Demystifying User Needs in Wardrobe Furniture Design: A Network Analysis via Text Mining and DEMATEL-ANP Integration

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Core user demands of wardrobe furniture design are becoming increasingly complex. Traditional design methods fail to systematically analyze the interrelationships among these multidimensional factors. This study integrated web text mining, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, and the Analytic Network Process (ANP) to construct a causal network model for wardrobe design, and further optimized design proposals through the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). By applying Python technology, user evaluation data were extracted from mainstream e-commerce platforms, with high-frequency user demand keywords being identified and categorized into four key dimensions. DEMATEL was employed to quantify the causal intensity and centrality of the identified factors; ANP was subsequently utilized to construct a network hierarchy, revealing the feedback mechanisms between functional modules and user experience. Finally, TOPSIS was applied to rank three design proposals, among which Option 3—featuring flexible space partitioning, auto-sensing lighting, and anti-tip design—was selected as the optimal solution. The findings demonstrate that integrating text mining with the DEMATEL-ANP-TOPSIS framework can effectively identify the prioritization of user needs, thereby providing scientific decision support for furniture design.

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INTRODUCTION

Early wardrobes were simple in structure—often just wooden boxes equipped with shelves and hanging rods—mainly serving to store a limited number of garments. In modern home environments, wardrobes have become a crucial component of furniture. They embody practices such as tidying, storage, divestment, and displacement (Klepp and Bjerck 2014). The extent of wardrobe use also reflects consumers' purchasing power (Choo *et al.* 2014) and has evolved far beyond a mere storage unit (Hu *et al.* 2021). A wardrobe comprises not only the physical structure but also the internal storage zones, designated clothing locations, and specific rules for garment placement and movement (Gregson and Beale 2004). Its design is intricately linked to space optimization, user convenience, and the overall aesthetic of the living area. From a basic storage solution, the wardrobe has evolved into a multifunctional system that integrates usability, aesthetics, and lifestyle adaptation, reflecting the changing needs of modern consumers. With the improvement in living standards, people are placing increasing emphasis on home décor and efficient storage solutions. Wardrobe designs have diversified in style, size, and material. For example, Iritani *et al.* (2015) proposed using wood waste in particleboard production as a sustainable material choice. Bang and Su (2022) emphasized that consumer attitudes toward virtual wardrobes significantly influence their intention to adopt them, highlighting the importance of user perception in virtual wardrobe design.

Traditional design approaches relying on intuition, prior experience, and generalized standards have been found to be inadequate for addressing the complex demands of contemporary users, whose needs diverge significantly due to lifestyle variations, fashion trends, spatial constraints, and budget limitations. Rapidly understanding user preferences for customized wardrobe aesthetics has become a pressing research topic (Zhang and Chen 2024). However, traditional methods often fail to consider multiple interrelated factors in a structured and comprehensive way (Muhammad Suandi *et al*. 2022). These include not only functionality and aesthetics but also psychological influences, material durability under different conditions, and environmental sustainability. Existing wardrobe design studies tend to focus on isolated factors and lack a systematic perspective. For instance, conventional wood-based panels (WBPs) are perceived by consumers as too heavy for some applications (Khojasteh-Khosro *et al.* 2022). Therefore, furniture designers should address the diverse development of wardrobe needs, including smart features, health-related features, and emotional aesthetics, while differentiating these requirements across different user segments.

To capture core user demands, this study applied web text mining techniques to extract and interpret user needs from large volumes of online content. Text mining is a process for discovering meaningful and non-obvious patterns in natural language data (Irfan *et al.* 2015). Wu *et al.* (2023) applied text mining and LDA topic modeling to analyze construction accident reports in China, identifying risk-related terms and categorizing risk types. Spinder *et al.* (2023) used web crawling and natural language processing (NLP)—including lexical, syntactic, and semantic analysis—to evaluate corporate sustainability through website text data. These examples demonstrate how text mining can offer objective, systematic insights into user needs, providing strong data support for design decisions. However, while text mining effectively captures user requirements, it does not directly yield actionable design solutions. In wardrobe design, designers must interpret these needs (Yuan and Guan 2014; Xu *et al.* 2024). This study integrated text mining with the DEMATEL (Decision Making Trial and Evaluation Laboratory) and ANP (Analytic Network Process) methods. DEMATEL is effective in identifying causal relationships among complex factors. By quantifying factors' influence degree, influenced degree, centrality, and cause degree, it identifies key design priorities and breaks the linear assumptions of traditional design. Xu *et al.* (2024) applied DEMATEL and Interpretive Structural Modeling (ISM) to analyze user needs for dining tables, building a hierarchical structure. Liang *et al.* (2022) and Kumar and Dixit (2018) similarly used DEMATEL-ISM to analyze influencing factors and identify root causes in various domains, such as EVCS operations and e-waste management.

ANP fully considers complex factor interdependencies and feedback mechanisms, constructing realistic network models. It expands one-way causality into multidimensional networks, overcoming linear analysis limitations. Mistarihi *et al.* (2020) proposed a human-computer implementation path for this wheelchair design by innovatively integrating QFD with FANP and applying TFNs to accurately characterize the importance of the factors and to determine the weights of their engineering properties. Lam *et al.* (2015) combined the analytical methods of QFD and ANP to identify four key customer requirements, providing new ideas and methods for the sustainable design of offshore supply chains. Asyraf *et al.* (2020) used the TRIZ Contradiction Matrix to refine the engineering parameters and combined morphological diagrams with ANP techniques to systematically develop a final conceptual design to improve the existing fire extinguishers that were difficult for users to use due to their weight and design.

Building on these studies, this paper proposes an integrated DEMATEL-ANP method to analyze factor interactions in wardrobe design, clarify causal relationships, and identify core design priorities. This method lays the groundwork for a scientific and practical design framework aligned with user expectations and market trends (Mubarik *et al.* 2021). Furthermore, by combining DEMATEL-ANP with the TOPSIS method, a complete decision-making framework is established—from factor identification to design solution ranking. DEMATEL clarifies causal relationships, ANP calculates global weights, and TOPSIS ranks alternatives based on proximity to the ideal solution (Olson 2004; Büyüközkan and Çifçi 2012). While widely applied in supplier evaluation, this integrated DEMATEL-ANP-TOPSIS framework remains underutilized in wardrobe design. Therefore, this study introduces a novel decision-making framework that integrates text mining, DEMATEL, ANP, and TOPSIS to systematically support complex wardrobe design optimization, offering both theoretical and practical value.

EXPERIMENTAL

Experimental Procedure

In this study, real user evaluations and demand information related to cabinet furniture were collected from multiple online platforms, including mainstream e-commerce websites, home furnishing forums, and social media groups by using Web Text Mining. Once a comprehensive and representative dataset of user reviews was obtained, the DEMATEL-ANP methodology was applied. First, DEMATEL was used to construct a direct influence matrix to clarify the causal relationships among various influencing factors. Through steps such as normalization and the calculation of the total influence matrix, the degree and direction of influence between factors were identified. Subsequently, ANP was employed to build a network structure that reflects the interdependencies and feedback among these factors. Using supermatrix operations, the relative importance of each factor was determined within the entire network. This integrated DEMATEL-ANP approach enabled a comprehensive and systematic analysis of the user demand system. Ultimately, the key demand elements most relevant to cabinet design were extracted and refined. The specific research flowchart is illustrated in Fig. 1.

