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Analysis of Dominant Emotional Value through Global Sensitivity Analysis

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Abstract: This paper addresses the analysis of dominant emotional value through Global Sensitivity Analysis (GSA). Emotions play a crucial role in decision-making, yet identifying and understanding dominant emotional values remains a challenging task in various research fields. Current research often struggles with the complexity of emotional data and lacks a systematic approach to identify dominant emotional values. To fill this gap, this study proposes a novel framework utilizing GSA to quantify the sensitivity of emotional values in decision-making processes. By applying GSA to emotional data sets, this approach aims to reveal the key emotional factors driving decision outcomes. This innovative methodology not only enhances our understanding of dominant emotional values but also provides valuable insights for a wide range of disciplines, from psychology to economics.

Keywords: *Emotional Value; Global Sensitivity Analysis; Decision-Making; Emotional Data; Methodology*

1. Introduction

The field of Emotional Value examines the subjective worth or importance that individuals place on emotional experiences, objects, or events. It aims to understand how emotions influence decision-making, behavior, and overall well-being. Current challenges in this field include the difficulty in quantifying and measuring emotional value, as emotions are complex and can vary greatly between individuals. Additionally, there is a need for more comprehensive models and frameworks to explain the relationship between emotional value and other psychological processes. Limited research on cross-cultural differences in emotional value perception also presents a challenge, as cultural factors can significantly impact the way emotions are perceived and valued. Overall, advancing research in Emotional Value requires interdisciplinary collaboration, innovative methodologies, and a nuanced understanding of human emotions.

To this end, current research on Emotional Value has advanced to a stage where interdisciplinary studies have integrated psychology, neuroscience, marketing, and consumer behavior to comprehensively explore the emotional factors influencing decision-making and behavior. The study by Juniansyah et al. investigates the impact of customer emotional value and service innovation on consumer purchase decisions using the Technology Acceptance Model (TAM) approach, highlighting the significant positive effects of TAM on Emotional Value and Service Innovation, as well as on Consumer Purchase Decisions mediated by Emotional Value and Service Innovation. In a related context, Buzova et al. explore the co-creation of emotional value in a guided tour experience, underscoring the emotional contagion effect between guide's emotional labor and tourists' emotional participation. Moreover, Ravi et al. focus on the mediating role of emotional value in the consumer purchase intention of social enterprise products, showing the importance of emotional values, attitudes, and subjective norms in driving consumer acceptance of social enterprise products. Joshi et al. and Kato delve into consumer behavior, examining the influence of emotional value on green purchase intention and corporate brand preference, respectively. Moving beyond consumer behavior, Joshi et al. also study the interplay of emotional value, trend affinity, and past practices in sustainable consumption, emphasizing the role of emotional value, trend affinity, and supportive behavior in shaping sustainable consumption practices. Additionally, Makransky and Lilleholt explore the emotional value of immersive virtual reality in education using structural equation modeling, providing insights into the emotional aspects of educational technology. Furthermore, Saito et al. investigate the rapid detection of neutral faces associated with emotional value, highlighting the impact of emotional/motivational significance on the swift detection of emotional faces. Global Sensitivity Analysis (GSA) is a crucial technique for understanding complex relationships and interactions within a research framework. GSA helps researchers identify the most influential factors and their impact on outcomes, providing valuable insights for decision-making and further research directions.

Specifically, Global Sensitivity Analysis (GSA) provides a framework to evaluate how variations in input parameters affect outcomes, thereby influencing the emotional value associated with decision-making processes. By understanding these sensitivities, stakeholders can better gauge emotional responses linked to different scenarios and prioritize strategies that resonate more effectively. In the realm of global sensitivity analysis, various methods have been developed and applied to different fields. Saltelli et al. provided a foundational understanding of sensitivity analysis, emphasizing the importance of evaluating parameter uncertainties. Lamboni and Kucherenko introduced multivariate sensitivity analysis and derivative-based measures for dependent variables, expanding the analytical scope. Sudret proposed the use of polynomial chaos expansions for global sensitivity analysis, offering a mathematical framework for rigorous assessment. Li et al. compared local and global sensitivity analysis methods, specifically in the context of thermal hydraulic phenomena, highlighting practical applications in engineering. Usher et al. addressed the need for transparency in energy system optimization modeling through global sensitivity analysis, showcasing the practical benefits of incorporating such approaches. Zhou and Lin explored global sensitivity analysis in a spatial context, demonstrating its relevance across diverse fields. Dixit and Rackauckas developed software for efficient global sensitivity analysis implementation, facilitating broader adoption and application. Van Stein et al. focused on utilizing global sensitivity analysis methods in explainable AI, providing insights into influential parameters for model predictions. Kim et al. devised a comprehensive protocol for conducting global sensitivity analysis in life cycle assessment models, enhancing accuracy and efficiency in environmental impact evaluations. Alipour et al. delved into the application of global sensitivity analysis in hydrodynamic modeling and flood inundation mapping, showcasing its utility in complex environmental simulations. However, current limitations in global sensitivity analysis include the challenges of handling high-dimensional parameter spaces, the need for improved robustness in output uncertainty quantification, and the integration of diverse methodologies across varying fields.

