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Emotional Value in Experiential Marketing: Driving Factors for Sales Growth – A Quantitative Study from the Eastern Coastal Region

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Abstract: This quantitative research investigates the impact of perceived emotional value in luxury experiential marketing, particularly its influence on the likelihood of repeat purchases. Conducted quantitatively in Shanghai, a city in the Eastern coastal region of China, the research collected data from 206 customers who purchased luxury goods. The findings show a significant positive correlation between customers' perception of emotional value and the likelihood of repeat luxury purchases. Customer satisfaction plays a crucial mediating role in linking customers' perception of emotional value to the likelihood of repeat purchases, while gender does not moderate this relationship. These results underscore the importance of integrating diverse emotional value services into smart marketing strategies. By doing so, businesses can not only enhance customer satisfaction but also significantly improve overall luxury sales performance. This research emphasizes the strategic value of nurturing meaningful customer experiences, thereby strengthening market presence and competitiveness in the dynamic luxury business environment.

Keywords: Smart marketing; emotional value; customer satisfaction; luxury goods

1. Introduction

The luxury goods industry is renowned for its unique purchasing and sales models. Buying luxury items often transcends mere transactional behavior; it embodies a symbolic experience expressing personal taste, status, and social identity. Compared to other sectors like food, fast-moving consumer goods, or tobacco and alcohol, luxury goods exhibit significant distinctions and connections. Consumers of luxury items typically possess refined tastes and specific social status, emphasizing product quality, uniqueness, brand history, and tradition. Simultaneously, they seek emotional satisfaction and special services when purchasing, projecting emotions and identity through these experiences. Marketing and sales strategies in the luxury industry should not rely solely on traditional methods. Intelligent marketing becomes crucial; brands can better understand and meet personalized consumer needs through data analysis and personalized recommendation systems, thereby enhancing shopping experiences and customer satisfaction. Successful data analysis in various fields indicates that the luxury industry can use extreme value mixed modeling to better predict market risks and optimize smart marketing strategies [1,2]. Research on emerging market growth shows that smart marketing can enhance brand

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strategic positioning and secure a competitive edge in a globalized context [3 – 5]. For example, improving unsupervised domain adaptation methods based on implicit contrastive learning enables brands to enhance data diversity and discernibility, allowing for more accurate capture of market demand and consumer preferences [6].

However, the luxury industry faces challenges. Due to high-end positioning and pricing strategies, consumer purchase decisions are complex and cautious, necessitating brands to build deep trust and effective communication to earn consumer loyalty and support. Additionally, while emotional value theoretically influences consumer decisions significantly, effectively measuring and leveraging this emotional impact requires further empirical research and exploration. Recent BERT-enhanced prompt engineering techniques offer strong support for improving news classification and text analysis in smart marketing, potentially enhancing emotional value delivery [7].

To gain deeper insights into consumer behavior and attitudes towards luxury goods, this study surveyed 206 customers in Shanghai. It found that customer satisfaction mediates between perceived emotional value and repeat purchase intention. Therefore, in enhancing customer satisfaction and promoting luxury goods sales, sales personnel should provide high-quality emotional value services to build closer customer relationships, enhance brand loyalty, and adapt service levels effectively. Cluster-based marketing strategies, successfully applied in logistics and network optimization, offer valuable insights for improving sales personnel scheduling and efficiency in the luxury industry [8, 9]. Leveraging the success of semi-supervised learning in image classification, the luxury industry can better capture market demand dynamics and refine marketing strategies [10].

2. Literature Review

2.1. Smart Marketing: More Than Just a Concept

In recent years, smart marketing has garnered increasing attention, emerging prominently within the contemporary landscape of technological advancements and the expansive luxury market environment. Chiu et al argued that smart marketing transcends mere technological application, embodying a strategic approach that integrates diverse elements such as data analytics, personalized recommendation systems, and enhanced consumer experiences [11].

