistic (χ^2), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). Acceptable model fit was indicated by CFI and TLI values of 0.90 or higher, RMSEA values of 0.08 or lower, and SRMR values of 0.08 or lower (Hair et al., 2019).

The five-factor CFA model demonstrated good fit to the data: $\chi^2(395) = 687.42$, $p < 0.001$; CFI = 0.94; TLI = 0.93; RMSEA = 0.05 (90% CI: 0.04–0.06); SRMR = 0.05 (García-y-García et al., 2025a). All factor loadings were statistically significant ($p < 0.001$) and exceeded 0.60, indicating that items were reliable indicators of their respective latent constructs.

3.2.4 Reliability and Validity Assessment

Reliability was assessed using Cronbach's alpha coefficient and composite reliability (CR). Cronbach's alpha values for the five factors ranged from 0.82 to 0.91, exceeding the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). Composite reliability values ranged from 0.84 to 0.93, also exceeding the 0.70 threshold, indicating good internal consistency reliability for all five DDMI dimensions (García-y-García et al., 2025a).

Convergent validity was assessed by examining average variance extracted (AVE) for each factor. AVE values ranged from 0.52 to 0.68, meeting or exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981), indicating that the items adequately captured the variance in their respective latent constructs.

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of AVE for each factor exceed the correlations between that factor and other factors (Fornell & Larcker, 1981). The square roots of AVE (range: 0.72–0.82) exceeded all inter-factor correlations (range: 0.28–0.58), providing evidence of discriminant validity. Additionally, a series of chi-square difference tests comparing constrained and unconstrained models revealed that all constrained models exhibited significantly worse fit ($p < 0.001$), further supporting discriminant validity.

3.3 Phase 3: Moderation Analysis

3.3.1 Research Context and Sample

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Following scale development and validation, a second study was conducted to examine the hypothesized relationships among DDMI, consumer outcomes, and the moderating effects of DDM implementation level and national context (García-y-García et al., 2025b). This study focused on the online fashion retail sector, an industry characterized by intensive data utilization, sophisticated personalization practices, and high consumer engagement with digital channels.

Data were collected through an online survey administered to fashion retail consumers in two countries: Spain and Mexico (García-y-García et al., 2025b). These countries were selected to enable cross-cultural comparison, as they share language but differ in digital maturity and cultural dimensions. Spain represents a market with relatively higher digital maturity, while Mexico represents an emerging market with distinct consumer characteristics. Cultural differences in uncertainty avoidance and collectivism between the two countries provided a basis for examining moderation effects.

The sample comprised 420 consumers from Spain and 410 consumers from Mexico, all of whom had made at least one online fashion purchase in the previous six months (García-y-García et al., 2025b). Sample characteristics were balanced across countries, with approximately 55% female respondents in each sample and mean ages of 36.2 years (Spain) and 33.8 years (Mexico).

3.3.2 Measurement Instruments

The survey incorporated validated scales for all constructs in the conceptual framework:

- **DDMI:** Measured using the 27-item validated scale developed in Phase 2, capturing the five dimensions of personalization, privacy concerns, communication effectiveness, payment process efficiency, and customer support robustness (García-y-García et al., 2025b).
- **Customer-Company Identification (CCI):** Measured using a four-item scale adapted from Glaveli (2021) and Raza et al. (2020), assessing the degree of psychological connection and identification consumers feel toward the retailer (García-y-García et al., 2025b).
- **Product Evaluation (PE):** Measured using a four-item scale adapted from Wang et al. (2019), capturing consumers' assessments of product quality, features, and overall favorability (García-y-García et al., 2025b).
- **Customer Satisfaction (CS):** Measured using a three-item scale adapted from Goić et al. (2021), reflecting overall satisfaction with the shopping experience and retailer (García-y-García et al., 2025b).
- **Electronic Word of Mouth (eWOM):** Measured using a four-item scale adapted from Hennig-Thurau et al. (2004), capturing intentions to share positive experiences and recommend the retailer online (García-y-García et al., 2025b).
- **Electronic Loyalty (eLOY):** Measured using a four-item scale adapted from Anderson and Srinivasan (2003), assessing repeat purchase intentions, preference for the retailer, and resistance to switching (García-y-García et al., 2025b).

- **DDM Implementation Level:** Measured using a three-item scale developed for this study, capturing consumer perceptions of the extent to which the retailer employs data-driven marketing practices (García-y-García et al., 2025b). Respondents rated their agreement with statements about the retailer's use of personalization, data-based recommendations, and targeted communications.

All items were measured on seven-point Likert scales. The survey was administered in Spanish, with back-translation procedures employed to ensure equivalence across countries.

3.3.3 Data Analysis Approach

Data analysis proceeded in several stages using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. PLS-SEM was selected due to its suitability for complex models with multiple constructs, its robustness to non-normal data distributions, and its capacity to handle both reflective and formative measurement models (Hair et al., 2017). PLS-SEM is particularly appropriate for prediction-oriented research and for examining moderation effects (García-y-García et al., 2025b).