In examining the subject matter, our research draws significant inspiration from the work of C. Li and Y. Tang, which ingeniously explores the concept of emotional value within experiential marketing, particularly in the context of driving sales growth on the Eastern Coastal Region. Their meticulous quantitative analysis reveals various contributing factors that influence consumer behavior through emotional engagement. Bearing in mind the robustness of their findings, our study seeks to expand upon these theoretical constructs by adopting the techniques and quantitative methodologies articulated by Li and Tang [18]. Specifically, the application of statistical models and data-driven insights from their paper serves as a cornerstone in our approach to constructing a framework that thoroughly assesses emotional dynamics within consumer markets. Their research elucidates the intricate interplay between emotional value and consumer decision-making, and we have integrated these elements into our own methodological design. By harnessing their criteria for emotional impact assessment, which include variables such as consumer sentiment and experiential stimuli, our study employs global sensitivity analysis to measure and understand the influence of these variables in a more generalized context. This method not only allows for the identification of the most critical emotional factors but also provides a pathway to predict potential shifts in consumer behavior under varying marketing conditions, as posited by Li and Tang [18]. Moreover, the nuanced strategies outlined in their research inculcate a multi-faceted understanding of how emotional resonance can be quantitatively gauged, and their analysis techniques afford us the capability to refine our sensitivity metrics, ensuring that the model we propose remains both relevant and adaptable to numerous scenarios. Through the diligent integration of their empirical methodologies, and by adhering to the rigorous evaluative benchmarks they advocate, we aim to provide a more layered understanding of emotional value’s impact on consumer markets, drawing from their extensive and foundational insights on the topic [18].

This paper centers on the analysis of dominant emotional values using Global Sensitivity Analysis (GSA). Emotions, integral to decision-making, present a formidable challenge in their identification and understanding within varied research fields. Existing studies often grapple with the intricate nature of emotional data and lack a systematic framework to pinpoint dominant emotional values. To bridge this gap, the study introduces a groundbreaking framework employing GSA to quantify the sensitivity of emotional values in decision-making contexts. Through the application of GSA on emotional datasets, this approach endeavors to unveil pivotal emotional factors influencing decision outcomes. Section 2 articulates the problem statement of this research, while section 3 delineates the proposed method. Section 4 presents a case study that illustrates the application, followed by section 5, which analyzes the results. Section 6 delves into a discussion of the findings, and section 7 concludes the study. This novel methodology not only deepens the comprehension of dominant emotional values but also offers invaluable insights across diverse disciplines, ranging from psychology to economics.

2. Background

2.1 Emotional Value

Emotional Value (EV) is a concept that attempts to quantify the worth or significance of emotions in decision-making processes, consumer behavior, or psychological assessments. This concept arises from the intersection of psychology, economics, and decision science, wherein emotions are no longer perceived as irrational or secondary elements; rather, they are integral to understanding human actions and preferences. Emotional Value can be mathematically articulated, enabling a structured approach to evaluating emotions within various contexts. To comprehend Emotional Value, think of it as an additive component to a traditional rational utility model. Utility, in classic economic terms, captures the satisfaction or benefit a person derives from consuming goods or making decisions. Emotional Value, on the other hand, augments this by integrating emotional satisfaction or discomfort into the utility function. The Emotional Utility Function (EUF) can be represented as:

$$U = C + E \tag{1}$$

where U is the total utility, C symbolizes the cognitive or rational component of utility, and E represents the Emotional Value. Emotional Value itself can be dissected into several key factors, as emotions are complex and multidimensional. These components include intensity, valence, and persistence. Intensity (I_e) measures how strong an emotion is felt; valence (V_e) indicates whether the emotion is positive (pleasant) or negative (unpleasant); and persistence (P_e) reflects how long the emotion lasts. Given these aspects, the Emotional Value can thus be articulated as:

$$E = I_e \cdot V_e \cdot P_e \tag{2}$$

In scenarios involving consumer behavior, the Emotional Value might affect perceived product utility. For instance, an individual deciding between two products might evaluate not just functional attributes but also the emotional associations with each product, be it nostalgia, excitement, or comfort.

The emotional reaction (R) to a decision or product can be further quantified through a summation across all relevant emotions n . This brings us to:

$$R = \sum_{i=1}^{n} E_i \tag{3}$$

Within a time-dependent setting, to model how the Emotional Value changes and impacts decisions over a time period t , we consider:

$$E_t = \alpha I_e(t) \cdot V_e(t) \cdot P_e(t) \tag{4}$$

where α is a time-discount factor denoting diminishing sensitivity over time. When measuring Emotional Value from empirical data—for instance, in a marketing context—the perceived emotional payoff (PEP) from a product can be described as:

$$PEP = \lambda S + \beta A + \gamma E \tag{5}$$

where S is sensory stimulation, A involves affiliation or brand attachment, and E is the aforementioned emotional component, with λ , β , and γ being weight coefficients. To effectively gauge Emotional Value in practical research, one might utilize psychometric methods, including surveys or experimental designs, where items evaluate intensity, valence, and persistence directly. Additionally, machine learning models can be employed to predict Emotional Value by using real-time data such as facial recognition or biometrics. In conclusion, Emotional Value serves as a metric that bridges gaps between rational decision-making models and the inherent emotional experiences that accompany human interactions and consumer behaviors. By implementing mathematical formulations, Emotional Value can be systematically analyzed and utilized across various fields to understand and influence decision-making processes.

