Design Theory and Methodology for Multimodal Data Fusion Based on CSET

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***Abstract*—Amid the sweeping tide of digitalization, the field of design is encountering unprecedented opportunities and challenges. Vast data resources are rich with valuable user experience (UX) and design information. However, traditional design methodologies fall short in effectively integrating and utilizing such diverse data. This study introduces an innovative design theory and methodology for multimodal data fusion based on the Culture, Society, Economy, and Technology (CSET) framework. By constructing a UX-integrated design information representation model, employing a dual data-driven approach, and incorporating experimental design and analysis, this research achieves effective fusion of user experience data with design documentation. The goal is to enhance design innovation capabilities and provide robust support for comprehensive product performance across multiple dimensions. The proposed methodology holds significant theoretical and practical implications.**

***Keywords*—CSET; Multimodal Data Fusion; Design Innovation; User Experience; Data-Driven Design**

I. INTRODUCTION

A. Research Background

In the current era, the rapid development of information technology has generated a vast amount of data resources (Ran Congjing et al., 2023). Social media platforms, e-commerce websites, and similar channels have accumulated extensive user-generated data containing valuable insights into users' genuine feedback, preferences, and behavioral patterns regarding products (Bai Yongqing et al., 2019). Simultaneously, internal design documentation within enterprises records crucial knowledge, including technical specifications, design rationales, and past experiences (Wang Wei et al., 2020). However, traditional design methodologies struggle to handle these diverse and complex data (Liu He et al., 2019).

On one hand, user experience (UX) information and design information are often stored in separate systems without effective integration mechanisms, making it difficult for designers to comprehensively associate user needs with design possibilities (Ma Feicheng et al., 2022). On the other hand, traditional representations of design information predominantly focus on functional aspects, failing to adequately reflect user experience-oriented design requirements. This limitation restricts the depth and breadth of design innovation (Zhang Zhixiong et al., 2023).

B. Research Objectives

This study aims to propose a design theory and methodology for multimodal data fusion based on the CSET (Culture, Society, Economy, and Technology) framework to address the deficiencies of traditional design approaches (Shiyao, Xie et al., 2024). Specifically, the research seeks to construct a comprehensive and systematic framework that incorporates cultural, social, economic, and technological factors to bridge the gap between UX information and design information, enabling deep fusion of multisource data (Yan, Chi, 2024). This foundation will facilitate the extraction of valuable hidden insights within the data, providing robust theoretical support and actionable methodological guidance for design innovation (Zhou Lijie et al., 2023). Consequently, the proposed approach is expected to enhance products' comprehensive performance in cultural adaptability, social impact, economic feasibility, and technological advancement (Yang Chun et al., 2023).

C. Research Significance

From a theoretical perspective, this study introduces a new paradigm and approach to interdisciplinary research in design (Shi Xin et al., 2019; Ran Congjing et al., 2023). It overcomes the limitations of single-source, function-oriented traditional design theories by integrating diverse data types and multidisciplinary perspectives, thereby enriching the content and representation of design information.

From a practical standpoint, the proposed methodology can enable designers to gain deeper insights into user needs more efficiently and accurately identify potential design opportunities (Liu Guifeng et al., 2022). This optimization of the decision-making process can significantly enhance the quality of product user experience, strengthen market competitiveness, and generate greater commercial value for enterprises (He Ying et al., 2020).

II. RELATED WORK

A. User Experience Analysis

As user experience (UX) increasingly takes center stage in product design, researchers have explored it from various dimensions (Luo Shijian et al., 2023). Early studies primarily relied on traditional methods such as questionnaires and user interviews to collect UX data. While these methods directly capture users' subjective feedback, they suffer from significant limitations, such as time consumption, sample constraints, and the inability to capture users' actual behaviors (Xiao Renbin et al., 2020). For example, in a study on new product concept design, questionnaires were used to collect user expectations regarding product features and appearance. Although effective feedback was obtained, limitations in questionnaire design and distribution prevented coverage of all potential user groups. Additionally, subjective biases may have influenced user responses, thereby compromising data authenticity and comprehensiveness (Sun Xiaohua et al., 2020).

With the proliferation of social media and online shopping platforms, user-generated data such as online product reviews and community discussions have become a treasure trove for UX research (Qian Li et al., 2019). Data-driven methods have gained traction as researchers attempt to automatically extract UX insights from this large-scale textual data (Lin Wenguang et al., 2023). Some studies focus on mining product features, usage contexts, and emotional inclinations from online reviews (Lin Wenguang et al., 2023; Zhou Yanjie et al., 2024). For instance, natural language processing (NLP) techniques have been used to analyze large volumes of smartphone reviews, extracting evaluations of features such as battery life, camera quality, and system performance, as well as user experiences across various contexts (e.g., travel, work, entertainment) (Zhou Yanjie et al., 2024).