First and foremost, data analysis plays an indispensable role in smart marketing. Through meticulous data analysis, luxury brands can delve deeply into consumer preferences and behaviors, enabling the formulation of precise marketing strategies [12]. Models like the attention-based DCGAN combined with autoencoders effectively improve classification accuracy, providing strong support for optimizing smart marketing [13]. Research in other fields shows that detailed data analysis can effectively identify potential risks, inspiring the luxury industry to better predict market trends and consumer behavior [14, 15]. By scrutinizing consumer purchase histories, browsing habits, and social media interactions, companies can pinpoint lucrative customer segments and craft targeted marketing campaigns. This precise market positioning not only boosts marketing effectiveness but also slashes operational costs. Studies show that integrating AI with market analysis improves consumer behavior prediction, leading to higher conversion rates and customer retention [16]. Federated learning, by sharing model weights while preserving data privacy, is increasingly used in luxury industry data analysis, enabling market-wide collaboration and enhancing privacy and personalization [17]. Additionally, domain-adaptation deep learning frameworks help brands bridge market distribution boundaries, enhancing understanding of consumer behavior diversity and improving the accuracy and efficiency of smart marketing in the luxury industry [18,19].

Secondly, personalized recommendation systems stand out as a cornerstone of smart marketing [20]. Leveraging advanced algorithms and user behavior data, these systems deliver tailored product suggestions to consumers. Recommendations are curated not only from consumers' historical purchase patterns but also from real-time browsing behaviors and preference analyses. For instance, when consumers explore a particular product category, the system automatically proposes related items, thereby heightening purchase probabilities. Such personalized recommendations elevate the shopping experience and significantly enhance conversion rates. Research indicates that integrating deep neural network-based image recommendation algorithms in social networks helps consumers more easily find products aligned with their preferences, thereby enhancing the overall shopping experience [21]. Fuzzy-label-based recommendation systems enhance information accuracy and personalized recommendations [22].

Lastly, optimizing consumer experiences constitutes a paramount objective of smart marketing. In the competitive luxury goods sector, differentiation extends beyond products to encompass service and overall experience [23]. Marketers' language proficiency, service acumen, and adaptability are pivotal in this regard. By deeply comprehending consumer needs and psychology, and delivering personalized, attentive service, brands can elevate consumer satisfaction. This premium service experience not only amplifies shopping gratification but also cultivates repeat purchases, fostering enduring customer loyalty. Optimizing emotional value services strengthens the emotional bond between brands and consumers, increasing customer loyalty [24]. Social media, as a digital marketing strategy, significantly influences consumer decision-making, providing key insights for optimizing online services in the luxury industry [25]. Applying active learning to optimize system reliability assessment helps the luxury industry better predict and enhance customer service quality [26–28].

In conclusion, smart marketing enables luxury goods companies to distinguish themselves in a competitive market by leveraging data analysis, personalized recommendations, and optimized consumer experiences. This approach not only boosts marketing efficacy but also enriches consumers' shopping experiences with greater personalization and enjoyment, creating a mutually beneficial outcome for both businesses and their clientele.

2.2. Emotional Value: A Key Element in Demonstrating Customer Respect

Emotional value has become a prominent topic in recent years, describing the emotional and psychological satisfaction consumers derive from purchasing and using products or services [29, 30]. This satisfaction is not only based on the functional aspects of the product but also encompasses intangible elements such as brand identity, service quality, and overall consumer experience. Hsu et al argued that the emotional value can be categorized into several types, including pleasure, respect, pride, and belonging. Respect value, especially in luxury consumption, stands out significantly, as luxury goods are not just commodities but symbols of social status [31]. Through acquiring and using luxury items, consumers achieve social recognition and affirm their status, fulfilling their need for respect.