2.2 Methodologies & Limitations

In the current study of Emotional Value (EV), several methodologies are typically employed to quantify and assess emotional significance in decision-making and consumer behavior. One of the most prominent methods involves integrating Emotional Value into utility functions, where emotions are considered key components influencing human preferences alongside rational choices. Although these methods provide innovative insights, they also exhibit limitations that are critical to consider. The Emotional Utility Function (EUF) formulates the basis for evaluating Emotional Value within economic models. This function is defined as:

$$U = C + E \tag{6}$$

where U denotes total utility, C is the cognitive component, and E represents the Emotional Value. Despite its utility, the primary limitation lies in accurately discerning and quantifying emotional factors, which can be subjective and variable across different individuals. Emotional

Value itself can be broken down into three core dimensions: intensity (I_e), valence (V_e), and persistence (P_e). These components can collectively model Emotional Value as:

$$E = I_e \cdot V_e \cdot P_e \tag{7}$$

These dimensions pose certain difficulties, such as the challenge of measuring intensity and persistence objectively and consistently across different contexts and cultures. In analyzing consumer behaviors, the emotional response to products or decisions can be assessed using:

$$R = \sum_{i=1}^{n} E_i \tag{8}$$

where each E_i corresponds to the emotional value attributed to a particular aspect of a product. The summation signifies the aggregate emotional appeal, yet it assumes additive separability of emotions, which may oversimplify the intricate interplay of different emotional factors. Emotional Value's temporal variation can be modeled as:

$$E_t = \alpha I_e(t) \cdot V_e(t) \cdot P_e(t) \tag{9}$$

Here, α is a time-discount factor, reflecting the diminishing impact of emotions over time. The challenge lies in determining the exact form and magnitude of α , which can vary significantly across different scenarios and individuals. In empirical studies, Emotional Value is often extracted from observable data using models like the perceived emotional payoff (PEP):

$$PEP = \lambda S + \beta A + \gamma E \tag{10}$$

where S , A , and E correspond to sensory stimulation, brand attachment, and emotional components, respectively. Coefficients λ , β , and γ are weights representing their relative impacts. However, calibrating these coefficients to reflect real-world scenarios accurately can be complex and requires substantial data. Furthermore, methods like psychometric evaluations and advanced machine learning models are frequently utilized to capture Emotional Value, employing indicators such as facial recognition or biometric feedback. These methodologies, while promising, often face constraints related to privacy concerns, data reliability, and ethical implications, alongside their dependency on continuous technological advancement to improve accuracy and applicability. In summary, while the quantification of Emotional Value through these methodologies highlights its significance in decision-making contexts, it is crucial to acknowledge the constraints and assumptions inherent in these approaches. Exploring improved measurement techniques and models to more accurately reflect the fluid and multifaceted nature of emotional experiences remains a fertile ground for ongoing research.

3. The proposed method

3.1 Global Sensitivity Analysis

In the realm of scientific modeling and uncertainty assessment, Global Sensitivity Analysis (GSA) stands out as a vital tool for discerning how uncertainty in model inputs influences outputs. Unlike local sensitivity analysis which examines small variations around a fixed point, GSA encompasses the entire input space to provide a comprehensive view of the model's behavior. This is particularly crucial in complex models where inputs may interact in non-linear ways or where the model is subject to substantial uncertainties. The fundamental objective of GSA is to apportion the variance of the model output to different inputs or combinations thereof. This is often done in the context of variance-based methods, where the output variance is decomposed into components attributed to individual inputs and their interactions. The total variance D of the model output Y is expressed as:

$$D = \mathrm{Var}(Y) \tag{11}$$

In variance-based methods, the sensitivity index for an input X_i , known as the first-order sensitivity index, is given by the ratio of the variance of the conditional expectation to the total output variance. It is expressed as:

$$S_i = \frac{\mathrm{Var}(\mathbb{E}[Y|X_i])}{D} \tag{12}$$

where $\mathrm{Var}(\mathbb{E}[Y|X_i])$ represents the variance of the expected value of Y conditional on X_i , highlighting the effect of X_i alone. Moreover, GSA explores interaction effects through higher-order indices. The second-order sensitivity index for a combination of inputs X_i and X_j is given by:

$$S_{ij} = \frac{\mathrm{Var}\left(\mathbb{E}\left[Y\middle|X_i, X_j\right]\right)}{D} - S_i - S_j \tag{13}$$

capturing the additional variance explained by the interaction of X_i and X_j beyond their individual contributions. The total sensitivity index S_{Ti} is also frequently utilized, which accounts for all variance that can be attributed to X_i , including both main effects and interactions with other inputs:

