Affective Evaluation of Timber Products Using BP Neural Network and Dempster-Shafer Evidence Theory

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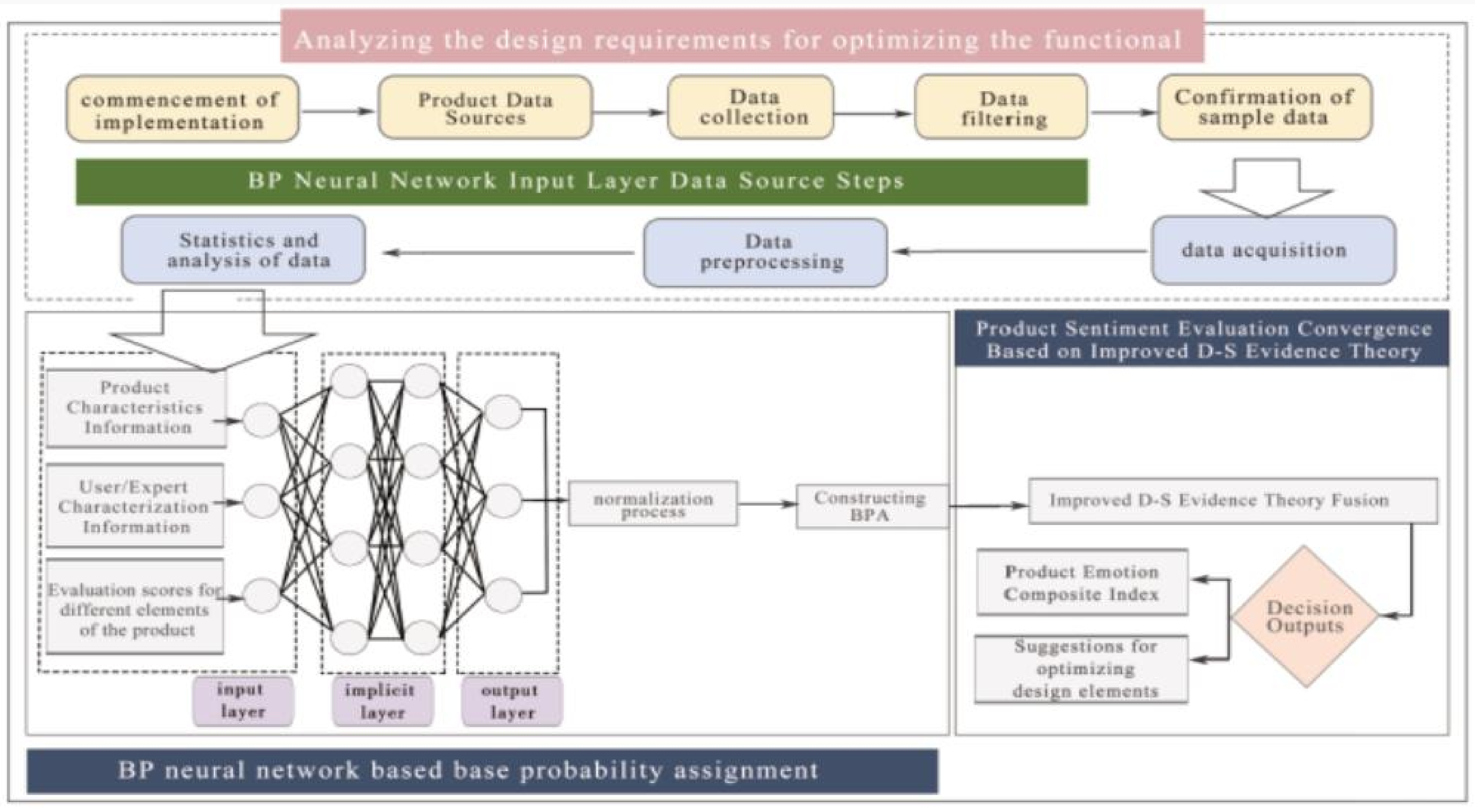
Introduction or abstract

This study proposes a subjective–objective integrated affective evaluation model that incorporates both user groups' emotional perceptions as an objective foundation and subjective recommendations from multiple product design experts. The BP neural network is employed to generate the basic probability assignment (BPA) required by Dempster–Shafer (D–S) evidence theory. An improved D–S evidence theory approach is then applied to weight and fuse expert evaluations, identifying key design elements for improvement along with their improvement indices, and forming a comprehensive product sentiment indicator. Using architectural timber products as a case study, the model calculates BPA based on user evaluations and integrates multiple experts' affective suggestions via the enhanced D–S fusion method, thereby pinpointing design elements requiring optimization and their corresponding improvement priorities, as well as deriving an overall emotional evaluation score. By integrating objective user perceptions with subjective expert judgments, this research offers a balanced affective evaluation strategy that enriches methodological approaches and provides actionable insights for product design improvement.

