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A multi-method analysis to foresight role of marketing intelligence, strategic and tactical decision-making in enhancing customer loyalty

Sushant Kumar Vishnoi [a], Smriti Mathur [b], Naveen Virmani [c], Teena Bagga [d], Sandeep Jagtap [e,*]

[a] Institute of Management Studies (IMS) Ghaziabad-B School, Ghaziabad, India
[b] Christ University, Bangalore, India
[c] Institute of Management Studies (IMS) Ghaziabad-B School, Ghaziabad, India
[d] Jamia Milia Islamia, New Delhi, India
[e] Division of Engineering Logistics, Lund University, Lund, Sweden

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ABSTRACT

Marketing intelligence implies the application of advanced and digital technologies in making strategic marketing decisions. The objective of the research is to analyze the impact of marketing intelligence, organizational-centered strategic and tactical decision-making on customer satisfaction and loyalty. The study collected responses from 366 industry professionals holding key strategic, tactical and operational positions and evaluated them through a two-stage process. In the first stage, structural equation modeling (SEM) was used to examine the linear relationship among the identified constructs. The second stage involves evaluating the predicting efficacy of the relevant parameters derived from the SEM using an artificial neural network (ANN) analysis. The results of SEM analysis indicate that strategic decision-making significantly impacts customer loyalty. Further, tactical decision-making is found to be negatively associated with customer satisfaction. The model also has acceptable predictive accuracy. The research results are highly useful for researchers and practitioners looking to enhance customer loyalty. The research proposes a novel framework to investigate how business organizations incorporate marketing intelligence as a developmental strategy for strategic and tactical decision-making to develop swift responses to enhance customer satisfaction and loyalty.

1. Introduction

Marketing agility helps organizations to attain market growth and respond quickly to changing market conditions (Friend et al., 2026). Technological disruption has equally impacted the marketing and customer-centric strategies of organizations and consumers' purchasing and consumption patterns. In a survey conducted by Gartner, 86 % of marketers said that they use data and analytics to measure the success of their marketing campaigns (Chaparak, 2025). In their quest for customer insights, organizations

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* Corresponding author.
E-mail addresses: sushant.vishnoi@imsgzb.ac.in (S.K. Vishnoi), drsmritimathur@gmail.com (S. Mathur), naveen.virmani@imsgzb.ac.in (N. Virmani), tbagga@jmi.ac.in (T. Bagga), sandeep.jagtap@tlog.lth.se (S. Jagtap).

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track customer journeys on a continuum, compounding the volume and variety of marketing information. To do so, marketers are employing technologies like big data analytics, the internet of things (IoT), social media analytics, and artificial intelligence (AI) to generate customer insights and intelligence for customer relationship management.

AI has transformed itself from a niche technological tool to a cornerstone of marketing strategies. A Statista report highlighted that global market revenues for AI use in marketing are anticipated to reach approximately 47 billion U.S. dollars in 2025 and to exceed 107 billion by 2028 (Guttmann, 2026). Further, a BCG (2024) report revealed that both predictive and generative AI will generate significant productivity gains ranging from 36 % in Germany to 62 % in China. Similarly, a Forbes Business Development Council study reported that marketing intelligence is driving the global industry boom. The sales intelligence market, valued at $4.4 billion in 2024, is projected to grow to $10.25 billion by 2032, reflecting an annual growth rate of more than 11 % (Drenik, 2025).

For a long time, marketing intelligence has attracted renowned researchers, practitioners, and policymakers from methodologically diverse and multidisciplinary perspectives for innovating information avenues and getting close to real customer insights. The emergence of the concept of marketing intelligence was traced to the 1960s when Kelley (1965) used it to provide reliable, consistent, and analyzed business information, based on which top management can formulate better policies and decisions. Furthermore, Pinkerton (1969) advocated the adoption of marketing intelligence systems by managers in industrial marketing. Additionally, Rehman (2025) conducted an empirical analysis and found that market intelligence impacts global technological competence, which further impacts international performance. The qualitative and quantitative impact it has on business organizations incites academic and practitioners' strong research interest (Kelley, 1968; Evans, 1988; Cornish, 1997; Kunle et al., 2017; Massoudi, 2018; Pinkerton, 1969).

The market intelligence process integrates timely, accurate, and reliable information on existing market dimensions from customers, competitors, and suppliers to inform competitive strategy (Maltz and Kohli, 1996). Marketing intelligence adoption by business organizations not only overhauls the quality of data generation avenues of business organizations but also improves their information management (Crosier and Pickton, 2003). The intelligence and insights thus generated enrich organizational strategic and tactical decision-making and policy initiatives. While recent literature on the impact of marketing intelligence is focused on firm performance (Vishnoi et al., 2019), product innovation (Falahat et al., 2020), creativity (Ameen et al., 2022), and non-food industrial applications (Adewale et al., 2022), there is a need for further investigation to understand how marketing intelligence centered on strategic and tactical decisions impacts customer satisfaction and loyalty. Therefore, this research proposition makes a novel attempt to explore the linkages between marketing intelligence, strategic and tactical decision-making, customer satisfaction, and customer loyalty. By examining these relationships, the research can highlight valuable insights for managers seeking to improve their marketing strategies and enhance customer loyalty. Hence, based on the identified gaps, this study advances the following research questions.

RQ1: How does marketing intelligence contribute to enhancing customer satisfaction and loyalty?
RQ2: How do strategic and tactical decision-making processes influence customer loyalty?

The significance of this study is three-pronged. Firstly, the current study fills the research gap in the literature and knowledge by building a new research model associating marketing intelligence-customer loyalty construct. Secondly, the model's uniqueness stems from utilizing the important determinants of resource-based view (RBV) theory and investigating their impact on customer satisfaction and loyalty creation. Third, an SEM-ANN technique is used in the study to capture linear-nonlinear and non-compensatory connections between endogenous and exogenous variables, thereby enriching the existing literature by validating the reliability of the intelligence-loyalty model and the resource-based view theory.

