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An Analysis and Modeling Method for Design Information Based on User Generated Reviews Mining and Extenics

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Abstract. To address the inapplicability of data classification results in industrial design, and the lack of theoretical research on design information analysis methods, a design information analysis method based on user experience data was proposed. User experience positive and negative user experience datasets were established through user experience data mining and applying text classification algorithms to perform initial processing of the data. Design features are obtained by extracting effective information from the data, and a design feature analysis is established by combining with the extension class element theory model. Effective information about users and products in the data is classified and analyzed; a conjugate relation between user information and product information is studied, and a design information correlation transformation model is established based on the extension compound theory. Finally, user and product information correlation analyses are combined to obtain an effective product design strategy. The effectiveness of this method is verified by taking electric scooters used by the elderly as an example.

Keywords. User experience; data mining; text classification; extension model

1. Introduction

E-commerce websites serve as a bridge for communication between users, and between users via enterprises. User generated reviews (UGR) has become an important strategic resource for current enterprises, and methods for obtaining useful information from UGR generated online are a hotspot in current research [1].

UGR is mostly composed of plain text, and its structure is diverse and vague, requiring tremendous efforts to extract relevant detailed information[2] . In the front-end analysis for design, it is necessary to extract effective information from the data, and analyze the data in combination with design theory. Current researches on the analysis of data generated by users online mainly focused on sentiment quantification [3], sentiment analysis [4], feature extraction [5], and user Kansei image extraction[6].

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The combination of Kansei engineering and UGR mining can help extract users' emotional requirements efficiently; however, when the subsequent data are applied to design procession, it is difficult to achieve the user information and product information fully to dominate the later product design and development planning effectively. In response to these problems, many related methods from the perspective of user data feature extraction were explored. For example, Zhou et al. [7] proposed an enhanced feature model based on emotional features and rough set methods, mining user preferences from user comment data related to specific product features and improving the quality and efficiency of product line planning to a certain extent. Guang-yao et al. [8] proposed a data conversion method by combining rough set theory and quality function deployment (QFD). By integrating Linguistics, Kansei engineering, and computers, Jiao Y et al. [9] proposed a method of Kansei knowledge extraction from UGR, and a relational extraction method to generate the relationship of product design features and user perceptual evaluation.

However, there is not enough attention on how to classify these product features and demand information, and how to guide the final product improvement, optimization and innovation. Product features were effectively correlated, and design problems were transformed to devise product design strategies to satisfy user requirements. Taking electric scooters used by the elderly as an example, the specific test and analysis procedure of the design information analysis method proposed in this paper were demonstrated.

Most current studies mainly focused on English. There is a significant difference between English and the dominant languages spoken in China. The techniques and methods used for English comments cannot be directly applied to Chinese comments [3]. research on mining UGR information in Chinese is imperative. Therefore, we developed a design information analysis and modeling method based on the extenics theory suitable for extracting user experience information from Chinese reviews.

2. Extenics theory

2.1. Extension elements and extension class elements

Extension elements include object elements, feature elements and relation elements. They are the logical cells of extenics and are collectively called elements. Extension element theory can help designers effectively and clearly express the relation among user requirements, functions, and the environments in the design process.

To describe a class of objects, the concept of class elements are defined in the extension element theory [10]. Given an object $\{O\}$, if for any $\{O\}$, regarding the feature c_i $(i = 1,2,\dots,n)$, $v_i = c_i(O) \in V_i$, then $\{B\}$ is expressed in Eq.(1):

$$\{B\} = \begin{bmatrix} \{O\}, & c_{1,} & v_1 \\ & c_{2,} & v_2 \\ & \vdots & \vdots \\ & c_{n,} & v_n \end{bmatrix} = (\{O\}, C, V) \tag{1}$$

Here, V_i is the value of feature C_i, and B is the class elements.

2.2. Extension analysis method

The extension analysis method is the basis of creativity generation in extension science, including two categories: extension analysis method and conjugate analysis method [11].

The extension analysis method is a formal method to expand elements and obtain multiple innovation paths or ideas for solving contradictory problems, including divergence tree method, correlation network method, implication system method, and split-combination chain method. In the analysis process of design problems in front-end design, how to define the interrelations between problems and determine the correlation between various factors are bottlenecks faced by designers.