The impact of emotional value on consumer behavior and psychology is profound. From a sales perspective, brands and products that possess high emotional value are more likely to capture consumer attention and trigger purchase decisions [32]. Once an emotional connection is established, consumers tend to exhibit greater brand loyalty and are more inclined to make repeat purchases, thereby enhancing the brand's market share and revenue potential [33]. Therefore, within the luxury goods sector, sales and marketing teams must consistently enhance the emotional value of their brands. This entails delivering personalized services and creating unique experiences that resonate with consumers' emotional desires. By doing so, companies can achieve sustainable business success and maintain a competitive edge in the luxury market.

2.3. Repeat Purchase as a Manifestation of Successful Smart Marketing

Repeat purchase is a cornerstone of successful smart marketing, directly reflecting customer trust and satisfaction with a brand or product [34]. When customers choose to make repeat purchases, they validate their initial decision and affirm the value and quality of service provided. This behavior is more than just a transaction; it signifies positive customer experiences and effective relationship management.

Knox and Walker highlighted that the repeat purchases not only drive sales growth but also play a critical role in sustaining brand development and securing market share [35]. Effective smart marketing strategies go beyond acquiring new customers; they prioritize enhancing customer satisfaction and loyalty through repeat purchases. By continuously refining products, optimizing emotional value service experiences, and executing targeted marketing campaigns, especially in luxury goods markets [36,37], companies can strengthen customer retention, achieve long-term business success, and maintain competitive advantages.

In summary, repeat purchases are a vital indicator of customer loyalty and satisfaction in smart marketing.

By focusing on enhancing customer experiences and fostering ongoing relationships, businesses can build a solid foundation for sustainable growth and market leadership.

Currently, most research focuses on how marketers influence customers' repeat purchase behavior by providing emotional value. However, there is relatively little research on the mediating role of customer satisfaction in this relationship and whether gender plays a moderating role. Emotional value as a marketing strategy emphasizes deepening customer brand experience through emotional experiences and connections, thereby enhancing their brand identification and loyalty. Despite the increasing importance of emotional value in customer relationship management, further research and discussion are needed on how to ensure that this emotional value positively influences subsequent sales and the critical role customer satisfaction plays in this process. In particular, whether gender differences will have differential impacts in this process is an important topic for further research. By deeply understanding the complex relationship between emotional value, customer satisfaction, and gender, more profound theoretical support and practical guidance can be provided for the precise formulation of marketing strategies. In summary, in this study, five research hypotheses were proposed to explore the relationships among different variables. These hypotheses focus on the following key variables:

1) Perception of Emotional Value (IV): This refers to the emotional value that consumers perceive when experiencing sales services. This variable serves as the independent variable of the study, used to predict changes in other variables.

2) Likelihood of Repeat Purchases (DV): This refers to the likelihood that consumers, after perceiving emotional value, are willing to purchase the product or service again. This variable is the dependent variable of the study, used to measure consumer behavioral responses.

3) Customer Satisfaction (Mediating Variable): Customer satisfaction mediates the relationship between the perception of emotional value and the likelihood of repeat purchases. The study hypothesizes that customer satisfaction can explain the mechanism through which the perception of emotional value influences the likelihood of repeat purchases.

4) Gender as a Moderator: The study also explores whether gender moderates the relationship between the perception of emotional value, customer satisfaction, and the likelihood of repeat purchases. The aim is to understand if gender influences these relationships (as shown in Figure 1).

Specifically, the five hypotheses include:

Hypothesis 1: There is a relationship between perception of emotional value (IV) and likelihood of repeat purchases (DV).

Hypothesis 2: There is a relationship between perception of emotional value (IV) and customer satisfaction.

Hypothesis 3: There is a relationship between customer satisfaction and likelihood of repeat purchases (DV).

Hypothesis 4: Customer satisfaction mediates the relationship between perception of emotional value (IV) and likelihood of repeat purchases (DV).

Hypothesis 5: Gender moderates these relationships.

