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Multidimensional User Experience Analysis of Chinese Battery Electric Vehicles' Competition: An Integrated Association Mining Framework

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Abstract: This study introduces an integrative framework for association mining within the Chinese battery electric vehicle market, aiming to reveal key user experience (UX) factors and their interrelationships through multidimensional analysis. Utilizing latent Dirichlet allocation (LDA), the study discerned primary themes from user-generated content (UGC). The entropy weight method categorized level 2 factors, while domain-adaptive sentiment analysis quantified emotional responses to BEV user experience dimensions, highlighting significant sentiment disparities among competitors. Co-occurrence network analysis deepened insights into the emotional fabric of UX by exploring tertiary factor associations. Theoretically, this study advances a novel framework informed by Norman's UX theory, integrating analytical techniques to capture the complexity of UX. Practically, it delivers strategic guidance for BEV manufacturers by analyzing emotional polarities and attribute associations, guiding product innovation and responding to market dynamics. The empirical evidence corroborates the framework's efficacy in revealing the emotional associations within BEVUX factors, offering valuable implications for both theoretical development and practical application.

Keywords: battery electric vehicle; user experience; multidimensional analysis; domain-adaptive sentiment analysis; co-occurrence network analysis

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1. Introduction

In the 21st century, battery electric vehicles (BEVs) driven by electric powertrains [1] are at the forefront of the transition to sustainable transportation. The International Energy Agency's (IEA's) Global Electric Vehicle Outlook 2024 indicated a total of 14 million electric vehicle sales in 2023, with China commanding 56.8% of the global BEV market, underscoring the critical nature of researching the Chinese battery electric vehicles' user experience (BEVUX) [2].

Despite an abundance of research on BEV performance and promotion, a systematic exploration of the multidimensional aspects of user experience (UX) remains sparse. UX constitutes a multidimensional construct that includes vehicle performance, charging convenience, after-sales service, user interface design, and brand image. These factors, both individually and in interaction, sculpt the overall user perception. Consequently, this study introduces an interdisciplinary framework aimed at identifying and analyzing the multidimensional factors that influence BEVUX in China, as well as exploring their interrelations and interactions.

User-generated content (UGC) serves as a valuable representation of user experience, capturing its multidimensional attributes. Platforms such as Zhihu, where users openly share their in-depth experiences and perspectives, provide a rich dataset for understanding the complexities of BEVUX. By analyzing UGC, this research aims to extract insights that go beyond the scope of traditional surveys, effectively capturing nuanced user sentiments and multifaceted interactions with BEVs. Therefore, the use of UGC-based data, such as from Zhihu, is crucial to comprehensively reflect the real-world user experience and its various dimensions, making multidimensional text mining a meaningful approach.

The research questions are delineated below:

RQ1: What comprehensive methodology can be employed to systematically evaluate the multidimensional factors affecting BEVUX in China?

RQ2: What are the emotional propensities of users toward these factors, and how do these interact and correlate?

The primary goal is to dissect and quantify the pivotal factors influencing BEVUX in China and their emotional associations through an interdisciplinary lens. Specifically, this research utilizes the latent Dirichlet allocation (LDA) model and entropy weight method (EWM) to identify and prioritize factors influencing BEVUX from UGC, employing domain-adaptive sentiment analysis (DASA) and co-occurrence network analysis (CONA) to quantify users' emotional inclinations and their interconnections.

The study's innovativeness and practical applicability are evident in the following aspects:

1. Methodological innovation: pioneering an interdisciplinary approach that integrates the LDA model, EWM, DASA, and CONA, thereby broadening the scope of UX research.
2. Data-driven: utilizing UGC from Zhihu, a rich and diverse dataset, offers a nuanced representation of user experiences that surpasses traditional surveys or interviews.
3. Addressing complexity: through multidimensional analysis, this study skillfully decodes the complexities of UX, revealing the salient factors and their dynamics.
4. Practical value: the findings provide strategic insights for BEV manufacturers to enhance design and services, elevate user satisfaction, and guide policymakers in formulating effective strategies.

By elucidating the key factors and their interrelationships influencing UX, this study contributes robust empirical evidence and a robust theoretical foundation to the electric vehicle sector.

2. Literature Review

2.1. Theoretical Foundations of UX

UX refers to the perceptions and behaviors users exhibit when engaging with products or services. In the context of BEVs, UX involves multiple aspects, such as vehicle performance, usability, user expectations, and affective responses. Norman identified three levels of user experience: visceral, focusing on immediate sensory reactions, such as design and comfort, behavioral, emphasizing usability and operational ease, and reflective, assessing alignment with personal values, such as sustainability [3]. Hassenzahl further added that UX is influenced by both utilitarian (functionality) and aesthetic (emotional appeal) aspects [4].

UGC has emerged as a valuable data source for UX research, offering insights through user-shared content on platforms such as social media and forums [5,6]. Compared to traditional methods, UGC captures real-time, context-rich experiences, reflecting user reactions at the visceral, behavioral, and reflective levels. For example, UGC may provide feedback on BEV features, such as charging convenience or design appeal [7]. UGC also captures social interactions, which reveal user opinions and influence decision-making [8]. This information is key to understanding collective sentiments and their effects on individual users. Through natural language processing techniques, such as topic modeling (e.g., LDA) and sentiment analysis, UGC helps identify key themes and emotional trends [9,10]. Compared to surveys, UGC's spontaneous nature provides more genuine insights, mitigating issues related to sample bias [11,12]. The integration of UGC with traditional UX models allows for deeper insights. Norman's experiential levels and Hassenzahl's utilitarian–aesthetic model offer theoretical frameworks, while UGC provides empirical data that enhance and extend these models. Together, they contribute to a comprehensive understanding of UX, supporting improvements in BEV design and user satisfaction.

Norman and Hassenzahl's UX models illustrate the multidimensional nature of user experience. The rise of UGC provides empirical data to support and extend these theories, offering context-rich and dynamic insights. This combination helps researchers comprehensively understand user emotions, behaviors, and interactions, thereby forming a solid basis for enhancing BEVUX design.

2.2. A Review of Factors Influencing BEVUX

Existing academic research primarily focuses on the technical feasibility of BEVs and initial user responses, typically emphasizing individual vehicle characteristics. For instance, Burgess et al. explored the critical role of UX in evaluating BEVs, highlighting advantages in areas such as low noise, driving pleasure, performance, and environmental friendliness [13–16]. Additionally, Cocron et al. investigated the implications of BEV quietness on driving safety, finding that experienced drivers tended to react more quickly in critical situations [17]. Rauh et al. introduced the concept of a "range comfort zone" to evaluate the impact of driving experience on range anxiety, suggesting that driving expertise significantly contributes to user satisfaction [18].

Advancing research has increasingly recognized the multifaceted nature of UX. Rezvani et al. performed an exhaustive synthesis of the literature to pinpoint determinants of electric vehicle adoption, encompassing technological characteristics, usage context, cost considerations, and personal and social factors [19]. Haustein and Jensen revealed the substantial impact of social norms and perceived behavioral control on the adoption of electric vehicles [20]. Kwon et al. determined the salient factors that undergird user satisfaction with BEVs, including vehicle performance, charging infrastructure availability, and supportive government policies [21].

Recent studies highlighted how various driving conditions impact BEV user experience. For instance, Hao et al. found the BEV range reduced to 64% in winter conditions due to cold temperatures [22]. Similarly, Al-Wreikat et al. observed that battery efficiency dropped significantly in colder climates, leading to decreased range [23]. Urban versus rural environments also create distinct experiences. Jonas et al. reported higher energy consumption in urban traffic, while rural users can optimize range by adjusting travel times [24].

Furthermore, Liu et al. scrutinized how the intricacies of BEV driving experience bolster user confidence and adoption intentions [25]. In particular, Karabasoglu and Michalek showed that BEVs perform more efficiently in urban driving but lose range at highway speeds [26]. In mountainous areas, frequent braking and acceleration elevate energy consumption and reduce range satisfaction. Franke and Krems highlighted that driving behaviors, such as acceleration and braking style, can extend the range and improve the UX when managed effectively [27].

This body of research highlights the critical need for a comprehensive, multidimensional approach that integrates a range of factors—including driving environment, seasonal climate variations, and user behaviors—into the evaluation of BEV user experience. Nevertheless, current studies predominantly emphasize singular factors, lacking a holistic framework that systematically considers these interconnected influences.

2.3. Limitations of Traditional Research Methods

Traditional UX research methods, such as interviews, surveys, and single data analysis techniques, have achieved some success in the field of UX research but exhibit several limitations in the rapidly evolving digital environment of today. Firstly, traditional methods rely heavily on the subjective judgment of researchers and lack a systematic, multidimensional data integration framework, which can introduce biases into the results and hinder a comprehensive understanding of the complexity and diversity of UX [28,29]. Secondly, the issue of small sample sizes affects the generalizability and reliability of research findings. For instance, studies by Cocron et al. and Rauh et al. were limited by small sample sizes, leading to biases that make the results difficult to generalize to larger user groups [14,18]. Additionally, traditional methods struggle to handle the large scale and diversity of UGC, making it challenging to effectively extract commonalities and trends from this vast dataset [8].

Moreover, traditional quantitative analysis tends to focus excessively on measurable indicators, overlooking the importance of deeper factors, such as emotions and motivations in UX. Emotional factors play a crucial role in user decision-making and satisfaction, but traditional quantitative methods often fail to adequately capture users' true feelings and motivations [10,11]. Finally, traditional approaches often concentrate on individual user experiences, making it difficult to reveal group behaviors and interactions within a community. This limitation restricts researchers' ability to fully understand emotional resonance among users and how it impacts the overall user experience [30].

In conclusion, traditional UX research methods show significant limitations in addressing diverse user contexts, deep emotional factors, and large-scale data analysis. There is an urgent need for innovative research methods and multidisciplinary techniques to better understand and analyze UX. To address these shortcomings, the introduction of multidisciplinary technologies provides a new pathway for UX research, helping to overcome the limitations of traditional methods and establish a more scientific basis for multidimensional UX analysis.

2.4. Application of Multidisciplinary Technologies in UX Research

In recent years, an increasing array of studies have integrated multidisciplinary technologies to deepen the comprehension of UX.

2.4.1. Latent Dirichlet Allocation (LDA) Model

The LDA model, proposed by Blei et al., posits that texts are constructed by latent topics, effectively identifying underlying themes and keywords [31]. The LDA model encapsulates documents within a probabilistic framework of topic distributions, with each topic characterized by a distribution of words. With broad applications in text mining and natural language processing (NLP), the LDA model excels in deciphering extensive UGC. In the realm of user experience research, the LDA model is routinely applied to distill predominant themes from user-generated discussions, shedding light on user concerns and needs. Wang and Manning harnessed the LDA model to parse online smartphone reviews, pinpointing pivotal factors that contribute to user satisfaction [32]. Schmalfuß et al. utilized the LDA model to dissect perceptions and acceptance of BEVs, surfacing key determinants that sway consumer choices [33]. Wu et al. leveraged the LDA model to extract pivotal themes from social media discourse on electric vehicles, underscoring user preoccupations with range, policy, charging infrastructure, and safety [34]. The LDA model is particularly valuable in UX research, providing nuanced insights into user discussions and contributing to the refinement of product experiences. By identifying and analyzing the topics of user discussions, the LDA model serves as an indispensable tool for user-centered design and product development, enhancing the understanding of users' needs and the improvement of product experiences.