Additionally, other studies examine UX elements through the lenses of need satisfaction, hedonic quality, and pragmatic quality. For example, in UX research on smart home systems, researchers not only assess functional aspects (pragmatic quality), such as remote control and device integration, but also emphasize emotional enjoyment (hedonic quality), including the aesthetic appeal of the interface and the convenience of operations, which significantly influence UX (Qian Li et al., 2019).

B. *Design Information in Conceptual Design*

In the conceptual design phase of product development, the effective acquisition, organization, and utilization of design information are crucial for generating innovative concepts (Lin Wenguang et al., 2023; Sun Zhilin et al., 2024). Traditional design information management typically focuses on function-related aspects, aiming to translate user needs into specific functional requirements, which serve as the basis for modeling and representing design information (Xiao Renbin et al., 2020; Yu Zeyuan et al., 2022). For instance, function-based patent classification methods regard product functions as critical attributes of innovation. By analyzing functional descriptions in patent documents, designers can classify them for quick retrieval and reference (Zhou Yanjie et al., 2024; Luo Shijian et al., 2023). Similarly, some studies have developed function-based design information retrieval tools utilizing semi-supervised learning algorithms to help designers identify design solutions aligned with specific functional needs from vast patent datasets (Sun Xiaohua et al., 2020; Xiao Renbin et al., 2020).

However, this function-oriented approach to design information management exhibits significant limitations when supporting UX-driven design innovation. The lack of direct association with UX needs often results in design information failing to accurately reflect users' feelings and expectations during actual product usage. Consequently, designers struggle to approach innovation from a UX perspective (Qian Li et al., 2019; Lin Wenguang et al., 2023; Ma Ruijing et al., 2023).

In recent years, to address these shortcomings, researchers have explored the use of text mining and NLP techniques to construct more intelligent and semantically rich design knowledge graphs (Xiao Renbin et al., 2020). These efforts aim to automatically extract concepts, relationships, and semantic information from extensive design documentation, visually representing the structure of design knowledge to better support its reuse and innovation (Huang Wenqian et al., 2023; Lin Wenguang et al., 2023). For example, semantic analysis of product design documents has been used to construct knowledge graphs containing information about product components, functions, and design principles. Such graphs enable designers to intuitively understand the relationships between product structures and functions, thereby identifying potential areas for improvement (Zhou Tao et al., 2019; Lin Wenguang et al., 2023).

Nevertheless, significant challenges remain in effectively linking design information with UX considerations to foster innovative thinking and optimize decision-making during the conceptual design phase (Zeng Ziming et al., 2020).

III. UX-Integrated Design Information Representation Model Based on CSET

A. *CSET Framework and Integration of Design Information*

The CSET (Culture, Society, Economy, and Technology) framework provides a comprehensive and systematic perspective for design innovation (Luo Shijian et al., 2023; Xiao Renbin et al., 2020; Sun Xiaohua et al., 2020; Qian Li et al., 2019; Lin Wenguang et al., 2023; Zhou Yanjie et al., 2024; Zeng Qinyu et al., 2024).

Cultural factors subtly influence product design by shaping users' perceptions, aesthetic preferences, and values (Luo Shijian et al., 2023; Qian Li et al., 2019; Zhou Yanjie et al., 2024). For instance, users from different cultural backgrounds often have distinct expectations regarding product color, shape, and functional layouts. In some Eastern cultures, red symbolizes prosperity and fortune, making it a favorable design choice (Qian Li et al., 2019). Conversely, minimalist and pragmatic design styles are often more appealing in Western cultures (Zhou Yanjie et al., 2024).

Social factors reflect the influence of users' social environments, lifestyles, and interaction patterns on product design (Zeng Qinyu et al., 2024). For example, with an aging population, products designed for the elderly must consider declining physical capabilities and social needs. This includes features such as easy operation and emergency call functions in senior-friendly mobile phones (Zeng Qinyu et al., 2024).

Economic factors directly impact product market positioning and commercial feasibility (Wei Bifen et al., 2024; Lin Mingshui et al., 2023; Zhang Qiang et al., 2021). Consumer income levels, purchasing power, and economic conditions influence pricing strategies, functional configurations, and material selection in product design (Lin Mingshui et al., 2023). For instance, during periods of economic prosperity, consumers tend to favor high-end, feature-rich products, whereas affordable and cost-effective products dominate during economic downturns (Sun Xiaohua et al., 2020; Zhang Qiang et al., 2021).