Web Text Mining

User evaluations, especially in the context of cabinet purchases, are a valuable source of text data that reflect users' conscious needs, emotional orientations, and behavioral tendencies. According to Xiong *et al.* (2022), this expression of cognition, emotion, and behavior forms the foundation for understanding and developing users' potential product demands. These reviews often include users' opinions on functionality, color coordination, aesthetics, and service experience, offering an authentic reflection of consumer expectations (An and Par 2020). To leverage this information effectively, a text clustering method is employed to categorize online reviews into attribute words and emotion words. To effectively leverage information, text mining methodologies are employed to extract users' emotional needs. The general process of text mining comprises data collection, preprocessing, analytical mining, and model evaluation: Data collection refers to the lawful acquisition of research texts (such as database extraction, web crawling); preprocessing involves cleaning redundant data and conducting structural processing on unstructured data to lay the foundation for subsequent analysis.

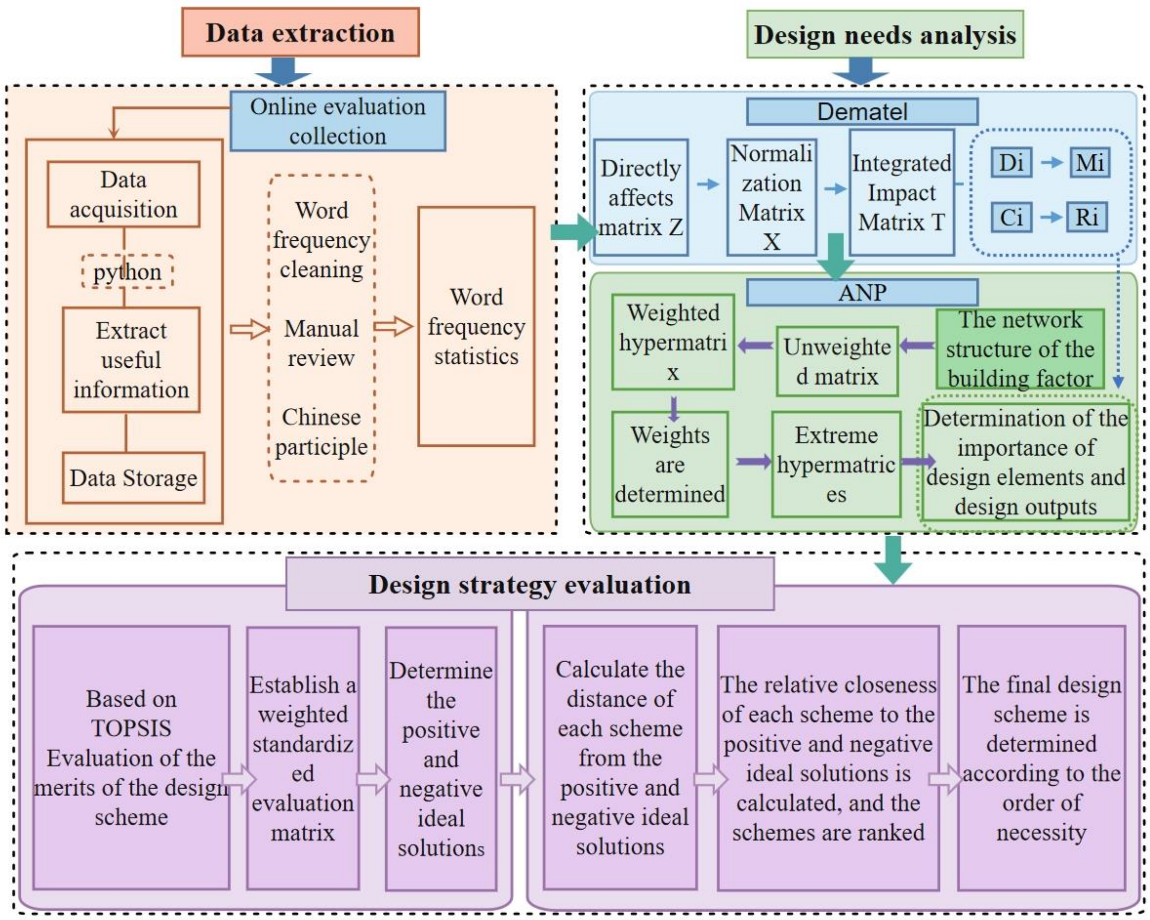

Fig. 1. Technology roadmap

In text collection and preprocessing, a web crawler is used to collect web pages (Yang *et al*. 2022). This study employed an automated data collection system based on Python crawler frameworks to acquire user review data from e-commerce platforms. Given the natural language characteristics and unstructured features of user-generated content, data preprocessing becomes a critical component for ensuring analytical quality. To guarantee consistency and comparability across multi-product data analysis, a standardized data cleaning pipeline was established, encompassing noise data filtering, redundant information removal, and format normalization processing. Addressing the specificity of Chinese text, which lacks explicit lexical boundary markers, a segmentation strategy based on statistical language models and domain knowledge bases was adopted.

In the empirical research phase, this study systematically collected user review data for the top 5 best-selling wardrobe products within the price range of 500 to 2000 RMB from the JD.com e-commerce platform, encompassing 15,762 review records from the past

6 months. To ensure objectivity and representativeness of data analysis, a rigorous multi-stage preprocessing pipeline was implemented. First, regular expression algorithms were employed to filter automatically generated standardized reviews, blank content, and logistics information unrelated to product performance evaluation. Subsequently, duplicate content was identified based on composite discriminant criteria of lexical semantic overlap and text length differences. Following this, text normalization processing was executed, including whitespace character standardization, special symbol filtering, and redundant expression compression. During the segmentation processing stage, the Jieba segmentation tool combined with domain-specific terminology dictionaries was employed for precise Chinese text segmentation. The dictionary contained wardrobe product-related professional terminology to enhance segmentation accuracy and domain adaptability. In the word frequency statistical analysis process, systematic frequency calculations identified the top 40 high-frequency user requirement terms. To improve feature quality and reduce noise data interference, a word frequency threshold of 20 was established, with low-frequency vocabulary below this threshold being systematically excluded. Finally, using visualization tools to present the vocabulary distribution of data in an intuitive visual form in Fig. 2.