2.4.2. Entropy Weight Method (EWM)

The entropy weight method (EWM) is predicated on information entropy, a foundational concept established by Shannon. Information entropy serves as a measure of uncertainty and disorder within datasets, where higher values indicate greater informational dispersion and diminished indicator significance [35]. The EWM calculates these values to evaluate the uncertainty of indicators, assigning weights and serving as a statistical approach for comprehensive assessments in multiple-indicator analyses. In UX research, the EWM is instrumental in quantifying the relevance of thematic keywords. Zhang et al.

introduced the En-LDA approach, optimizing topic modeling for bug resolution with significant recall and precision [36]. Hu et al. applied the EWM to inform user classification after two-stage clustering, presenting a comprehensive strategy for categorizing EV users [37].

2.4.3. Sentiment Analysis (SA)

Affective theory delineates the pivotal role of emotions in shaping the user experience by influencing consumer reactions and decision-making processes. Ekman's theory classifies emotions into basic categories—joy, anger, sadness, and fear—which serve as a reference for emotional response analysis [38]. Sentiment analysis (SA), bolstered by NLP, detects emotional nuances within text [39,40]. Applications of sentiment analysis (SA) span a spectrum of fields, including product reviews [41], financial market predictions [42–44], policymaking [45], and electoral analysis [30]. Pang and Lee's review synthesizes a variety of SA methodologies, from lexicon-based to machine learning approaches [46]. In the realm of UX, sentiment analysis (SA) quantifies emotional reactions to experiential elements, offering a metric for user satisfaction. Liu et al. utilized supervised learning techniques to discern consumer emotions from online reviews, facilitating comparative analysis of product features [47]. Integrating LDA with SA enhances the depth of insights into user emotions, revealing the underpinnings of emotional responses [33]. Qin et al. applied an unsupervised algorithm referencing an affective lexicon to quantify social media sentiments, employing LDA to uncover emotional response dynamics [48]. The convergence of LDA and SA provides a holistic understanding of users' emotions, shedding light on public interest and preferences regarding electric vehicles [49]. This integrated approach not only deepens the scope of UX studies but also aids in the development and refinement of products and services designed to meet users' needs and expectations more effectively.

2.4.4. Co-Occurrence Network Analysis (CONA)

Network analysis (NA) is a framework for examining the interconnections and structural configurations within complex systems. Wasserman and Faust pioneered social network analysis (SNA), employing network diagrams to expose node relationships and interactions [50]. Newman advanced NA by devising techniques that graphically represent node relationships and interactions through network diagrams [51]. Co-occurrence network analysis (CONA) is a methodological approach that uncovers factor associations and interactions through the analysis of term co-occurrence. The TextRank algorithm of Mihalcea and Tarau efficiently identifies salient concepts within text based on the principle of lexical co-occurrence [52]. Despite its promise, CONA faces challenges, including the selection of terms, determination of co-occurrence thresholds, and potential neglect of semantic nuances. When integrated with other analytical methods, such as SA and the LDA model, CONA can offer a more nuanced understanding of UX [53]. The application of CONA in UX research is extensive, often revealing intricate factor associations and providing visual representations of these dynamics, thus aiding researchers in intuitively comprehending the multifaceted complexities of UX.

2.4.5. Research Review Summary

A thorough examination of existing literature revealed a predominant focus on single-factor analysis, with a notable absence of systematic, multidimensional approaches, particularly pronounced in the BEVUX domain. Challenges, including inadequate sample sizes, homogeneous analytical methods, and constrained data sources, impede a holistic understanding of UX dynamics and complexity. Traditional surveys and interviews harbor subjective biases, complicating the thorough apprehension of UX. Concentrating exclusively on isolated aspects, such as technical performance, charging infrastructure, after-sales service, or user interface design, fails to encapsulate the full complexity and multidimensionality of UX. Furthermore, current methodologies grapple with elucidating the interrelationships and synergistic effects of multiple factors, which constrains a comprehensive understanding of UX.

To counter this gap, the present study endeavors to systematically identify and analyze the multidimensional factors that influence BEVUX in China. This study introduces an integrative approach that encompasses LDA, EWM, DASA, and CONA. This approach not only exposes the core elements of the UX but also quantifies users' emotional inclinations and uncovers intricate associations among multidimensional factors, offering strategic insights and guidance for BEV manufacturers and policymakers. The novelty of this approach is underpinned by its comprehensive and systematic nature, providing a scientifically rigorous and exhaustive analytical framework for UX research, adeptly addressing existing research gaps, and fostering the growth of the BEV market and the escalation of user satisfaction.

3. Research Methods

3.1. Proposed Framework: Multidimensional Sentiment and Association Comprehensive Analysis (MDSACA)

The MDSACA framework integrates LDA, EWM, DASA, and CONA. This integrative approach is meticulously designed to systematically identify and analyze the multidimensional factors influencing the UX and the emotional inclinations of BEV users in China. By employing LDA to distill core themes from user discussions, applying the EWM for assessing keyword significance, utilizing DASA for gauging emotional inclinations, and employing CONA to reveal the interplay of concepts, MDSACA offers a rigorous and holistic analytical structure. This framework adeptly captures the multidimensional characteristics and emotional responses inherent to the UX, yielding strategic insights and guidance for BEV manufacturers and policymakers to optimize product design, enhance user satisfaction, and bolster market competitiveness.

The framework (Figure 1) includes the following key steps, outlined below.

Step 1. Data collection: leveraging web-crawling technology to aggregate UX textual data from targeted platforms, prioritizing Zhihu for its extensive UX sharing and comprehensive usage narratives.

Step 2. Data screening: addressing the unstructured nature of the collected textual data through noise reduction and preprocessing, including lexical tokenization, part-of-speech tagging, stop word elimination, and the careful management of domain-specific jargon.

Step 3. Data analysis: engaging LDA to extract core themes from user discussions, applying the entropy method for keyword significance assessment, DASA for gauging emotional inclinations, and CONA for elucidating the interplay of concepts.

Step 4. Data visualization: crafting visual representations of keywords based on centrality measures within co-occurrence networks to facilitate a clear and intuitive comprehension of the results.

Step 5. Results' interpretation and application: dissecting the analytical outcomes to attain a nuanced understanding of UX influencers, integrating these insights into the product development lifecycle, enhancing service delivery, and devising strategic market initiatives.

Step 6. Evaluation and iteration: evaluating the efficacy of the analytical framework, refining it in response to stakeholder feedback, and iterating to ensure adaptability across diverse research contexts.

Adhering to this framework, we constructed a robust, multidimensional BEVUX dataset, laying a solid foundation for in-depth analysis. The anticipated research outcomes are poised to provide profound insights for BEV manufacturers, aiding in the strategic optimization of product design, bolstering UX, and securing a competitive edge in China's burgeoning EV market. The structural schema of this study is delineated in Figure 1, offering an at-a-glance overview of the research design and methodology flow.

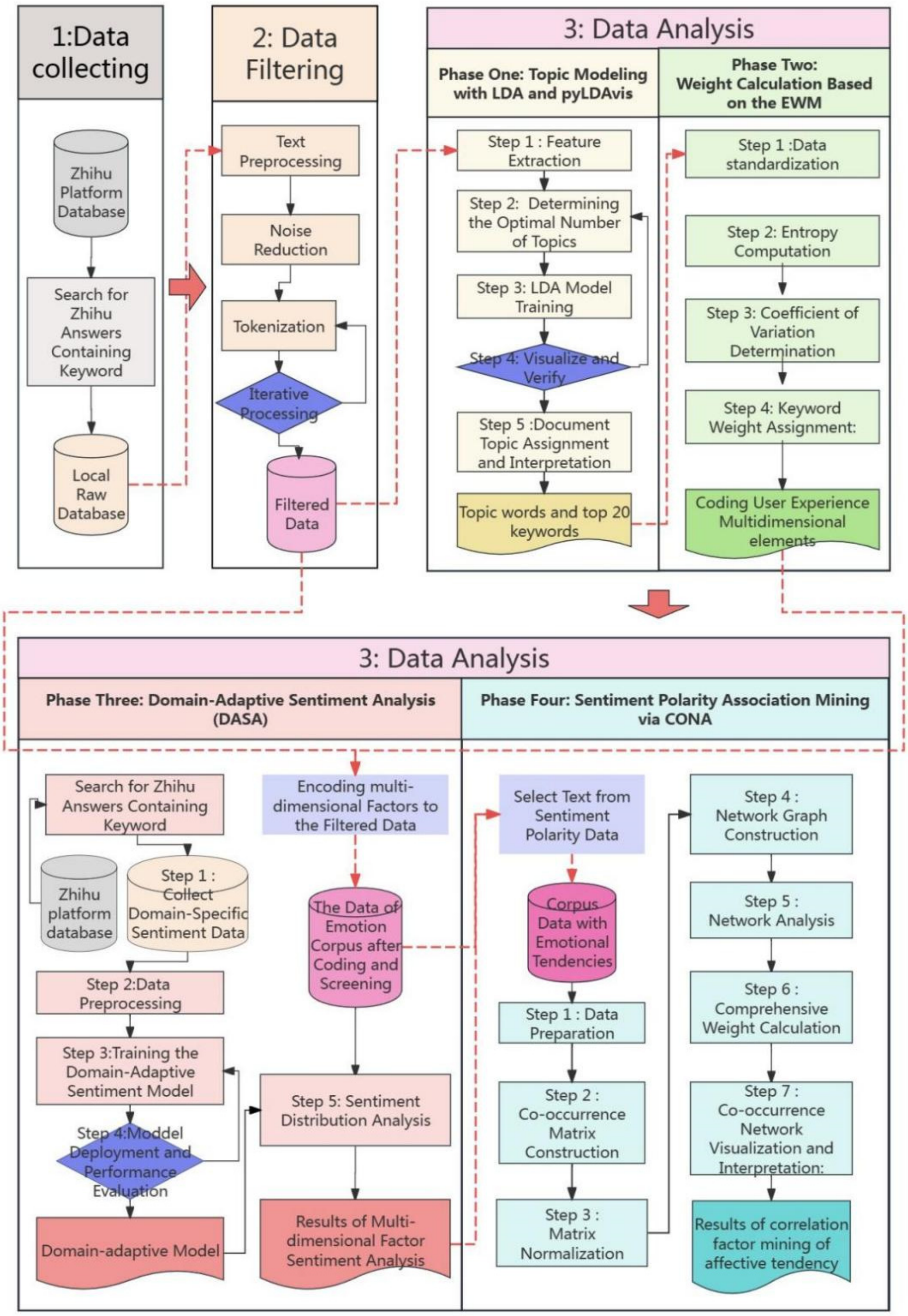


Figure 1. Research technical framework.