The conjugate analysis method divides objects into four different sets in terms of its materiality, systematicness, dynamicity, and opposition: imaginary, real, and intermediate parts; soft, hard, and intermediate parts; latent, visible, and intermediate parts; and positive, negative, and intermediate parts, respectively, thus totaling four groups of eight pairs of conjugate parts [12].

3. Data *min*ing experiment

3.1. Experimental process

Electric scooter used by the elderly are taken as an example to mine the user experience data of the product from Jingdong E-mall (www.jd.com).

- The requests library in the Python programming language was used in the form of a lightweight web crawler, and a total of 4,523 pieces of data were crawled. After deleting invalid data, 2,042 pieces of data were obtained for analysis
- The small amount of noise was cleaned up and invalid characters and punctuations were removed; Jieba library was applied to obtain segmented data.
- In the stage of calculating the word vector, the Word2Vec word vector training model [13] was used to calculate the word vector for word segmentation.
- In the data classification stage, the Bi-LSTM algorithm [14] was used for text classification. Based on the emotional polarity, the UGR data were divided into positive data and negative data. And both positive and negative user UGR datasets were established.

3.2. Results of data classification

After data classification, a total of 1,800 positive UGR data and 246 negative UGR data were obtained, as shown in Table 1.

Table 1. Positive and negative UGR dataset

Positive user experience data
I bought it for grandpa. It is inconvenient for old people to commute in. Yes, I like it very much. The scooter is small, easy to assemble, easy to operate, and smooth to drive. Recommend!
…
Negative user experience data
Except for the lack of battery volume, everything is OK. The seat is not high enough, so I have to adjust it to the highest Position.
…

Through the analyzing of Table 1, it is found that the data obtained through the data classification algorithm are relatively formless and hard to be applied to design analysis and practice directly. The data contain many types of effective information related to product design, and further effective information should be extracted. Effective design information is mainly concentrated in negative user data [15].

4. Methodology

4.1. Design information and feature extraction

Python was applied to segment the negative data content. And data statistics was performed on the part of speech and word frequency of each word obtained.

Initial data statistics shows that UGR cover users (elderly, etc.), products (battery, seat, charger, wheels, etc.), behavior (traveling, shopping, ordering, etc.), performance (slow, speed, braking, workmanship, etc.), service (attitude, after-sales service, poor, etc.), and other related information, which will be specifically classified in subsequent research.

By analyzing the content of negative data, relevant user and problem descriptions are obtained, as shown in Table 2.

Table 2. User descriptions and problem descriptions

Negative UGR data	User description	Problem description
Power display on the dashboard needs improving, difficult to recognize for the elderly.	Decreased vision	Small instrument panel display
There is no speed gear; there is only one speed; ; the old man responds slowly.	Slow response	There is no speed gear
…	…	…

Based on Table 2, the hidden design information was extracted and classified, as shown in Table 3.

Table 3. Design feature extraction

Design information	Feature attribute	Feature classification
safety and stability	psychological	User Feature
tire material, scooter body material, chassis material	material	Product Feature
…	…	…

4.2. Design feature classification

From the design feature extraction results reported in Section 4.1, the design features can be divided into user features and product features. The former includes physiological features, psychological features, demand features, and behavior features. The latter includes internal and external features. Internal features refer to the information about each component of the product, including structure, material, and function; external features refer to the information that reflects the interaction between users and products, and between products and the environment.

4.3. Extension design information analysis and modeling

To efficiently obtain, identify, sort, and classify the useful and meaningful design information data of different dimensions from UGR, an extension design information analysis method based on the extension element theory, conjugate analysis method, extension composite element theory, and extension transformation theory was proposed. The method was shown in Fig. 1.