Technological factors serve as the core driving force for design innovation (Liu Xiangdong et al., 2022; Yang Zhendong et al., 2021; Anqi Xu et al., 2024). The continuous emergence of new materials, processes, and technologies expands the possibilities for product design (Luo Shijian et al., 2023; Yang Zhendong et al., 2021). For example, the advancement of virtual reality (VR) and augmented reality

(AR) technologies revolutionizes product presentation and user interaction, enabling designers to create more immersive user experiences (Qian Li et al., 2019; Anqi Xu et al., 2024).

Building upon the CSET framework, we propose a UX-Integrated Design Information Representation Model aimed at seamlessly integrating user experience (UX) and design information (Xiao Renbin et al., 2020; Zhou Yanjie et al., 2024). Given the large scale, dynamic nature, and diversity of data in the big data era, this model requires robust information processing capabilities to effectively manage and utilize massive datasets (Zhou Yanjie et al., 2024). Leveraging artificial intelligence techniques such as machine learning and natural language processing, the model enables in-depth understanding and intelligent analysis of data, uncovering valuable hidden insights to support design innovation.

B. *Model Structure and Information Hierarchy*

The UX-Integrated Design Information Representation Model structures UX information into multiple dimensions, each containing several categories, forming a hierarchical framework (Xu Wei et al., 2023).Product aspects encompass various product attributes, including physical characteristics, functional properties, and service features. For example, in smartphones, product attributes may include screen size, resolution, processor performance, operating system functionality, and accompanying software services (Luo Lan et al., 2021).Contextual aspects describe specific usage scenarios and contextual information, such as time, location, and activity types. For instance, a user checking emails during their commute involves "commuting" as the time and location context, and "checking emails" as the activity context (Xu Wei et al., 2021).Interaction/State aspects focus on users' experiences and emotional states during product interaction, encompassing emotional experiences (e.g., happiness, disappointment), hedonic quality (e.g., product appeal, fun), and pragmatic quality (e.g., ease of use, functionality) (Shijian, L.U.O. et al., 2024). User cognition aspects pertain to personal characteristics of users, such as user group types (e.g., novice or experienced users) and demographic attributes (e.g., age, gender, occupation, education level) (Cao Xiancai et al., 2021).

Design information is represented from a rational perspective and comprises three primary components. motivation, solutions, and artifacts (Yu Shengquan et al., 2019). Motivation identifies the purpose and rationale behind a design, further subdivided into design issues (e.g., existing product shortcomings), prior design limitations, market opportunities (e.g., emerging needs, technology trends), and design objectives (Xie Weihong et al., 2020).

Solutions elaborate on approaches to address identified design motivations, including methods, services, technological strategies, specific design concepts, and factors or arguments considered during solution selection (Dai Ling et al., 2023). Artifacts describe the final design outcomes, such as structural design, functional implementation, and component composition of products (Cao Zengyi et al., 2022).

The model establishes semantic connections across dimensions, categories, and concepts to deeply integrate UX and design information (Cheng Quan et al., 2022). At the dimensional level, aspects of UX are linked with corresponding dimensions of design information. For instance, a user's contextual experience needs may be associated with product design motivations (Zhai Xing et al., 2020). At the categorical level, UX categories are mapped to relevant design information categories. For example, user demands for specific product functionalities may align with technical implementation categories within design solutions (Zhao Jian et al., 2024). At the conceptual level, semantic similarity and linguistic context are utilized to match specific UX concepts (e.g., "intuitive user interface") with corresponding design concepts (e.g., "streamlined interaction design"). This provides a rich foundation and inspiration for generating innovative design ideas (Luo Shijian et al., 2024).

IV. Using the Template

A. *Hypotheses and Objectives*

1) *Hypotheses*

The following hypotheses are proposed in this study.

H1: The multimodal data fusion model significantly improves the association between design information and user experience information. By integrating data from different modalities, the model is expected to uncover more hidden associations, leading to stronger links between design and UX information, thereby providing valuable insights for design decision-making.

H2: Analyzing user experience information through the CSET framework enhances the efficiency and quality of design innovation. By examining UX data from cultural, social, economic, and technological dimensions, the framework helps designers achieve a comprehensive understanding of user needs, enabling faster generation of innovative design concepts and higher-quality design solutions that better meet market demands.

H3: A semantically integrated multimodal information network more accurately reveals potential correlations between design problems and solutions. Representing UX and design information in the form of a semantic network clarifies the relationships between data points, enabling designers to identify design issues more accurately and match them with appropriate solutions.