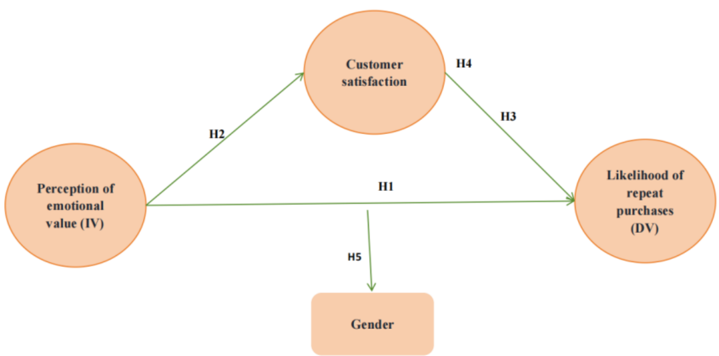

Figure 1. illustrates the research framework.

By validating these hypotheses, the study aims to gain a deeper understanding of the role of emotional value in sales services and to explore the mechanism of customer satisfaction as a mediating variable. It also seeks to confirm whether gender plays a moderating role in these relationships. These findings can help sales personnel in smart marketing strategies to offer diverse emotional value services, enhance customer satisfaction, and increase the likelihood of repeat purchases, thereby achieving sales growth.

3. Methods

This study aims to explore the relationships among perception of emotional value, customer satisfaction, and the likelihood of repeat purchases. It employs the PERVAL scale developed by Sweeney and Soutar to objectively assess customers' perceived emotional value from sales interactions [38]. The PERVAL scale provides a structured approach to measuring emotional value, ensuring a comprehensive evaluation of customer perceptions in sales contexts. This instrument is essential for understanding how emotional value influences customer satisfaction and subsequent purchase behaviors. Additionally, to comprehensively understand overall customer satisfaction with sales personnel, the study utilizes the three-item scale designed by Ramsey and Sohi [39]. This scale assesses customers' satisfaction levels based on the quality of service received, the responsiveness of sales personnel, and overall satisfaction with the sales experience.

Measurement in the study utilizes a five-point Likert scale ranging from 5 (very satisfied/very likely) to 1 (extremely dissatisfied/unlikely), reflecting customers' willingness and likelihood to make repeat purchases. This approach ensures a nuanced assessment of customer satisfaction, crucial for identifying the specific drivers of repeat purchase intentions.

Located in the eastern coastal region of China, Shanghai serves as a key market for luxury goods consumption. Shanghai not only boasts a diverse consumer base but also features a highly competitive retail environment, attracting numerous domestic and international luxury brands. To ensure sample diversity and representativeness, the study selected three major shopping centers with high foot traffic as research sites. These centers include multiple luxury brands such as LV, Gucci, Hermès, and Prada, making them ideal locations for purchasing luxury goods. Additionally, these shopping centers attract a large number of high-end consumers with their rich brand combinations and exceptional shopping experiences, providing a more accurate reflection of the luxury goods market dynamics. This also enhances the practical value of the study's results, offering strong support for the luxury goods industry to improve competitiveness in a rapidly changing market [40–42].

The study successfully collected 206 valid customer questionnaires, achieving a response rate of 98.5%. These data provide a solid foundation for subsequent in-depth analysis, aiding in a more precise understanding of the role of emotional value in sales services and its specific impacts on customer satisfaction and purchase intentions. The high response rate ensures the reliability and validity of the findings, highlighting the study's contribution to the field of emotional value and consumer behavior in retail settings.

Researchers utilized SPSS software for comprehensive data analysis, including descriptive statistics, Pearson correlation exploration, and testing of mediation and moderation models, to comprehensively investigate relationships among variables. These analytical approaches not only helped uncover underlying patterns and correlations in the data but also deepened the understanding of the mechanisms through which emotional value operates in the sales process, providing valuable guidance for further research and practical applications.

4. Results

4.1. Overview of Sample Demographics and Characteristics

To gain an understanding of the sample's characteristics, SPSS was used to conduct a descriptive statistical analysis, focusing on gender, age group, work style, and educational level.

Table 1. Sample Demographics.