The upcoming sections of the research study are planned as follows. Section 2 presents the theoretical framework aligning the proposed theory, i.e., RBV, with the constructs of the research study. Section 3 discusses the research methodology employed for the research study. After that, Section 4 presents the data analysis procedure centered on applying PLS-SEM. Furthermore, Section 5 presents the discussion and implications of the research study. Finally, Section 6 discusses conclusions, limitations and future research directions.

2. Literature review

2.1. Theoretical framework and core constructs

The RBV theory asserts that a firm's resources and capabilities are the primary drivers of its competitive advantage and sustained success (Barsky and Labagh, 1992). In this view, marketing intelligence is crucial for informing a firm's strategic and tactical decision-making, thereby positively impacting customer satisfaction and loyalty. The RBV posits that a firm that invests in gathering and analyzing marketing intelligence about its target customers, competitors, and industry trends can make more informed strategic decisions about which products and services to offer, how to price them, and how to position them in the market. Similarly, tactical decisions about product features, distribution channels, and promotional activities can be informed by marketing intelligence to increase customer satisfaction and loyalty. Several studies have explored the application of RBV in the marketing intelligence domain (Makadok and Barney, 2001; Helm et al., 2014). For instance, Kim and Li (2009) found that a firm's dynamic capabilities (the ability to adapt and change in response to market conditions) positively impact strategic decision-making and, in turn, improve customer satisfaction and loyalty. Another study by Homburg et al. (2009) found that a firm's marketing capabilities (the ability to develop and execute marketing strategies effectively) positively impact both strategic and tactical decision-making, leading to improved customer satisfaction and loyalty. Driving marketing intelligence depends on resources, technological capabilities, and skilled employees, all of which are part of organizational resources. The constructs of the study are shared in Table 1.

2.2. Hypothesis development

2.2.1. Marketing intelligence - customer loyalty

Vishnoi et al. (2025) define marketing intelligence as the "systematic, ethical, and technology-driven process of collecting, analyzing, and synthesizing customer insights, market trends, and competitive dynamics to innovatively enhance customer-centric strategic decision-making". Marketing intelligence helps businesses adapt quickly and flexibly to changing market conditions by continuously monitoring customer feedback. A study by Faryabi et al. (2013) found that marketing intelligence is related to trust, and commitment, i.e., indicators of customer loyalty. By incorporating these trending attributes into their product characteristics, companies influence customer frequency, volume, and word-of-mouth-related purchases and promotions (Ndubisi, 2007). Furthermore, marketing intelligence helps in syncing customer-driven reviews with organizational strategies. Additionally, to gain a competitive edge, organizational learning must be linked to marketing (Lee and Trim, 2006). Fig. 1 shows the proposed research model. Therefore, this research posits the following hypothesis.

H1. Marketing intelligence is positively associated with customer loyalty.

2.2.2. Marketing intelligence, customer satisfaction, strategic decision-making, tactical decision-making

Marketing intelligence enables organizations to understand market requirements and act accordingly with ease (Trainor et al., 2013). Moreover, it helps to understand the market conditions effectively and efficiently (Alamsyah and Saviera, 2018). Additionally, a study by Golestanizadeh et al. (2025) analyzed the impact of business intelligence on customer satisfaction and computed its positive impact. Literature review reveals the role of marketing intelligence in making decisions effectively. It helps organizations to understand the market and take action accordingly. It further helps to analyze the present market situation to gain a sustainable competitive advantage (Lackman et al., 2000). Moreover, it helps the salesforce to align their business strategy for effective decision-making (Daabes and Kharbat, 2017). Therefore, this research proposes the following hypothesis: For effectively managing the business toward success, it is important to consider factors at both macro and micro levels. In this competitive scenario, marketing intelligence helps in providing customized marketing solutions. Sentiment-based analysis provides researchers with a platform to effectively design their marketing strategies through social media (Alamsyah and Saviera, 2018).

H2. Marketing intelligence is positively associated with customer satisfaction.

H3. Marketing intelligence is positively associated with strategic decision-making.

H4. Marketing intelligence is positively associated with tactical decision-making.

2.2.3. Strategic decision-making and customer satisfaction

Strategic decisions are guided by top management and aim to reshape the entire business landscape. For a long time, business strategy has been embedded in the product and service components of successful businesses. Customer service and product strategy come closest to merging customer satisfaction with a strategic orientation (Jacobs et al., 1998). Through strategic decision-making, top management captures and addresses the customer's immediate and potential requirements. Customer interests and motives (visible and hidden) can be gathered through information generation tools (social media and internet behavior), and insights can be developed. These customer insights can then be conceptualized into customized product features and service deliverables. A study by Barsky and Labagh (1992) empirically demonstrates that customized product offerings not only improve the satisfaction of existing customers but also inspire confidence in new customers about improved product conformance and performance standards. Strategic decisions based on research-centric business planning and forecasting positively influence brand positioning, new product development, and the transformation of business organizations (Chien and Su, 2003). Furthermore, strategic decisions based on regular customer reviews

Table 1
Conceptualization of study constructs.

Constructs	Definition	Author
Marketing Intelligence (MI)	Marketing intelligence is the ongoing process of comprehending, evaluating, and analyzing a company's internal and external environments related to clients, rivals, and markets, and then applying the learned data and expertise to assist the company's marketing-related choices.	(Alamsyah and Saviera, 2018)
Strategic Decision Making (SDM)	An entity's developing idea of winning high-stakes problems through power-creating utilization of resources and opportunities in uncertain contexts is known as strategy, and it is expressed as a coherent core of guiding decisions.	(Khalifa, 2020, p. 16)
Tactical Decision Making (TDM)	Tactical decision-making refers to "the power of creating use of resources to gain a partial advantage, in specific domains, over external actors".	(Khalifa, 2021, p. 10)
Customer Satisfaction (CS)	Customer satisfaction is the behavioral or attitudinal response of customers about the post-purchase utility of a product or service.	Barsky and Labagh (1992)
Customer Loyalty (CL)	Customer loyalty is defined as the long-lasting exchanges or engagements formed between marketers and customers.	Bowen and Shinag-Lih (2001)