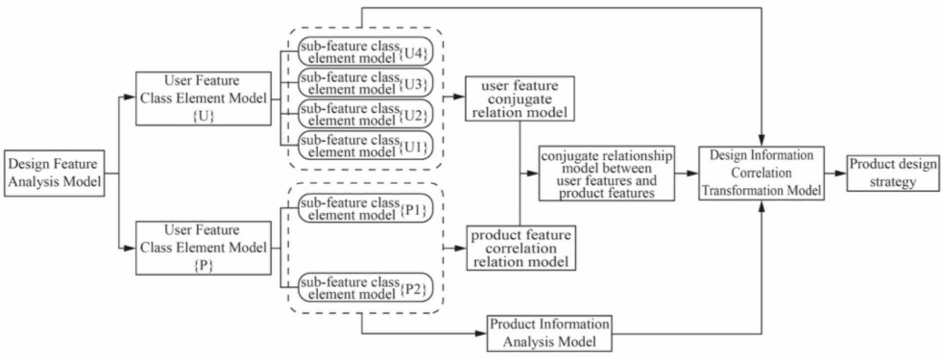

Figure 1. Extension design information analysis

4.3.1 Design feature analysis model

A design feature analysis model is constructed based on the extension class element theory, including a user feature class element model and a product feature class element model. The user feature class element model is expressed in Eq. (2):

$$\{U\} \Rightarrow \{U_1\} \wedge \{U_2\} \wedge \{U_3\} \wedge \{U_4\} \tag{2}$$

$\{U\}$represents the user feature class element: user physiology feature class element, user psychology feature class element, user demand feature class element, and user behavior feature class element; "∧" represents the juxtaposition relations of the four sub-feature class elements.

$$\{U_1\} = \begin{bmatrix} \{O_1\}, & C_{11}, & V_{11} \\ & \cdots & \cdots \\ \{O_n\}, & C_{ij}, & V_{ij} \\ & \cdots & \cdots \end{bmatrix} \tag{3}$$

where$\{O\}$represents the object of the sub-feature element, C represents the feature, V represents the value of the object O about the feature C, $n \geq 1$, $i \geq 1$, and $j \geq 1$. And the mutual influence relation between the sub-feature class elements is described:

$$mid_U = \{U_1\}\otimes\{U_2\}\otimes\{U_3\}\otimes\{U_4\} \tag{4}$$

The product feature class element model is expressed in Eq. (5):

$$\{P\} \Rightarrow \{P_1\} \wedge \{P_2\} \tag{5}$$

$\{P\}$ represents the product feature class element, and $\{P_1\} \wedge \{P_2\}$ represents the juxtaposition relation between the product internal feature class element $\{P_1\}$ and the product external feature class element $\{P_2\}$. $\{P_1\}$ is expressed in Eq. (6):

$$\{P_1\} = \begin{bmatrix} \{O_1\}, & C_{11}, & V_{11} \\ & \cdots & \cdots \\ \{O_n\}, & C_{ij}, & V_{ij} \\ & & \cdots \end{bmatrix} \tag{6}$$

where $\{O\}$, C, and V respectively represent the object, the feature of the object and the value of $\{O\}$ about the feature, $n \geq 1$, $i \geq 1$, and $j \geq 1$.

There are interrelations within the product feature class elements and within each sub-feature class element. The correlation net method [23] is used to describe this interrelated relation, as expressed in Eq. (7):

$$\{P_1\}(O_1 \wedge \ldots \wedge O_n) \sim \{P_2\}(O_1 \wedge \ldots \wedge O_n) \tag{7}$$

The correlation among each sub-feature class element is expressed in Eq. (8):

$$\{P_1\} \sim (O_1 \sim O_2 \sim \cdots \sim O_n) \tag{8}$$

4.3.2 Product information analysis model

A product information analysis model was established to obtain and analyze the product information from the product feature class element in depth. The product information class element and its sub-feature class element were established on the basis of the objects in the product sub-feature class element.