Name	Item	Frequency	Percentage (%)	Cumulative Percentage (%)
Gender	Male	72	34.95	34.95
	Female	134	65.05	100.00
Age	26-30 years old	12	5.83	5.83
	31-35 years old	47	22.82	28.64
	36-40 years old	63	30.58	59.22
	41-45 years old	48	23.30	82.52
	46-50 years old	11	5.34	87.86
	Above 51 years old	17	8.25	96.12
	Under 25 years old	8	3.88	100.00
Work style	Agriculture	5	2.43	2.43
	Arts and Culture	21	10.19	12.62
	Construction	5	2.43	15.05
	Education	12	5.83	20.87
	Energy	11	5.34	26.21
	Entertainment and Media	11	5.34	31.55
	Finance	13	6.31	37.86
	Healthcare	9	4.37	42.23
	Information Technology	13	6.31	48.54
	Legal Services	10	4.85	53.40
	Manufacturing	5	2.43	55.83
	Nonprofit Organizations	1	0.49	56.31
	Public Services and Government	10	4.85	61.17
	Real Estate	10	4.85	66.02
	Research and Development	10	4.85	70.87
	Retail	11	5.34	76.21
	Services	13	6.31	82.52
	Telecommunications	10	4.85	87.38
	Tourism and Hospitality Management	15	7.28	94.66
	Transportation and Logistics	11	5.34	100.00
Educational level	Junior High School	19	9.22	9.22
	Master	42	20.39	29.61
	None	10	4.85	34.47
	Ph.D.	26	12.62	47.09

Cont.

Name	Item	Frequency	Percentage (%)	Cumulative Percentage (%)
	Primary	19	9.22	56.31
	Senior High School	6	2.91	59.22
	Undergraduate	84	40.78	100.00
Summary		206	100.0	100.0

Table 1 showed a higher proportion of females (65.05%) compared to males (34.95%). The majority fell within the 36-40 (30.58%) and 41-45 (23.30%) age brackets. Participants worked in a variety of industries, with notable representation in arts and culture (10.19%), finance (6.31%), information technology (6.31%), and tourism and hospitality management (7.28%). Regarding educational level, the largest group held undergraduate degrees (40.78%), followed by those with master's degrees (20.39%). The sample included participants with diverse educational backgrounds, ranging from primary school to Ph.D. holders. Overall, the sample comprised 206 respondents, providing a comprehensive overview of various demographic and occupational categories.

4.2. The Relationship Between Perception of Emotional Value (IV) and Likelihood of Repeat Purchases (DV)

To investigate the correlation between the perception of emotional value (IV) and the likelihood of repeat purchases (DV), a Pearson correlation analysis was conducted using SPSS.

Table 2. Overview of Correlation Coefficients between IV and DV.

	Perception of emotional value (IV)
Likelihood of repeat purchases (DV)	0.562**

* $p<0.05$ ** $p<0.01$

Table 2 presented the correlation coefficients between customers' perception of emotional value and their likelihood of repeat purchases. A significant positive correlation was indicated between the two variables, with a correlation coefficient of 0.562, which was significant at the 0.01 level (**p<0.01). This suggested that as consumers' perception of emotional value increased, their likelihood of making repeat purchases also rose.

4.3. The Relationship Between Perception of Emotional Value (IV) and Customer Satisfaction (Mediating Variable)

To examine the relationship between the perception of emotional value (IV) and customer satisfaction (mediating variable), a Pearson correlation test was conducted.

Table 3. Overview of Correlation Coefficients between perception of emotional value and customer satisfaction.

	Perception of emotional value (IV)
Customer satisfaction	0.604**

* $p<0.05$ ** $p<0.01$

Table 3 showed the correlation coefficients between customers' perception of emotional value and their satisfaction. A significant positive correlation was revealed, with a coefficient of 0.604, significant at the 0.01 level (**p<0.01). This indicated that a higher perception of emotional value was associated with increased customer satisfaction.