3.2. Data Collection

This study selected UGC platforms, such as Zhihu and Quora, as data sources. These platforms are characterized by knowledge-sharing content, where users typically share their personal experiences through long-form texts, which are distinct from the short-text user reviews found on other UGC platforms. Such long-form content provides extensive, detailed user experiences and discussions, offering a comprehensive view of users' multidimensional experiences with electric vehicles, thus providing a reliable foundation for research validation.

During the data collection phase, the study focused on gathering responses related to the usage experiences of battery electric vehicle (BEV) users shared on these knowledge-sharing platforms. These UGC data encompass multiple aspects of BEV use, including product performance, emotional expression, and specific usage scenarios, which aid in understanding different dimensions of the user experience more comprehensively.

To facilitate effective data collection, web crawling and API calls were employed to automate the process of retrieving relevant data from the UGC platforms. These techniques involved searching for specific keywords and parsing web content to ensure precise data acquisition and storage. The collected data were then organized in a structured format, including fields such as user ID, publication date, and text content, ensuring orderly management and easy retrieval for subsequent analysis. Throughout the data collection process, strict adherence to legal and ethical standards was maintained to ensure compliance with regulations, including obtaining user consent when necessary. Furthermore, regular monitoring and manual review mechanisms were employed to maintain data accuracy and quality.

This data collection strategy enabled the construction of a comprehensive, multidimensional dataset of user experiences, providing a solid foundation for subsequent stages of text preprocessing, sentiment analysis, and other data analysis methods.

3.3. Data Screening and Cleaning

Data screening and cleaning are critical for ensuring the quality and reliability of the analysis. The process involves four key steps:

Step 1. Relevance screening: Each piece of raw data was manually reviewed to remove irrelevant Q&A entries, ensuring that the content represented genuine personal usage experiences. Additionally, the data were filtered to retain only relevant and complete records that aligned with the research objectives.

Step 2. Text de-noising: special characters, HTML tags, and irrelevant metadata were removed to enhance data quality.

Step 3. Text tokenization: the text was segmented, part-of-speech tagging was performed, stop words were removed, and specialized terms were handled to ensure meaningful content extraction.

Step 4. Iterative processing: iterative screening and refinement were conducted to identify and correct any residual issues, ensuring data accuracy and consistency.

This systematic approach to data screening and cleaning provided a reliable dataset for subsequent empirical analysis.

3.4. Data Analysis

The data analysis phase encompassed a suite of text analytical techniques designed to uncover the central themes and keywords of UX, evaluate emotional inclinations of users toward these elements, and investigate the underlying connections between factors across various emotional dimensions. The principal stages of analysis involved topic modeling with LDA and visualization via pyLDAvis, keyword weighting through the EWM, DASA employing SnowNLP, and CONA for mining sentiment associations.

3.4.1. Phase One: Topic Modeling with Latent Dirichlet Allocation (LDA) and pyLDAvis

Topic modeling is fundamental for identifying latent thematic structures in extensive text corpora. In this study, LDA was employed, which posits that documents are composed of a mixture of latent topics, each characterized by a distribution across the vocabulary [54]. The analysis used LDA for topic extraction and pyLDAvis for interactive visualization to help interpret the topics.

The procedure was as follows:

Step 1. Feature extraction: Prior to applying the LDA model, feature extraction was conducted to convert text data into a bag-of-words model. Important feature words were extracted by setting appropriate parameters, ensuring that subsequent topic modeling focused on the most significant feature words.

Step 2. Determining the optimal number of topics: The number of topics was determined by evaluating the model's perplexity. Lower perplexity indicates better generalization ability. The formula for perplexity is (1):

$$\text{Perplexity} = \exp\left\{-\frac{1}{N}\sum_{d=1}^{D}\log P(w_d)\right\} \tag{1}$$

where N is the total number of words, and $P(w_d)$ is the probability of words in document d. Lower perplexity indicates better model performance, but excessive topics can lead to overfitting and reduced interpretability. The elbow method was used to find the "elbow point" of the curve, where adding more topics has diminishing returns in reducing perplexity.

Step 3. LDA model training: The document–word matrix was trained using the LDA model, setting the number of topics K and iterating for optimization. The objective was to maximize the likelihood function of the document's topic distribution and the topic's word distribution (2):

$$Maximize\ P(w|\alpha,\beta) = \prod_{d=1}^{D}\int\left(\prod_{n=1}^{N_d}\sum_{k=1}^{K}P(w_{dn}|z_{dn},\beta_k)P(z_{dn}|\theta_d)\right)P(\theta_d|\alpha)d\theta_d \tag{2}$$

where w is the word, α and β are hyperparameters, D is the number of documents, N_d is the number of words in document d, and K is the number of topics. Gibbs sampling was employed to update the topic assignments (3).

The process involved setting the number of topics K and Dirichlet distribution hyperparameters α and β, randomly assigning a topic to each word in each document, and using Gibbs sampling to update the topic assignment for each word based on the current topic distribution and word distribution, as shown in Equation (3). Then, the document–topic distribution, θ_d, and topic–word distribution, φ_k, parameters were updated based on the current topic assignments, as indicated in Equations (4) and (5). This was repeated until the likelihood function converged or the maximum number of iterations was reached.

$$P(z_{dn} = k|z_{-dn}, w) \propto \frac{n_{dk}^{-dn} + \alpha}{n_d^{-dn} + K\alpha}\cdot\frac{n_{kw}^{-dn} + \beta}{n_k^{-dn} + V\beta} \tag{3}$$

where z_{-dn} is the topic assignment for the n-th word in document d, n_{dk}^{-dn} is the count of words assigned to topic k, excluding the current word, and V is the vocabulary size.

The model parameters θ and ϕ were updated iteratively, as indicated in Equations (4) and (5):

$$\theta_{dk} = \frac{n_{dk} + \alpha}{n_d + K\alpha} \tag{4}$$

$$\phi_{kw} = \frac{n_{kw} + \beta}{n_k + V\beta} \tag{5}$$

These parameters represent the probability of topic k in document d and the probability of word w in topic k, respectively, providing a probabilistic interpretation of topic distributions.

Step 4. Visualizing and validating topics: pyLDAvis was used to visualize the fitted LDA model, aiding in intuitive understanding of topics. It offers an interactive web-based view, ranking the representative words by importance within each topic, which helps to evaluate model coherence—an indicator of model quality. High coherence means stronger word associations, effectively capturing the main content of each topic.

Step 5. Document topic assignment and interpretation: Each document was assigned to a topic based on the probability distribution derived from the LDA model. Topics were then interpreted using domain-specific knowledge, focusing on feature words that define each topic. This helped identify significant themes related to BEVUX and classify potential influencing factors.

This topic modeling process facilitated a deeper understanding of the complexity of the UX, providing actionable insights for BEV manufacturers to improve product design and user satisfaction.

3.4.2. Phase Two: Weight Calculation of Multidimensional Factors Based on the Entropy Weight Method (EWM)

The EWM determines the significance of keywords in user reviews by measuring informational entropy, highlighting their relevance in the context of user experience. The EWM refines unstructured review data into precise and unbiased keyword weights, which are critical for subsequent sentiment analysis and association mining. Based on information theory, the EWM evaluates information uncertainty by computing the entropy of each keyword's distribution in the dataset. A higher entropy value indicates greater information dispersion and lower relevance, whereas lower entropy suggests concentrated information and a higher weight.

The procedure was as follows:

Step 1. Data standardization: The frequency data of each keyword was normalized to mitigate discrepancies in the frequency data across different keywords. The normalization formula is as follows, see Equation (6):

$$p_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{n} x_{ij}} \tag{6}$$

where p_{ij} represents the relative frequency of the j-th keyword within the i-th document, x_{ij} is the original frequency, and n is the total number of documents.

Step 2. Entropy computation: The normalized data were used to ascertain the entropy for each keyword, employing the entropy formula as follows (7):

$$E_j = -k\sum_{i=1}^{n} p_{ij} \log p_{ij} \tag{7}$$

where k is a constant, usually taken as $k = \frac{1}{\log n}$. If p_{ij} = 0, then define log p_{ij} = 0.

Step 3. Coefficient of variation determination: The coefficient of variation was computed for each keyword, applying the formula as follows (8):

$$CV_j = \frac{\sqrt{\sum\limits_{i=1}^{n} \left(p_{ij} - \overline{p}_j\right)^2}}{\overline{p}_j} \tag{8}$$

where CV_j represents the coefficient of variation for the j-th keyword. The term p_{ij} denotes the relative frequency of the j-th keyword in the i-th document, while $\overline{p}_j$ is the average relative frequency of the j-th keyword across all documents, calculated as $\overline{p}_j = \frac{1}{n}\sum\limits_{i=1}^{n} p_{ij}$. The variable n stands for the total number of documents.

Step 4. Keyword weight assignment: The weight of each keyword was determined based on its coefficient of variation, using the formula as follows (9):

$$W_j = \frac{1}{m} \cdot \frac{1}{CV_j} \tag{9}$$

where W_j is the weight of the j-th keyword, and m is the number of keywords.

These steps ensured that the frequency data of different keywords were standardized, and their importance weights were calculated based on their distribution in the texts. This process provides a solid foundation for subsequent SA and association mining, facilitating comprehensive and systematic analysis of the multidimensional factors affecting BEVUX.

3.4.3. Phase Three: Domain-Adaptive Sentiment Analysis (DASA)

This phase aimed to assess user emotional inclinations concerning battery electric vehicle user experience (BEVUX) factors by employing domain-adaptive sentiment analysis (DASA). The analysis quantified user sentiments within the Chinese market regarding various BEV determinants. SnowNLP, introduced by Song et al. [55], serves as a Chinese natural language processing toolkit capable of sentiment analysis.

The customized sentiment classification model was trained using domain-specific positive and negative review samples, enhancing the understanding of emotional lexicons specific to BEV user experiences.

The procedure was as follows:

Step 1. Collect domain-specific sentiment data: we assembled a collection of positive and negative review samples sourced from electric vehicle platforms, forums, blog articles, and similar venues.

Step 2. Data preparation and preprocessing: the outcomes of topic modeling and multidimensional factor weight assessments were translated into a coded format, selecting texts with strong relevance from the initial dataset and conducting preprocessing tasks, including word segmentation and part-of-speech tagging, to prepare for subsequent analysis.

Step 3. Training the domain-adaptive sentiment model: After preprocessing, we labeled the review samples (1 for positive and 0 for negative) and trained the sentiment analysis model using SnowNLP. The model relies on a Naive Bayes classifier to adaptively learn from domain-specific text features.