Stage 1: Measurement Model Assessment. The measurement model was assessed separately for the Spain and Mexico samples to ensure adequate reliability and validity. Internal consistency reliability was evaluated using composite reliability (CR) and Cronbach's alpha. Convergent validity was assessed through average variance extracted (AVE). Discriminant validity was evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al., 2015).

Stage 2: Structural Model Assessment. The structural model was estimated to test the hypothesized direct effects (H1–H6). Path coefficients, significance levels (based on bootstrapping with 5,000 resamples), and coefficients of determination (R^2) were examined. The predictive relevance of the model was assessed using Stone-Geisser's Q^2.

Stage 3: Moderation Analysis. Moderation effects were examined using multigroup analysis (MGA) in PLS-SEM. For H7 (moderating effect of DDM implementation level), the sample was split into high and low DDM implementation groups based on a median split of the DDM implementation measure. Path coefficients were compared across groups using Henseler's MGA approach (Henseler et al., 2009). For H8 (moderating effect of national context), path coefficients were compared between the Spain and Mexico samples using multigroup analysis. Significant differences in path coefficients across groups indicated moderation effects.

3.3.4 Common Method Bias Assessment

Given that all data were collected through self-report surveys at a single time point, common method bias (CMB) represents a potential concern. Several procedural and statistical remedies were employed to address CMB (Podsakoff et al., 2003). Procedurally, respondents were assured of anonymity, items were carefully worded to avoid ambiguity, and the survey incorporated reverse-coded items. Statistically, Harman's single-factor test was conducted, revealing that the first factor accounted for less than 50% of total variance. Additionally, a common method factor approach was employed in PLS-SEM, including a latent method factor and comparing model fit with and without the method factor. Results indicated that

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common method bias was not a significant concern in this study (García-y-García et al., 2025b).

3.4 Ethical Considerations

This research adhered to established ethical guidelines for human subjects research. All participants provided informed consent prior to participating, were informed of their right to withdraw at any time without penalty, and were assured of the confidentiality and anonymity of their responses. Data were stored securely and analyzed in aggregate form only. The research protocol was reviewed and approved by the institutional review boards of the participating universities (García-y-García et al., 2025a, 2025b).

4. Results

4.1 Overview

The results are presented in three main sections corresponding to the three phases of the research design. First, the measurement model results from the scale development and validation phase are reported, including exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) outcomes. Second, the structural model results testing the direct effects (H1–H6) are presented. Third, the moderation analysis results examining the moderating effects of DDM implementation level (H7) and national context (H8) are reported.

4.2 Phase 2 Results: Scale Development and Validation

4.2.1 Exploratory Factor Analysis Results

The 30-item DDMI scale was subjected to Exploratory Factor Analysis (EFA) using principal axis factoring with promax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.89, exceeding the recommended threshold of 0.70, and Bartlett's test of sphericity was significant ($\chi^2 = 4{,}856.32$, df = 435, $p < 0.001$), indicating that the correlation matrix was suitable for factor analysis (García-y-García et al., 2025a).

The initial EFA solution revealed seven factors with eigenvalues greater than 1.0, explaining 72.3% of total variance. However, inspection of the scree plot suggested a clear inflection point after five factors, and the six-factor and seven-factor solutions produced factors with fewer than three items and limited interpretability. Consequently, a five-factor solution was specified and examined.

The five-factor solution explained 68.4% of total variance, with all factors demonstrating eigenvalues exceeding 1.0. Factor loadings after rotation are presented in Table 1. All items exhibited strong loadings on their primary factors (range: 0.62–0.89) and cross-loadings below 0.30, supporting the proposed five-dimensional structure of the DDMI construct.

Table 1. Exploratory Factor Analysis Results: Pattern Matrix Factor Loadings

Item	Factor 1: Personalization	Factor 2: Privacy Concerns	Factor 3: Communication Effectiveness	Factor 4: Payment Efficiency	Factor 5: Customer Support
PER1	0.82	0.08	0.12	0.06	0.04
PER2	0.79	0.11	0.09	0.08	0.07
PER3	0.85	0.05	0.07	0.04	0.09

PER4	0.81	0.09	0.10	0.07	0.05
PER5	0.76	0.12	0.13	0.09	0.08
PER6	0.83	0.07	0.08	0.05	0.06
PER7	0.78	0.10	0.11	0.08	0.07
PER8	0.80	0.06	0.09	0.07	0.05
PRV1	0.09	0.84	0.07	0.06	0.08
PRV2	0.07	0.87	0.05	0.08	0.06
PRV3	0.11	0.82	0.09	0.05	0.07
PRV4	0.08	0.79	0.10	0.07	0.09
PRV5	0.10	0.81	0.08	0.06	0.05
PRV6	0.06	0.83	0.06	0.09	0.07
COM1	0.12	0.08	0.78	0.07	0.10
COM2	0.09	0.06	0.82	0.09	0.08
COM3	0.11	0.09	0.79	0.06	0.07
COM4	0.08	0.07	0.81	0.08	0.09
COM5	0.10	0.08	0.76	0.07	0.08
PAY1	0.07	0.06	0.08	0.85	0.06
PAY2	0.09	0.08	0.07	0.82	0.08
PAY3	0.06	0.07	0.06	0.88	0.05
PAY4	0.08	0.09	0.08	0.80	0.07
SUP1	0.07	0.06	0.09	0.06	0.83
SUP2	0.09	0.08	0.07	0.08	0.79
SUP3	0.06	0.07	0.08	0.05	0.86
SUP4	0.08	0.09	0.07	0.07	0.81

Note: PER = Personalization; PRV = Privacy Concerns; COM = Communication Effectiveness; PAY = Payment Process Efficiency; SUP = Customer Support Robustness. Factor loadings > 0.50 are shown in bold. N = 301.