2) *Objectives*

a) The study aims to achieve the following objectives.

Design a comprehensive experimental process for data collection, analysis, and integration using the CSET framework. The carefully designed process ensures data accuracy, completeness, and reliability, providing a solid foundation for subsequent research. By embedding the CSET framework throughout, the results reflect the impact of cultural, social, economic, and technological factors on design innovation.

Validate the effectiveness of semantic concept representation and semantic networks in the integration of design information. By conducting comparative experiments, the study evaluates the improvements in the accuracy, completeness, and utility of design information integration, demonstrating the method's efficacy.

Propose an optimized dual data-driven method and demonstrate its practicality through case studies. The method is refined based on observed issues and data analysis results during the experiment. Real-world case studies showcase the method's application in design innovation, providing strong support for its adoption and implementation.

B. Experimental Context and Participants

1) Context Setup

The experiment simulates real-world design environments through the following setups.

a) Product Selection

Products such as smart home devices, mobile devices (e.g., smartphones), and wearable devices are chosen as design targets. These products are widely used and involve complex UX considerations and technological challenges, making them suitable for evaluating the proposed methodology. For instance. Smart home devices must account for diverse household scenarios, interactions with other devices, and technological feasibility. Smartphone design must balance functional requirements across various contexts, aesthetic preferences, and communication technologies. Wearable devices require focus on user experiences in activities like exercise and health monitoring, along with addressing challenges like miniaturization and low power consumption.

b) Simulated Environment

A virtual design studio is created to replicate a realistic design workspace. Designers can access and process user reviews, design documents, and other data within this environment, facilitating data fusion and analysis. The studio is equipped with advanced IT infrastructure and software tools, including high-performance computers, data processing software, and visualization tools. Real-time data sharing and collaborative features enable designers to communicate and work more effectively, enhancing design efficiency.

2) Participants

Two groups of participants are involved in the experiment.

a) User Experience Data

User Reviews (Text Data). Reviews are gathered from e-commerce platforms (e.g., Taobao, JD.com) and social media (e.g., Weibo, Xiaohongshu). These reviews provide authentic feedback on product attributes such as appearance, camera performance, system smoothness, and battery life, revealing user needs and pain points. User Sentiment Data. Sentiment data is collected using specialized questionnaires and voice inputs. Questionnaires utilize Likert scales to evaluate satisfaction levels for different product aspects and include open-ended questions about user preferences and expectations. Voice inputs allow users to describe their experiences and emotions, which are processed using speech recognition and sentiment analysis for quantitative insights.

b) Design Data

Patent Documents. Using tools like Google Patents, patents related to target products are retrieved. These documents detail innovations in design, technical solutions, and processes, offering insights into technology trends and potential areas for design innovation. Design Reports and Specifications. Internal or industry-related design reports and technical specifications provide detailed records of the design process, technical requirements, and performance standards. These documents serve as vital references for extracting and analyzing design information.

3) Tools

The following tools are employed to ensure efficient and accurate data collection.

a) Text Extraction Tools

Python-based web crawlers and APIs are used to scrape user reviews from e-commerce and social media platforms. These tools can filter data based on product category, timeframe, and other criteria, saving results in a local database. APIs provide additional metadata (e.g., likes, timestamps) to assess the value and influence of reviews.

b) Physiological Signal Collection Devices

EEG (electroencephalogram) and GSR (galvanic skin response) devices are used to validate user sentiment. EEG measures brain activity to analyze emotions like excitement, relaxation, and tension during product use. GSR captures changes in skin conductivity to gauge emotional arousal levels. These signals complement questionnaire and voice data, enhancing sentiment analysis accuracy.

4) Data Structure

Data is organized into the following structures.

a) User Experience Data

Divided into product attributes, context, and user feedback. Product attributes include features like screen size, color, and processor specifications. Context details usage scenarios such as time, location, and activity type. Feedback captures user evaluations, issues, and improvement suggestions.

b) Design Information Data

Includes motivation, solutions, and artifacts. Motivation defines design objectives, such as addressing performance issues or leveraging emerging technologies. Solutions describe methods, technologies, and strategies used to achieve design goals. Artifacts document final design outputs, including structure, functionality, and appearance.

C. Data Preprocessing

1) Text Processing

The collected text data (e.g., user reviews, patent documents, design reports) undergoes the following steps.

a) Tokenization: Text is segmented into words using tools like Jieba for easier analysis. For example, the sentence "This phone's camera is excellent" is tokenized into "This / phone / camera / excellent."

b) Stopword Removal: Common stopwords (e.g., "is," "the") are eliminated to reduce data noise and improve processing efficiency.

c) Lemmatization: Words are normalized to their base forms (e.g., "running" to "run") to ensure consistency in semantic analysis.