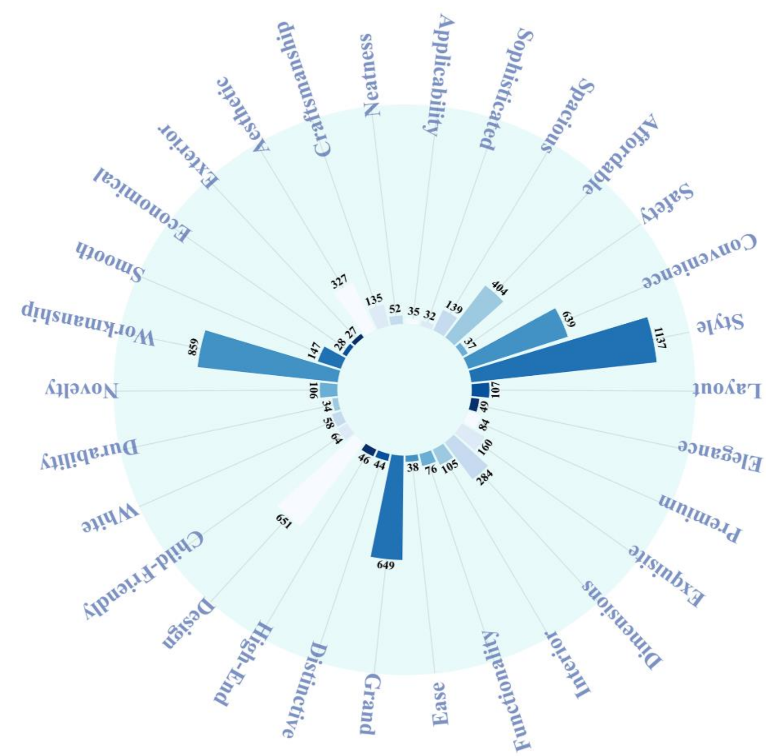

Fig. 2. High frequency words summary chart

The smart wardrobe requirement hierarchy model constructed from word cloud analysis results, in conjunction with professional expertise from QuanU furniture designers, categorizes user needs into four dimensions: Styling Design, Material Design, Functional Design, and User Experience. The Styling Design dimension, based on high-frequency word cloud terms like “Elegance” and “Sophisticated,” corresponds to design languages of “Simple and Grand” and “Personalized Appearance,” integrating QuanU’s brand interpretation of modern home aesthetics. The Material Design dimension combines semantics such as "Workmanship" and "Neatness" to not only relate to material selections like "Composite Material" and "Natural Texture" but also incorporates designers' recommendations on eco-friendly panels and hardware craftsmanship to enhance material-process adaptability. The Functional Design dimension, centered on "Convenience" and "Spacious," covers basic functions such as "Large Storage Space" and "Multifunctional Modules," while expanding differentiated requirements based on product-line characteristics highlighted by experts as user priorities.

The User Experience dimension extends from "Safety" and "Ease" to scenarios such as "Suitable for Children" and "Easy to Clean," supplemented with expert-recommended experience optimizations. Following systematic calibration of all mapping relationships by design team, the final User Requirement Hierarchy Expansion Table (Table 1) comprises four dimensions and 12 sub-requirements. This model ensuring design elements reflect authentic user feedback while incorporating cutting-edge industry insights to deliver a structured solution for smart wardrobe development that balances market orientation and brand specificity.

Table 1. Classification of Elements of Wardrobe Design

Dimension	Code	Word Cloud Terms	User Requirement
Styling Design A	A1	Elegance, Sophisticated, Grand	Simple and Grand
	A2	Style, Distinctive, Exquisite	Personalized Appearance
	A3	Smooth, Ease	Light and Smooth
Material Design B	B1	Scaling needs(Additional Requirements)	Natural Texture
	B2	Workmanship	Composite Material
	B3	Safety, Workmanship	Stable Structure
Functional Design C	C1	Spacious, Dimensions	Large Storage Space
	C2	Convenience, Ease	Easy to Use
	C3	Functionality, Interior	Multifunctional Modules
	C4	Safety	Wardrobe Disinfection
User Experience D	D1	Safety, Workmanship	Safety in Use
	D2	Scaling needs(Additional Requirements)	Suitable for Children
	D3	Neatness	Easy to Clean

Constructing Direct Affect Matrix

In this research project, based on the identified user-specific requirements framework, the research team formed a 12-member expert panel. These included four designers from the furniture manufacturing industry, six professors of design, and two master's degree students in related disciplines. A systematic, all-encompassing, and multidimensional consideration of the production phase of wardrobe furniture was carried out by the experts using an organic blend of quantitative analysis and qualitative judgment (Fang *et al.* 2025).

The direct influence matrix represents the direct mutual relationships between influencing factors, including the direct influence between each pair of factors within the research scope. These influences are quantified according to varying degrees. Evaluation criteria were defined with values ranging from 0 to 4, where each value is described in Table 2.

Table 2. Table of Values of Influencing Factors

Assessment criteria	Description of definitions
0	i does not affect j
1	i has a low impact on j
2	i has a medium impact on j
3	A higher degree of influence of i on j
4	i has a very high degree of influence on j

Based on the scoring results of 12 experts, each indicator was evaluated by these experts, and the evaluation results were averaged using the arithmetic mean. The final direct influence matrix was determined according to Eq. 1.

$$b_{ij} = \begin{pmatrix} 0,0 \le \bar{b} < 0.5 \\ 1,0.5 \le \bar{b} < 1.5 \\ 2,1.5 \le \bar{b} < 2.5 \\ 3,2.5 \le \bar{b} < 3.5 \\ 3,3.5 \le \bar{b} < 4 \end{pmatrix} \tag{1}$$

According to the interactions among the influencing factors of wardrobe design elements, the strength of interactions is determined through expert panel assessment, whereby b_{ij} denotes the correlation degree between the i-th and j-th influencing factors. The element b_{ij} reflects the correlation strength between the i-th and j-th factors. When i=j, b_{ii}=0, indicating that no influencing factor exhibits self-correlation. Thus, the direct influence matrix *Z* is constructed, as shown in Eq. 2.

$$Z = \begin{bmatrix} 0 & b_{12} & \ldots\ldots & b_{1j} \\ b_{21} & 0 & \ldots\ldots & b_{2j} \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ b_{i1} & b_{i2} & \ldots\ldots & 0 \end{bmatrix} \tag{2}$$

Based on the evaluation process described above, quantitative analyses and data processing were carried out on the first-level evaluation indicators to construct and obtain the direct impact matrix *X*. The details of the matrix are shown in Table 3.

Table 3. Direct Impact Matrix

	A1	A2	A3	B1	B2	B3	C1	C2	C3	C4	D1	D2	D3
A1	0	3	3	0	0	0	1	0	1	0	1	0	0
A2	3	0	0	0	0	0	0	0	0	0	0	0	0
A3	3	0	0	0	0	0	0	0	0	0	0	0	0
B1	0	0	0	0	1	0	0	0	0	0	0	0	0
B2	0	0	0	1	0	0	0	0	0	0	3	0	0
B3	0	0	0	0	0	0	0	0	3	0	0	0	0
C1	1	2	2	1	2	0	0	3	3	2	2	1	1
C2	1	0	1	1	1	3	3	0	3	2	1	3	2
C3	2	2	0	0	0	0	3	3	0	1	3	2	0
C4	1	1	1	0	0	0	0	0	1	0	0	3	0
D1	1	1	2	1	1	3	2	2	3	2	0	3	1
D2	0	3	0	0	2	0	2	3	3	0	3	0	0
D3	0	1	1	0	0	0	0	0	0	0	1	0	0

Calculation of the Integrated Impact Matrix

First, calculate the total sum of elements in each row (row sum) and each column (column sum) of the direct influence matrix. After identifying the maximum row sum and the maximum column sum, take the smaller value of their reciprocals as the normalization factor. Then, multiply each element of the original matrix by this factor to obtain the normalized matrix. This approach ensures that both row sums and column sums do not exceed 1, eliminates dimensional discrepancies, guarantees the convergence of subsequent comprehensive influence matrix calculations, and balances the comparability of interaction strengths among factors (Eq. 3 and 4).

$$E = \min\left[\frac{1}{\max\sum_{i=1}^{n} b_{ij}}, \frac{1}{\max\sum_{j=1}^{n} b_{ij}}\right] \tag{3}$$

$$X = EZ \tag{4}$$

Once the normalization is complete, Eq. 5 is further applied to calculate the combined impact matrix:

$$T = Y(1-Y)^{-1} = \begin{bmatrix} t_{11} & t_{12} & \cdots\cdots & t_{1j} \\ t_{21} & t_{22} & \cdots\cdots & t_{1j} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ t_{i1} & t_{i2} & \cdots\cdots & t_{ij} \end{bmatrix} \tag{5}$$

The integrated impact matrix T represents the interrelationships and cumulative effects among the influencing factors of wardrobe design. Based on this matrix T, calculate the influence degree D_i, influenced degree C_i, centrality degree M_i, and cause degree R_i for each factor.