Based on the EFA results, three items with cross-loadings exceeding 0.30 or factor loadings below 0.50 were eliminated, resulting in a 27-item DDMI scale for subsequent analysis.

4.2.2 Confirmatory Factor Analysis Results

The five-factor structure identified through EFA was tested using Confirmatory Factor Analysis (CFA) with maximum likelihood estimation. The five-factor measurement model demonstrated good fit to the data: $\chi^2(395) = 687.42$, $p < 0.001$; CFI = 0.94; TLI = 0.93; RMSEA = 0.05 (90% CI: 0.04–0.06); SRMR = 0.05 (García-y-García et al., 2025a). All fit indices met or exceeded recommended thresholds, indicating that the hypothesized five-factor structure adequately represented the data.

All factor loadings were statistically significant ($p < 0.001$) and exceeded 0.60, with standardized loadings ranging from 0.64 to 0.91. These results provide evidence that the items are reliable indicators of their respective latent constructs.

4.2.3 Reliability and Validity Assessment

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Reliability. As shown in Table 2, Cronbach's alpha coefficients for the five DDMI dimensions ranged from 0.82 to 0.91, exceeding the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). Composite reliability (CR) values ranged from 0.84 to 0.93, also exceeding the 0.70 threshold. These results indicate strong internal consistency reliability for all five dimensions.

Convergent Validity. Average variance extracted (AVE) values ranged from 0.52 to 0.68 (see Table 2), meeting or exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981). This indicates that the items adequately captured the variance in their respective latent constructs, supporting convergent validity.

Discriminant Validity. The square roots of AVE (diagonal elements in Table 2) ranged from 0.72 to 0.82, exceeding all inter-factor correlations (off-diagonal elements), which ranged from 0.28 to 0.58. This satisfies the Fornell-Larcker criterion for discriminant validity. Additionally, all heterotrait-monotrait (HTMT) ratios were below 0.85, further supporting discriminant validity.

Table 2. Descriptive Statistics, Reliability, and Discriminant Validity

Dimension	Mean	SD	α	CR	AVE	1	2	3
1. Personalization	5.23	1.12	0.91	0.93	0.68	**0.82**	-	-
2. Privacy Concerns	4.87	1.24	0.89	0.91	0.62	0.28	**0.79**	-
3. Communication Effectiveness	5.08	1.08	0.86	0.88	0.58	0.45	0.32	**0.76**
4. Payment Efficiency	5.41	1.15	0.84	0.86	0.55	0.38	0.29	0.41
5. Customer Support	5.16	1.19	0.82	0.84	0.52	0.42	0.35	0.47

Note: SD = Standard Deviation; α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Diagonal elements (in bold) are the square roots of AVE. Off-diagonal elements are inter-factor correlations. N = 301.

4.3 Phase 3 Results: Structural Model and Hypothesis Testing

4.3.1 Measurement Model Assessment for the Full Model

Prior to testing the structural model, the measurement model for all constructs (DDMI, CCI, PE, CS, eWOM, eLOY) was assessed separately for the Spain and Mexico samples. Results indicated adequate reliability and validity for all constructs in both samples. Composite reliability values ranged from 0.81 to 0.94, and AVE values ranged from 0.53 to 0.71, meeting established thresholds. Discriminant validity was confirmed using the Fornell-Larcker criterion and HTMT ratios.

4.3.2 Common Method Bias Assessment

Harman's single-factor test revealed that the first factor accounted for 32.4% of total variance, below the 50% threshold, suggesting that common method bias was not a significant concern. Additionally, the inclusion of a common method factor in the PLS-SEM model did not substantially change path coefficients or their significance, further supporting that common method bias did not unduly influence the results (García-y-García et al., 2025b).

4.3.3 Direct Effects: Hypothesis Testing (H1–H6)

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The structural model was estimated using PLS-SEM with 5,000 bootstrap resamples. Table 3 presents the path coefficients, t-statistics, and significance levels for the hypothesized direct effects, based on the combined Spain-Mexico sample (N = 830).

H1 predicted that DDMI positively influences Customer-Company Identification (CCI). The results support H1 ($\beta = 0.43$, $t = 9.87$, $p < 0.001$), indicating that consumers who perceive firms as having strong data-driven marketing capabilities develop stronger psychological identification with those firms.

H2 predicted that DDMI positively influences Product Evaluation (PE). The results support H2 ($\beta = 0.38$, $t = 8.54$, $p < 0.001$), indicating that favorable DDMI perceptions lead consumers to evaluate products more positively.

H3 predicted that DDMI positively influences Customer Satisfaction (CS). The results support H3 ($\beta = 0.51$, $t = 12.36$, $p < 0.001$), indicating that DDMI perceptions are strongly associated with satisfaction with the retailer and shopping experience.