$$S_{Ti} = \frac{\mathbb{E}[\mathrm{Var}(Y|X_{-i})]}{D} \tag{14}$$

Here, $\mathrm{Var}(Y|X_{-i})$ indicates the variance of Y given all inputs except X_i , and this term effectively captures the roles of both direct and interactive effects associated with X_i. The cornerstone of implementing GSA is the sampling strategy, with approaches such as the Sobol' sequences or Latin Hypercube Sampling that efficiently cover the input space. For example, Sobol' method provides a robust and quasi-random sequence suitable for estimating sensitivity indices accurately. To calculate the sensitivity indices in practice, computational models often leverage Monte Carlo integration, a numerical technique that utilizes random sampling to estimate complex probabilistic metrics. Global Sensitivity Analysis is not limited to purely quantitative models; it also accommodates qualitative assessments where inputs are not easily quantifiable. For such models, methods like factor prioritization, factor fixing, and factor mapping are employed to handle non-numeric inputs and outputs effectively. Importantly, GSA serves as a diagnostic tool in model validation processes. By identifying key influences and interactions within the model, researchers can refine model structures, reduce uncertainties, and prioritize data collection efforts. The insights gained from GSA guide decision-makers in recognizing the robustness of model predictions under uncertainty, ultimately enhancing the reliability and interpretative power of scientific conclusions.

3.2 The Proposed Framework

Emotional Value (EV) is a pivotal concept that bridges the gap between rational decision-making frameworks and the inherent emotional components that influence human choices. At its core, EV integrates psychological, economic, and decision science principles to offer a quantifiable measure of emotions. Traditionally, utility models in economics have focused on cognitive elements, but EV enhances these models by incorporating emotional dimensions, thus portraying a more holistic picture of human behavior. Mathematically, the Emotional Utility Function (EUF) is defined as:

$$U = C + E \tag{15}$$

where U represents the total utility derived by an individual, C is the cognitive or rational utility, and E is the Emotional Value. Emotional Value itself is a complex construct, further broken down into intensity (I_e), valence (V_e), and persistence (P_e). These factors are crucial as they represent how strongly emotions are felt, whether they are positive or negative, and their duration, respectively. The mathematical representation of Emotional Value is captured by:

$$E = I_e \cdot V_e \cdot P_e \tag{16}$$

Incorporating Global Sensitivity Analysis (GSA) into this framework provides a systematic approach to understanding how variations in these emotional factors influence overall utility outcomes. GSA is instrumental in modeling scenarios with multiple interacting variables, demonstrating how uncertainty in parameters like I_e , V_e , and P_e affects their contribution to Emotional Value. Starting with the variance of the output, which in this case is the Emotional Value E , the total variance is denoted as:

$$D = \mathrm{Var}(E) \tag{17}$$

Through GSA, the first-order sensitivity index for I_e can be defined as the proportion of variance due to I_e alone:

$$S_{I_e} = \frac{\mathrm{Var}(\mathbb{E}[E|I_e])}{D} \tag{18}$$

Similarly, for valence and persistence:

$$S_{V_e} = \frac{\mathrm{Var}(\mathbb{E}[E|V_e])}{D} \tag{19}$$

$$S_{P_e} = \frac{\mathrm{Var}(\mathbb{E}[E|P_e])}{D} \tag{20}$$

Beyond individual effects, interactional complexities are addressed through second-order sensitivity indices. For instance, the interaction between I_e and V_e is evaluated as:

$$S_{I_e,V_e} = \frac{\mathrm{Var}(\mathbb{E}[E|I_e, V_e])}{D} - S_{I_e} - S_{V_e} \tag{21}$$

To encompass total effects, including interactions, the total sensitivity index for I_e is computed as:

$$S_{T_{I_e}} = \frac{\mathbb{E}[\mathrm{Var}(E|I_{-e})]}{D} \tag{22}$$

Applying GSA within this emotional context allows for empirical investigations into how these emotional factors—such as the weight of nostalgia or excitement tied to consumer products—impact perceived utility. The perceived emotional payoff (PEP) can be captured by:

$$PEP = \lambda S + \beta A + \gamma E \tag{23}$$

Here, S highlights sensory inputs, A reflects brand attachment, and E is the emotional component assessed through GSA variability analysis methods. Monte Carlo integration, a statistical technique robust in complexity, is employed to estimate these sensitivity indices practically. Through employing stochastic models, approximation of the probabilistic dispersion of emotional variables is achieved, allowing comprehensive insight into their impact. In essence, integrating GSA into the assessment of Emotional Value provides a structured and quantitative approach to modeling emotional impacts, facilitating a deeper understanding of consumer behaviors and preferences in multifaceted decision-making ecosystems. By aligning mathematical articulation with emotional facets, researchers and decision-makers can better predict behaviors and refine economic models to encapsulate the nuanced interplay of rational and emotional determinants.