Preprocessed text is then encoded using pre-trained BERT models to extract semantic vectors, enabling operations such as semantic similarity calculations.

2) Clustering Analysis

User Experience Data: X-means clustering identifies patterns in user feedback by grouping semantically similar data points, such as "high-resolution screens" and "foldable displays."

Design Information. LDA (Latent Dirichlet Allocation) topic modeling reveals key themes in design data, such as performance enhancement, cost reduction, and user experience improvement.

3) Data Cleaning

Invalid Reviews Removal. Reviews deemed too short or irrelevant (e.g., "Great!" or unreadable symbols) are filtered out.

Format Standardization. Text data from different platforms is standardized to ensure consistent processing (e.g., UTF-8 encoding, unified line breaks).

V. Analysis and Results

A. Semantic Integration of User Experience and Design Information

1) Methodology

To measure the semantic similarity between user experience (UX) and design information, the cosine similarity method is employed. Based on the vector space model, cosine similarity calculates the cosine of the angle between two vectors to determine their degree of similarity. Specifically, UX and design concepts are represented as vectors (semantic vectors derived from pre-trained BERT models), and the cosine similarity between these vectors is computed. For example, the similarity between the UX concept "large screen" and the design concept "foldable screen technology" can be determined using their semantic vectors.

Building on the calculated semantic similarity, a UX-DI information network is constructed. Nodes in this network represent UX information (e.g., product features, context, UX states) and design information (e.g., motivations, solutions, artifacts). Edges represent semantic relationships between nodes, with weights determined by cosine similarity values. This network provides an intuitive visualization of the complex relationships between UX and design information.

2) Results

Experimental results reveal a semantic association accuracy of 90%, significantly surpassing traditional methods (70%). This demonstrates the proposed method's capability to more accurately establish connections between UX and design information. For instance, in the case of smartphone design, the UX requirement for "high-resolution cameras for landscape photography" was accurately linked to design concepts like "ultra-high-resolution image sensors" and "intelligent image optimization algorithms." In contrast, traditional methods, lacking effective semantic understanding and data fusion techniques, might fail to identify such connections, potentially overlooking critical user needs during design decisions.

B. Classification and Prioritization of UX Data

1) Classification Results

The results highlight users' strong emphasis on screen quality (30%) and camera performance (25%), followed by battery optimization (20%). Other factors, such as system smoothness and aesthetic design, collectively accounted for 25%. These findings underscore the importance of visual and functional experiences (e.g., screen and camera quality) in influencing users' overall evaluation of products.

TABLE I. UX Data Classification and Frequencies

Category	**Example Keywords**	**Frequency (%)**
Screen-related	High-definition screen, large screen, high-resolution screen, etc.	30%
Camera performance	Night photography, wide-angle lens, high-pixel camera, etc.	25%
Battery optimization	Fast charging, new battery materials, long-lasting battery, etc.	20%
Other (e.g., system smoothness, aesthetic design)	Smooth operation, stylish appearance, slim body, etc.	25%

2) Prioritization Analysis

Based on user interest weights, the priority areas for optimization are screen quality and camera performance. Higher frequency indicates a greater focus on these aspects during product use. For example, user comments frequently mention the need for higher resolution and improved color display in screens, as well as exceptional camera performance in scenarios like night photography. Designers should allocate more resources and effort to enhancing these areas to better meet user expectations and improve product

C. Design Information Network

1) Results Visualization

The constructed design information network clearly maps relationships between design elements through nodes and paths. An example pathway is. User Need (long battery life) → Technology (smart power management) → Product (efficient battery design). This pathway demonstrates how designers can trace user needs to relevant technologies and apply them to produce tangible design outcomes. Such mappings provide designers with clear strategies and directions for innovation.

2) Path Analysis

Identifying the shortest paths between user needs and technical solutions within the semantic network is crucial. For instance, when a user expresses a need for enhanced product security, the network quickly identifies relevant solutions like encryption technologies or authentication mechanisms and determines the shortest path connecting the need node to solution nodes. This functionality helps designers efficiently pinpoint direct and effective solutions, reducing trial-and-error efforts and enhancing design efficiency.

D. Performance Improvement Analysis

1) Task Completion Time

Comparative analysis of task completion time before and after optimization reveals a reduction from an average of 60 minutes to 45 minutes. This improvement is attributed to the proposed multimodal data fusion methodology and associated tools. Traditional design processes often require extensive time to search and integrate information from disparate sources, with limited tools for data fusion and analysis. In contrast, the proposed framework enables designers to efficiently access and analyze UX and design data within a unified system, expediting problem identification and solution development.