The influence degree D_i is the sum of the elements in the corresponding row of matrix T. A larger D_i value implies a higher influence of the factor on other elements within the entire system (Eq. 6).

The influenced degree C_i is obtained by summing the elements in the corresponding column of matrix T. A large C_i value indicates that the element is significantly influenced by other elements (Eq. 7).

The centrality degree Mi is the sum of D_i and C_i. A higher M_i value suggests that the element plays a more crucial role in the system's operational mechanism, structural composition, functional realization, *etc*. (Eq. 8).

The cause degree R_i is the difference between D_i and C_i. If R_i>0, the factor exerts more influence than it receives during interactions with other factors; if R_i<0, it receives more influence from other factors (Eq. 9).

$$D_{\mathrm{i}} = \sum_{\mathrm{j}=1}^{\mathrm{n}} t_{ij} \tag{6}$$

$$C_{\mathrm{i}} = \sum_{\mathrm{j}=1}^{\mathrm{n}} t_{ij} \tag{7}$$

$$M_i = D_i + C_i \tag{8}$$

$$R_i = D_i - C_i \tag{9}$$

Based on these indicators, which quantify the characteristics and status of the elements in the system in different dimensions, the results of the calculation of the primary and secondary indicators are shown in Table 4.

Table 4. Degree of Influence (D_i), Degree of Being Influenced (C_i), Degree of Centrality (M_i), and Degree of Cause (R_i)

Factors	D_i	C_i	M_i	R_i	Factor Attribute
A1	0.736	1.194	1.93	-0.458	result factor
A2	0.237	1.278	1.515	-1.041	result factor
A3	0.237	0.948	1.185	-0.711	result factor
B1	0.067	0.378	0.445	-0.311	result factor
B2	0.466	0.662	1.128	-0.196	result factor
B3	0.385	0.613	0.998	-0.228	result factor
C1	1.896	1.16	3.056	0.736	cause factor
C2	2.005	1.16	3.165	0.845	cause factor
C3	1.822	1.604	3.426	0.218	cause factor
C4	0.698	0.724	1.422	-0.026	result factor
D1	2.063	1.337	3.4	0.726	cause factor
D2	1.778	1.183	2.961	0.595	cause factor
D3	0.252	0.401	0.653	-0.149	result factor

Constructing the ANP Network Structure

In the decision-making process, it is crucial to assess the importance of the criteria and structures to enhance decision quality (Kamranfar *et al.* 2022). A recursive grid hierarchy is developed, consisting of a control layer and a network layer. The control layer's criterion element includes four primary indicators: A (styling design), B (material design), C (functional design), and D (user experience). The network layer encompasses the secondary indicators beneath each primary criterion, including A1-A3, B1-B3, C1-C4, and D1-D3. Based on the results from the DEMATEL comprehensive impact matrix, each element group displays a self-looping feedback relationship within the group. Additionally, bidirectional interactions and unidirectional interactions exist between different element groups, ultimately forming a network structure that illustrates the influence mechanism between the indicators.

According to the ANP network structure diagram, an element comparison matrix can be formed by comparing the importance of elements within each group under the same elemental criterion, while an element group comparison matrix is also formed by comparing the importance of elements between groups of elements under the same elemental group criterion. The importance of the factors is analyzed quantitatively using values 1-9 (Table 5), where each value represents a different meaning. This method of analysis provides a more scientific assessment of the relative importance of the factors, which can be used to support decision-making (Zhang *et al.* 2024). In the control layer of the ANP network structure, there are m criteria denoted as $a_1, a_2, \cdots\cdots, a_m$. In the network layer, there are n element groups, namely $c_1, c_2, \cdots\cdots, c_n$. The elements within element group ci are denoted as $e_{i1}, e_{i2}, \cdots\cdots, e_{ik}$. Taking a certain element e_{jl} from element group c_j as a criterion, pairwise comparisons are carried out for all elements in element group c_i that have an impact on e_{jl}.

Table 5. Between the Above Assessment Scales

Assessment criteria	Description of definitions
1	i is as important as j
3	i is slightly more important than j.
5	i is more important than j
7	i is significantly more important than j
9	i is very important than j.
2, 4, 6, 8	Between the above assessment scales

For each set of judgment matrices, consistency should be checked by *CI* and one *CR*. (Eq. 10-11),

$$CR = \frac{CI}{RI} \tag{10}$$

$$CI = \frac{(\lambda \max - n)}{n-1} \tag{11}$$

where *CI* stands for the consistency index, which measures the degree of deviation from consistency in the judgment matrix. *RI* is the random consistency index, calculated by determining the consistency index of a large number of randomly generated judgment matrices of the same order and averaging the values.

If $CR < 0.1$, the judgment matrix is considered to have acceptable consistency; however, if $CR \geq 0.1$, the expert scores should be re-examined and adjusted to correct the judgment matrix until it meets the consistency requirements (Pazand and Hezarkhani 2015; Büyüközkan and Güleryüz 2016).

The normalized eigenvectors derived from constructing judgment matrices for all elements in the element group concerning the elements under the group are combined to form the weight vector matrix W_{ij} (Eq. 12).

$$W_{ij} = \begin{bmatrix} w_{i1}^{j1} & w_{i1}^{j2} & \cdots\cdots & w_{il}^{jl} \\ w_{i2}^{j1} & w_{i2}^{j2} & \cdots\cdots & w_{i2}^{jl} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ w_{ik}^{j1} & w_{ik}^{j2} & \cdots\cdots & w_{ik}^{jl} \end{bmatrix} \tag{12}$$

The column vectors in W_{ij} are normalized eigenvectors computed after constructing a judgment matrix using the elements of the element group affecting that element as a sub-criterion.

Constructing the Supermatrix

In applying the network analysis method (ANP) to construct the supermatrix, the existence of n groups of elements and a control layer containing multiple control factors are first determined. For these n-element groups, the reference elements are selected one by one from the group, and the judgment matrix is constructed by applying the 1 - 9 scaling method for the elements affecting a specific element e_{jl}, and then the normalized eigenvectors are computed by the eigenroot method, and the above operation is repeated for each element of the group and the vectors are combined to get the weight vectors for the element groups.