1. Bayes' theorem: the core of the Naive Bayes classifier is given by (10):

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)} \tag{10}$$

where $P(C/X)$ is the posterior probability of class C given feature X, $P(X/C)$ denotes the likelihood of feature X given class C, $P(C)$ indicates the prior probability of class C, and $P(X)$ stands for the marginal probability of feature X.

2. Naive Bayes classifier: for text X consisting of words w_1, w_2, …, w_n, assuming independence among words (11):

$$P(C|w_1, w_2, \ldots, w_n) = \frac{P(C) \cdot \prod_{i=1}^{n} P(w_i|C)}{P(w_1, w_2, \ldots, w_n)} \tag{11}$$

where $P(C/w_1$, w_2, …,$w_n)$ denotes the probability that text X belongs to class C, $P(C)$ represents the prior probability of class C, estimated from the frequency of classes in the training data, and $P(w_i/C)$ is the probability of word w_i occurring in class C, estimated from the frequency of words in class C.

3. Prior probability calculation of $P(C)$ (12):

$$P(C) = \frac{N_C}{N} \tag{12}$$

where $P(C)$ represents the prior probability of class C, N_C denotes the number of documents belonging to class C in the training data, and N indicates the total number of documents in the training data.

4. Likelihood probability calculation (13):

$$P(w_i \middle| C) = \frac{n_{w_i} + \alpha}{n_C + V\alpha} \tag{13}$$

where n_{w_i} is the occurrence of word w_i in class C, V is the vocabulary size, and α is the smoothing parameter.

5. Sentiment score calculation: To preclude underflow issues, computations were conventionally executed in logarithmic space. The text was categorized into positive or negative sentiment bins, with the respective sentiment score being determined.

Step 4. Model deployment and performance evaluation: The trained model was deployed to assess its sentiment classification accuracy on new review texts. The accuracy was quantified by comparing the model's predictions against labeled validation data.

Step 5. Sentiment distribution analysis: Sentiment scores were classified into categories: "very good", "good", "average", "poor", and "very poor". This analysis provided a nuanced understanding of users' emotional inclinations and helped identify key areas for product improvement.

Step 6. Sentiment calculation: using a sentiment lexicon, we calculated the sentiment score for text T (14):

$$S_T = \sum_{i=1}^{n} (s_i \cdot f_i) \tag{14}$$

where s_i is the sentiment score of word w_i, f_i is the frequency of word w_i in text T, and n is the total number of sentiment-bearing words in text T.

This computation is crucial for identifying the overarching sentiment concerning diverse aspects of pure electric vehicles, thereby furnishing vital data to underpin product enhancement and the recalibration of market strategies.

3.4.4. Phase Four: Sentiment Association Mining via Co-Occurrence Network Analysis (CONA)

Following DASA, data filtration and subsequent CONA on polarized data facilitated the discovery of associations between sentiment tendencies and multiple dimensions, thereby aiding in the optimization of product design and the enhancement of user satisfaction. This CONA method, with extensive applications in graph-based NLP, introduced by Zhang, Zweigenbaum, and Yin [56], encompasses key object extraction [53] and word sense disambiguation [57]. Co-occurrence is defined by the closeness of two words within a document, recognized when the distance between them is less than a predetermined window size [58]. The co-occurrence matrix captures word vectors, detailing their co-occurrence patterns with other words.

The Jaccard similarity coefficient [59] measures the similarity between word pairs, indicating the strength of connections between keywords. Centrality indicators, such as eigenvector centrality (EC) [60], evaluate a node's importance by considering its connections and the influence of adjacent nodes. A co-occurrence matrix was used to quantify the strength of keyword associations and visualize them in a graphical network, where nodes represent keywords and edges indicate their relationships.

The procedure was as follows:

Step 1. Data preparation: we reviewed sentiment polarity data and extracted representative keywords, focusing on clearly polarized (positive or negative) entries to ensure relevancy.

Step 2. Co-occurrence matrix construction: we calculated the co-occurrence frequency for each keyword pair (C_{ij}) using (15):

$$C_{ij} = \frac{1}{N} \sum_{k=1}^{N} A_{ik} A_{jk} \tag{15}$$

where N is the text count, and A_{ik} signifies the presence of keyword i in text k (1 if present and 0 otherwise).

Step 3. Matrix normalization: we adjusted the co-occurrence matrix to standardize keyword frequency dimensions, as illustrated by Equation (16):

$$M_{ij} = \frac{C_{ij}}{\sqrt{C_{i+} \cdot C_{j+}}} \tag{16}$$

where M_{ij} represents the normalized frequency, C_{ij} denotes the raw frequency, and C_i and C_j represent the total co-occurrence frequencies of keywords i and j, respectively.

Step 4. Network graph construction: This step translated the co-occurrence matrix into a graphical representation, symbolizing words as nodes and co-occurrence relationships as edges. The weight of the edges was determined by the frequency of word co-occurrence.

Step 5. Network analysis: computation of the EC and Jaccard similarity indices was executed to assess keyword importance and co-occurrence strength, calculated using the subsequent Equation (17):

$$EC_i = \frac{1}{\lambda}\sum_{j=1}^{N} A_{ij}EC_j \tag{17}$$

where EC_i is the centrality of node i, A_{ij} signifies an edge between nodes i and j, and λ is the eigenvalue. The Jaccard contribution (JC) similarity index was determined using Formula (18):

$$JC_{ij} = \frac{|N(i) \cap N(j)|}{|N(i) \cup N(j)|} \tag{18}$$

where $N(i)$ and $N(j)$ are the sets of neighboring nodes for keywords i and j, respectively.

Step 6. Comprehensive weight calculation: The calculation of comprehensive weight integrates multiple indicators, standardizing and aggregating their weighted values to measure keyword importance. It was obtained by normalizing and summing the weighted values of the EC, JC, and term frequency (TF), with the following Formulas (19) and (20):

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{19}$$

where X is the raw value, X' is the normalized value, and $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the indicator, respectively.

$$CW = w_1 \cdot EC' + w_2 \cdot F' + w_3 \cdot JC' \tag{20}$$

where CW is the comprehensive weight, EC' is the normalized EC, F' is the normalized TF, JC' is the normalized JC, and w_1, w_2, and w_3 are the weights of the respective indicators.

Step 7. Co-occurrence network visualization and interpretation: The calculated indicators were visually depicted and interpreted. Node color intensity corresponds to the magnitude of EC of the keywords, the edges between nodes and their associated values indicate the strength of the JC values, and node size represents term frequency values.

By conducting a CONA of sentiment polarity, potential factors and interrelationships of sentiment polarity can be unearthed, aiding researchers in gaining a deeper understanding of users' emotional experiences and focal points, thereby providing data support for further product improvement and optimization of UX.

4. Empirical Study

This section presents an empirical study that validated the effectiveness of the proposed methodology for extracting key focal points, keywords, sentiment polarities, and interrelationships from the online discourse of competing BEVUX offerings.

4.1. Data Collection and Screening

In this study, BEV models in direct competition with the subject company were selected to ensure the market relevance of the findings, thereby offering targeted insights into the determinants of UX pivotal for future product development. The selected competing BEVs encompassed Target Competitor 1 (TC1) from Company A, an established international electric vehicle brand, Target Competitor 2 (TC2) from Company B, a renowned traditional Chinese automotive manufacturer, Target Competitor 3 (TC3) from Company C, an emerging Chinese electric vehicle brand, and Target Competitor 4 (TC4) from Company D, a prestigious international automotive brand. Parameter details are delineated in Table 1.

Table 1. Information on data collection objects.

	TC1	TC2	TC3	TC4
Level	Mid-size car	Mid-to-large car	Mid-size car	Mid-size car
Release Date	May 2019	July 2020	December 2021	March 2022
NEDC Pure Electric Range (km)	445	550	-	-
CLTC Pure Electric Range (km)	-	-	710	526
Body Structure	4-door, 5-seat	4-door, 5-seat	4-door, 5-seat	4-door, 5-seat
Dimensions (mm)	4694 × 1850 × 1443	4980 × 1910 × 1495	4790 × 1960 × 1499	4872 × 1846 × 1481
Official 0–100 km/h Acceleration (s)	5.6	3.9	4	6.2

4.1.1. Data Collection

This study selected Zhihu, a prominent Q&A platform, as the data source. Zhihu is a well-known social Q&A platform in China, distinguished by users' in-depth sharing of personal experiences and unique insights. The long-form content available on Zhihu provides detailed UX data, encompassing diverse and authentic feedback from users regarding their use of BEVs. This makes it highly valuable for analytical purposes. The wealth of firsthand experiences and insights shared by Zhihu users provides insightful information for comprehending UX. By choosing Zhihu as the data source, this study ensured access to representative user experience data rich in multidimensional information, thereby laying a solid foundation for constructing and validating the BEVUX model.

The data collection strategy gives precedence to actual UX over speculative discourse. Keywords, including "target competitor" and "experience", directed the search to ensure the data accurately captured users' interactions with BEVs. Octoparse, a web-scraping tool, was employed to extract raw data from Zhihu for the four models, with the corpus archived in CSV format. The dataset, compiled until 17 November 2022, included 435,097 words from 1126 users for TC1, 161,791 words from 442 users for TC2, 269,917 words from 524 users for TC3, and 85,200 words from 128 users for TC4. Detailed information regarding the dataset is presented in Table 2.

Table 2. Raw data collection information.

	TC1	TC2	TC3	TC4
Response Time	1 April 2016 to 17 November 2022	10 May 2020 to 14 November 2022	9 January 2021 to 14 November 2022	3 August 2013 to 15 November 2022
Number of Respondents	1126	442	524	128
Number of Words	435,097	161,791	269,917	85,200

4.1.2. Data Screening

Text mining from platforms such as Zhihu inherently involves inherent noise and potential inaccuracies, necessitating meticulous text preprocessing, including automated procedures and manual refinements [61,62]. In this study, a series of rigorous preprocessing steps were undertaken before the formal analysis. For example, irrelevant data unrelated to the subject's core experience, such as special characters, blank information, and URLs, were manually excised. Then, phrases prone to fragmentation, such as "range", "driving experience", and "monthly sales", were designated as domain-specific terms prior to tokenization and part-of-speech tagging. Finally, text de-noising was applied, where colloquial words, such as "please", "also", and "too", were categorized as stop words. Moreover, the data-screening process was iteratively refined until it was appropriate for the subsequent analytical procedures.

4.2. Analysis and Results

4.2.1. Phase One: Topic Modeling Utilizing Latent Dirichlet Allocation (LDA) and pyLDAvis

In this section, an effective topic model was constructed to analyze potential UX factors related to BEVs. The LDA model, selected for its robust capability, served as the primary analytical tool owing to its capacity for revealing latent topics within textual data.