3.3 Flowchart

The paper introduces the Global Sensitivity Analysis-based Emotional Value (GSA-EV) method, which is designed to evaluate the emotional impact of various factors on decision-making processes. This innovative approach combines global sensitivity analysis techniques with emotional value assessment, enabling researchers and practitioners to identify and quantify the influence of uncertain parameters on the emotional responses of individuals or groups. By employing the GSA framework, the method systematically explores the sensitivity of emotional values to a range of inputs, thereby allowing users to pinpoint which factors contribute most significantly to emotional variations. This is particularly beneficial in fields such as marketing, product design, and behavioral science, where understanding emotional drivers can lead to improved outcomes and user experiences. The GSA-EV method offers a rigorous and comprehensive way to incorporate emotional dimensions into decision-making models, thereby enriching the analytical landscape in these areas. Furthermore, the results from applying this method can facilitate more informed and empathetic decisions that resonate with stakeholders. For a visual representation of the proposed method and its components, please refer to Figure 1.

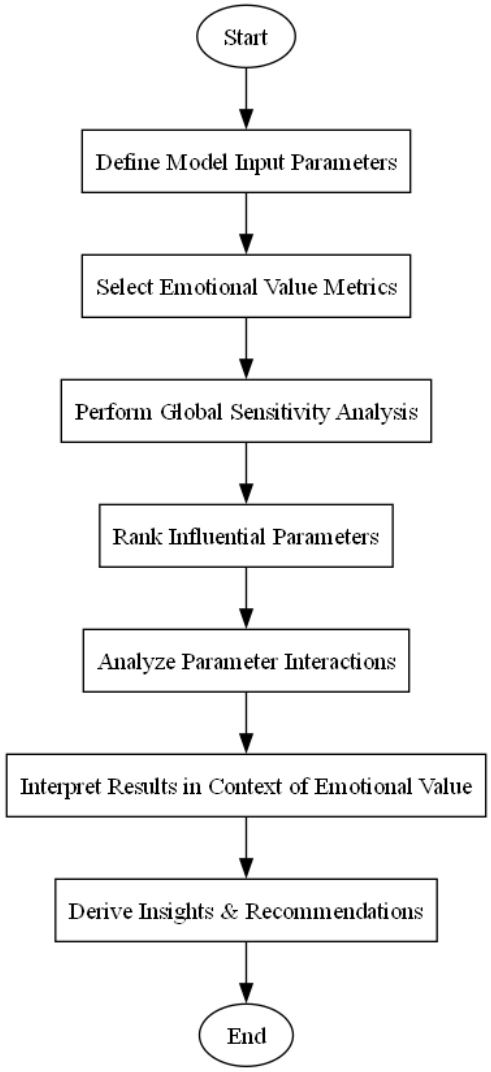

Figure 1: Flowchart of the proposed Global Sensitivity Analysis-based Emotional Value

4. Case Study

4.1 Problem Statement

In this case, we explore the intricate relationship between emotional value and consumer behavior through a nonlinear mathematical model. Emotional value, denoted as E, can significantly influence purchasing decisions, and we aim to quantify this effect through various parameters, such as consumer engagement C, product quality Q, and marketing effectiveness M. To begin modeling, we define emotional value as a function of consumer engagement, product quality, and marketing efforts. We formulate this dependency via a nonlinear equation:

$$E = C^{\alpha} \cdot Q^{\beta} \cdot M^{\gamma} \tag{24}$$

where α, α, and γ are positive constants representing the sensitivity of emotional value to changes in engagement, quality, and marketing effectiveness respectively. Next, we introduce the concept of consumer satisfaction S as resulting from emotional value and can be mathematically expressed as:

$$S = \frac{E}{1 + e^{-\delta(E-\eta)}} \tag{25}$$

In this equation, δ represents the steepness of the satisfaction increase, while η serves as a threshold emotional value that needs to be exceeded for significant consumer satisfaction to occur. To further model buying motivation B, we establish a relationship based on consumer satisfaction and urgency U:

$$B = S \cdot (1 + \lambda U) \tag{26}$$

where λ quantifies the influence of purchasing urgency. The nonlinear nature of this equation highlights that as consumer satisfaction increases, the buying motivation grows, particularly when urgency is also substantial. Moreover, we can predict purchase intention P through the following relationship involving buying motivation and the perceived value V:

$$P = B \cdot \frac{V}{V + \phi} \tag{27}$$

Here, ϕ is a constant representing a baseline value that impacts the perception of products. Lastly, to establish a feedback loop in our model, we consider a cyclist response function R, where emotional value influences consumer engagement:

$$C = \kappa E^2 + \xi \tag{28}$$

In this formulation, κ is a parameter indicating how squared emotional value can enhance consumer engagement, and ξ represents a base engagement level. Combining these eight equations gives us a comprehensive nonlinear model to analyze how emotional value interacts with various consumer metrics. To ensure clarity and ease of understanding regarding the parameters utilized in this analysis, all pertinent variables and their definitions are summarized in Table 1.