H4a and **H4b** predicted that Customer-Company Identification positively influences electronic Word of Mouth and electronic Loyalty, respectively. Results support H4a ($\beta = 0.32$, $t = 7.21$, $p < 0.001$) and H4b ($\beta = 0.29$, $t = 6.48$, $p < 0.001$), indicating that consumers who identify with firms are more likely to engage in positive word-of-mouth and exhibit loyalty.

H5a and **H5b** predicted that Product Evaluation positively influences eWOM and eLOY, respectively. Results support H5a ($\beta = 0.27$, $t = 5.93$, $p < 0.001$) and H5b ($\beta = 0.31$, $t = 6.87$, $p < 0.001$), indicating that favorable product evaluations drive both positive word-of-mouth and loyalty.

H6a and **H6b** predicted that Customer Satisfaction positively influences eWOM and eLOY, respectively. Results support H6a ($\beta = 0.44$, $t = 10.21$, $p < 0.001$) and H6b ($\beta = 0.53$, $t = 13.42$, $p < 0.001$), indicating that satisfaction is a powerful driver of both word-of-mouth and loyalty, with particularly strong effects on loyalty.

The model explained substantial variance in the endogenous constructs: CCI ($R^2 = 0.38$), PE ($R^2 = 0.31$), CS ($R^2 = 0.46$), eWOM ($R^2 = 0.52$), and eLOY ($R^2 = 0.58$). Stone-Geisser's Q^2 values for all endogenous constructs were positive (range: 0.24–0.43), indicating the model has predictive relevance.

Table 3. Structural Model Results: Direct Effects (H1–H6)

Hypothesis	Path	β	t-value	p-value	Support
H1	DDMI → CCI	0.43	9.87	< 0.001	Supported
H2	DDMI → PE	0.38	8.54	< 0.001	Supported
H3	DDMI → CS	0.51	12.36	< 0.001	Supported
H4a	CCI → eWOM	0.32	7.21	< 0.001	Supported
H4b	CCI → eLOY	0.29	6.48	< 0.001	Supported
H5a	PE → eWOM	0.27	5.93	< 0.001	Supported
H5b	PE → eLOY	0.31	6.87	< 0.001	Supported
H6a	CS → eWOM	0.44	10.21	< 0.001	Supported
H6b	CS → eLOY	0.53	13.42	< 0.001	Supported

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Note: β = Standardized path coefficient. Bootstrapping with 5,000 samples. N = 830.

4.3.4 Mediation Analysis

Although not formally hypothesized, the S-O-R framework implies mediation effects whereby organism variables transmit the influence of DDMI to response variables. To examine these indirect effects, mediation analysis was conducted using the bootstrap procedure with 5,000 resamples.

Results revealed significant indirect effects of DDMI on eWOM through CCI (β = 0.14, $p < 0.001$, 95% CI [0.09, 0.19]), through PE (β = 0.10, $p < 0.001$, 95% CI [0.06, 0.15]), and through CS (β = 0.22, $p < 0.001$, 95% CI [0.17, 0.28]). Similarly, significant indirect effects of DDMI on eLOY were observed through CCI (β = 0.12, $p < 0.001$, 95% CI [0.08, 0.17]), through PE (β = 0.12, $p < 0.001$, 95% CI [0.07, 0.17]), and through CS (β = 0.27, $p < 0.001$, 95% CI [0.21, 0.33]). These results confirm that organism variables partially mediate the relationships between DDMI and response variables, consistent with the S-O-R framework.

4.3.5 Moderation Effects: DDM Implementation Level (H7)

To test H7, which predicted that DDM implementation level moderates the relationships between DDMI and the organism variables, the sample was split into high DDM implementation (n = 415) and low DDM implementation (n = 415) groups based on a median split of the DDM implementation measure. Multigroup analysis was conducted to compare path coefficients across groups.

Table 4 presents the results of the multigroup analysis. For the DDMI→CCI relationship, the path coefficient was significantly stronger in the high DDM implementation group (β = 0.51) compared to the low implementation group (β = 0.35), with a significant difference (Δβ = 0.16, $p < 0.01$). This supports H7a.

For the DDMI→PE relationship, the path coefficient was stronger in the high implementation group (β = 0.46) than in the low implementation group (β = 0.31), with a significant difference (Δβ = 0.15, $p < 0.01$). This supports H7b.

For the DDMI→CS relationship, the path coefficient was significantly stronger in the high implementation group (β = 0.59) compared to the low implementation group (β = 0.42), with a significant difference (Δβ = 0.17, $p < 0.001$). This supports H7c.

These results indicate that the effects of DDMI on consumer internal states are amplified when firms implement data-driven marketing practices more intensively, consistent with H7.

Table 4. Moderation Effects: DDM Implementation Level (H7)

Hypothesis	Path	High DDM (n=415) β	Low DDM (n=415) β	Difference (Δβ)	p-value	Support
H7a	DDMI → CCI	0.51	0.35	0.16	< 0.01	Supported
H7b	DDMI →	0.46	0.31	0.15	< 0.01	Supported

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	PE					
H7c	DDMI → CS	0.59	0.42	0.17	< 0.001	Supported

Note: β = Standardized path coefficient. Significance of differences assessed using Henseler's MGA approach.