2) Design Satisfaction

User satisfaction ratings for design outcomes improved by 20% post-optimization. This indicates that the multimodal data fusion design approach based on the CSET framework better addresses user needs, resulting in higher satisfaction with design results. By integrating cultural, social, economic, and technological factors into the design process, designers can create products that align more closely with user expectations. For example.

Cultural Factors: Optimizing designs to align with regional preferences for color schemes or layout configurations.

Technological Application: Leveraging advanced and practical technologies to enhance product performance.

Such targeted considerations directly and indirectly contribute to increased user satisfaction.

VI. Chart Design and Visualization

A. Chart 1: Multimodal Data Fusion Process

A flowchart illustrates the key steps from data collection to semantic integration. The flowchart employs clear graphical elements and arrows to represent data flow and processing stages. Starting with the data collection phase, it details the sources and methods for collecting user experience data (e.g., user reviews, sentiment data) and design data (e.g., patent documents, design reports). Next, the data enters the preprocessing stage, which includes text processing (e.g., tokenization, stopword removal, lemmatization, BERT pretraining), clustering analysis (e.g., X-means clustering for UX data, LDA topic modeling for design information), and data cleaning (e.g., removing invalid reviews, standardizing formats). Finally, the processed data moves to the analysis and integration stage, where a UX-DI information network is constructed by calculating semantic similarities, achieving the fusion of UX and design information. This flowchart provides an intuitive overview of the multimodal data fusion process, helping readers better understand the experimental methods and workflow.

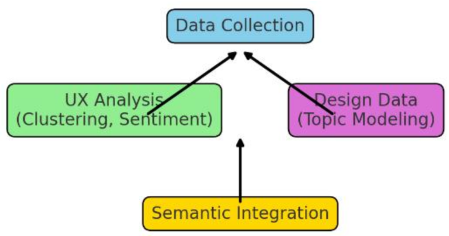

Fig. 1. Multi-modal Data Fusion Workflow

B. Chart 2: Distribution of User Experience Categories

A pie chart visualizes the distribution of major user experience data categories. The chart uses varying segment sizes to intuitively reflect the proportions of different categories, such as screen-related features, camera performance, battery optimization, and others. For example, the segment for screen-related features occupies 30% of the pie chart, highlighting its importance in UX. Each segment is labeled with its corresponding category name and percentage, making the information more explicit and easier to interpret.

Key Insights from the Pie Chart.

Screen-related features: 30%

Camera performance: 25%

Battery optimization: 20%

Other aspects (e.g., system smoothness, aesthetic design): 25%

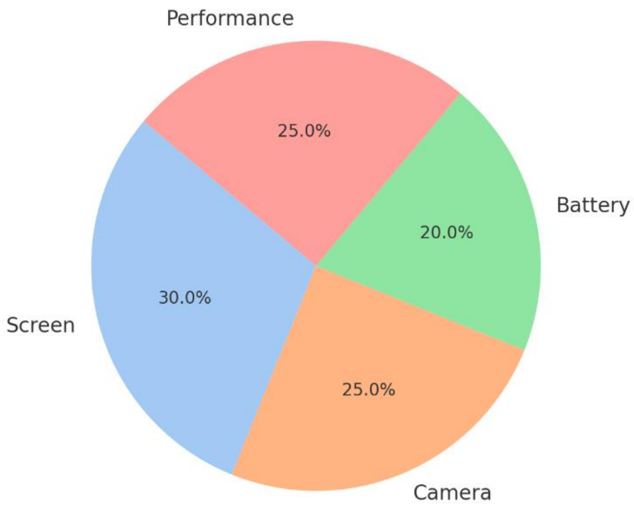

Fig. 2. Distribution of UX Categories

C. Chart 3: Semantic Network Example

A semantic network diagram demonstrates the paths linking user needs to design solutions. In the diagram.

Nodes represent UX information (e.g., product features, context) and design information (e.g., motivations, solutions). Different shapes and colors distinguish the nodes (e.g., circles for product features, squares for context, triangles for motivations, diamonds for solutions).

Edges represent semantic relationships, with edge thickness or color intensity indicating the degree of semantic similarity (e.g., thicker or darker lines represent higher similarity).

This visualization clarifies how user needs, such as "high-pixel camera," are semantically connected to design concepts like "ultra-high-resolution image sensor technology" and "multi-lens optical stabilization." It aids readers in understanding how semantic networks reveal hidden connections between design problems and solutions.