4.4. The Relationship Between Customer Satisfaction (Mediating Variable) and Likelihood of Repeat Purchases

To analyze the relationship between customer satisfaction (mediating variable) and the likelihood of repeat purchases, researchers utilized SPSS to perform a Pearson correlation assessment.

Table 4. Overview of Correlation Coefficients between perception of emotional value and customer satisfaction.

	Customer satisfaction
Likelihood of repeat purchases (DV)	0.762**

* *p*<0.05 ** *p*<0.01

Table 4 presented the correlation coefficients between customer satisfaction and the likelihood of repeat purchases. The results show a significant positive correlation, with a coefficient of 0.762, significant at the 0.01 level (**p<0.01). This indicates that higher levels of customer satisfaction are strongly associated with an increased likelihood of repeat purchases.

4.5. Testing the Mediating Effect of Customer Satisfaction Between Perception of Emotional Value (IV) and Likelihood of Repeat Purchases (DV)

To investigate whether customer satisfaction (mediating variable) mediates the relationship between perception of emotional value (independent variable) and likelihood of repeat purchases (dependent variable), the mediation model was tested using SPSS.

Table 5. Mediation Effect Test.

Item	**Symbol**	**Meaning**	**Effect value Effect**	**95% CI**		**Standard Error Devalued**	***z* value /*t* value**	***p* value**	**Summary**
IV=> Mediator=> DV	a*b	Indirect	0.063	0.085	0.222	0.034	1.827	0.068	Full Mediation
IV=> Mediator	a	X=>M	0.185	0.080	0.290	0.054	3.460	0.001	
Mediator =>DV	b	M=>Y	0.340	0.287	0.393	0.027	12.546	0.000	
IV=>DV	c'	Direct	0.032	-0.010	0.074	0.021	1.496	0.136	
IV=>DV	c	Total Effect	0.095	0.041	0.149	0.028	3.445	0.001	

Table 5 showed the mediation effect test reveals that the independent variable (IV) has a significant indirect effect on the dependent variable (DV) through the mediator, with an effect value of 0.063 and a 95% confidence interval ranging from 0.085 to 0.222, indicating full mediation. The IV significantly impacts the mediator (effect value of 0.185) and the mediator significantly influences the DV (effect value of 0.340). In contrast, the direct effect of the IV on the DV is not significant (effect value of 0.032). The total effect of the IV on the DV is significant (effect value of 0.095), confirming that the mediator fully explains the relationship between the IV and DV.

4.6. Testing for Gender Moderation Effect

To test the gender moderation effect, the SPSS were used and three models were compared, as displayed in Table 6. Model 1 did not consider the gender effect, Model 2 adds the moderator variable (i.e., gender) to Model 1; and Model 3 includes an interaction term between the IV and gender in addition to Model 2.

Table 6. Testing for gender moderation effect (*n*=206).

	Model 1					**Model 2**					**Model3**				
	B	**Standard error**	***t***	***p***	***β***	***B***	**Standard error**	***t***	***p***	***β***	***B***	**Standard error**	***t***	***p***	***β***
Constant	4.680	0.034	138.379	0.000**	-	4.680	0.033	141.354	0.000**	-	4.681	0.034	139.052	0.000**	-
IV	0.095	0.028	3.445	0.001**	0.234	0.080	0.027	2.911	0.004**	0.197	0.081	0.029	2.849	0.005**	0.201
Gender						-0.222	0.071	-3.141	0.002**	-0.213	-0.222	0.071	-3.141	0.002**	-0.213
IV*gender											0.012	0.055	0.221	0.825	0.015
R 2	0.055					0.099					0.099				
Adjust R 2	0.050					0.090					0.086				
F value	*F* (1,204) =11.865, *p*=0.001					*F* (2,203) =11.123, *p*=0.000					*F* (3,202) =7.397, *p*=0.000				
R 2	0.055					0.044					0.000				
F value	*F* (1,204) =11.865, *p*=0.001					*F* (1,203) =9.865, *p*=0.002					*F* (1,202) =0.049, *p*=0.825				

* p<0.05 ** p<0.01

Model 1 showed a significant positive effect of the independent variable on the dependent variable (B = 0.095, t = 3.445, p = 0.001, β = 0.234). Model 2 revealed that after adding the gender variable, the effect of the independent variable on the dependent variable remained significant (B = 0.080, t = 2.911, p = 0.004, β = 0.197), while gender had a significant negative effect on the dependent variable (B = -0.222, t = -3.141, p = 0.002, β = -0.213).