Table 6. Weighted Supermatrix Table

	A1	A2	B1	B2	B3	C1	C2	C3	C4	D1	D2	D3
A1	0.000	0.250	0.000	0.000	0.000	0.136	0.000	0.136	0.000	0.228	0.000	0.000
A2	0.167	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A3	0.083	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B1	0.000	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
B2	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.000	0.000	0.295	0.000	0.000
B3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.340	0.000	0.000	0.000	0.000
C1	0.098	0.123	0.200	0.267	0.000	0.000	0.144	0.119	0.089	0.080	0.062	0.254
C2	0.057	0.000	0.200	0.133	0.400	0.144	0.000	0.094	0.142	0.209	0.062	0.127
C3	0.064	0.078	0.000	0.000	0.000	0.144	0.144	0.000	0.056	0.091	0.106	0.000
C4	0.032	0.049	0.000	0.000	0.000	0.000	0.000	0.075	0.000	0.000	0.150	0.000
D1	0.500	0.098	0.200	0.067	0.200	0.079	0.079	0.158	0.237	0.000	0.097	0.097
D2	0.000	0.155	0.000	0.133	0.000	0.158	0.158	0.079	0.000	0.032	0.000	0.000
D3	0.000	0.247	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.065	0.000	0.000

Table 7. Extreme Supermatrix Table

	A1	A2	A3	B1	B2	B3	C1	C2	C3	C4	D1	D2	D3
A1	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090
A2	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015
A3	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
B1	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
B2	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062
B3	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
C1	0.135	0.135	0.135	0.135	0.135	0.135	0.135	0.135	0.135	0.135	0.135	0.135	0.135
C2	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156	0.156
C3	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123	0.123
C4	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
D1	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176	0.176
D2	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105
D3	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017

After that, the two-by-two comparison matrices generated for each group of elements are normalized and transposed to obtain the feature root vectors W_{ij}. These vectors are summarized to obtain the supermatrix W (Eq. 13).

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots\cdots & w_{1n} \\ w_{21} & w_{22} & \cdots\cdots & w_{2n} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ w_{n1} & w_{n2} & \cdots\cdots & w_{nn} \end{bmatrix} \tag{13}$$

Although each W_{ij} in the unweighted supermatrix is normalized, the overall unweighted supermatrix is not normalized. For this reason, the supermatrix is normalized by multiplying the normalized importance judgment matrix for each dimension with the unweighted supermatrix, and a weighted supermatrix is obtained (Rad *et al.* 2018).

The judgment matrix between the groups of elements is normalized and multiplied with the unweighted supermatrix W to obtain the weighted supermatrix W^{α} (Table 6).

Determine the Limiting Supermatrix

To obtain the limit supermatrix, multiple multiplications of the weighted supermatrix were calculated. The power of W^{α} is that the limit exists when W^{α} is at $t \to \infty$ (Eq. 14). The limiting supermatrix results are shown in Table 7.

$$W^{\infty} = \lim_{t \to \infty} W^{\alpha t} \tag{14}$$

The ANP weight calculation process integrates the direct and indirect influences between elements through the iterative operation of the supermatrix and finally forms a comprehensive weight that includes the feedback mechanism between elements. As a result, the importance ranking of the elements based on the limit supermatrix is shown in Table 8.

Table 8. Weighting Table

Code	Weights	Code	Weights	Comprehensive weight	Rank
A	0.1127	A1	0.799	0.090	6
		A2	0.133	0.015	12
		A3	0.071	0.008	13
B	0.1287	B1	0.194	0.025	10
		B2	0.482	0.062	7
		B3	0.326	0.042	9
C	0.4601	C1	0.293	0.135	3
		C2	0.339	0.156	2
		C3	0.267	0.123	4
		C4	0.100	0.046	8
D	0.2985	D1	0.590	0.176	1
		D2	0.352	0.105	5
		D3	0.057	0.017	11

RESULTS AND DISCUSSION

Results

According to the DEMATEL-ANP analysis, the core influencing factors in wardrobe design are dominated by functional design and user experience. Among these, operational convenience (Ri=0.845) and safety in use (Mi=3.4) serve as the core driving factors, guiding the design direction from the perspectives of practicality and safety, respectively. Operational convenience enhances user efficiency through intelligent adjustment systems and simplified processes, while safety in use establishes the underlying logic of the design *via* anti-tipping structures, eco-friendly materials, and other measures. Storage space (Mi=3.056), as the physical foundation for functional implementation, determines the feasibility of internal layout and aesthetic design, and must be integrated with multifunctional modules (Mi=3.426) to meet diverse storage needs. Styling design and material design are contingent on core driving factors, a simple and elegant appearance (A1) relies on the rational planning of storage space, while composite materials (B2) and stable structures (B3) serve the requirements of safety (D1) and functional modules (C3).

Functional design holds a dominant position in the overall system, with a weight of 0.4601. The reasonableness and practicality of the function directly determine whether the wardrobe meets the user's needs, while the weight of user experience is 0.2985. In addition to focusing on function, a comfortable and safe user experience significantly enhances the product's market competitiveness. Both modeling design and material design serve as secondary elements in wardrobe design.

The weight of operational convenience is 0.1557, space capacity is 0.1347, the weight of multi-functional modules is 0.1233, and the weight of the disinfection function is 0.0463. Operational convenience directly influences the efficiency and experience of users when using the wardrobe and is a key indicator of functional design. Space capacity determines the wardrobe's storage ability, which is essential for meeting basic user needs. Module compatibility offers the possibility of expanding and customizing the wardrobe's functions. The relatively low weight of the disinfection function reflects its non-core status in current user demand; however, as health awareness increases, its importance may gradually grow.

The attributes of the safety of use, with a weight of 0.1763, child appropriateness at 0.1052, and ease of cleaning at 0.017, are highly consistent as cause elements. Safety of use is the primary consideration for user experience, ensuring the safety of users' lives and property. Child-friendliness caters to families with children, while ease of cleaning has a lower weight. The weight of simplicity and atmosphere, at 0.0902, dominates the design. A simple design style not only aligns with modern aesthetic trends but also reduces cognitive load for users and integrates well with functional design.

The weight of composite materials is 0.0620. Composite materials possess a variety of excellent properties, such as high strength and low weight, which can meet the diverse functional and aesthetic needs of the wardrobe. In the design process, operational convenience and safety of use must be optimized by ergonomic principles to ensure that the wardrobe is easy and convenient to use. Reliable materials and structural design should be used to improve the wardrobe's stability and safety, preventing accidents. Space capacity and multi-functional modules form a functional linkage that can be designed to automatically adjust based on the user's height and usage habits to improve space utilization. At the same time, standardized interface designs allow users to easily add or replace modules as needed, enhancing the wardrobe's expandability.

Based on the above analysis, the research team proposed three design options (Fig. 3). Option 1 integrates the wardrobe and clothes disinfection area and desk, featuring a disinfection display interface. This option breaks from traditional wardrobe designs and meets the demand for large-capacity storage. The storage area is logically arranged for easy access to clothing, while the desk and wardrobe linkage facilitates smooth movement lines, enhancing operational convenience. This option includes multi-functional modules such as clothing storage, disinfection, sterilization, and office use, truly achieving one cabinet for multiple purposes and adapting perfectly to diverse life scenarios.

Option 2 features simple geometric modeling and internal layout planning with hanging areas, drawers, and shelves for organizing clothes, bedding, and other items, fulfilling large-capacity storage needs. The storage is scientifically arranged to facilitate easy access to items, and the desk is linked to the wardrobe, ensuring smooth movement between office and storage spaces.