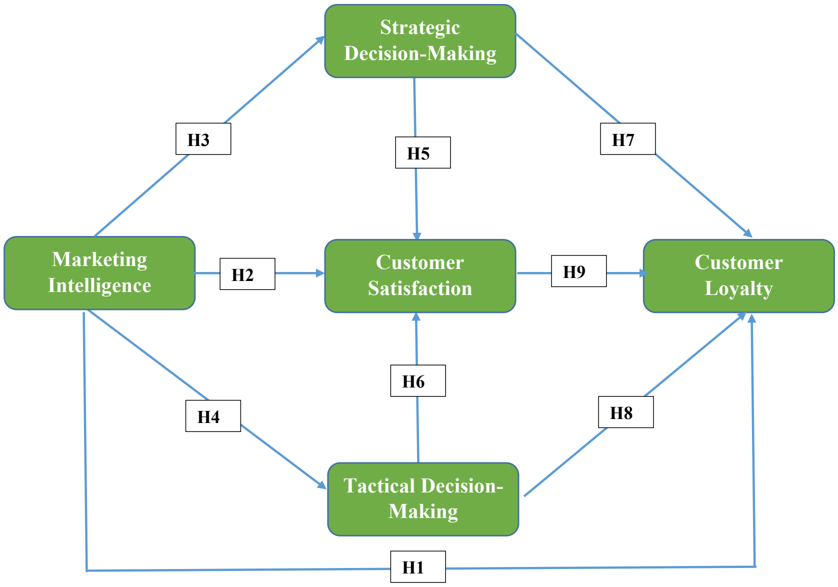

Fig. 1. Proposed loyalty model.

and feedback through available platforms reinforce value creation for businesses and enhance satisfaction levels among customers. Therefore, this research proposes the following hypothesis.

H5. Strategic decision-making is positively associated with customer satisfaction.

2.2.4. Tactical decision-making and customer satisfaction

Tactical decisions aim at strengthening and streamlining structured or routine decisions related to the organization's products, processes, personnel, and programs. Tactical decision-making enables the planning of key accounts or prospects by using proper research tools and channels with the overall objective of satisfying customer needs (Medjoudj et al., 2012). Hence, organizations continuously scan their immediate macro and micro-business environments to design targeting, segmentation, and product pricing policies to provide customers with desired satisfaction levels (Huber et al., 2001). Additionally, marketing communication or promotional campaigns must be designed in such a way that the right product message can be delivered to the right customers at the right time, creating maximum impact and customer value. The selection of the right marketing channels holds great prominence in sparking customer satisfaction in such a cut-throat competitive environment. Overall, tactical decision-making influences and empowers customer satisfaction checkpoints through daily routine managerial decisions (Morgan et al., 2005). Therefore, this research proposes the following hypothesis.

H6. Tactical decision-making is positively associated with customer satisfaction.

2.2.5. Strategic decision-making and customer loyalty

Many published works relate customer satisfaction to customer loyalty. As customer satisfaction is one of the antecedents of customer loyalty, many studies in the literature directly and positively relate customer satisfaction to customer loyalty. However, some posit that customer satisfaction is positively associated with customer loyalty through mediating variables such as customer relationships, trust, and commitment. Similarly, strategic decision-making is found to be directly and positively associated with customer loyalty (Jalali et al., 2016). Other studies empirically establish a positive association between strategic decision-making and customer loyalty through mediating relationships with customer satisfaction (Duffy, 2003). Moreover, strategic marketing-centric decision-making enables organizations to market customer-preferred products with the required features, which in turn motivates customers to engage in repurchase, positive word of mouth (WOM) for the brand, and maintain long relationship tenure with the same organization's products and services (Heskett, 2002). Therefore, this research proposes the following hypothesis.

H7. Strategic decision-making is positively associated with customer loyalty.

2.2.6. Tactical decision-making and customer loyalty

Among the published works on the antecedents of customer loyalty, tactical decision-making stands out as an important indicator. Several studies in the literature identify a positive association between tactical decision-making dimensions and customer loyalty. Tactical decision strategies of value pricing and personalized segmentation positively reinforce customers' behavior toward purchasing stated brands (Srikanth and Kumari, 2015). Overall, customer purchases of the brand grow over time despite price increases. This level of customer commitment toward the same brand repurchases signifies the extent of their loyalty. Additionally, the extent of customer word of mouth and other brand-related endorsements to associated customers and family members or friends also defines their loyalty to the brand (Uncles et al., 2003). Finally, tactical decision-making positively accentuates customer satisfaction through refined organizational strategic initiatives and increases customer retention with the same brands and organizations. Therefore, this research proposes the following hypothesis.

H8. Tactical decision-making is positively associated with customer loyalty.

2.2.7. Customer satisfaction and customer loyalty

If customer satisfaction is the marketer's priority, customer loyalty is the customer commitment to regular purchases of the brand (Shankar et al., 2002). As defined by Oliver (1999), "satisfaction is the perception of pleasurable fulfillment of service and loyalty is a deep commitment to the service provider". Customer satisfaction connects the process of the culmination of purchase intentions and post-consumption phenomena with attitudinal change, repeat purchases, and finally, brand loyalty (Churchill and Surprenant, 1982; Jamal and Naser, 2003; Mishra and Mishra, 2009). Research studies indicate that customer satisfaction can be programmed to customer loyalty by applying the principles of customized attention, periodic service and product refinement, and regular reinforcement through personalized marketing communication. A large number of empirical studies worldwide have shown a positive relationship between customer satisfaction and customer loyalty, with various mediating and moderating variables (Donio et al., 2006; Story and Hess, 2006). One of the most studied variables in this context is service quality, which influences customer satisfaction and generates customer loyalty (Chang et al., 2009; Zeithaml et al., 2008; Heskett, 1997). Furthermore, Caruana (2002) positively links service quality and loyalty through the mediating relationship of customer satisfaction. Most researchers associate customer satisfaction with predicting customer loyalty (Leverin and Liljander, 2006; Terblanche, 2006; Faullant et al., 2008). A research study by