Step 1. Feature extraction: This involved converting raw text data into a numerical format suitable for machine learning techniques. Employing a bag-of-words approach, the 1000 most prominent feature words were identified, chosen for their prevalence and relevance within the corpus. Words occurring at the extremes of frequency were omitted to concentrate on significant terms, thereby generating a numerical feature set that was well suited for LDA analysis.

Step 2. Optimal topic number determination: An experimental approach was utilized, with varying numbers of topics established and corresponding perplexity scores calculated to evaluate model performance. The optimal topic count was determined through perplexity measurements and the application of the elbow method, balancing topic clarity and model intricacy. The detailed perplexity outcomes and LDA model visualizations for the UX corpora of the four TCs are provided in Appendix A, Table A1. Specifically, these experiments identified seven topics for TC1, five topics for TC2, six topics for TC3, and three topics for TC4. Iterative experimentation ensured model stability and convergence. Visualization with pyLDAvis facilitated an intuitive comprehension of each topic, enhancing the interpretation and presentation of the model.

Step 3. LDA model analysis: Once the optimal number of topics was validated, the LDA model analysis proceeded to extract topics and corresponding keywords, along with the proportion of each topic in the documents. For instance, in the case of TC1, the top 20 keywords for each topic were identified according to their probability distribution, normalized on a scale from 0 to 1. The detailed results are delineated in Appendix A, Table A2.

Phase one results—classification of topic labels: The intrinsic nature of each topic was identified by examining the top 20 keywords extracted from each topic. The model assigned each review document to a specific topic, thereby streamlining the data-labeling process. Expanding upon the research of Edmond et al. on plug-in electric vehicles (PEVs) [63], which encompassed the BEVUX, this study analyzed 6492 references from diverse sources to identify a range of topics related to UX, typically divided into driving and travel behavior, interaction with the vehicle, and subjective aspects of UX. In alignment with Norman's three levels of UX theory, the topic labels were categorized as "subjective perception (SP)", "driving behavior experience (DBE)", "interaction behavior (IB)", and "social symbolism (SS)". The SB label corresponds to the visceral level of UX theory, with DBE and IB corresponding to the behavioral level, and SS to the reflective level. The SP topic label is shown in Table 3, with more data, and the rest of the data in the table is replaced by ". . .".

Table 3. Keywords for the topic labels of subjective perception.

	Topic Number	Top 20 Keywords	Summarized Topic Label
TC1	T3	Space, Rear Seat, Mode, Feeling, Experience, Power, Seat, Design, Chassis, Vehicle Use, Brake, Vehicle, Interior, Exterior, Condition, Car, Model, Price, Overall, Sound Insulation	SP
	. . .	. . .	. . .
TC2	T0	Interior, Seat, Feeling, Space, Rear Seat, Design, Exterior, Steering Wheel, Function, Chassis, Experience, Leather, Voice, Car Machine, Price, Air Conditioning, Adjustment, Overall, Ventilation, Technology	SP
	. . .	. . .	. . .
TC3	T3	Feeling, Electric Car, Interior, Car Owner, Space, Rear Seat, Fuel Car, Seat, Steering Wheel, Sales, Brake, Exterior, Chassis, Friend, Suggestion, Power, Brand, Time, Buying Car, Mode	SP
	. . .	. . .	. . .
TC4	T1	Feeling, Power, Space, Brake, Rear Seat, Interior, Steering Wheel, Experience, Car Owner, Gearbox, Mode, Function, Chassis, Speed, Seat, Key, Throttle, Engine, Friend, Price	SP
	. . .	. . .	. . .

4.2.2. Phase Two: Multidimensional Factor Weighting via EWM

Step 1. Keyword entropy calculation and normalization: For each keyword within a topic, we calculated the information entropy and normalized the values to a scale between 0 and 1. This facilitated the evaluation of keyword distribution evenness within the text and confirmed the precision of the keywords extracted by the LDA model.

Step 2. Integrated scoring and output of results: Integrating the topic proportion per document with the information entropy and keyword probability for each topic, the resultant metrics were combined through multiplication to derive an integrated score, which was used to rank the keywords. The detailed ranking results are provided in Appendix B, Table A3.

Step 3. Calculation of comprehensive weights: Comprehensive weight calculations were conducted on the outcomes from various target competitors, establishing a hierarchy of topic keywords. The results are presented in Appendix B, Table A4.

Phase two results—multidimensional factor encoding: Through summarization and generalization of keywords across topics for the four vehicle models, and categorization by topic probability to enhance analysis efficiency, 10 keyword codes were established under unified topic tags, as illustrated in Table 4. These contents delineated the overarching UX themes of target competitors and the associated influencing factor keywords, laying the groundwork for sentiment analysis of these factors in subsequent stages.

Table 4. Topic label encoding of four types of BEVs.

Topic Number	Primary Factor (Topic Label)	Secondary Factors (Top 10 Keywords' Ranking)
T1	SP	Space, Design, Model, Feeling, Interior, Rear Seat, Mode, Experience, Seat, Body
T2	IB	Voice, Car Owner, Mode, Music, Car Machine, Mobile Phone, Assistance, Key, Intelligent, Autonomous Driving
T3	SS	Brand, Price, Model, Product, Market, Consumer, Service, Tradition, Subsidy, Domestic
T4	DE	Battery, Brake, Mileage, Parking, Route, Parking Lot, Platform, Map, Power, Temperature

4.2.3. Phase Three: Domain-Adaptive Sentiment Analysis (DASA)

This section aims to quantify and clarify the emotional tendencies of thematic elements in the UX of competitive BEVs through DASA. We conducted a comprehensive investigation of users' emotional reactions to various influencing factors.

Step 1. Corpus preprocessing: We standardized and refined the original data from competing products, aligning them with the multidimensional influencing factors identified in the previous stage. Separately, we extracted text data relevant to the topic keywords to form a corpus for DASA. This corpus included four topic-specific sub-corpora and ten corresponding independent sub-corpora for the influencing factors.

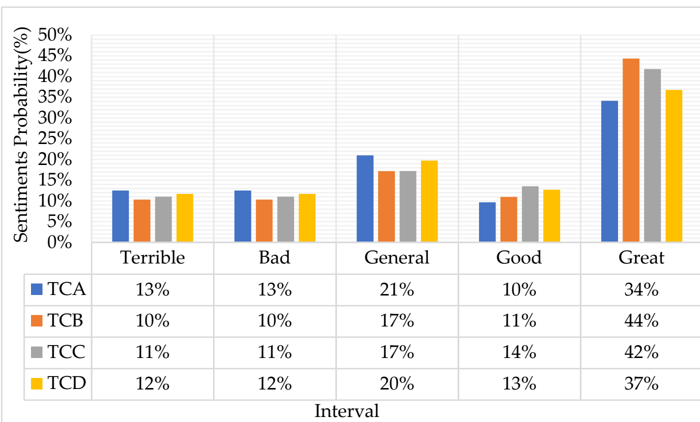
Step 2. Constructing a training set for DASA: We used the Python-based sentiment analysis package SnowNLP to analyze the extracted corpus. To enhance the accuracy of DASA, a pre-trained model was developed using manual labeling as the training dataset. DASA of UX texts for four types of BEVs was performed. Initially, we gathered texts with the keyword "BEV experience" from the platform where the test dataset was sourced. We employed the built-in training dataset for sentiment scoring, manually selected the appropriate positive and negative review samples, and integrated them into the training dataset to create a customized corpus. Subsequently, we manually assigned sentiment scores to the extracted theme-related corpus, which acted as the test dataset. We used the customized corpus for machine learning, assigned sentiment scores to the test dataset, and compared these with manual labeling, repeating this process until an accuracy of 83.9% was attained in the evaluation test, thereby creating a specialized training dataset.

Ultimately, we applied the optimized training dataset to calculate sentiment scores for BEVs and presented the semantic sentiment probabilities.

Step 3. DASA for thematic keywords: We conducted DASA on the extracted thematic keywords with the refined training set, quantified the sentiment of influencing factors in user experiences of competitive products, pinpointed pain points, and identified best practices for enhancing product UX. Initially, we performed a comprehensive DASA on the thematic corpus. We employed the refined training set to assign sentiment scores ranging from 0 to 1, with the following categorizations: scores of 0.9 or above are “excellent”, 0.7 to 0.9 are “good”, 0.3 to 0.7 are “neutral”, 0.1 to 0.3 are “poor”, and below 0.1 are “very poor”. We created a histogram of sentiment scores and determined the proportion of each sentiment category. Subsequently, using “interior” as an example, we conducted a detailed analysis of UX sentiment, adjusted the score range to 0–1 with a granularity of 0.02, excluded data at the extremes of 0 and 1, and created a histogram.

Results of phase three:

1. From the analysis of T1, Figure 2 shows a pronounced positive sentiment, “excellent”, comprising over one-third of the responses. TC2 exhibited the highest proportion of positive sentiment at 44%, whereas TC1 had the lowest at 34%. Users of TC1 reported the highest rate of extremely negative evaluations, 13%, while those of TC2 reported the lowest, at 10%. Accordingly, in the comparison of overall subjective experience levels, TC2 outperformed the others, with the most favorable positive sentiment, while TC1 lagged with the least favorable negative sentiment.
2. Variety in the visualization approaches yielded diverse insights. Continuing to filter the top-five subjective experience keywords—”design”, “space”, “interior”, “exterior”, and “rear seat”—and presenting them visually, as depicted in Appendix C, Table A5, revealed the following insights: The appeal of design elements was consistently moderate, with minimal variance; yet, TC3 showed a lower proportion of extremely negative evaluations, indicating a comparable UX in design performance among the four companies. Spatial attributes displayed considerable sentiment variability, with notably negative perceptions for TC1, succeeded by TC3, and TC2 users exhibited strong positive evaluations. Exterior sentiment encompassed a range of evaluations, with TC2 receiving the highest and TC4 the lowest ratings. Interior and rear seat sentiments were largely negative, with the exception of a superior performance by TC2.
3. From the focused analysis of the “interior” keyword, Figure 3 indicates that the interior sentiment metric leaned toward zero, indicating a general negative perception. TC1, approaching 0, recorded the highest proportion of negative evaluations at 28.00%, implying that TC2’s interior could be a benchmark for addressing product “pain points”; conversely, TC2, approaching 1, recorded the highest proportion of extremely positive evaluations at 11.02%, indicating that TC2’s interior could be a benchmark for “best practices” in product development.



	Terrible	Bad	General	Good	Great
TCA	13%	13%	21%	10%	34%
TCB	10%	10%	17%	11%	44%
TCC	11%	11%	17%	14%	42%
TCD	12%	12%	20%	13%	37%

Figure 2. Sentiment score histogram for the “subjective perception” theme in target competitors.