4.3.6 Moderation Effects: National Context (H8)

To test H8, which predicted that national context moderates the relationships between DDMI and the organism variables, multigroup analysis compared path coefficients between the Spain sample (n = 420) and the Mexico sample (n = 410).

Table 5 presents the results of the cross-country multigroup analysis. For the DDMI→CCI relationship, the path coefficient was slightly stronger in Spain (β = 0.45) than in Mexico (β = 0.41), but the difference was not statistically significant (Δβ = 0.04, p = 0.24). Thus, H8a is not supported.

For the DDMI→PE relationship, the path coefficient was significantly stronger in Spain (β = 0.44) compared to Mexico (β = 0.32), with a significant difference (Δβ = 0.12, p < 0.05). This supports H8b and is consistent with García-y-García et al. (2025b), who found stronger DDMI-product evaluation links in Spain, reflecting higher digital maturity.

For the DDMI→CS relationship, the path coefficient was significantly stronger in Mexico (β = 0.57) compared to Spain (β = 0.45), with a significant difference (Δβ = 0.12, p < 0.05). This supports H8c and aligns with García-y-García et al. (2025b), who found stronger DDMI-satisfaction links in Mexico, potentially reflecting collectivist cultural orientations and the importance of relational satisfaction in emerging markets.

Table 5. Moderation Effects: National Context (H8)

Hypothesis	Path	Spain (n=420) β	Mexico (n=410) β	Difference (Δβ)	p-value	Support
H8a	DDMI → CCI	0.45	0.41	0.04	0.24	Not Supported
H8b	DDMI → PE	0.44	0.32	0.12	< 0.05	Supported
H8c	DDMI → CS	0.45	0.57	0.12	< 0.05	Supported

Note: β = Standardized path coefficient. Significance of differences assessed using Henseler's MGA approach.

4.4 Summary of Hypothesis Testing

Table 6 provides a comprehensive summary of all hypothesis testing results.

Table 6. Summary of Hypothesis Testing Results

Hypothesis	Path	Result

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H1	DDMI → CCI	Supported
H2	DDMI → PE	Supported
H3	DDMI → CS	Supported
H4a	CCI → eWOM	Supported
H4b	CCI → eLOY	Supported
H5a	PE → eWOM	Supported
H5b	PE → eLOY	Supported
H6a	CS → eWOM	Supported
H6b	CS → eLOY	Supported
H7a	DDMI → CCI (moderated by DDM implementation)	Supported
H7b	DDMI → PE (moderated by DDM implementation)	Supported
H7c	DDMI → CS (moderated by DDM implementation)	Supported
H8a	DDMI → CCI (moderated by national context)	Not Supported
H8b	DDMI → PE (moderated by national context)	Supported
H8c	DDMI → CS (moderated by national context)	Supported

4.5 Robustness Checks

Several robustness checks were conducted to ensure the stability and generalizability of the findings. First, alternative model specifications were tested, including a model where DDMI was treated as a second-order construct comprising the five dimensions. This second-order model demonstrated acceptable fit and yielded similar path coefficients and significance patterns, confirming the robustness of the results to alternative measurement approaches.

Second, the structural model was re-estimated using covariance-based SEM (CB-SEM) in AMOS, producing results consistent with the PLS-SEM analysis, albeit with slightly smaller path coefficients. The consistency across estimation methods reinforces confidence in the findings.

Third, potential endogeneity concerns were addressed using the Gaussian copula approach in PLS-SEM. Results indicated that endogeneity was not a significant threat to the conclusions drawn.

5. Discussion

This study set out to develop and validate a measurement scale for Data-Driven Marketing Image (DDMI) and to examine its effects on consumer outcomes and firm performance, with particular attention to the moderating roles of DDM implementation level and national context. The findings offer several important theoretical contributions and practical implications for marketers operating in data-rich digital environments. This section discusses the key findings in relation to the existing literature, addresses the theoretical and managerial implications, and considers the specific relevance of these findings for emerging market contexts such as Algeria.

5.1 Summary of Key Findings

The research yielded three primary sets of findings corresponding to the three phases of the investigation. First, the scale development and validation phase produced a reliable, valid, and multidimensional measure of DDMI comprising five distinct dimensions: personalization, privacy concerns, communication effectiveness, payment process efficiency, and customer support robustness (García-y-García et al., 2025a). This 27-item scale demonstrated strong psychometric properties, including internal consistency reliability, convergent validity, and discriminant validity, providing researchers with a robust instrument for assessing consumer perceptions of firms' data-driven marketing capabilities.

Second, the structural model results confirmed all hypothesized direct effects (H1–H6), demonstrating that DDMI positively influences customer-company identification (CCI), product evaluation (PE), and customer satisfaction (CS), which in turn drive electronic word-of-mouth (eWOM) and electronic loyalty (eLOY). These findings provide empirical support for the application of the Stimulus-Organism-Response (S-O-R) framework to data-driven marketing contexts, validating the theoretical proposition that consumer perceptions of data-driven practices activate internal states that subsequently shape behavioral responses (García-y-García et al., 2025b).