Option 3 primarily adopts a wooden color scheme, avoiding complex decorations, with an integrated wardrobe and desk design. The design emphasizes simplicity and naturalness through wood materials and organic textures, which not only infuse the space with warmth but also establish a harmonious connection to nature. To enhance practicality, the internal layout is systematically organized into distinct hanging and storage zones, enabling users to access items efficiently. Additionally, the integrated desk-wardrobe module streamlines daily routines by optimizing workspace utilization and improving task efficiency. These design features collectively culminate in the scheme illustrated in Fig. 6, which balances aesthetic appeal, functionality, and spatial efficiency.

Fig. 3. Drawing of the final design

To derive a robust and valid design solution, this study employed the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a well-established multi-criteria decision-making method (Tyagi *et al*. 2014). The core principle of TOPSIS is to maximize the distance from the negative ideal solution while minimizing proximity to the positive ideal solution (Sindhu *et al.* 2017), enabling comprehensive evaluation of alternatives across multiple criteria.

A total of 43 consumers with explicit wardrobe purchase intent were recruited through a mixed online-offline approach to evaluate the three proposed design solutions. Guided by a unified set of 13 key user requirements for wardrobe design, all design proposals were re-evaluated against these consistent criteria. Evaluation data provided by participants formed the original assessment matrix (Table 9), ensuring a standardized framework for comparative analysis.

Table 9. Evaluation Matrix Table

	Code	Option 1	Option 2	Option 3
Evaluation of the best solution	A1	5.256	5.721	6.070
	A2	4.302	5.233	5.651
	A3	5.372	4.930	6.047
	B1	4.977	5.767	5.907
	B2	5.605	3.837	5.953
	B3	6.070	4.837	5.814
	C1	5.093	4.953	5.767
	C2	5.488	3.674	5.488
	C3	5.674	4.837	5.674
	C4	5.884	6.163	6.279
	D1	5.837	5.558	5.721
	D2	5.256	5.814	6.070
	D3	4.558	5.791	5.512

The raw matrix data collected for the three design options were weighted and normalized according to Eqs. 15 and 16 (Bathrinath *et al*. 2021; Aastha and Karthick 2024). The weighted standardized evaluation matrix is shown in Table 10.

Table 10. Weighted Standardized Evaluation Matrix

	Code	Option 1	Option 2	Option 3
Evaluation of the best solution	A1	0.533	0.580	0.616
	A2	0.488	0.593	0.641
	A3	0.567	0.520	0.638
	B1	0.516	0.598	0.613
	B2	0.621	0.425	0.659
	B3	0.626	0.499	0.600
	C1	0.557	0.541	0.630
	C2	0.639	0.428	0.639
	C3	0.606	0.516	0.606
	C4	0.556	0.582	0.593
	D1	0.591	0.562	0.579
	D2	0.530	0.587	0.612
	D3	0.495	0.629	0.599

$$Y_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}}, (i = 1,2\ldots\ldots m, j = 1,2,\ldots\ldots n) \quad (15)$$

$$Z_{ij} = W_j Y_{ij}, (i = 1,2\ldots\ldots m, j = 1,2,\ldots\ldots n) \quad (16)$$

To establish reference benchmarks for evaluation, the positive ideal solution and negative ideal solution were computed. The positive ideal solution, defined in Eq. 17, aggregates the optimal values for all criteria, while the negative ideal solution, specified in Eq. 18, comprises the worst-case values.

$$Z^{+} = (Z_1^{+}, Z_2^{+}, \ldots\ldots Z_n^{+}) \tag{17}$$

$$Z^{-} = (Z_1^{-}, Z_2^{-}, \ldots\ldots Z_n^{-}) \tag{18}$$

The optimal solution calculates the distances (D^+ and D^-) to the positive and negative ideal solutions Z^+ and Z^- according to Eqs. 19 to 21, see Table 11.

$$D_i^{+} = \sqrt{\sum_{j=1}^{n} (Z^{+} - Z_{ij})^2} \tag{19}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{n} (Z^{-} - Z_{ij})^2} \tag{20}$$

$$C_i = \frac{D_i^{+}}{D_i^{+} + D_i^{-}}, (i = 1,2,\ldots\ldots, \ \ m) \tag{21}$$

Table 11. Program Ranking List

Indicators	D^+	D^-	C_i	Rank
Option 1	0.016	0.038	0.702	2
Option 2	0.040	0.008	0.168	3
Option 3	0.002	0.042	0.945	1

Discussion

When the degree of closeness is nearly equal to 1, it indicates that the program has performed exceptionally well across multiple evaluation dimensions. Option 3 was evaluated as the most effective in achieving the desired outcomes. The wardrobe in Option 3 (Fig. 4) features adjustable dividers, enabling users to flexibly modify the storage space according to the type and quantity of clothing, thereby significantly improving space utilization.

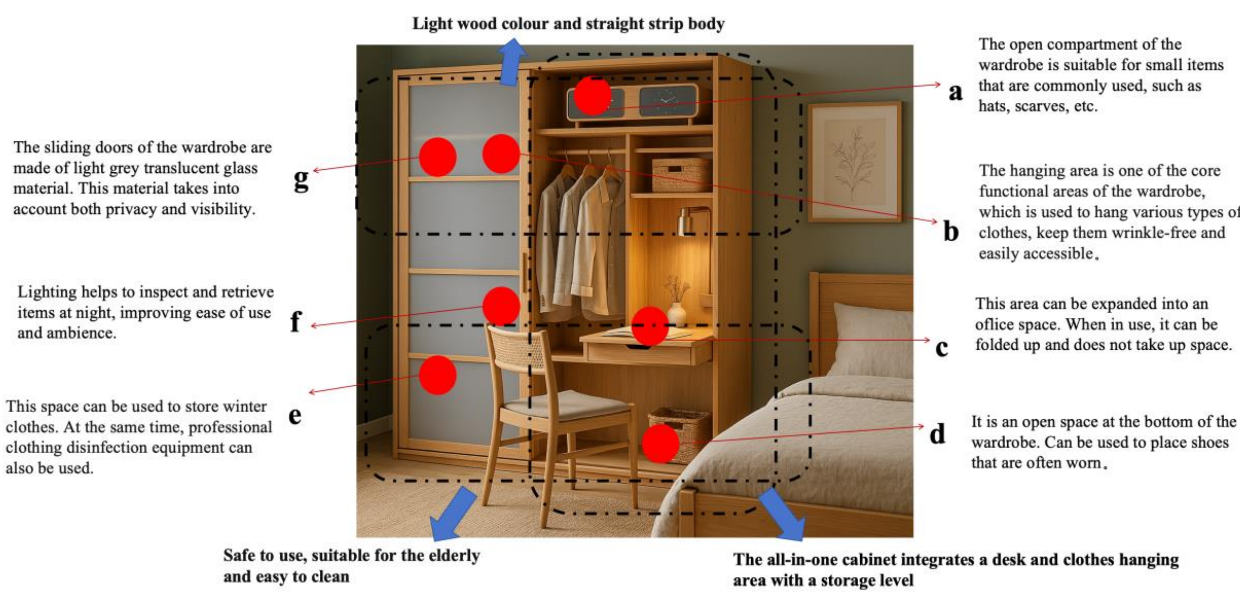

Fig. 4. Optimal design solution

It also includes a built-in auto-sensing lighting system that automatically illuminates when the wardrobe is opened, helping users quickly locate their clothes and greatly enhancing ease of use. In terms of safety design, the wardrobe incorporates an anti-tipping structure, which effectively improves stability and prevents tipping caused by external impacts or imbalances in the center of gravity, reducing the likelihood of safety incidents. Additionally, the corners of the wardrobe are rounded to minimize the risk of accidental bumps and injuries, especially to children, making it ideal for families with children.