The product information analysis model was expressed in Eq. (9):

$$\{I\} \Rightarrow [\{I_1\} \wedge \{I_2\} \wedge \{I_3\} \wedge \ldots \wedge \{I_n\}] \tag{9}$$

$\{I\}$ represents the product information class element, $\{I_1\} \wedge \ldots \wedge \{I_n\}$ represents the sub-class elements of the product information class element and their juxtaposition relation. The sub-class element model is expressed in Eq. (10):

$$\{I_1\} = \begin{bmatrix} \{O_1\}, & C_{11}, & V_{11} \\ & \cdots & \cdots \\ \{O_n\}, & C_{ij}, & V_{ij} \\ & \cdots & \cdots \end{bmatrix} \tag{10}$$

where $\{O\}$, C, and V represent the object, the feature of the object, and the value of $\{O\}$ about the character respectively, $n \geq 1$, $i \geq 1$, and $j \geq 1$.

4.3.3 Design information correlation transformation model

During the design analyzing and problem solving, there is often a conjugate relation between user information and product information, as expressed in Eq. (11):

$$mid_{U-P} = \{U\} \otimes \{P\} = A \tag{11}$$

Therefore, it is necessary to perform a correlation analysis on the extracted and classified information based on their conjugate and correlation relations, as shown in Fig. 2

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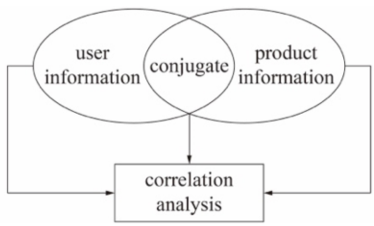

Figure 2. Conjugate analysis chart of user information and product information

The design information correlation transformation model was established on the basis of the extension compound theory of the matter and affair elements. We supposed A taken multiple user feature class elements with conjugate relations as the product function element, as expressed in Eq. (12):

$$A(\{U_1\} \wedge \ldots \wedge \{U_n\}) = \begin{bmatrix} U_1\{O_1\} \wedge \ldots \wedge U_n\{O_n\}, & AC_1, & AV_1 \\ & \cdots & \cdots \\ & AC_n, & AV_n \\ & C_{DA}, & V_{DA} \\ & \cdots & \cdots \end{bmatrix} \to TA = \begin{bmatrix} U_1\{O_1\} \wedge \ldots \wedge U_n\{O_n\}, & C'_{DA}, & V'_{DA} \\ & \cdots & \cdots \end{bmatrix}$$

(12)

Here, the model takes multiple sub-feature class elements in the user feature class elements as objects $U_1\{O_1\} \wedge \ldots \wedge U_n\{O_n\}$; AC is the feature value related to the multiple sub-feature class elements in the user feature class element; AV is the value of AC, and C_{DA} is the design feature analyzed from the object $U_1\{O_1\} \wedge \ldots \wedge U_n\{O_n\}$;$V_{DA}$ is the value of C_{DA}; TA represents the new product function element obtained by transformation, that is, the new product design strategies. The feature C'_{DA} is the optimization direction of TA, and V'_{DA} is the value of C'_{DA}.

5. Deduction of the new product strategies

5.1. Design feature analysis model

5.1.1 User feature analysis model

Using Eqs. (2) and (3) to analyze the user feature and combining with the data listed in Table 1, the user feature of the electric scooter was obtained. The users are elderly people over 60; the user physiological feature $\{U_1\}$ were expressed as Eq. (13):

$$\{U_1\} = \begin{bmatrix} \text{vision loss,} & \text{Affecting the distinction of things,} & \text{Simplification of manipulation the display} \\ & & \text{The bright color of the font} \\ & & \text{Enhancing text recognition} \\ \text{memory decay,} & \text{Affecting product operation,} & \text{Simplification of control settings} \\ \text{slow response,} & \text{Affecting judgment} & \text{Simplification of driving control} \\ & \text{of driving obstacles,} & \text{Intelligent auxiliary speed regulation} \\ \text{reduced mobility,} & \text{Weak control,} & \text{Simplification of operation} \\ & & \text{Intelligent aided emergency control} \end{bmatrix} \quad (13)$$

Similarly, the user psychological feature $\{U_2\}$, user demand feature $\{U_3\}$, and user behavior feature class element $\{U_4\}$ were obtained, and a user feature analysis model is constructed.