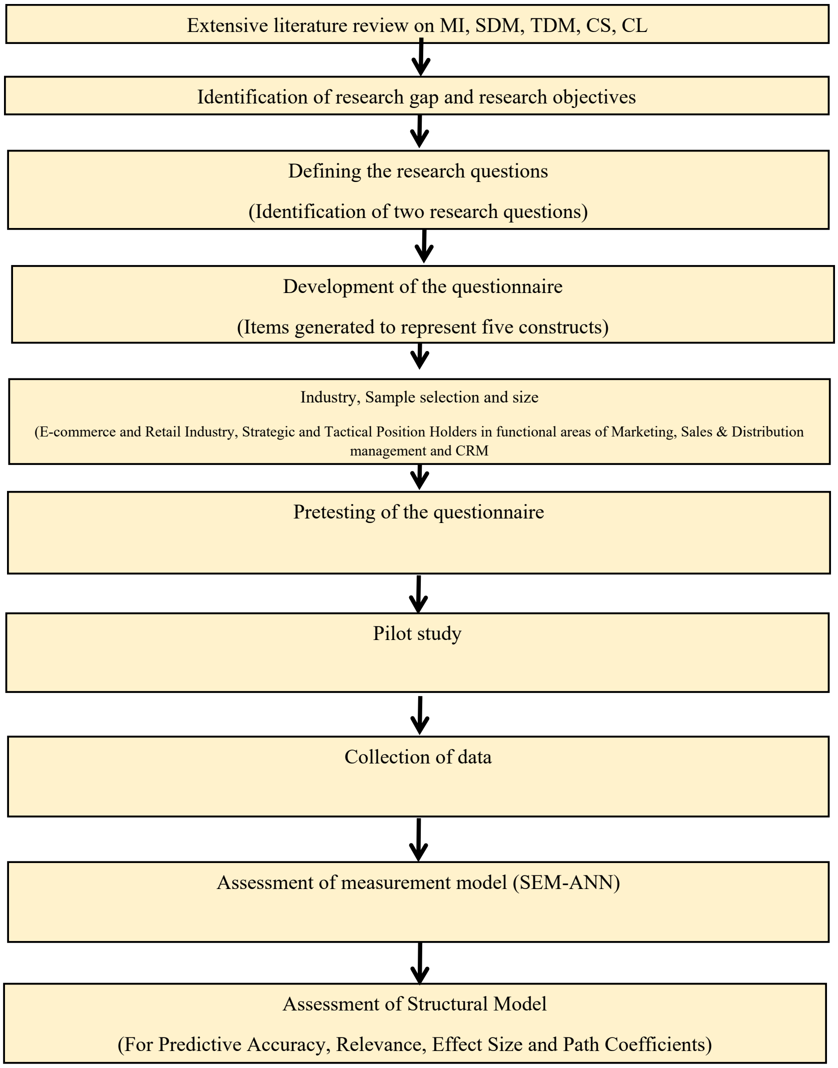

Fig. 2. Research methodology roadmap.

Pont and McQuilken (2005) validates that customer satisfaction and loyalty are related; furthermore, they point out that satisfied customers are not always loyal. Alternatively, research studies by Pleshko (2009), Al-Wugayan and Pleshko (2010) contradict most customer satisfaction-customer loyalty literature by concluding no correlation or relationship between customer satisfaction and loyalty, especially in the banking sector. Therefore, this research proposes the following hypothesis.

H9. Customer satisfaction is positively associated with customer loyalty.

3. Research methodology

The overall research procedure followed in the study is discussed in this section. Fig. 2 illustrates the research methodology framework of the study.

3.1. Data collection and instrument development

The structured, closed-ended questionnaire for this study was developed using pre-validated scales, with minor adjustments to the vocabulary. Before fieldwork, pretesting and pilot testing were conducted. In the pretest, five academicians knowledgeable in marketing intelligence and marketing analytics applications were interviewed in sync with Leong et al. (2020), who investigated survey instrument validity. A pilot study with 40 participants was then conducted to assess the internal consistency of the survey instruments. Once the questionnaire was found to be satisfactory, the data collection process was started. As the study aims to explore the industry-wide impact of the marketing intelligence concept, a non-probability sampling technique called convenience sampling was used to gather the required sample (Koon et al., 2020). The use of convenience sampling was deemed appropriate given the need to access respondents with domain-specific expertise in marketing intelligence and decision-making processes, where a comprehensive sampling frame is not readily available (Hair et al., 2021; Etikan et al., 2016). The study specifically targeted professionals from marketing, sales, and CRM functions to ensure the contextual relevance of responses.

Overall, the survey questionnaire was circulated to 473 respondents, out of which 366 filled the questionnaire; therefore, the response rate was quite high, i.e., 77.38%. As mentioned by Kline (1994), there should be 10 responses per measuring item; this research study has five constructs and 28 items. Therefore, a minimum of 280 responses was needed to ensure an adequate sample size for structural equation modeling. Table 2 reveals the demographic characteristics of the respondents. Moreover, three hierarchical positions exist in any business organization: strategic, tactical and operational (Khalifa, 2021). The targeted population of this research primarily comprises strategic (51.9 %) and tactical position holders (43.7 %) in business organizations, as these roles are directly involved in interpreting marketing intelligence and shaping organizational decisions. Operational-level respondents (4.4 %) were comparatively fewer, as their roles are primarily execution-oriented rather than decision-centric (Khalifa, 2021).

3.2. Instrument development

The research instrument should be competent to provide the solution to two important questions relating to what is to be measured

Table 2
Respondents' profile.