This study first identified wardrobe user needs elements through text mining, aligning with the research approach of Ma *et al.* (2024), who proposed wardrobe color design *via* web text mining and successfully developed color styles meeting user requirements. The research reveals that functional design and user experience are the core driving factors in wardrobe design, while styling design holds relatively minimal importance. This conclusion resonates with Chen and Lyu (2014), who further indicated that color has a minor impact on furniture design, consistent with the present finding that styling design exhibits weak direct influence on functional requirements. Operational convenience and usability safety demonstrate a strong correlation. Liu *et al.* (2025) emphasized in their study on bamboo furniture that safety and usability are primary design considerations, prompting this research to further reveal that modern wardrobes have evolved into dynamic living hubs integrating practical efficiency and emotional safety. Additionally, Liu *et al*. (2021) discovered in urban furniture design research that hygiene and health are core user needs, collectively corroborating the irreplaceable role of safety attributes in furniture design. Morais and Montagna (2015) pointed out that consumers often discard clothing not due to low quality or obsolescence but because of failed user-product relationships. Therefore, this study invited representative users to evaluate design proposals, confirming that Design Option 3 optimizes user-product interaction experiences more effectively.

CONCLUSIONS

This study constructed a data-driven wardrobe furniture design decision-making framework by integrating Web text mining, DEMATEL-ANP, and TOPSIS methods, revealing the intrinsic correlations between user needs and design elements. The main conclusions are as follows:

1. Through DEMATEL analysis, it was identified that safety design (D1, Mi=3.4), usability (C2, Ri=0.845), and storage space (C1, Mi=3.056) serve as the core causal factors in wardrobe design, forming the active driving layer of the system. Safety design directly influences elements such as craftsmanship quality and functional modules, acting as the underlying logic for product reliability; usability, with the highest net influence degree, serves as the foundational support for user experience; and storage space layout determines the feasibility and practicality of aesthetic design. ANP weight analysis further indicates that functional design (0.4601) and user experience (0.2985) are the core dimensions of user needs, significantly surpassing modeling design (0.1127) and material design (0.1287), which highlights the dual driving role of practicality and emotional satisfaction.
2. The optimal solution (Option 3) screened by TOPSIS takes natural log design as its

core language, simultaneously meeting user needs for Easy to Use (0.156), Large Storage Space (0.135), and Multifunctional Modules (0.123). At the operational level, Option 3 proposes the adoption of one-touch intelligent adjustment buttons, which enhance efficiency compared to traditional manual adjustment methods and reduce the usage threshold for elderly and child users. In the dimension of inclusive design, Option 3 integrates an ergonomic intelligent sensor lighting system, addressing the pain point of insufficient internal lighting in traditional wardrobes, particularly facilitating nighttime item retrieval for elderly users with visual impairments. In terms of safety structure, the use of anti-tipping wall fixtures and fully rounded corner treatments effectively reduces the risk of collision injuries, meeting the safety needs of multi-generational families. This design logic of "functional modularization-experience intelligence-safety standardization" provides a reusable innovative paradigm for the furniture industry, especially in subdivided fields such as customized home furnishings and elderly care furniture.

3. A primary limitation of this study arises from the predominantly design-professional-focused expert consultation, which may have underrepresented the authentic needs of ordinary users. Additionally, the research focused on pre-design evaluation, lacking systematic tracking of post-implementation user feedback. For future inquiry, the authors will incorporate interdisciplinary stakeholders to diversify the indicator system, ensure comprehensive representation of multifaceted needs, and integrate user emotion analysis with real-time consumption data to develop a dynamic furniture design framework adaptive to evolving user preferences.

REFERENCES CITED

Aastha, M., and Karthick, P. (2024). "Optimizing RPL for load balancing and congestion mitigation in IoT network," *Wireless Personal Communications* 136(3), 1619-1636. DOI: 10.1007/s11277-024-11346-2

An, H., and Park, M. (2020). "Approaching fashion design trend applications using text mining and semantic network analysis," *Fashion and Textiles* 7(1), article 34. DOI: 10.1186/s40691-020-00221-w

Asyraf, M. R. M., Rafidah, M., Ishak, M. R., Sapuan, S. M., Yidris, N., Ilyas, R. A., and Razman, M. R. (2020). "Integration of TRIZ, morphological chart and ANP method for development of FRP composite portable fire extinguisher," *Polymer Composites* 41(7), 2917-2932. DOI: 10.1002/pc.25587

Bang, H., and Su, J. (2022). "Who uses virtual wardrobes? Investigating the role of consumer traits in the intention to adopt virtual wardrobes," *Sustainability* 14(3), article 1209. DOI: 10.3390/su14031209

Bathrinath, S., Bhalaji, R. K. A., and Saravanasankar, S. (2021). "Risk analysis in textile industries using AHP-TOPSIS," *Materials Today: Proceedings* 45, 1257-1263. DOI: 10.1016/j.matpr.2020.04.722

Büyüközkan, G., and Çifçi, G. (2012). "A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP, and fuzzy TOPSIS to evaluate green suppliers," *Expert Systems with Applications* 39(3), 3000-3011. DOI: 10.1016/j.eswa.2011.08.162

Büyüközkan, G., and Güleryüz, S. (2016). "An integrated DEMATEL-ANP approach for renewable energy resources selection in Turkey," *International Journal of Production*