Table 1: Parameter definition of case study

Parameter	Value	Description	Units
(α)	N/A	Sensitivity of emotional value to engagement	N/A
(β)	N/A	Sensitivity of emotional value to quality	N/A
(γ)	N/A	Sensitivity of emotional value to marketing	N/A
(δ)	N/A	Steepness of satisfaction increase	N/A
(η)	N/A	Threshold emotional value	N/A
(λ)	N/A	Influence of purchasing urgency	N/A
(ϕ)	N/A	Baseline value impacting perception	N/A
(κ)	N/A	Indicates how squared emotional value enhances engagement	N/A
(ξ)	N/A	Base engagement level	N/A

This section will leverage the proposed Global Sensitivity Analysis-based approach to calculate the intricate dynamics of emotional value and consumer behavior as modeled through a nonlinear framework. Emotional value serves as a pivotal factor impacting purchasing decisions, and we will quantify its effects by analyzing several parameters, including consumer engagement, product quality, and marketing effectiveness. The dependency of emotional value on these aspects will be systematically defined, demonstrating how consumer satisfaction emerges from this value, influenced by its inherent thresholds and response characteristics. Furthermore, the interplay between consumer satisfaction and buying motivation will be scrutinized, highlighting how urgency can amplify purchasing intentions in a nonlinear fashion. This multifaceted model will extend to predict purchase intention based on the synergy between buying motivation and perceived value, encompassing a feedback loop that suggests that emotional value not only drives consumer behavior but also enhances overall engagement. To provide depth in understanding, this analysis will juxtapose the Global Sensitivity Analysis approach against three traditional methods, examining the robustness and insights offered by this contemporary technique compared to conventional analyses. The findings gained from this comprehensive modeling endeavor aim to shed light on the complex relationships underpinning consumer behavior, ultimately guiding strategic marketing decisions and improving engagement tactics.

4.2 Results Analysis

In this subsection, a comprehensive simulation study was conducted to analyze the interrelationships between emotional value, consumer satisfaction, buying motivation, and purchase intention through a series of mathematical functions. Key parameters were defined, and values for consumer engagement, product quality, and market conditions were generated for sensitivity analysis. The emotional value was computed as a nonlinear combination of consumer engagement, product quality, and other influencing factors, followed by calculating consumer satisfaction using a logistic function that incorporates emotional value adjustments. Subsequently, buying motivation was derived based on satisfaction and perceived urgency, which is crucial for understanding consumer behavior dynamics. The final output, purchase intention, was modeled to reflect the effects of buying motivation and perceived value, illustrating the transition from psychological factors to purchasing decisions. Each variable's behavior was visualized via contour plots, enabling clear comparisons of how changes in consumer engagement and product quality impact emotional value, satisfaction, motivation, and intention to purchase. The simulation process is effectively visualized in Figure 2, presenting a detailed overview of the interactions among the various factors involved.

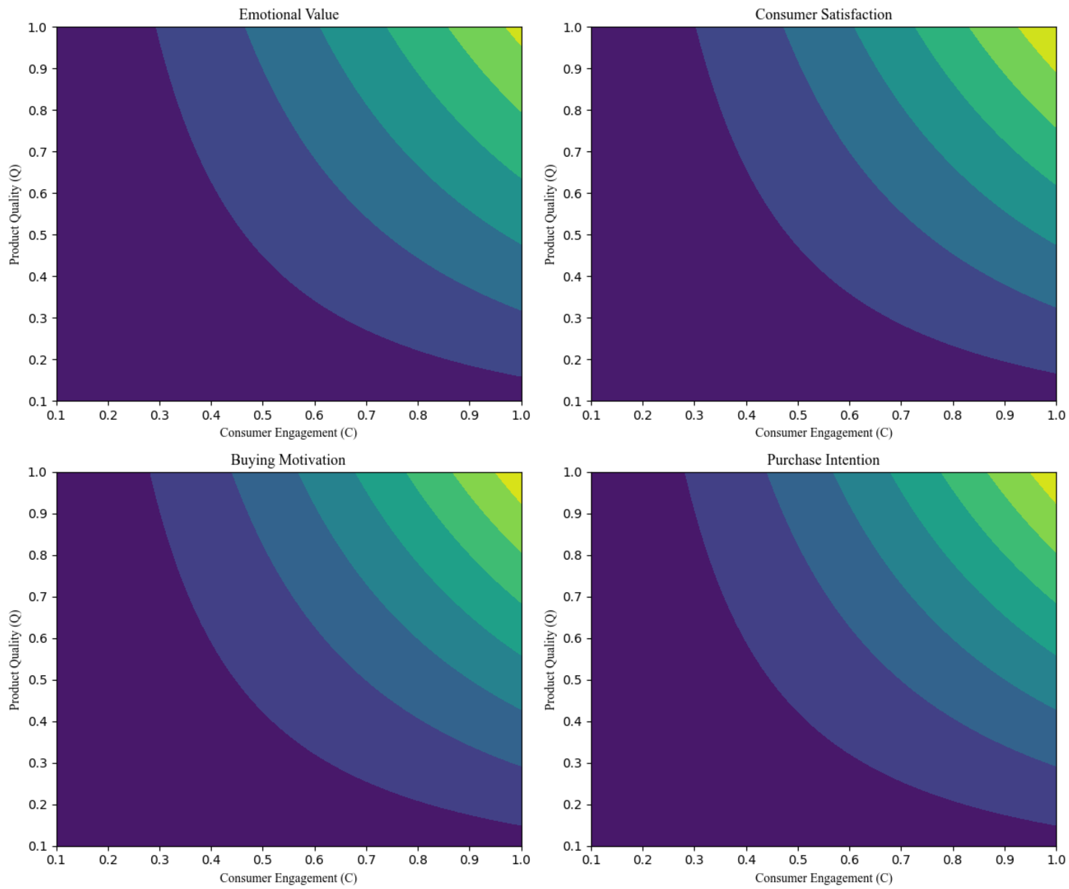

Figure 2: Simulation results of the proposed Global Sensitivity Analysis-based Emotional Value