Characteristics/Category	Frequency (N = 366)	Percentage (%)
Age (Years)		
20–30	152	41.5
30–40	166	45.5
More than 40	48	13.1
Gender		
Male	239	65.3
Female	127	34.7
Education		
Graduation	88	24.0
Postgraduation	210	57.4
Above Postgraduation	68	18.6
Work Experience		
Less than 2 years	63	17.2
2–5 years	88	24
5–10 years	95	26
More than 10 years	120	32.8
Functional Area		
Marketing	119	32.5
Sales and Business Development	200	54.6
Customer Relationship Management	47	12.8
Key Responsibility Area (KRA)		
Strategic Level	190	51.9
Tactical Level	160	43.7
Operational Level	16	4.4

(construct validity) and how it is to be measured (construct reliability) (Sekaran, 2000; Zikmund, 2003). Instrument items were adapted from the Marketing Intelligence scale (Al-Weshah, 2017), the Strategic Decision-making scale (Kline, 1994), the Tactical Decision-making scale (Kline, 1994), Customer Satisfaction scale (Jiang and Rosenbloom, 2005) and Customer Loyalty scale (Zhang and Bloemer, 2008) (Table 3). The scale items are customized to fulfill the purpose of the present research. The anchor points of the five-point Likert scale are summed up as 1 = strongly disagree to 5 = strongly agree. (Likert, 1932).

4. Data analysis

4.1. Common method bias

This research evaluates the possibility of common method bias (CMB) in our data. We employed Harman's single-factor analysis (Harrison and Cupman, 2008). We used the same instrument to gather predictor and outcome variables (Podsakoff et al., 2003, p. 889). Our statistical analysis revealed that only 32.2 % of the total variance was explained by a single factor, suggesting that common method bias is unlikely to be a significant concern in this study.

4.2. Model evaluation

The model evaluation process involves two phases: assessing the measurement (outer) model followed by the structural (inner) model. To check the reliability of each separate item, we considered factor loadings and recommended a threshold of 0.70 (Hair et al., 2021). The factor loadings for all the items are shown in Table 3. In continuation of this, composite reliability was computed, which must be more than 0.70 (Chien and Su, 2003). Moreover, to support convergent validity, all AVE values should exceed the recommended threshold of 0.50 (Fornell and Larcker, 1981). To assess discriminant validity, the Fornell-Larcker criterion compares the square root of each AVE with the correlation coefficients of the other reflective constructs (Fornell and Larcker, 1981) (refer to Table 4). Hair et al. (2021) recommend that all the square root coefficients should be greater than the correlations.

Table 3
Reliability and validity of study constructs.

Constructs	Items/Indicators	FL	CR	AVE	CA
Marketing Intelligence (MI) (Al-Weshah, 2017)	MI1: The organization systematically collects customer-related information from multiple sources	0.793	0.919	0.591	0.898
	MI2: Customer engagement data are continuously monitored and interpreted to support marketing decisions	0.914			
	MI3: Customer insights derived from data analysis are used to guide marketing-related decision-making	0.778			
	MI4: Information obtained from customer interactions is analyzed to enhance the quality of managerial decisions	0.777			
	MI5: Customer surveys are regularly employed to generate actionable market intelligence	0.710			
	MI6: Marketing intelligence is utilized to identify opportunities for customer value creation	0.836			
	MI7: Key account information is systematically analyzed to support organizational planning decisions	0.678			
	MI8: Market segmentation decisions are based on analyzed customer and market data	0.623			
Strategic Decision- Making (SDM) (Kline, 1994)	SDM1: The organization is using customer information for business planning	0.813	0.906	0.618	0.849
	SDM2: Organizations are aligning projects with business strategy	0.869			
	SDM3: The organization is creating value for businesses	0.830			
	SDM4: Organizations are attracting new customers to improve business performance	0.692			
	SDM5: The organization maintains existing customers to generate sales	0.672			
	SDM6: The organization is using business information for "strategic marketing"	0.821			
Tactical Decision- Making (TDM) (Kline, 1994)	TDM1: The pricing strategies of your organization are competitive	0.744	0.845	0.524	0.849
	TDM2: Product categories of your organization are well-received	0.795			
	TDM3: Customer insights are helpful in driving business planning	0.772			
	TDM4: Prospect planning by your organization is generating sales	0.627			
	TDM5: Customer surveys by your organization are used for planning successful marketing campaigns	0.669			
Customer Satisfaction (CS) (Jiang and Rosenbloom, 2005)	CS1: Customers are delighted with their previous experience with your organization	0.704	0.878	0.643	0.790
	CS2: Customer issues were easily resolved by your organization	0.878			
	CS3: Customers positively review your organization	0.784			
	CS4: Customers feel that they have chosen the right organization	0.832			
Customer Loyalty (CL) (Zhang and Bloemer, 2008)	CL1: Customers recommend products of your organization	0.779	0.892	0.624	0.837
	CL2: Customers spread positive word of mouth about your organization	0.753			
	CL3: Customers repurchase from your organization	0.806			
	CL4: Customers are willing to pay a premium for purchases from your organization	0.770			
	CL5: Customers are willing to extend their relationship tenure with your organization	0.838			

Note: FL: Factor loading; CA: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted.

4.3. Structural model

Higher R^2 values indicate stronger explanatory power. According to Henseler et al. (2009) and Hair et al. (2021), R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. Another means to assess the PLS path model's predictive accuracy is by calculating the Q^2 value (Story and Hess, 2006). Last, we evaluate the path estimates' significance and the dependent variables' level of variation explained to evaluate the structural model. We use a bootstrap of 5000 resamples to test the path estimations. The following are the R^2 and Q^2 values for each dependent variable (as shown in Table 5): customer satisfaction (0.303 and 0.18), customer loyalty (0.557 and 0.38), tactical decision-making (0.50 and 0.30), and strategic decision-making (0.56 and 0.30). Hence, the model has reported modest predictive potential because its root mean square error is smaller than that of a linear model. Thus, the results confirm the model's explanatory and predictive power required to assess the statistical significance and relevance of the path coefficients presented in Table 6.