5.1.2 Product feature analysis model

The product features were analyzed according to Eqs. (5) and (6.) The product features of the electric scooter are divided into internal feature class element $\{P_1\}$ and external feature class element $\{P_2\}$, where $\{P_1\}$ includes three objects, namely the $\{O_1\}$ structure, $\{O_2\}$ material, and $\{O_3\}$ function, and $\{P_2\}$ includes two objects, namely the $\{O_1\}$ interactivity and $\{O_2\}$ environment. Hence, the model of the product feature class element, part of which was shown in Table 4.

Table 4. Product feature class element model

Product feature class element $\{P\}$	**Object $\{O\}$**	**Feature value C**	**Amount-value V**
Product internal feature class element $\{P_1\}$	$P_1\{O_1\}$ Structure	P_1C_{11} Chassis	P_1V_{111} Low chassis
		P_1C_{12} Absorb shock	P_1V_{121} Lack of shock absorbable function
		...	...
Product external feature class element $\{P_2\}$	$P_2\{O_1\}$ Interactivity	P_2C_{11} Seat	P_2V_{111} Low seat P_2V_{112} Unadjustable height seat P_2V_{113} Too narrow seat
		...	...
...	...	...	...

5.2. Product information analysis model

Based on the above analysis of the product features, the objects in the internal and external features of the product were extracted, and an independent analysis was carried out using Eqs.(9) and (10) to determine the problems in the product. Table 5 presents part of the product information analysis model.

Table 5. Product information analysis model

Product information class element $\{\boldsymbol{I}\}$	**Object** $\{\boldsymbol{O}\}$	**Feature value** $\boldsymbol{C}$	**Amount-value** $\boldsymbol{V}$
Structure $\{I_1\}$	$I_1\{O_1\}$ Scooter assembly	I_1C_{11} Assembly	I_1V_{111} Difficult assembly
	$I_1\{O_2\}$ Chassis	I_1C_{21} Chassis	I_1V_{211} Low chassis/thick chassis/small wheels
	...	...	...
Material $\{I_2\}$	$I_2\{O_1\}$ Scooter body	I_2C_{11} Plastic	I_2V_{111} Poor seismic and compressive resistance
	...	...	...
...	...	...	...

5.3. Establishing conjugate relation and correlation criterion

5.3.1 Conjugate relation criterion

It was found that there is a conjugate relation between user features as well as between user and product features. Therefore, the following conjugate relation criterion was established:

- In the same class elements, the features or values of objects belonging to different subclass elements have conjugate relations of the same factors. For example, there are similar value related to the speed factor of U_1V_{312} (Lack of speed regulation), U_2V_{151} (Lack of speed regulation), and U_4V_{211} (low speed), which are values of different sub-class element all belongs to user class element.
- The objects belonging to different class elements have conjugated relations of the same feature or values. For example, the feature value of $\{O_1\}$ (safety) of the object $\{U_2\}$ belonging to the user psychological features has the same factor (speed) as the feature of $\{O_3\}$ (function) of the object $\{P_1\}$ belonging to the internal features of the product.

5.3.2 Correlation criterion

There is a correlation between the values of different objects within product features. For example, there is a correlation between the value P_1V_{121} (Lack of shock absorbable function) and the value P_2V_{221} (bump road conditions), which are of different objects .

5.4. Design information correlation and transformation

Through the analysis of the user features, product features, and product information, the existing product design problems are integrated from the user perspective are integrated. It is necessary to establish a design information correlation transformation model based on user features based on the conjugate relation and correlation between each feature class element.

Based on the conjugate relation criterion, we divided the conjugate relation in the user features into the following three groups:

- User physiological feature $\{U_1\}$ "slow response,", user psychological feature $\{U_2\}$ "safety", and user behavior feature $\{U_4\}$ "short distance travel" have conjugate relations, as expressed in Eq. (14):

$$mid_{Ua} = \{U_1\}(\text{slow response}) \otimes \{U_2\}(\text{safety}) \otimes \{U_4\}(\text{short distance travel}) \quad (14)$$

- "reduced mobility" and "memory decay" of $\{U_1\}$, and user demand feature $\{U_3\}$ "convenience" have conjugate relations, as expressed in Eq. (15):

$$\mathrm{mid}_{\mathrm{Ub}} = \{U_1\}(\text{reduced mobility}) \otimes \{U_1\}(\text{memory decay}) \otimes \{U_3\}(\text{convenience}) \quad (15)$$