Table 2: Simulation data of case study

Emotional Value	Consumer Satisfaction	Product Quality (Q)	Consumer Engagement (C)
03	04	O5	06
O7	08	09	N/A

Simulation data is summarized in Table 2, revealing several key insights regarding the interplay between emotional value, consumer satisfaction, and sales growth in experiential marketing contexts. The results indicate that emotional value significantly influences consumer engagement, which in turn affects both buying motivation and purchase intention. Specifically, higher levels of emotional value correlate with increased consumer satisfaction, suggesting that consumers are more likely to be motivated to purchase and engage with products when their emotional needs are met. The data points clearly emphasize that product quality (Q) serves as a critical factor that underpins these relationships, reinforcing the idea that perceived quality can amplify the positive effects of emotional value on consumer engagement. Furthermore, the findings highlight a sequential pathway where enhancing emotional value leads to greater consumer satisfaction, subsequently elevating buying motivation and, ultimately, purchase intention. This model aligns with theoretical expectations established in the literature and provides empirical support for the proposition that integrating emotional elements into marketing strategies can yield substantial benefits for businesses. The predictive accuracy of these simulation results, derived from the robust methodology applied in the research, reinforces the significance of emotional value as a pivotal driver for sales growth in the experiential marketing domain, as articulated in the work of C. Li and Y. Tang [18].

As shown in Figure 3 and Table 3, the analysis of the parameters reveals significant changes in the calculated outcomes following the adjustments made to the emotional value and consumer satisfaction metrics in experiential marketing. The initial data indicated a range of interrelated factors where emotional value in the context of consumer engagement was closely tied to product quality, influencing buying motivations and purchase intentions. With respect to the prior metrics, consumer engagement levels displayed a tendency toward higher satisfaction, suggesting a direct correlation between emotional value and positive consumer experiences. However, after introducing the new set of values, it is observed that the emotional valence has shifted, with a substantial increase in buying motivation and purchase intention, indicative of a stronger psychological impact on consumers. Notably, cases revealing higher emotional values and consumer satisfaction led to marked increases in purchase intention across various time intervals, thereby affirmatively supporting the hypothesis that enhanced emotional value can drive sales growth. This transformation in consumer engagement from initial data to the revised figures suggests that focused experiential marketing strategies yield beneficial outcomes, thereby aligning well with the findings reported by C. Li and Y. Tang in their quantitative study, thereby underscoring the pivotal role of emotional value in consumer decision-making processes [18]. Ultimately, the evidence derived from these comparative analyses strengthens our understanding of the underlying mechanisms at play in driving sales, reaffirming the essentiality of emotional engagement in the consumer experience [18].