To be more precise, the R^2 value for the customer loyalty construct (0.557) exceeds the moderate threshold and is nearing the substantial level of predictive accuracy; therefore, the model predicts the customer loyalty construct more accurately. The least-predicted model construct is customer satisfaction, with an R^2 of 0.303 (slightly above the weak level of predictive accuracy). Furthermore, the SDM and TDM constructs with R^2 values of 0.560 and 0.500 reflect moderate predictive accuracy. Furthermore, a medium effect of MI is observed on CS ($f^2 = 0.133$) and CL ($f^2 = 0.141$), which signifies that MI affects CS almost as much as CL development. The study's findings also reveal that MI strongly affects SDM ($f^2 = 1.256$) and TDM ($f^2 = 1$). It can be said that marketing intelligence strongly affects the implementation of SDM compared to TDM. Additionally, Stone-Geisser's (Q^2) values of endogenous constructs range from 0.180 to 0.380, signifying the small and medium level of predictive relevance of study variables (Hair et al., 2021). In comparison, the values of the endogenous construct, i.e., CS, lies at the lower bound, signifying the small degree of predictive relevance (CS: $Q^2 < 0.25$); on the other hand, the Q^2 values of all other endogenous constructs namely SDM, TDM, and CL, exceed 0.25 (SDM, TDM, CL: $Q^2 > 0.25$) and therefore signify the existence of a medium degree of model predictive relevance.

Smart PLS software evaluates the structural equation model using 5000 bootstraps. The statistical results indicate that all nine paths derived from the structural model bootstrapping are significant. We have applied t-statistics to measure the relationship's importance. A relationship is significant if the value of t is greater than or equal to 2. Therefore, in our model, the hypothesized relationship of MI with CL ($\beta = 0.378$, $t = 5.612$), CS ($\beta = 0.490$, $t = 4.827$), SDM ($\beta = 0.746$, $t = 7.286$) and TDM ($\beta = 0.707$, $t = 7.681$) are significant. Similarly, the hypothesized relationship of SDM with CL ($\beta = 0.263$, $t = 3.583$) and CS ($\beta = 0.249$, $t = 2.572$) is also significant. Furthermore, the hypothesized relationship of TDM is positively associated with CL ($\beta = 0.139$, $t = 3.500$) and is significant. However, the relationship between TDM is negatively associated with CS ($\beta = -0.215$, $t = 2.456$) yet significant. Finally, the hypothesized relationship between CS and CL ($\beta = 0.165$, $t = 4.234$) is again significant. All hypothesized relationships are positive and significant, except the negative association between variables TDM and CS.

4.4. ANN analysis

This study also used ANN analysis to supplement SEM analysis. ANN analysis is quite effective when analyzing non-linear relationships. However, because of its black-box nature, ANN is not suitable for testing hypotheses. Therefore, the present study used dual techniques, i.e., SEM and ANN. The ANN model was executed using SPSS 23. Around 90 % of the total data was used for testing, and the remaining for training (Leong et al., 2020). The model comprises input, hidden and output layers. Sigmoid was used as the activation function for both the hidden and output layers. Overfitting was avoided using Ten-fold cross-validation, and the resulting RMSE values were pooled. ANN results are shown in Fig. 3.

ANN models' prediction accuracy was evaluated using RMSE values. RMSE values for the training and testing data for the models are shown in Table 7. The average RMSE values for the model's training and testing phases are 0.367 and 0.304, respectively, showing that the developed ANN model has a high level of predictive accuracy. The main predictor of customer loyalty is customer satisfaction. Additionally, Table 8 shows the neural network sensitivity analysis.

5. Discussion

This study proposes an intelligence-loyalty model by unfolding the linkages between marketing intelligence, strategic decision-making, tactical decision-making, customer satisfaction and customer loyalty. Marketing intelligence presents plentiful

Table 4
Discriminant validity (Fornell-Larcker criterion).

Constructs	Customer Loyalty	Customer Satisfaction	Marketing Intelligence	Strategic Decision Making	Tactical Decision Making
Customer Loyalty	**0.779**				
Customer Satisfaction	0.526	**0.784**			
Marketing Intelligence	0.759	0.524	**0.769**		
Strategic Decision Making	0.722	0.457	0.746	**0.754**	
Tactical Decision Making	0.65	0.313	0.707	0.731	**0.79**

Note: Values along the diagonals (bold) are the square root of AVE, while the off-diagonals are correlations.

Table 5
Effect sizes.

Construct	R^2	f^2	Q^2
Strategic Decision Making	0.560	1.256	0.30
Tactical Decision Making	0.500	1.000	0.30
Customer Satisfaction	0.303	0.133	0.18
Customer Loyalty	0.557	0.141	0.38

Note: 1. $Q^2 > 0$ for a particular endogenous construct indicates the predictive relevance of that particular construct, but it does not reflect the prediction quality.
2. R^2 – Predictive Accuracy, f^2 – Effect Size, Q^2 – Predictive Relevance.

Table 6
Hypothesized constructs.

Hypotheses	Path	Beta (β)	*t*-value	*p*-value	Decision
H1	MI → CL	0.378	5.612	0.00	Supported
H2	MI → CS	0.490	4.827	0.00	Supported
H3	MI → SDM	0.746	7.286	0.00	Supported
H4	MI → TDM	0.707	7.681	0.00	Supported
H5	SDM → CS	0.249	2.572	0.010	Supported
H6	TDM → CS	−0.215	2.456	0.014	Supported
H7	SDM → CL	0.263	3.583	0.00	Supported
H8	TDM → CL	0.139	3.500	0.00	Supported
H9	CS → CL	0.165	4.234	0.00	Supported