- "stability" of $\{U_2\}$ and "comfort" of $\{U_3\}$, and "shopping" of $\{U_4\}$ have conjugate relations, as expressed in Eq. (16):

$$\mathrm{mid}_{\mathrm{Uc}} = \{U_2\}(\text{stability}) \otimes \{U_3\}(\text{comfort}) \otimes \{U_4\}(\text{shopping}) \quad (16)$$

- We group the object user physiological feature $\{U_1\}$ "visual loss" separately based on the correlation criterion, as expressed in Eq. (17):

$$\text{vision loss} \sim (\text{environment} \wedge \text{structure} \wedge \text{interactivity}) \quad (17)$$

The design information correlation transformation model was established based on the above conjugate relations, part of which was shown in Table 6 .

Table 6. The design information correlation transformation model

Product function affair element $A(\{U_1\} \wedge \ldots \wedge \{U_n\})$	**Object** $U_1\{O_1\} \wedge \ldots \wedge U_n\{O_n\}$	**Feature** AC/C_{DA}	**Value** AV/V_{DA}
$A_1\begin{pmatrix}\{U_1\}\wedge\{U_2\}\wedge \\ \{U_4\}\end{pmatrix}$	slow response∧safety∧ short distance travel	product features	function, interactivity, structure, material, environment
		be affected objects	speed, speed regulation, brake, use environment, operating mode, chassis height, tire material, wheel size, battery life
		design analysis	Nonconformity between theoretical and actual speeds/low efficiency of motor power utilization; ...
New product function affair element	**Object**	**Feature value**	**Amount-value**
TA_1	slow response∧safety∧ short distance travel	optimization direction	1. Improving motor power and utilization efficiency; ...

5.5. Product design strategies

According to the analyses reported in Sections 5.1–5.3, based on the design feature analysis model, the product information analysis model, and the correlation transformation analysis model of the electric scooter, the design strategies of new products were deduced, which can be divided into four parts, as shown in Table 7.

Table 7. Product design strategies

product	product feature	product design strategies
electricscooter used by the elderly	function	1. Increasing power and utilization efficiency;
		2. Adding anti-backward tilting device and shock absorber;
		3. Adding speed regulation gear;
		4. Optimizing battery life and increasing battery waterproof, anti-theft, and anti-leakage functions;
		5. Adding smart auxiliary speed adjust and control function to treat sloping road, adding smart braking control function.
		6. Adding GPS positioning function;
		7. Adding voice auxiliary operation.
	material	1. Optimizing the tire material to avoid slipping;
		2. Optimizing the material of scooter body and increasing the strength of scooter body.
	structure	1. Increasing control display area;
		2. Optimizing product structure design and connection mode to facilitate assembly;
		3. Improving product structure and materials to reduce product weight;
		4. Optimizing structural design of the seat to enhance the stability;
		5. Increasing the wheel size and raise the chassis height.
	Interactivity	1. Separating the brake and accelerator operation;
		2. Adding voice controlled emergency electronic brake;
		3. Optimizing the product display area/Optimizing the font size design, and making the color more pleasing;
		4. Optimizing the ergonomic design of the seat (in terms of the length, width, height, and the rotation angle);
		5. Increasing the length of the scooter body, improving its stability, and expanding the loading space.

6. Conclusions

In the era of big data, applying big data analysis technology to the field of industrial design can help designers solve these problems and enable an efficient data-led design practice. Although UGR are of great value to industrial design, the efficiency of data conversion and application for practical purposes needs further improvement.

To solve the insufficient data conversion and application efficiency in data application, a user experience data design information analysis method for industrial design was proposed, which is combined with the extension theory to establish an extension design information analysis method. Through a case analysis of scooters intended for the elderly, it is proved that this method can improve the conversion and application efficiency of user experience data, providing a new theoretical method for product design based on UGR. However, the proposed extension design information analysis method is currently in the stage of theoretical research. In the future, research on intelligent design information extraction and analysis will be conducted with this method.

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