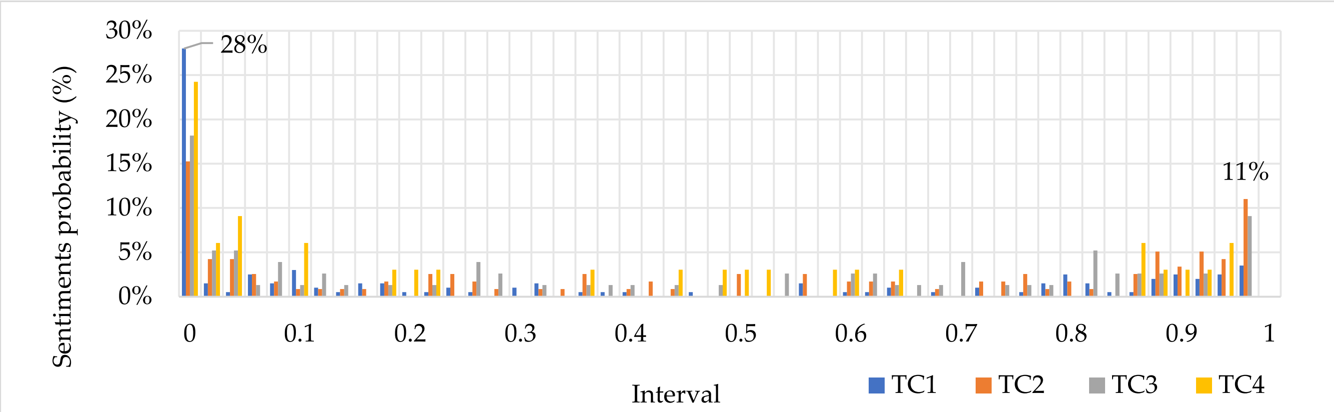


Figure 3. Sentiment score comparison for the "interior" keyword in subjective perception.

4.2.4. Phase Four: Sentiment Polarity Association Mining via Co-Occurrence Network Analysis (CONA)

The objective of this research phase was to explore the associations between sentiment-tendency keywords of the target competitors identified in the previous stage using CONA. This analysis helped to uncover how affective polarity terms interact with other aspects of UX, thereby identifying key elements and potential factors of affective evaluations.

Step 1. Sentiment-tendency text screening and data preprocessing: based on the DASA results of keywords in each theme, we selected texts with strong positive ($\geq$0.9) and very negative (<0.1) sentiments from the target competitors for corpus mining and preprocessing the data.

Step 2. Construction of co-occurrence matrix: for each preprocessed comment, we set criteria for the top 100 noun frequency and technical terms, with a window size encompassing the entire document, thereby considering the co-occurrence of keywords throughout the text to construct a co-occurrence matrix based on frequency.

Step 3. Calculation of network characteristics and comprehensive weights: by calculating EC, JC, and TF, the nodes and interconnections of the co-occurrence network were established.

Step 4. Calculation of comprehensive weights: Normalization of network characteristic values was followed by the computation of comprehensive weights for each keyword. EC, JC, and TF were allocated weights of 0.5, 0.3, and 0.2, respectively. The results for the keyword "interior", indicative of "pain points" due to very negative sentiment extremity within TC1, are outlined in Appendix D, Table A6. On the other hand, Table A7 presents the results for the keyword "interior" in TC2, which demonstrated strong positive sentiment extremity and served as a reference for "best practices". Following the computation of weights for all keywords across various themes of the target competitors, we derived the association factors and weight coefficients. As an example, within the theme of SP, the factor calculation results for the keyword "interior" with very negative and strong positive sentiment extremities for all competitors are illustrated in Appendix D, Tables A8 and A9, respectively.

Results of phase four—visualization and interpretation of co-occurrence networks:

1. Taking the keyword "interior" as an example, the co-occurrence networks of TC1 and TC2 for the "interior" were presented as typical results. The depth of the node color indicates the EC of the keywords, where darker blue signifies higher centrality, representing strongly positive evaluations, and yellow indicates lower centrality, suggesting more peripheral terms. Orange and purple represent strongly negative evaluations. The connections and numerical values between nodes denote the strength of the associations.
2. As represented in Figure 4, in the realm of very negative interior experience, TC1's issues were primarily concentrated on poor material quality and large gaps. For

TC2, the focus was on the red interior decoration and the chrome high-gloss trim, which were significantly influenced by individual preferences. TC3 did not exhibit any notably related results. In contrast, TC4's concerns were centered on the design of the dashboard and the use of carbon fiber shells and suede decorations.

3. As represented in Figure 5, on the other hand, regarding the strongly positive interior experience, TC1 received higher evaluations for its sense of technology and brand-representing design and style. TC2, however, garnered attention for the quality of its leather interior, the texture of its seats, and the masterful design.

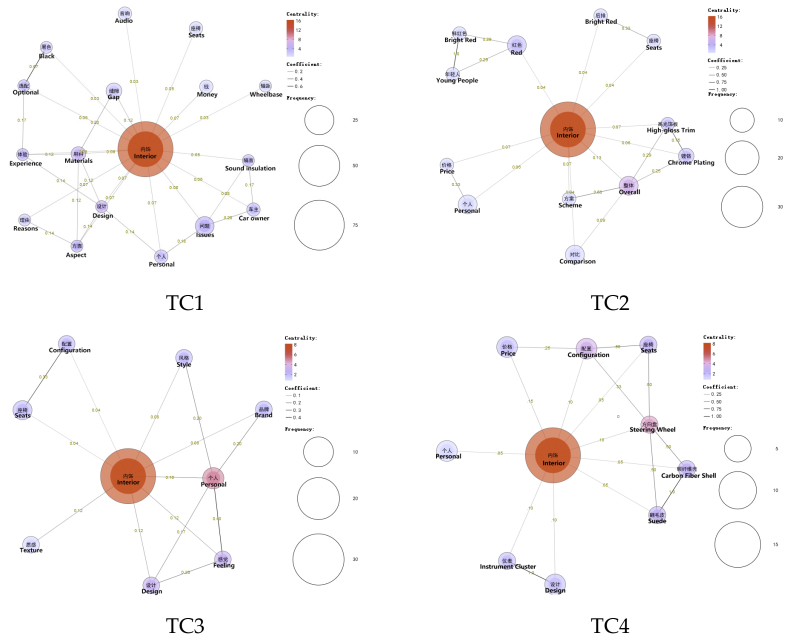


Figure 4. Co-occurrence network of keyword eigenvector centrality for the extremely negative "interior" label.

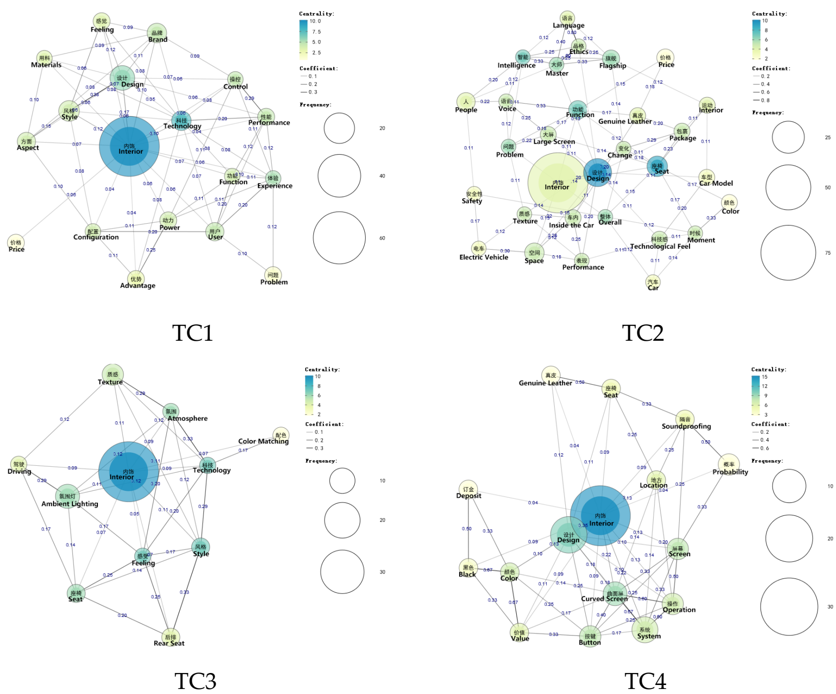


Figure 5. Co-occurrence network of keyword eigenvector centrality for the strongly positive "interior" label.

5. Discussion

5.1. Interpretation of Results

The study's initial phase utilized LDA and pyLDAvis for thematic modeling, successfully identifying core topics within the UGC related to BEVs. These topics were found to be highly correlated with key dimensions of the UX, including subjective perception, interaction behavior, social symbolism, and driving experience. By mapping these topics onto Norman's hierarchical UX theory, the study achieved a systematic understanding of user commentary, establishing a foundation for DASA and providing a structured framework for elucidating the holistic BEVUX. This approach not only identified specific aspects of user concern but also revealed their relative significance within the UX paradigm, offering theoretical guidance for electric vehicle improvements and corroborating the thematic modeling method's effectiveness with existing literature.

In the second phase, the establishment of a coding system for the top 10 keywords (level 2 factor) under each comprehensive theme label (level 1 factor) streamlined data complexity, enhancing the precision and efficiency of subsequent analyses. Under the SP theme, users placed particular emphasis on aspects such as space, design, and vehicle models. These keywords exposed the core elements of the UX and offered a solid foundation for DASA. The multidimensional factor coding provided a more comprehensive perspective compared to traditional single-dimensional analysis methods, capturing key factors in the UX more accurately.

The third phase employed SnowNLP for DASA, revealing significant differences in users' subjective feelings toward different competitive products. TC2 outperformed the others in positive evaluations, while TC1 had a higher proportion of negative evaluations within the primary influencing factor of subjective feelings. This finding is of considerable importance for manufacturers looking to optimize product design. Additionally, sentiment measurement analysis of the secondary influencing factor "interior" indicated that TC1 had the highest proportion of negative assessments, whereas TC2 had the highest proportion of positive evaluations. These insights unveiled specific user demands and expectations regarding interior design, showcasing the practicality of DASA in identifying emotional tendencies and quantifying the performance of various competitors in specific aspects.

The fourth phase involved CONA, which uncovered the complex associations between different emotional factors. By analyzing the co-occurrence association network of the extremely negative and strongly positive experiences of the level 2 factor "interior", specific tertiary associating factors affecting UX polarity were identified. TC1's negative sentiment was primarily concentrated on material and gap issues, while TC2 faced criticism for its red interior trim and high-gloss panels. On the other hand, TC1's technological sense and design style, along with TC2's leather texture and seat design, received high praise from users. The EC analysis identified key emotional factors in user commentary, offering a novel perspective for understanding the emotional associations in UX and providing abundant data for further sentiment analysis.

Although this study presented conclusions based on the emotional associations of tertiary factors within the level 1 factor "subjective perception" and the level 2 factor "interior", its core value lies in constructing a systematic and multi-level research framework for the multidimensional elements of UX. This framework provides a new perspective for understanding UX and reveals potential connections between different factors through multi-level analysis.