However, after including the interaction term between the independent variable and gender, Model 3 showed that the p-value for the interaction term was 0.825, which is far greater than 0.05, indicating that the interaction term is not significant. Therefore, the researcher further compared the F-value and R^2 value results between Model 2 and Model 3.

As displayed in Table 6, the F-value decreased from 11.123 in Model 2 to 7.397 in Model 3. Additionally, the adjusted R^2 value for Model 3 was 0.086, lower than the corresponding value of 0.09 in Model 2. These results suggest that the interaction term did not significantly improve the model's explanatory power. In other words, gender did not play a significant moderating role in this study.

The results of the above analysis indicate that the likelihood of repeat purchases is significantly associated with customers' perception of emotional value and their satisfaction. Specifically, the stronger the perception of emotional value provided by sales personnel, the higher the satisfaction levels among customers, thereby increasing the likelihood of repeat purchases. Furthermore, satisfaction mediates the relationship between perception of emotional value and likelihood of repeat purchases, with gender showing no significant moderating effect in these dynamics. Overall, this study provides valuable insights into understanding smart marketing strategies.

5. Discussion & Conclusion

Firstly, the research findings reveal how sales personnel in the luxury goods market significantly influence customer experience by providing emotional value. Emotional value is not only reflected in the characteristics of the product itself but also in the emotional connections and personalized services established during the sales process. Therefore, companies aiming to enhance customer satisfaction and boost repeat purchase intention need to prioritize the emotional intelligence and service quality of their sales staff.

Secondly, higher customer satisfaction correlates with stronger repeat purchase intentions and increased sales [43 – 45]. Overall, there is a close relationship between high customer satisfaction and strong repeat purchase intentions, directly impacting sales performance and market share growth. Hence, companies should strive to continually elevate customer satisfaction levels by offering superior emotional value and personalized services to enhance customer loyalty and drive sales growth [46–49].

Additionally, customer satisfaction plays a crucial mediating role between perceived emotional value and repeat purchase intentions, with gender having a minor influence on these relationships. This finding underscores the mediating role of customer satisfaction between emotional value and repeat purchase intentions, irrespective of customer gender. Therefore, when devising marketing strategies, companies should focus on enhancing overall customer satisfaction levels rather than overly considering gender factors.

In summary, companies should enhance training in emotional intelligence for sales personnel to improve their abilities in emotional communication and personalized service delivery, thereby enhancing their capability to provide emotional value. Secondly, optimizing customer experience design by implementing strategies and processes that enhance customer satisfaction is crucial to ensuring positive emotional connections in every interaction. Furthermore, companies can delve deeper into understanding the specific mechanisms through which customer satisfaction affects the relationship between emotional value and purchase intentions, enabling precise adjustments to marketing strategies and service designs to maximize their impact. These recommendations will aid companies in leveraging emotional value and customer satisfaction to enhance sales performance and competitive advantage in the luxury goods market, thereby achieving sustained business success. Moreover, intelligent methods can be also investigated to explore the efficiency of the proposed method [50–52].

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Conceptualization, C.L. and Y.T.; writing—original draft preparation and writing—review and editing, C.L. and Y.T. All of the authors read and agreed to the published the final manuscript.

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Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Upon reasonable request, the primary author is prepared to furnish the data that underpins the findings presented in this study. Please feel free to reach out should you require access to this information, as transparency and accessibility are priorities in our research practice.

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Conflicts of Interest

The authors have disclosed that there are no conflicts of interest to declare regarding the publication of this article.

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