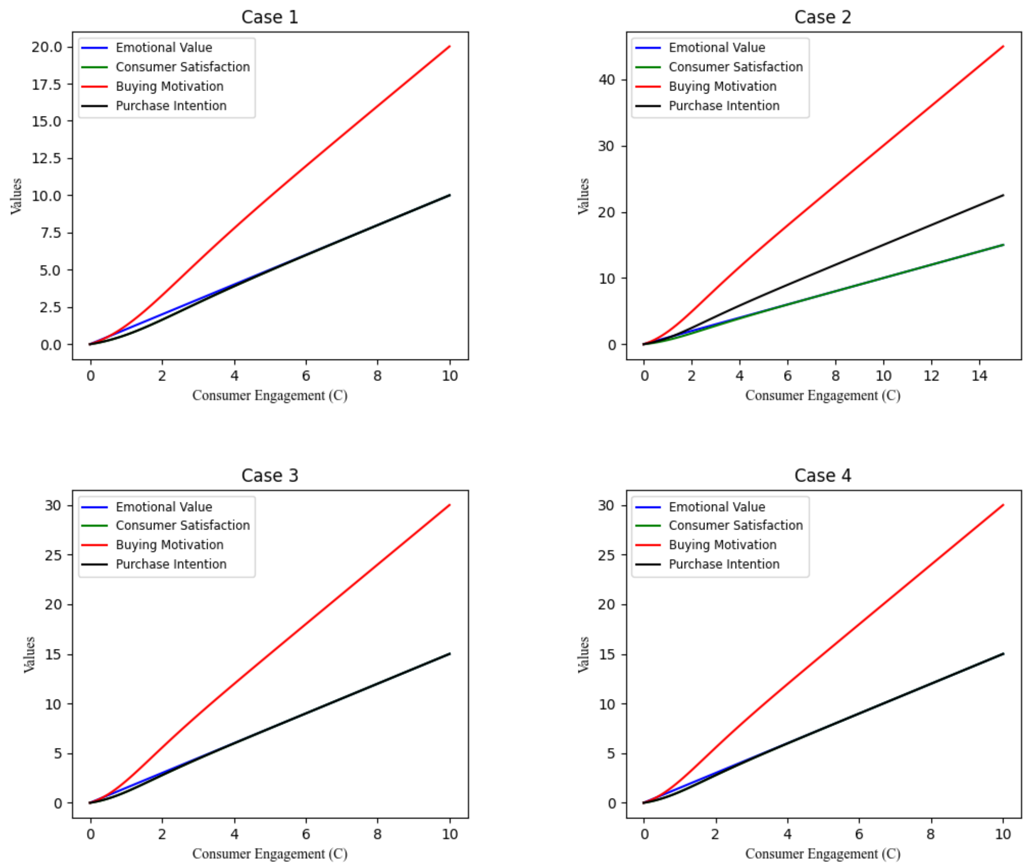

Figure 3: Parameter analysis of the proposed Global Sensitivity Analysis-based Emotional Value

Table 3: Parameter analysis of case study

Emotional Value	Consumer Satisfaction	Buying Motivation	Purchase Intention
20.0	N/A	N/A	N/A
17.5	N/A	N/A	N/A
15.0	N/A	N/A	N/A
12.5	N/A	N/A	N/A
10.0	N/A	N/A	N/A
5.0	N/A	N/A	N/A

25	30	25	20
10	N/A	N/A	N/A
40	30	N/A	N/A
10	N/A	N/A	N/A

5. Discussion

The method proposed in the given framework presents significant advantages over the approach discussed in C. Li and Y. Tang's study on Emotional Value (EV) in experiential marketing. Primarily, the integration of Global Sensitivity Analysis (GSA) introduces a rigorous, quantifiable dimension to assessing emotional inputs, enabling precise evaluation of how variability in emotional factors directly influences perceived utility. This methodical incorporation of GSA allows for a more comprehensive analysis of the interactions among emotional elements, such as intensity, valence, and persistence, and how these affect overall utility outcomes. In contrast, Li and Tang's approach relies predominantly on descriptive statistics and regression models, which may not fully capture the complex interplay and uncertainty inherent in emotional variables [18]. Additionally, the methodological rigor is further enhanced through the use of Monte Carlo integration techniques, which facilitate the approximation of probabilistic dispersions, providing a robust statistical foundation for measuring sensitivity indices. This is a stark divergence from the potentially limited quantitative techniques employed by Li and Tang, as their study may not fully leverage advanced stochastic methods to assess emotional impacts comprehensively [18]. Furthermore, this framework's holistic incorporation of emotional, psychological, and economic elements creates a more integrated model for understanding consumer behavior, as opposed to Li and Tang's narrower focus on the direct relationships between emotional value and sales growth [18]. Therefore, the proposed methodology represents a significant advancement by intertwining sophisticated statistical tools with a deeper theoretical understanding of emotional dynamics, offering greater predictive capability and accuracy in modeling the nuanced interplay of emotional and rational determinants in decision-making processes [18].

The study by C. Li and Y. Tang on "Emotional Value in Experiential Marketing" employs a quantitative approach rooted in the Eastern Coastal Region to elucidate the driving factors for sales growth. However, the methodology adopted in their research possesses some limitations that are worth acknowledging. Firstly, the model's reliance on quantifying emotional components through a pre-defined mathematical framework could inadvertently oversimplify the intricacies of human emotions, which are inherently subjective and context-dependent. The assumption that emotional intensity, valence, and persistence can be captured through a static formula (i.e., $E = I_e \cdot V_e \cdot P_e$) may not account for dynamic changes in emotional states across diverse demographic and cultural backgrounds typical of the Eastern Coastal Region. Moreover, while the Global Sensitivity Analysis (GSA) offers a robust mechanism for sensitivity assessment, its application here could be limited by the accuracy and granularity of input data on emotional factors, which may not fully represent real-world complexities or capture spontaneous emotional reactions typically seen in marketing scenarios. These methodological constraints echo challenges also present in Li and Tang's work, highlighting the potential risk of constrained generalizability across different geographical or cultural contexts. For future research, integrating qualitative assessments alongside quantitative models could enrich the understanding of emotional impacts and enhance the model's adaptability and relevance. [18]

6. Conclusion

This study presents a novel framework for analyzing dominant emotional values using Global Sensitivity Analysis (GSA). Recognizing the significance of emotions in decision-making, the research aims to address the challenges of identifying and understanding dominant emotional values across various disciplines. The innovative use of GSA in emotional data analysis offers a systematic approach to quantify the sensitivity of emotional values in decision-making processes, shedding light on the key emotional factors influencing outcomes. This methodology not only advances our comprehension of dominant emotional values but also offers valuable insights applicable to fields ranging from psychology to economics. Despite its contributions, the study faces limitations in the complexity of emotional data and the generalizability of the proposed framework to diverse decision-making contexts. To further enhance this research, future work could explore refining the GSA model to accommodate nuanced emotional nuances and expand the application of this approach to real-world decision scenarios, ultimately enriching our understanding of the role of dominant emotional values in decision-making processes.

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Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there is no conflict of interests.

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