Economics 182, 435-448. DOI: 10.1016/j.ijpe.2016.09.015
Chen, M., and Lyu, J. H. (2014). "Aesthetic evaluation of furniture design based on ANP method," *Applied Mechanics and Materials* 574, 318-323. DOI: 10.4028/www.scientific.net/AMM.(574), 318
Choo, H. J., Sim, S. Y., Lee, H. K., and Kim, H. B. (2014). "The effect of consumers' involvement and innovativeness on the utilization of fashion wardrobe," *International Journal of Consumer Studies* 38(2), 175-182. DOI: 10.1111/ijcs.12078
Fang, J., Ye, L., Zhou, W., and Xiong, L. (2025). "A new model of emergency supply management for swift transition from peacetime to emergency considering demand urgency and supplier evaluation," *Systems* 13(1), article 54. DOI: 10.3390/systems13010054
Gregson, N., and Beale, V. (2004). "Wardrobe matter: The sorting, displacement, and circulation of women's clothing," *Geoforum* 35(6), 689-700. DOI: 10.1016/j.geoforum.2004.03.014
Hu, S., Fu, K. J., Jiang, X., *et al*. (2021). "Wardrobe styling design based on sensory engineering," *Journal of Forestry Engineering* 6(04), 176-183. DOI: DOI: 10.13360/j.issn.2096-1359.202010007
Irfan, R., aKing, C. K., Grages, D., Ewen, S., Khan, S. U., Madani, S. A., Kolodziej, J., Wang, L., Chen, D., Rayes, A., Tziritas, N., Xu, C., Zomaya, A., Alzhrani, S. S., and Li, H. (2015). "A survey on text mining in social networks," *The Knowledge Engineering Review* 30(2), 157-170. DOI: 10.1017/S0269888914000277
Iritani, D. R., Silva, D. L., Saavedra, Y. M. B., Grael, P. F. F., and Ometto, A. R. (2015). "Sustainable strategies analysis through life cycle assessment: A case study in a furniture industry," *Journal of Cleaner Production* (96), 308-318. DOI: 10.1016/j.jclepro.2014.05.029
Kamranfar, S., Azimi, Y., Gheibi, M., Fathollahi-Fard, A. M., and Hajiaghaei-Keshteli, M. (2022). "Analyzing green construction development barriers by a hybrid decision-making method based on DEMATEL and the ANP," *Buildings* 12(10), article 1641. DOI: 10.3390/buildings12101641
Khojasteh-Khosro, S., Shalbafan, A., and Thoemen, H. (2022). "Consumer behavior assessment regarding lightweight furniture as an environmentally-friendly product," *Wood Material Science and Engineering* 17(3), 192-201. DOI: 10.1080/17480272.2020.1847187
Klepp, I. G., and Bjerck, M. (2014). "A methodological approach to the materiality of clothing: Wardrobe studies," *International Journal of Social Research Methodology* 17(4), 373-386. DOI: 10.1080/13645579.2012.737148
Kumar, A., and Dixit, G. (2018). "An analysis of barriers affecting the implementation of e-waste management practices in India: A novel ISM-DEMATEL approach," *Sustainable Production and Consumption* 14, 36-52. DOI: 10.1016/j.spc.2018.01.002
Lam, J. S. L. (2015). "Designing a sustainable maritime supply chain: A hybrid QFD–ANP approach," *Transportation Research Part E: Logistics and Transportation Review* 78, 70-81. DOI: 10.1016/j.tre.2014.10.003
Liang, Y., Wang, H., and Zhao, X. (2022). "Analysis of factors affecting the economic operation of electric vehicle charging station based on DEMATEL-ISM," *Computers and Industrial Engineering* 163, article 107818. DOI: 10.1016/j.cie.2021.107818
Liu, J., Kamarudin, K. M., Liu, Y., and Zou, J. (2021). "Developing pandemic prevention and control by ANP-QFD approach: A case study on urban furniture design in China communities," *International Journal of Environmental Research and Public Health*

18(5), article 2653. DOI: 10.3390/ijerph18052653

Liu, W., Fei, Y. N., Yu, C. L., Hu, Z. Y., and Chen, J. Q. (2025). "Unveiling the core design elements of bamboo furniture," *IEEE Access* 13, 13341-13355. DOI: 10.1109/ACCESS.2025.3529779

Ma, X., Chen, Y., Liang, Q., and Wang, J. (2024). "Wardrobe furniture color design based on interactive genetic algorithm," *BioResources* 19(3), 6230-6246. DOI: 10.15376/biores.19.3.6230-6246

Mistarihi, M. Z., Okour, R. A., and Mumani, A. A. (2020). "An integration of a QFD model with Fuzzy-ANP approach for determining the importance weights for engineering characteristics of the proposed wheelchair design," *Applied Soft Computing* 90, article 106136. DOI: 10.1016/j.asoc.2020.106136

Morais, C., and Montagna, G. (2015). "Customized wardrobe: Clothing according to user," *Procedia Manufacturing* 3, 5814-5821. DOI: 10.1016/j.promfg.2015.07.833

Mubarik, M. S., Kazmi, S. H. A., and Zaman, S. I. (2021). "Application of gray DEMATEL-ANP in green-strategic sourcing," *Technology in Society* 64, article 101524. DOI: 10.1016/j.techsoc.2020.101524

Muhammad Suandi, M. E., Amlus, M. H., Hemdi, A. R., Abd Rahim, S. Z., Ghazali, M. F., and Rahim, N. L. (2022). "A review on sustainability characteristics development for wooden furniture design," *Sustainability* 14(14), article 8748. DOI: 10.3390/su14148748

Olson, D. L. (2004). "Comparison of weights in TOPSIS models," *Mathematical and Computer Modelling* 40(7-8), 721-727. DOI: 10.1016/j.mcm.2004.10.003

Pazand, K., and Hezarkhani, A. (2015). "Porphyry Cu potential area selection using the combine AHP-TOPSIS methods: A case study in Siahrud area (NW, Iran)," *Earth Science Informatics* (8), 207-220. DOI: 10.1007/s12145-014-0153-7

Rad, T. G., Sadeghi-Niaraki, A., Abbasi, A., and Choi, S. M. (2018). "A methodological framework for assessment of ubiquitous cities using ANP and DEMATEL methods," *Sustainable Cities and Society* 37, 608-618. DOI: 10.1016/j.scs.2017.11.024

Sindhu, S., Nehra, V., and Luthra, S. (2017). "Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India," *Renewable and Sustainable Energy Reviews* 73, 496-511. DOI: 10.1016/j.rser.2017.01.135

Spinder, S., Frasincar, F., Matsiiako, V., Boekestijn, D., and Brandt, T. (2023). "A text mining approach to identifying sustainability in the private sector," *Computers in Industry* 149, article 103932. DOI: 10.1016/j.compind.2023.103932

Tyagi, M., Kumar, P., and Kumar, D. (2014). "A hybrid approach using AHP-TOPSIS for analyzing e-SCM performance," *Procedia Engineering* 97, 2195-2203. DOI: 10.1016/j.proeng.2014.12.463

Wu, K., Zhang, J., Huang, Y., Wang, H., Li, H., and Chen, H. (2023). "Research on safety risk transfer in subway shield construction based on text mining and complex networks," *Buildings* 13(11), article 2700. DOI: 10.3390/buildings13112700

Xiong, Z., Yan, Z., Yao, H., and Liang, S. (2022). "Design demand trend acquisition method based on short text mining of user comments in shopping websites," *Information* 13(3), article 110. DOI: 10.3390/info13030110

Xu, J., Wei, D., Zhang, X., Li, X., and Chen, Y. (2024). "Dining table design research based on user needs hierarchy and DEMATEL-ISM," *BioResources* 19(4), 8959-8975. DOI: 10.15376/biores.19.4.8959-8975

Xu, J., Zhang, X., Liao, A., Yu, S., Chen, Y., and Chen, L. (2024). "Research on innovative design of towable caravans integrating Kano-AHP and TRIZ theories," *International Journal of Advanced Computer Science and Applications* 15(3), 991-1001. DOI: 10.14569/IJACSA.2024.0150399

Yang, J., Yang, B., Sun, Q., Yan, S., and Miao, Y. (2022). "Research on the key technology of web data extraction and mining based on the probability distribution," *Wireless Communications and Mobile Computing* 2022(1), article 6714785. DOI: 10.1155/2022/6714785

Yuan, Y., and Guan, T. (2014). "Design of individualized wheelchairs using AHP and Kano model," *Advances in Mechanical Engineering* 6, article 242034. DOI: 10.1155/2014/242034

Zhang, C., Huang, Y., Zhou, D., Dong, Z., He, S., and Zhou, Z. (2024). "A MCDM-based analysis method of testability allocation for multi-functional integrated rf system," *Electronics* 13(18), article 3618. DOI: 10.3390/electronics13183618

Zhang, J., and Chen, Y. (2024). "Research on color and texture characteristics and visual perception of custom wardrobe finishes," *BioResources* 19(3), 5109-5128. DOI: 10.15376/biores.19.3.5109-5128

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