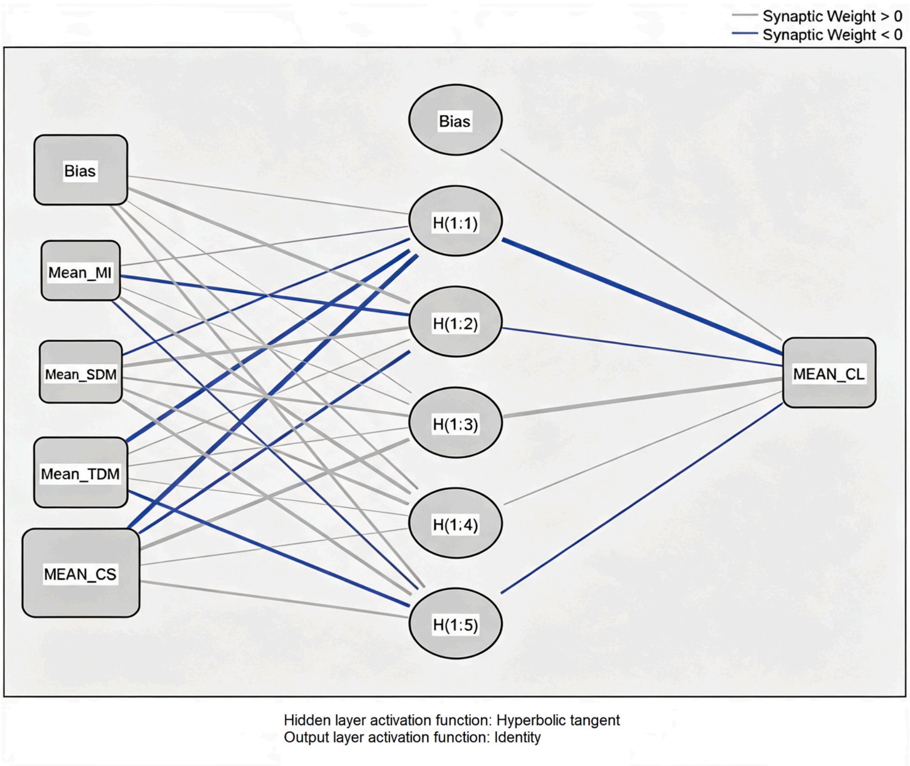

Fig. 3. ANN results.

opportunities for managers, academicians, and practitioners to innovate data generation avenues for business organizations. Drawing its essence from the RBV theory, this research discusses the modalities of empirical association between marketing intelligence and customer loyalty. Several studies establish a positive association between marketing intelligence and customer satisfaction and loyalty (Al-Weshah, 2017; Donio et al., 2006; Kiani et al., 2018; Lee and Trim, 2006; Yang et al., 2015). The high strength of the relationship between MI and CL indicates that MI activities and initiatives primarily help improve customer loyalty quotients. Further analysis of

Table 7
RMSE values for neural networks for Model A.

"Model A (Input Neuron: MI, SDM, TDM, CS; Output Neuron: CL)"						
Training			Testing			Total Sample
N	SSE	RMSE	*N*	SSE	RMSE	
326	44.430	0.369	40	2.416	0.246	366
330	39.414	0.346	36	3.874	0.328	366
329	51.557	0.396	37	2.495	0.260	366
326	39.378	0.348	40	3.133	0.280	366
320	42.073	0.363	46	5.343	0.341	366
332	43.139	0.360	34	3.976	0.342	366
324	44.597	0.371	42	4.391	0.323	366
330	45.84	0.373	36	3.537	0.313	366
322	41.358	0.358	44	3.982	0.301	366
329	50.532	0.392	37	3.503	0.308	366
Mean		0.367	**Mean**		0.304	

Table 8
Neural network sensitivity analysis.

Neural network	Model A relative importance			
	MI	SDM	TDM	CS
Network1	0.17	0.50	0.50	1.00
Network2	0.12	0.58	0.33	1.00
Network3	0.10	0.86	1.00	0.47
Network4	0.09	0.59	0.34	1.00
Network5	0.22	0.28	0.52	1.00
Network6	0.11	0.47	0.63	1.00
Network7	0.12	0.58	0.35	1.00
Network8	0.42	0.49	0.35	1.00
Network9	0.22	0.31	0.24	1.00
Network10	0.53	0.89	1.00	0.94
Avg. Importance	0.20	0.55	0.52	0.94
Normalized Importance	22%	59%	56%	100%

Cohen's (f^2) effect sizes reveals that MI affects the attainment of CS ($f^2 = 0.133$) almost as much as it affects improving their loyalty quotients ($f^2 = 0.141$)

Moreover, the relationship between customer satisfaction and customer loyalty was observed on the lower side, indicating a weak positive association between these two constructs. These results were also confirmed by Cohen's (f^2) values ($f^2 = 0.055$), indicating small effect sizes and a weak positive association between customer satisfaction and customer loyalty. The results of the current study align with those of Hallowell (1996) and Gronholdt et al. (2000); very few studies have established these constructs as only marginally positively related (Bodet, 2008) or even negatively related (Anderson, 1996; Izogo and Ogba, 2015). However, the ANN results indicate that customer satisfaction is the strongest indicator of customer loyalty. Furthermore, MI is positively related to SDM. The relationship also draws attention to the proposition that SDM, which draws heavily from MI, is the function of top management, including the Sr. Managers, vice presidents who hold important managerial and strategic positions in organizations. Furthermore, the study's analysis also establishes that MI has a large effect on SDM ($f^2 = 1.256$), indicating that MI strongly promotes the application of strategic decision-making-synced policy-making in business organizations. Alternatively, the relationship between MI and TDM also indicates a strong association; therefore, the Cohen's (f^2) value for MI on TDM is on the higher side ($f^2 = 1.00$), indicating a large effect size. It indicates that TDM indicators also draw heavily from MI systems. However, it is worth noting that the Cohen's (f^2) values show MI aligns more closely with organizations' strategic decision-making initiatives than tactical decision-making (Cohen's f^2 values for SDM are higher than TDM), so we can infer that MI is more strongly associated with SDM as compared to TDM.

Furthermore, SDM is found to be positively associated with CS, while TDM is found to be negatively correlated with CS. Though both of these hypotheses are statistically supported, general arguments behind the inverse association between TDM and CS are that SDM policy initiatives of top management directly build, manage, and influence customer satisfaction quotients through timely loyalty programs, point of sale or purchase rewards and discounts, pricing of products and brand positioning initiatives. Alternatively, an organization's tactical decision-makers—frontline staff and sales personnel, as well as middle managers who engage with customers through routine service, product, and brand interactions—require support to create differentiators that enhances and enriches customer satisfaction parameters. While prior literature predominantly suggests a positive association between tactical decision-making and customer satisfaction (Hadi, 2017; Morgan et al., 2005), emerging perspectives indicate that excessive reliance on short-term, performance-driven tactical actions may create inconsistencies in customer experience. Frequent changes in pricing, promotional strategies, or communication may lead to customer confusion and reduced perceived value, thereby negatively influencing satisfaction (Guenzi and Troilo, 2007). This suggests that the effectiveness of tactical decision-making is contingent upon its alignment with broader strategic objectives.