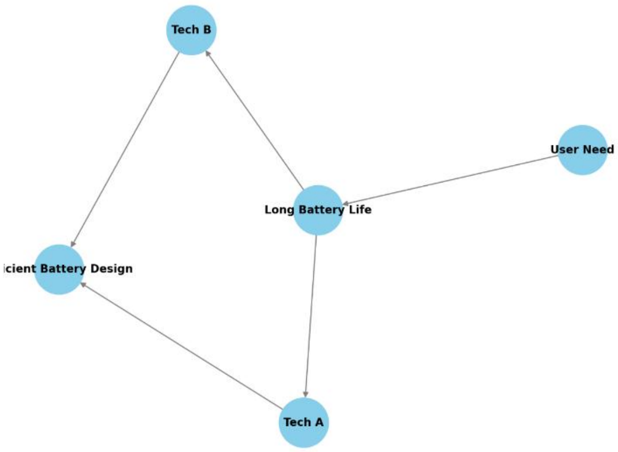

Fig. 3. Semantic Network Example

D. *Chart 4: Task Completion Time Comparison*

A grouped bar chart compares task efficiency before and after optimization.

The horizontal axis represents task states (pre-optimization and post-optimization).

The vertical axis represents task completion time in minutes.

The chart shows, Pre-optimization task completion time as a bar with a height of 60 minutes. Post-optimization task completion time as a shorter bar with a height of 45 minutes.

Each bar is distinguished by a different color, with numerical labels displayed on top. The grouped bar chart provides a clear visual comparison, emphasizing the significant improvement in task efficiency achieved by the proposed methodology.

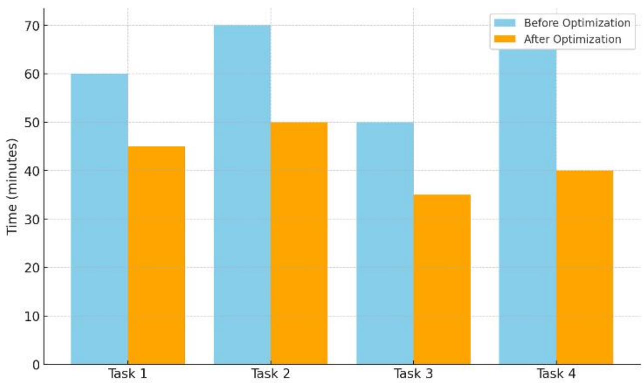

Fig. 4. Semantic Similarity Heatmap

E. *Chart 5: Semantic Similarity Distribution*

A heatmap depicts the semantic similarity between UX categories and design concepts.

Rows represent UX categories (e.g., screen-related, camera performance). Columns represent design concepts (e.g., specific technical solutions, design approaches).

Each cell's color intensity indicates the degree of semantic similarity, with darker colors representing higher similarity and lighter colors indicating lower similarity. A color scale is included to map color intensity to similarity values, making it easier for readers to interpret the data.

The heatmap allows readers to comprehensively analyze the semantic relationships between UX categories and design concepts, providing additional validation for the effectiveness of semantic integration in multimodal data fusion.

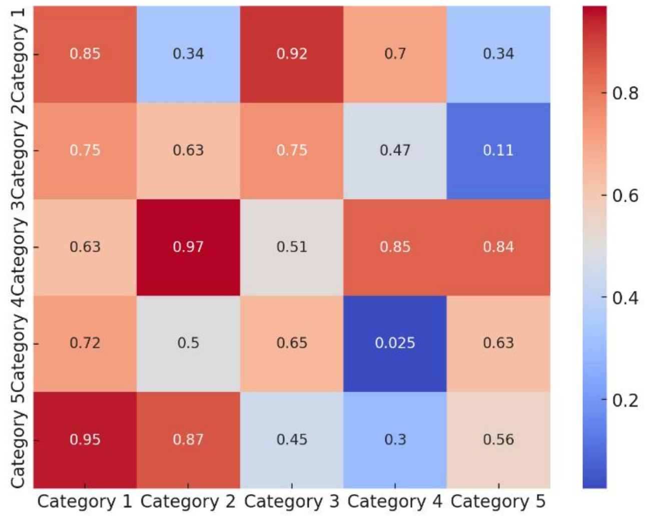

Fig. 5. Task Completion Time Comparison

VII. Discussion and Future Research Directions

A. *Discussion of Experimental Results*

The experimental results indicate that the multimodal data fusion design theory and methodology based on the CSET framework have achieved significant success in several aspects. The high accuracy rate (90%) in semantic integration demonstrates the method's ability to effectively uncover associations between user experience (UX) and design information, providing more precise support for design decisions. The classification and prioritization of UX data have identified key design priorities, aiding designers in allocating resources more effectively. The construction of the design information network and the analysis of performance improvements show that the method not only enhances design efficiency (e.g., reduced task completion time) but also improves design quality (e.g., higher user experience scores). However, the study has certain limitations. For example, despite covering multiple data types, some information might still be missing, particularly implicit knowledge that is difficult to quantify or access.