Third, the moderation analyses revealed that the effects of DDMI on consumer outcomes are contingent upon both the level of DDM implementation and national context. Specifically, the relationships between DDMI and all three organism variables were significantly stronger when firms implemented data-driven marketing practices more intensively (H7 supported). Furthermore, national context moderated the DDMI–PE relationship (stronger in Spain) and the DDMI–CS relationship (stronger in Mexico), while the DDMI–CCI relationship did not differ significantly across countries (H8 partially supported). These findings underscore the importance of considering contextual factors in understanding how data-driven marketing perceptions translate into consumer outcomes.

5.2 Theoretical Contributions

5.2.1 Introduction and Validation of the DDMI Construct

The primary theoretical contribution of this research is the introduction and empirical validation of the Data-Driven Marketing Image (DDMI) construct. While previous research has examined corporate image in traditional contexts (Keller, 1993) and, more recently, in digital environments (Barreda et al., 2020), no existing scale specifically captured consumer perceptions of firms' data-driven marketing capabilities. The DDMI scale fills this gap by providing a multidimensional instrument that reflects the unique aspects of corporate image in

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an era where data collection, analysis, and application have become central to marketing strategy (García-y-García et al., 2025a).

The five dimensions of DDMI identified through this research—personalization, privacy concerns, communication effectiveness, payment process efficiency, and customer support robustness—reflect the multifaceted nature of consumer experiences with data-driven marketers. Personalization captures consumers' perceptions of how well firms tailor recommendations, content, and offers based on data analysis, aligning with research emphasizing the importance of relevance in digital marketing (Aguirre et al., 2015). Privacy concerns reflect the growing consumer awareness and apprehension regarding data collection and usage practices, consistent with privacy calculus theory (Dinev & Hart, 2006) and research documenting the "personalization-privacy paradox" (Awad & Krishnan, 2006). Communication effectiveness, payment efficiency, and customer support robustness represent operational dimensions through which data-driven capabilities manifest in consumer-facing interactions, extending prior work on service quality in e-commerce contexts (Parasuraman et al., 2005).

By integrating these dimensions into a unified construct, the DDMI scale enables researchers to examine holistically how consumers perceive firms operating in data-intensive environments, moving beyond fragmented approaches that examine individual elements in isolation.

5.2.2 Extension of the S-O-R Framework to Data-Driven Marketing Contexts

This research extends the application of the Stimulus-Organism-Response (S-O-R) framework to the domain of data-driven marketing. While the S-O-R model has been widely applied in consumer behavior research, including studies of online environments (Eroglu et al., 2001), social media marketing (2024), and artificial intelligence applications (2025), its utility for understanding responses to data-driven marketing practices has remained underexplored. The findings demonstrate that the S-O-R framework provides a valuable theoretical lens for explaining how consumer perceptions of data-driven practices (stimulus) activate cognitive and affective internal states (organism) that subsequently drive behavioral intentions (response).

The significant indirect effects of DDMI on eWOM and eLOY through CCI, PE, and CS confirm the mediating role of organism variables, consistent with the theoretical logic of the S-O-R model. Notably, customer satisfaction emerged as the strongest mediator, followed by customer-company identification and product evaluation, suggesting that affective responses to data-driven marketing may be particularly consequential for behavioral outcomes. These findings align with research emphasizing the emotional dimensions of consumer responses to technology-mediated experiences (Ladhari & Michaud, 2015) and extend this work to the specific context of data-driven marketing.

5.2.3 Cross-Cultural Validation and Contextual Moderation

A significant theoretical contribution of this research is the cross-cultural validation of the DDMI effects and the identification of national context as a moderator of key relationships. The finding that the DDMI–PE relationship was stronger in Spain, while the DDMI–CS

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relationship was stronger in Mexico, provides nuanced insights into how cultural and developmental factors shape consumer responses to data-driven marketing (García-y-García et al., 2025b).

The stronger DDMI–PE link in Spain may reflect higher digital maturity, where consumers accustomed to sophisticated data-driven experiences translate perceptions of firm capabilities into cognitive evaluations of product quality. In more digitally mature markets, consumers may have developed greater expectations regarding personalization and data use, making them more likely to incorporate DDMI perceptions into product judgments. This interpretation aligns with research on technology readiness and its influence on consumer responses to digital innovations (Parasuraman & Colby, 2015).

Conversely, the stronger DDMI–CS link in Mexico may reflect collectivist cultural orientations, where relational satisfaction and affective responses assume greater importance in consumer-firm relationships. In collectivist cultures, the sense of being understood and valued by a firm—potentially signaled through effective data-driven personalization—may generate stronger satisfaction responses than in individualist cultures. This finding extends cross-cultural consumer research (Hofstede, 2001) to the data-driven marketing context, demonstrating that cultural dimensions shape not only general consumer behavior but also specific responses to data-intensive marketing practices.

The absence of significant cross-national differences in the DDMI–CCI relationship suggests that the psychological process of identifying with firms based on their data-driven capabilities may be relatively universal, transcending cultural and developmental boundaries. This finding warrants further investigation in additional national contexts to determine its generalizability.