Similarly, analysis of these two relationships through Cohen's (f^2) values also confirms the same results. Although both hypotheses have small effect sizes, the effect size of SDM on CS ($f^2 = 0.32$) is marginally larger than those of TDM and CS ($f^2 = 0.27$), thereby providing greater strength and power to strategic decision-making practices in improving customer satisfaction. Finally, the relationship between SDM and CL is more powerful than that between TDM and CL. While both relationships were similar in direction (positive association) and supported the hypothesis, the degree of association between strategic decision-making and customer loyalty is on the higher side. This higher association indicates that strategic marketing-centric decision-making enables organizations in manufacturing and marketing to prefer customer products with the required features and customizations, which in turn motivates customers to engage in repurchase, positive word of mouth (WOM or e-WOM) for brands and maintain long relationship tenure with the same organization's products and services. These relationships were also verified from statistical analysis of Cohen's (f^2) values.

5.1. *Theoretical implications*

The study extends the scholarly literature by applying RBV theory to the linkages among marketing intelligence, customer satisfaction, and customer loyalty. RBV helps strategically position valuable organizational resources, thereby enabling the achievement of a sustainable competitive advantage. The results show marketing intelligence as a valuable intangible asset, positioned as a resource when applied to organizational processes and decision-making. The study shows that customer loyalty is not only dependent on customer satisfaction but also on the role of marketing intelligence, which also plays a significant role through strategic and tactical decision-making. Additionally, the application of SEM and ANN tools validates predictive efficacy, reinforcing the theoretical background of using RBV perspectives in marketing research. Also, the research results show that marketing intelligence is a valuable organizational asset rather than merely facilitating support or data repository, therefore managers and policy-makers must prioritize long-term intelligence-driven strategies. These competences help organizations to build resilient marketing strategies that effectively respond to environmental factors such as changes in product demand and price.

5.2. *Managerial implications*

Marketing intelligence is at the core of practitioner research. It is highly oriented toward providing strategic solutions to real-time business problems by providing valuable insights into market trends, customer preferences, and competitor behavior. This information can help managers make more informed strategic decisions, such as identifying new market opportunities (Jensen et al., 2016), developing new products (Kuester and Rauch, 2016), or entering new geographic regions. By using marketing intelligence, managers can make better-informed decisions that are more likely to lead to successful business outcomes. Additionally, data gathered from marketing intelligence systems can be used to optimize pricing strategies (Mochtar and Arditi, 2001), promotional campaigns (Crosier and Pickton, 2003), and distribution channels. By using marketing intelligence to make these decisions, managers can ensure that their tactics are effective and aligned with overall strategic goals. Moreover, marketing intelligence can also help managers to identify areas where customer satisfaction can be improved. For example, by analyzing customer feedback, managers can identify common customer complaints or issues with the company's products or services. This information can then be used to make changes that address these issues and improve customer satisfaction (Alamsyah and Saviera, 2018), customer loyalty (Faryabi et al., 2013; Kiani et al., 2018) and higher revenues (Harrison and Cupman, 2008). Finally, marketing intelligence can help managers identify factors influencing customer loyalty. Managers can identify different types of products or services that customers are most interested in, analyze their behavior, and then develop strategies to increase customer loyalty in these areas. Additionally, marketing intelligence can help managers identify the most effective ways to communicate with customers and build stronger relationships with them over time. Overall, marketing intelligence provides managers with valuable insights to make more informed decisions, improve customer satisfaction and loyalty, and drive business success. By leveraging marketing intelligence effectively, managers can gain a competitive advantage and position their companies for long-term growth and profitability.

6. Conclusion, limitations, and future research directions

6.1. *Conclusions*

Current research endeavors to unfold and statistically validate the literature-centric linkages between MI, SDM, TDM, CS, and CL. The theoretical implications of the research study are three-pronged. First, this research advances the theoretical understanding of the impact of marketing intelligence on various aspects of decision-making (both strategic and tactical) and customer satisfaction and loyalty, contributing to existing literature and adding a deeper understanding of the underlying mechanisms and processes involved. Second, this research fills the gaps in existing literature by integrating these five key variables stated above through hypothetical associations and integrating existing literature into the variable relationships assigned through a conceptual framework. Third, this research study validated the proposed variable relationships by assessing the measurement and structural model by employing PLS-SEM and ANN. By providing empirical evidence on the impact of marketing intelligence on strategic and tactical decision-making, customer satisfaction, and customer loyalty, researchers have tried to provide statistical validation of the degree and direction of relationships among these variables in the marketing field. This can help firms make more informed decisions and allocate resources more effectively. Overall, marketing intelligence provides managers with valuable insights that can be used to make more informed decisions, improve customer satisfaction and loyalty, and drive business success. By leveraging marketing intelligence effectively, managers can gain a competitive advantage and position their companies for long-term growth and profitability.

6.2. Limitations and future research directions

Although utmost prudence is exercised during the entire research study process, limitations are inevitable. First, this study only assessed the direct impact of strategic and tactical decision-making constructs on customer satisfaction and loyalty, which can otherwise be used as mediators and moderators. Future researchers can consider using these variables in mediating or moderating relationships between marketing intelligence and customer loyalty. Second, studies can explore the dimensions of negative relationships between TDM and CS and conceptualize the relationships using different contextual variables. Finally, given the impact of marketing intelligence in influencing customer acquisition, retention and loyalty, the existing variables can be used to explore the implications for customer lifetime value. By exploring these areas of inquiry, businesses can better understand the drivers of success in a constantly evolving market and make informed decisions. The proposed framework is tested in the context of India; hence, similar research can be done in developed economies, and the results can be compared. Since the concept of marketing intelligence is evolving, new variables may emerge with reference to diverse cultures, business ecosystems and decision-making environments of different countries, and therefore, emerging trends can be explored further to test the model in different contexts.

Ethics statement

Not applicable because this work does not involve the use of animal or human subjects.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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