5.2. Methodological Reflection

The composite methodological framework constructed in this study demonstrated significant advantages in deeply analyzing and understanding the multidimensional elements of BEVUX. However, challenges remain, particularly regarding the subjectivity in determining the optimal number of topics for the LDA model and the limitations on the accuracy of sentiment analysis due to the quality and diversity of the training dataset. Furthermore, while CONA revealed associations between factors, it did not delve into causal or conditional relationships. Future research should explore more objective methods for determining topic numbers, adopt advanced NLP technologies to enhance sentiment analysis accuracy, and introduce time series analysis or causal inference methods to explore the dynamic connections and interactions between factors. Consideration of data source diversity and representativeness is also essential to enhance the universality of conclusions. Ultimately, iterative methodological improvement, interdisciplinary method integration, and transparency in technology and method application will be key to advancing the field of UX research.

5.3. Limitations

This study focused on the multidimensional user experience analysis of the Chinese battery electric vehicle (BEV) market. Although a comprehensive analytical framework has been established, several limitations remain that may affect the generalizability and applicability of the findings in other contexts.

First, the research data were primarily sourced from the Chinese Q&A platform "Zhihu". While the UGC from Zhihu is relatively authentic and comprehensive, providing deeper insights compared to short-text reviews, the user demographics tend to be younger, more highly educated, and more technologically inclined. These biases limit the representativeness of the data, which may not fully capture the diversity of the broader Chinese BEV user market.

Second, the sentiment analysis used a domain-adaptive model (e.g., SnowNLP) to enhance adaptability to specific BEV-related terminology. However, as the base training data were mainly derived from general Chinese texts, the model's performance may be limited when analyzing users' experiences from different regions, affecting its cross-regional applicability.

Third, while the co-occurrence network analysis (CONA) revealed complex associations between various emotional factors, it did not delve into causal relationships or temporal dynamics. Therefore, although key factors, such as interior design, and their links to users' emotions were identified, the nature of these associations, particularly regarding causality, remains unclear.

In summary, the limitations of this study are largely related to its focus on the Chinese BEV market and the specific constraints of data sources and methodologies. These limitations affect the generalizability of the findings and, to some extent, restrict their applicability to other regions or industries. Future research should aim to expand the diversity of data sources and employ more advanced natural language processing techniques to enhance the external validity and applicability of the conclusions.

5.4. Future Research Directions

To address the identified limitations, future research should prioritize the following areas to enhance the robustness and generalizability of the proposed framework:

First, expanding the diversity of data sources, including social media, product review platforms, and industry forums, is essential to improve data representativeness. A broader scope of data collection will facilitate a more comprehensive understanding of battery electric vehicle (BEV) users, encompassing various demographic groups, geographic regions, and user backgrounds.

Second, enhancing the sentiment analysis model by employing larger, domain-specific datasets and leveraging advanced techniques, such as transfer learning, is crucial for improving adaptability. These refinements would enable the model to accurately capture subtle emotional nuances across diverse regions and contexts, thereby increasing its cross-regional applicability and ensuring more reliable sentiment detection.

Lastly, integrating event extraction techniques is recommended to reveal causal relationships and temporal dynamics among emotional factors identified through co-occurrence network analysis (CONA). The incorporation of causal inference and time-series analysis will provide deeper insights into the evolution of these emotional factors and their impacts on user experience, thereby contributing to a more nuanced understanding of the user journey.

These directions aim to enhance the generalizability and applicability of the findings, thereby laying a stronger foundation for practical improvements in user experience within the BEV industry and extending the utility of the framework to other sectors.

6. Conclusions

6.1. Main Conclusions

The aim of this study was to develop and validate a systematic analytical framework for understanding the multidimensional factors and their complexities within battery electric vehicle user experience (BEVUX). Multiple text-mining techniques were employed to uncover core themes, emotional responses, and interrelationships among different factors in the user experience. The main conclusions of the study are as follows:

1. The results based on the LDA model demonstrated a high degree of alignment between the core themes in UGC and the key elements of UX theory, offering a systematic framework for understanding users' needs.
2. The EWM was employed to assess the multidimensional factors affecting the BEVUX, including level 1 factors, such as subjective perception, driving behavior experience, interactive behavior, and social symbolic significance, as well as level 2 factors under these themes. These dimensions collectively constitute the overall perception of BEVs by users.
3. The DASA quantified users' emotional responses to the multidimensional factors of BEV UX, revealing significant differences in emotional tendencies among different competitors, providing key references for "pain points" and "best practices" in product development.
4. The CONA exposed the complex associations between level 2 influencing factors and level 3 factors with emotional polarity in BEVUX, offering a new perspective for understanding the emotional structure within the UX.

6.2. Research Contributions

The contributions of this study are reflected in both theoretical and practical aspects:

1. Theoretical contribution: Based on Norman's UX theory, a new analytical framework was constructed, significantly enriching the theoretical understanding of the UX. The integration of techniques, such as LDA, EWM, DASA, and CONA, proposed a systematic approach to identify and understand the multidimensionality and complexity of UX. Specifically, the combination of these methods better revealed the relationships among various factors in the UX and how these relationships influence users' overall perception and emotional responses.
2. Practical contribution: This study provided a multidimensional, multi-level framework of factors influencing the UX, offering scientific guidance for product development in the BEV industry. For instance, the results of DASA enabled manufacturers to identify negative emotional "pain points" among users, which can be prioritized for resolution in product design. The results of CONA, on the other hand, provided insights into the complex associations between product features and users' emotions, pointing manufacturers toward directions for optimization and innovation. Furthermore, the detailed analysis of users' emotional tendencies has enhanced companies' understanding of market dynamics, supporting precise formulation of market strategies. Notably, in contexts where there are significant emotional differences between competitors, these findings provide data-driven support for targeted strategy development.
3. Through these contributions, this research not only enriches the methodology of UX analysis from a theoretical perspective but also provides practical guidance for product development and market strategies in the BEV industry.

6.3. Universality of the Methodological Framework

The methodological framework proposed in this study has shown significant universality, applicable to UX analysis across different fields. The framework is capable of comprehensively capturing and deeply analyzing the complexity of UX. Its flexibility and adaptability ensure efficient application in various research designs, enhancing the transparency and practicality of research.

6.4. Epilogue

This study aspired to inspire further in-depth research to jointly promote the development of the electric vehicle industry toward a more humanized and intelligent direction. It is recommended that future work further explores the dynamic connections between multi-level factors and employs diverse data sources. At the same time, when designing and developing BEVs, enterprises should pay more attention to the multidimensional elements of UX and continuously optimize products using data analysis technology.

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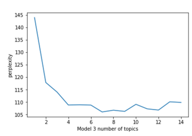
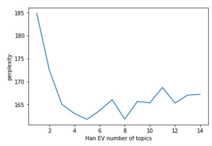
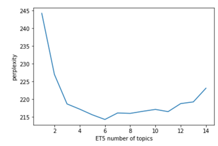
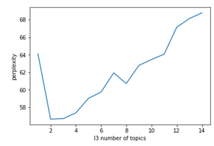
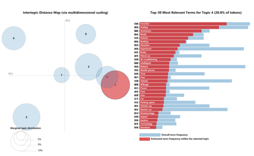
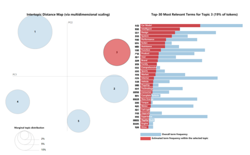
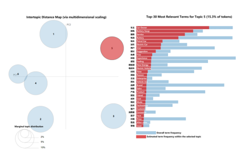
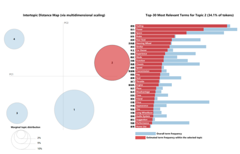
Appendix A. Detailed Experimental Data for Optimal Topic Number Determination and LDA Model Analysis

This appendix provides detailed data for determining the optimal topic number for the LDA model and subsequent analysis, including perplexity calculations and topic keyword extraction.

The following table presents the perplexity scores for different numbers of topics used in the process of determining the optimal topic count. The elbow method was used to identify the optimal number of topics.

Table A1. Perplexity calculation and visualization of topics for different target competitors.

	TC1	TC2	TC3	TC4
Perplexity				
LDA visualization				

The LDA model analysis proceeded to extract the top 20 keywords for each topic identified in the corpus TC1, with corresponding probabilities normalized between 0 and 1.

Table A2. Topic proportion and corresponding top 20 keywords (probability) for TC1.

Topic Number	Topic Rank	Topic Proportion	Top 20 Keywords with Probabilities
T0	3	18.65%	Advantage (0.0481), Price (0.0454), Performance (0.0432), Battery (0.0374), Model (0.0362), Market (0.0361), Price Increase (0.0336), Brand (0.0321), New Energy (0.0310), Domestic (0.0286), Intelligent (0.0268), User (0.0264), Price Range (0.0255), Motor (0.0231), Fuel (0.0229), Interior (0.0228), Level (0.0214), Traditional (0.0212), Technology (0.0204), Consumer (0.0182)
T1	2	19.18%	Features (0.0617), Electric Vehicle (0.0577), Battery (0.0513), Assistance (0.0495), Fuel Vehicle (0.0448), Experience (0.0373), Car Machine (0.0346), Time (0.0299), Feeling (0.0273), Automatic (0.0271), Upgrade (0.0262), Mobile Phone (0.0250), Situation (0.0246), Mileage (0.0212), Parking Space (0.0207), Vehicle Use (0.0201), Air Conditioning (0.0184), New Car (0.0176), Software (0.0170), Data (0.0170)
T2	4	11.25%	Deposit (0.0436), Car Purchase (0.0414), Car Price (0.0384), Wheel Rim (0.0364), Interior (0.0347), Unit (0.0322), Car Owner (0.0290), Vehicle (0.0274), Black (0.0264), Official (0.0258), Little Partner (0.0250), Price Increase (0.0243), Parking Space (0.0225), Home Use (0.0221), Bank (0.0208), Interest Rate (0.0193), Full Payment (0.0190), Final Payment (0.0179), Content (0.0177), Sales (0.0175)
T3	1	20.03%	Space (0.0981), Rear Seat (0.0468), Feeling (0.0363), Mode (0.0362), Experience (0.0308), Power (0.0294), Seat (0.0286), Design (0.0276), Chassis (0.0263), Brake (0.0225), Vehicle Use (0.0221), Vehicle (0.0216), Interior (0.0216), Exterior (0.0209), Car (0.0186), Model (0.0184), Price (0.0182), Situation (0.0177), Soundproofing (0.0146), Overall (0.0146)
T4	6	10.38%	Car Enthusiast (0.1158), Subsidy (0.0395), Price (0.0383), Insurance (0.0355), Save Money (0.0329), Official (0.0299), Car Enthusiasts (0.0279), Basic (0.0248), Process (0.0238), Handle (0.0233), New Energy (0.0218), Film (0.0203), Save (0.0196), Entire Network (0.0194), Purchase Tax (0.0184), Interest Rate (0.0181), Official Website (0.0179), Region (0.0172), Local (0.0169), Glass (0.0158)
T5	7	9.32%	Car Owner (0.0955), Maodou (0.0886), Brand (0.0753), Film (0.0670), Car Paint (0.0366), Sales (0.0349), Feeling (0.0344), Free (0.0270), Consumer (0.0262), Performance (0.0240), Difference (0.0224), New Car (0.0212), Development (0.0208), Color (0.0196), Domestic (0.0184), Vehicle (0.0176), Price (0.0174), Degree (0.0173), Glass (0.0167), Seat (0.0162)
T6	5	9.75%	Subsidy (0.1917), Suggestion (0.1095), Car Owner (0.0638), Sales (0.0565), New Energy (0.0519), Standard Continuation (0.0462), Price Reduction (0.0318), Family (0.0313), Vehicle (0.0295), Difference (0.0287), Electric Vehicle (0.0274), Friend (0.0242), Car Purchase (0.0241), Version (0.0229), Upgrade (0.0190), Basic (0.0188), Fuel Vehicle (0.0162), Car Purchase (0.0157), Data (0.0135), Mileage (0.0122)

Appendix B. Multidimensional Factor Weighting via the EWM

This appendix provides detailed tables for the integrated scoring and comprehensive weight calculation results derived during the multidimensional factor weighting process.