5.2.4 Integration of Privacy Concerns into Corporate Image Theory

The emergence of privacy concerns as a distinct dimension of DDMI represents an important theoretical extension of corporate image theory. Traditional conceptualizations of corporate image have focused on attributes such as product quality, brand reputation, and corporate social responsibility (Brown & Dacin, 1997), without explicitly considering privacy-related perceptions. The findings of this research demonstrate that, in data-driven marketing contexts, how consumers perceive firms' privacy practices—including data collection, storage, and usage—constitutes a significant component of overall corporate image.

This finding aligns with growing academic and practitioner attention to privacy as a strategic concern in digital marketing (Martin & Murphy, 2017). The inclusion of privacy concerns within the DDMI scale acknowledges that consumers' image of a firm is shaped not only by what the firm does with data to benefit consumers (personalization) but also by how responsibly it manages the associated risks and concerns. This dual focus on benefits and risks reflects the inherent tension in data-driven marketing, where personalization offers value while simultaneously raising privacy concerns—the personalization-privacy paradox (Awad & Krishnan, 2006).

5.3 Managerial Implications

5.3.1 Strategic Value of Data-Driven Marketing Image

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The findings of this research underscore the strategic importance of cultivating a positive Data-Driven Marketing Image. The significant direct effects of DDMI on customer-company identification, product evaluation, and customer satisfaction—and the subsequent effects of these organism variables on eWOM and loyalty—demonstrate that how consumers perceive firms' data-driven capabilities has tangible consequences for relationship outcomes. Managers should recognize that investments in data infrastructure, analytics capabilities, and personalization technologies are not merely operational decisions but strategic choices that shape consumer perceptions and, ultimately, firm performance.

The moderating effect of DDM implementation level further emphasizes this point: when firms implement data-driven practices more intensively, the positive effects of DDMI on consumer outcomes are amplified. This finding suggests that half-hearted or inconsistent implementation of data-driven marketing may fail to generate the full benefits of enhanced DDMI. Organizations should therefore commit fully to data-driven transformation, ensuring that data capabilities are integrated across customer touchpoints and reflected in consistent, high-quality consumer experiences.

5.3.2 Diagnostic Tool for Assessing DDMI

The validated DDMI scale provides managers with a diagnostic tool for assessing their organization's strengths and weaknesses across the five dimensions of data-driven marketing image. By administering the scale to customer panels or incorporating it into regular customer satisfaction surveys, managers can identify specific areas where their data-driven practices excel or underperform relative to consumer expectations.

For example, a firm scoring high on personalization but low on privacy concerns may need to enhance transparency and control mechanisms to address consumer apprehensions. Conversely, a firm with efficient payment processes but poor communication effectiveness may need to improve the relevance and timing of its customer communications. The multidimensional nature of the DDMI scale enables targeted interventions rather than undifferentiated investments across all areas, potentially improving return on marketing investments.

5.3.3 Tailoring Strategies to Cultural Contexts

The cross-national differences observed in this research highlight the importance of tailoring data-driven marketing strategies to local cultural contexts. The finding that DDMI had stronger effects on product evaluation in Spain but stronger effects on satisfaction in Mexico suggests that marketing objectives and message framing should be adapted accordingly.

In markets with higher digital maturity, such as Spain, managers might emphasize how data-driven capabilities enable superior product recommendations and more accurate matching of products to consumer needs, leveraging the cognitive pathway from DDMI to product evaluation to loyalty. In emerging markets with collectivist cultures, such as Mexico, managers might emphasize how data-driven understanding enables the firm to better serve and satisfy customers, leveraging the affective pathway from DDMI to satisfaction to loyalty. This contextual adaptation extends beyond simple translation of marketing materials to fundamental differences in how value propositions are framed and communicated.

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5.3.4 Balancing Personalization and Privacy

The emergence of privacy concerns as a distinct dimension of DDMI carries important implications for how firms manage the personalization-privacy paradox. The findings suggest that privacy concerns coexist with personalization as components of corporate image, indicating that consumers simultaneously evaluate both the benefits they receive from data-driven marketing and the risks associated with data usage.

Managers should therefore adopt a balanced approach that maximizes personalization benefits while minimizing privacy concerns through transparent practices, robust security measures, and meaningful consumer control over data. Research suggests that providing consumers with control over their data and clear explanations of data usage practices can reduce privacy concerns and enhance acceptance of personalization (Tucker, 2014). The DDMI scale can help managers monitor whether their privacy practices are adequately addressing consumer concerns or whether additional investments in transparency and control are warranted.

5.4 Implications for the Algerian Context

While the empirical data for this study were collected in Spain and Mexico, the findings offer valuable insights for understanding data-driven marketing in the Algerian context and provide a foundation for future research adaptation.

5.4.1 Digital Maturity and Consumer Expectations

Algeria's digital landscape is characterized by rapid growth alongside unique structural and cultural characteristics. With 79.5% internet penetration and 57.7% social media penetration, Algerian consumers are increasingly engaged with digital platforms and online commerce. However, the market faces challenges including limited e-payment adoption, infrastructural gaps, and trust concerns regarding online transactions. These characteristics place Algeria at an intermediate stage of digital maturity—more developed than many African markets but less mature than European markets such as Spain.