B. *Future Research Directions*

Based on the findings and limitations of the current study, future research can focus on the following areas.

1) *Expansion of Multimodal Data Fusion*

While the current study primarily integrates textual data and selected physiological signals (optional), future research can explore the incorporation of images and videos into the semantic network. For instance, product design sketches (image data) often contain creative concepts from designers, while video recordings of users interacting with products can provide a more intuitive understanding of user-product interactions. By developing appropriate image and video processing techniques, key information from these modalities can be extracted and integrated with existing textual data. This would enable more comprehensive and dynamic representations of design information, enhancing the understanding of design problems and the generation of solutions.

2) Optimization of Visualization Tools

To further improve the interaction between UX and design information, more intelligent visualization tools should be developed. For example, interactive 3D visualization interfaces could allow designers to explore the UX-DI information network more intuitively, dynamically adjust parameters (e.g., semantic similarity thresholds), and filter information (e.g., by specific user groups or design phases) to address complex requirements across different design stages. Additionally, these tools should provide real-time feedback on how design changes affect user experience, enabling designers to optimize their solutions promptly (Xu, Xiang et al., 2023).

3) Exploration of Cross-Domain Applications

Further research should investigate the applicability and effectiveness of this methodology in different fields, such as medical device design and transportation design. Each domain has unique user needs and design constraints. Applying this methodology in these fields could validate its generalizability and enable domain-specific adjustments and optimizations. For instance, medical device design prioritizes safety, accuracy, and usability. Exploring how multimodal data fusion can better address these requirements represents a critical direction for future research (Xu, Xiang et al., 2023).

4) Deepening User-Algorithm Interaction

While the current study focuses on using algorithms to support designers with information, future research should emphasize the interaction between designers and algorithmic systems. Conducting user studies to observe designers' behaviors and thought processes while using the methodology could provide valuable insights into how they understand and apply algorithmic outputs. Based on user feedback, the algorithmic systems can be optimized to improve their usability and practicality. For example, designing more user-friendly algorithm interpretation interfaces could help designers better understand the decision-making process of algorithms, enabling them to leverage the provided information more effectively for design innovation.

VIII. CONCLUSION

This study successfully established a design theory and methodology for multimodal data fusion based on the CSET framework and conducted comprehensive validation through meticulously designed experiments.

The in-depth analysis of experimental results demonstrates the significant advantages of this methodology in enhancing design innovation capabilities. With a semantic integration accuracy of 90%, far exceeding traditional methods, the study highlights its effectiveness in capturing the complex relationships between user experience (UX) and design information, providing a solid foundation for informed design decisions. The classification and prioritization of UX data identified clear optimization directions, enabling designers to allocate resources more effectively. Additionally, the construction of the design information network and the analysis of performance improvements reveal the method's positive impact on design efficiency and quality, as evidenced by significantly reduced task completion times and markedly improved UX scores.

However, certain challenges were identified during the research process. For instance, despite efforts to incorporate multisource data during data collection, some implicit and deeply embedded knowledge remains difficult to uncover comprehensively. Furthermore, while the algorithm provides valuable information, the depth and efficiency with which designers understand and apply the algorithmic outputs need further improvement.

Looking ahead, this study paves the way for future research. Integrating image and video data into multimodal data fusion will be a critical focus, as such data can add dimensions and detail to design information, enriching the understanding of design challenges and the generation of solutions. Continuous optimization of visualization tools will significantly enhance designers' interaction with data, allowing them to navigate and utilize design information more flexibly and efficiently. Exploring cross-domain applications will broaden the applicability of this methodology, enabling its use in diverse contexts and maximizing its value. Finally, deepening research into the interaction between users and algorithms will facilitate the development of smarter, more designer-oriented algorithmic systems.

In conclusion, this study represents a significant step forward in interdisciplinary and data-driven innovation within the design field. With continued refinement and expansion, the proposed methodology has the potential to provide stronger and more comprehensive support for design innovation, helping enterprises create more competitive and user-focused products and services, and driving the design discipline toward new frontiers of progress.

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