Table A3 presents the integrated scores, calculated by combining topic proportion, information entropy, and keyword probabilities for each topic. These scores were used to rank the keywords accordingly.

Table A3. Integrated scoring and ranking of topic keywords.

Topic Number	Keyword	Normalized Probability	Normalized Entropy	Topic Proportion	Combined Weight
T3	Space	1	1	20.03%	0.20030313
T3	Rear Seat	0.385918963	0.491727751	20.03%	0.03801094
T3	Mode	0.260287718	0.35383107	20.03%	0.01844749
T3	Feeling	0.258500724	0.351748857	20.03%	0.01821303
T3	Experience	0.194348095	0.274412914	20.03%	0.01068249
T3	Power	0.178247795	0.254157799	20.03%	0.00907435
T3	Seat	0.168682113	0.241949559	20.03%	0.00817488
T3	Design	0.155791772	0.225285283	20.03%	0.00703016
T3	Chassis	0.141033034	0.205894088	20.03%	0.00581638
T3	Car Usage	0.095078409	0.143210437	20.03%	0.00272737
T3	Brake	0.090702407	0.137045586	20.03%	0.00248984
T3	Vehicle	0.084463887	0.12819386	20.03%	0.00216883
T3	Interior	0.084148387	0.127744209	20.03%	0.00215315
T3	Exterior	0.076531178	0.116828786	20.03%	0.00179092
T3	Situation	0.048101581	0.075031622	20.03%	0.00072292
T3	Car	0.046323578	0.072359155	20.03%	0.00067140
T3	Car Model	0.044151031	0.069083872	20.03%	0.00061095
T3	Price	0.03788204	0.059571574	20.03%	0.00045202
T3	Overall	0.000207031	0.000336081	20.03%	0.00000001
T3	Sound Insulation	0	0	20.03%	0.0000000

Table A4 details the comprehensive weight calculations for various target competitors, establishing a hierarchical ranking of the keywords based on multiple factors.

Table A4. Comprehensive weight calculation of topic keywords.

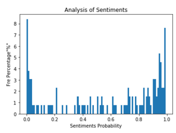
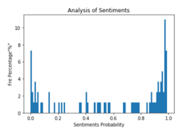
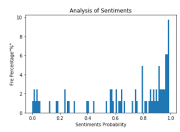
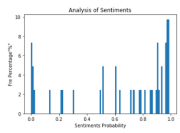
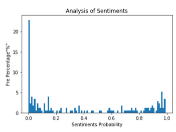
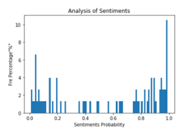
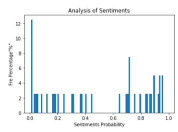
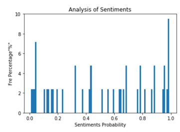
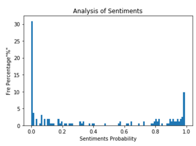
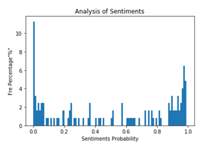
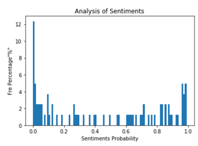
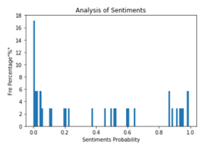
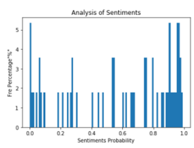
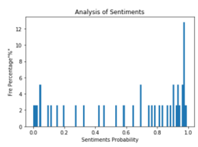
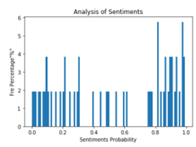
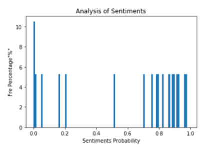
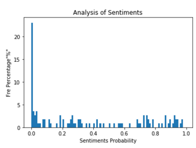
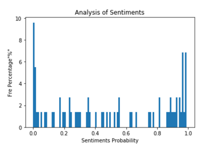
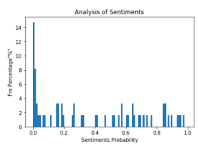
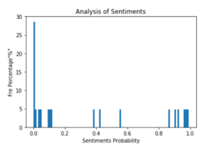
Keyword	Weight of TC1	Weight of TC2	Weight of TC3	Weight of TC4	Comprehensive Weight
Space	0.200303132	-	-	-	0.200303
Design	0.007030158	0.227203459	0.131563853	0.272058935	0.13473
Model	0.000671403	-	0.098291411	0.053455357	0.05341
Feeling	0.018447494	0.063410163	-	-	0.041858
Interior	0.002153152	0.055795244	0.020718663	-	0.039667
Rear Seat	0.038010937	-	-	-	0.038011
Mode	0.01821303	-	0.007896615	-	0.02611
Experience	0.010682492	0.015807939	-	0	0.01244
Seat	0.008174884	-	0.003169486	-	0.01134
Body	-	0.009849655	0.009849655	-	0.00985

Appendix C. Domain-Adaptive Sentiment Analysis

This appendix presents detailed tables related to the DASA for the selected top-five subjective experience keywords. The table below provides a comprehensive visualization of sentiment analysis outcomes for each keyword across different target competitors.

Table A5 provides the visualization and detailed breakdown of sentiment analysis for the keywords ”design”, “space”, “interior”, “exterior”, and “rear seat” across all target competitors. This table highlights the variations in sentiment across different domains, indicating significant differences in UX evaluations, which are crucial for understanding the domain-specific user feedback.

Table A5. Visual comparison of sentiment scores for the top 5 keywords in subjective perception themes.

	TC1	TC2	TC3	TC4
“Design” label				
“Space” label				
“Interior” label				
“Exterior” label				
“Rear Seat” label				

Appendix D. Sentiment Polarity Association Mining via Co-Occurrence Network Analysis (CONA)

This appendix provides detailed tables for the CONA (co-occurrence network analysis) results, which include the comprehensive weight calculations and association factors derived for specific keywords under different sentiment polarities.

Table A6 outlines the comprehensive weights computed for the keyword "interior" in TC1, characterized by very negative sentiment extremity, identifying it as a "pain point" for the target competitor.

Table A6. Comprehensive weight calculation for keywords with very negative sentiment in TC1's "interior" tag.

Word	EC	JC	Normalized TF	Comprehensive Weights
Interior	0.663071849	0.034785239	1	0.606797891
Gap	0.1045055	2.046825397	0.033333333	0.462147242
Material	0.108194489	1.622161172	0.022222222	0.379210531
Owner	0.104695556	1.346825397	0.011111111	0.321022815
Rim	0.088080172	1.336446886	0.022222222	0.31096858
Feeling	0.104851921	0.957936508	0.011111111	0.24512081
Slot	0.135149266	0.802020202	0.055555556	0.24222699
Audio	0.104998341	0.784437784	0.011111111	0.211305206
Space	0.166491493	0.465151515	0.111111111	0.206837322
Domestic	0.109944761	0.63525641	0.011111111	0.185202411

Table A7 presents the comprehensive weights for the keyword "interior" in TC2, which indicated strong positive sentiment extremity and served as a "best practice" reference for the UX.

Table A7. Comprehensive weight calculation for keywords with strong positive sentiment in TC2's "interior" tag.

Word	EC	JC	Normalized TF	Comprehensive Weights
Interior	0.592284163	0.039215686	1	0.607136115
Carbon Fiber	0.072272343	1.813095238	0.012195122	0.354302794
Embrace	0.088655321	1.44675643	0.024390244	0.301989804
Seat	0.154745784	0.917814918	0.06097561	0.261104985
Tradition	0.198734645	0.552991453	0.06097561	0.226699165
Function	0.121187093	0.816977467	0.024390244	0.211040079
Technology	0.147888913	0.661669703	0.06097561	0.209508815
Color	0.111026294	0.267857143	0.012195122	0.101289857
Texture	0.125514678	0.273387723	0.036585366	0.060642182
Leather	0.042104428	0.252891156	0.024390244	0.050896889

Table A8 provides the factor calculation results for the keyword "interior" within the theme of SP, specifically focusing on the very negative sentiment extremities observed across all competitors.

Table A9 illustrates the factor calculation results for the keyword "interior" with strong positive sentiment extremity for all competitors, highlighting positive aspects in sentiment analysis.

Table A8. Ranking of level 3 factors (top 10 keywords) for "interior" with very negative sentiment in the "subjective perception" theme.

Competitor ID	Secondary Factors (Top 10 Keywords' Ranking)
TC1	Interior, Gap, Material, Owner, Rim, Feeling, Slot, Audio, Space, Domestic
TC2	Interior, Red, Difference, Chrome, Leather, Paint, Character, High-Gloss Trim, Price, Bright Red
TC3	Interior, Seat, Plastic, Texture, Trash, Simple, Full Range, Style, Owner, Brand
TC4	Interior, Rim, Audio, Harman, Kardan, Oil, Fur, Steering Wheel, Carbon Fiber, Dashboard

Table A9. Ranking of level 3 factors (top 10 keywords) for "interior" with strong positive sentiment in the "subjective perception" theme.

Competitor ID	Secondary Factors (Top 10 Keywords' Ranking)
TC1	Interior, Technology, Style, Brand, New Energy, User, Rim, Power, Advantage, Performance
TC2	Interior, Carbon Fiber, Embrace, Seat, Tradition, Function, Technology, Color, Texture, Genuine Leather
TC3	Interior, Seat, Plastic, Texture, Junk, Simple, Full Range, Style, Owner, Brand
TC4	Inch, Curved, Black, Rim, Button, Screen, Location, Sound Insulation, Seat, Value

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