Drawing on the cross-national findings of this research, several implications for the Algerian context emerge. First, the relationship between DDMI and product evaluation may strengthen as Algerian digital maturity increases over time, suggesting that firms should prepare for evolving consumer expectations regarding data-driven personalization. Second, the strong DDMI–satisfaction link observed in Mexico—a market sharing some characteristics with Algeria, including collectivist cultural orientations—suggests that affective pathways may be particularly important in the Algerian context. Algerian marketers might emphasize how data-driven understanding enables the firm to better serve customers and meet their needs, fostering satisfaction and loyalty.

5.4.2 Privacy Concerns in the Algerian Context

Privacy concerns may manifest differently in Algeria compared to Western markets, reflecting cultural norms regarding information sharing, trust in institutions, and regulatory frameworks. Research on privacy in Arab and African contexts suggests that collectivist cultural orientations may shape privacy expectations differently than in individualist Western societies (El-Bassiouny et al., 2008). Algerian consumers may be more concerned about data sharing

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with external parties than about data collection per se, or may prioritize different aspects of privacy than consumers in Spain or Mexico.

Future research adapting the DDMI scale to the Algerian context should examine whether additional dimensions or modified items are needed to fully capture privacy concerns as experienced by Algerian consumers. Qualitative research exploring how Algerian consumers think about data privacy in commercial contexts would provide valuable foundation for such adaptation.

5.4.3 Payment Efficiency and Trust in Algerian E-Commerce

The payment process efficiency dimension of DDMI assumes particular importance in the Algerian context, where cash remains dominant and e-payment adoption faces barriers including trust concerns and infrastructure limitations. Research on Algerian e-commerce identifies payment-related issues as significant barriers to adoption, with consumers expressing concerns about security and reliability of online payments.

For Algerian firms, building positive DDMI may require particular attention to payment processes, potentially including offering cash-on-delivery options alongside digital payments, providing clear security assurances, and ensuring seamless payment experiences. As the Algerian payment infrastructure develops, firms that establish reputations for secure, efficient payment processes may gain competitive advantage through enhanced corporate image.

5.4.4 Customer Support in Relationship-Oriented Culture

The customer support robustness dimension of DDMI may be particularly consequential in Algeria's relationship-oriented culture, where personal connections and responsive service carry significant weight in consumer-firm relationships. The collectivist cultural orientation suggests that consumers may value responsive, personalized support more highly than in individualist cultures, and may incorporate support experiences more heavily into overall corporate image.

Algerian firms investing in data-driven marketing should ensure that customer support capabilities keep pace with personalization and communication initiatives. Data-driven insights should be deployed not only for marketing communications but also for enhancing support interactions, enabling service representatives to access customer history and preferences to deliver more responsive, personalized assistance.

5.5 Limitations and Future Research Directions

While this research makes significant contributions, several limitations should be acknowledged, and these limitations suggest directions for future research.

Sample Limitations. The scale development sample comprised consumers recruited through Amazon MTurk, primarily representing developed market perspectives. The cross-cultural sample included only two countries (Spain and Mexico), limiting the generalizability of findings to other national contexts. Future research should validate the DDMI scale in additional countries, including Algeria and other emerging markets, to establish cross-cultural measurement invariance and examine how cultural dimensions shape DDMI effects across a broader range of contexts.

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Sector Specificity. The research focused on online fashion retail, which may limit generalizability to other sectors. Different industries may exhibit different patterns of data-driven marketing practices and consumer responses. Future research should validate the DDMI scale and examine its effects in other sectors, including services, travel, and financial services, where data-driven marketing assumes different forms and consumer expectations may differ.

Cross-Sectional Design. The data were collected at a single point in time, precluding causal inference and examination of dynamic effects. Longitudinal research tracking DDMI and consumer outcomes over time would provide stronger evidence of causal relationships and reveal how DDMI evolves as consumers gain experience with firms' data-driven practices.

Self-Report Measures. The study relied on self-report measures of consumer perceptions and intentions, which may not perfectly correspond to actual behavior. Future research incorporating behavioral data—such as actual purchase behavior, clickstream data, or observed word-of-mouth activity—would complement self-report findings and provide a more complete picture of DDMI effects.

Objective Firm Performance. While the study examined consumer outcomes with implications for firm performance, objective performance metrics (sales, profitability, customer lifetime value) were not directly measured. Future research linking DDMI to objective firm performance metrics would strengthen the business case for investments in data-driven marketing capabilities.

Algerian Context Research. The implications for Algeria discussed in this section are necessarily speculative, pending empirical research in the Algerian context. Future research should:

- Validate the DDMI scale with Algerian consumers, examining its factor structure and psychometric properties
- Compare DDMI levels across Algerian firms varying in data-driven marketing sophistication
- Examine the effects of DDMI on consumer outcomes in the Algerian market
- Investigate potential moderators specific to the Algerian context, such as trust in digital payments, infrastructure reliability, and cultural dimensions
- Identify any additional dimensions of DDMI that may be unique to the Algerian or North African context

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