Objectives



1. Develop a scientific affective evaluation framework integrating user data and expert knowledge to address the limitations of traditional subjective or single-data evaluation methods. 2. Use BP neural network to objectively generate BPA and improve the rationality of D-S evidence theory in handling conflicting multi-source information. 3. Identify key design elements and their improvement priorities for timber products, and output a comprehensive sentiment index to support product forward design.

Materials & Methods

Materials: 1,040 valid user reviews, 1,438 timber product images 98 valid samples after preprocessing , 300 valid user questionnaires, and evaluations from 5 experts with over 10 years of experience . Methods:

Serial number	Tagged Words	Word Frequency	Document Frequency
1	Antique	331	313
2	Sturdy	322	322
3	Sophisticated	179	175
4	Practical	150	145
...	...	...	...
76	Aesthetics	50	48

1. Extract sentiment feature words via sentiment analysis APIs and K-means clustering.

Classification results of user characteristics.

Age (X_1)	Gender(X_2)	Purpose of use (X_3)	Characteristics of the environment in which it is used (X_4)
18~30 years old (X_{11})	Male(X_{15})	Strengthening of Beams and Columns of Ancient Buildings (X_{20})	Long-term exposure to ultraviolet light (X_{30})
31~45 years old (X_{12})		Landscape Wooden Facilities for Courtyards (X_{21})	Intermittent wet/dry cycles (X_{31})
46~60 years old (X_{13})	Female(X_{16})	Construction of Outdoor Stacks/Pavilions (X_{22})	Alternating freeze-thaw environments (X_{32})
61 years old and above (X_{14})		Decorative Works for Imitation of Ancient Buildings (X_{23})	Areas susceptible to insect infestation (X_{33})

Product characterization codes.

Sample number	Color (C_1)	Texture (C_2)	Material (C_3)	Shape (C_4)	Size (C_5)
1	(C_{13})	(C_{21})	(C_{31})	(C_{40})	(C_{51})
2	(C_{18})	(C_{23})	(C_{33})	(C_{41})	(C_{53})
3	(C_{12})	(C_{20})	(C_{30})	(C_{40})	(C_{50})
4	(C_{14})	(C_{21})	(C_{31})	(C_{40})	(C_{51})
...	...	...	...	...	...
15	(C_{18})	(C_{18})	(C_{33})	(C_{41})	(C_{53})

2. Construct a four-layer BP neural network.input: product attributes/user characteristics/design ratings; output: design element labels to generate BPA.

Neural network setup key parameters.

neural network	Implicit Layer Number of nodes	performance target	learning rate	Maximum number of iterations
BP neural network	[10, 8]	0.01	0.05	300

3. Adopt refined D-S evidence theory. introducing average evidence distance for weighting to fuse expert evaluations.

Comparative Performance of Affective Evaluation Models

Method	Accuracy	Precision	Recall	F1-Score
Expert Average Scoring Method	0.733	0.701	0.752	0.726
Independent BP Neural Network Method	0.833	0.798	0.853	0.825
Traditional D-S Evidence Theory Method	0.785	0.746	0.801	0.773
BP-DS Model	0.917	0.885	0.947	0.915

4. Compare the proposed BP-DS model with expert averaging, independent BP network, and traditional D-S methods.

Results

Sample number	Mass (A1)	Mass (A2)	Mass (A3)	Mass (A4)	Mass (A5)	Mass (N)
2	0.268	0	0	0	0	0.732
6	0.109	0	0	0	0	0.891
9	0	0	0	0.005	0	0.950

results indicate that Sample 9 exhibits an extremely low improvement index across all elements, with a comprehensive emotional index of 0.950. This demonstrates its high compatibility with the "Antique" aesthetic, requiring no significant improvements. Sample 6 shows an improvement index of 0.109 for color elements, necessitating moderate optimization. Sample 2 exhibits a color improvement index of 0.268, identifying it as a key area for optimization. This integrated approach effectively identifies design optimization priorities by combining user perception with expert evaluation, providing quantitative evidence for the forward design of modular materials for ancient architecture.

Conlcusion

This study developed a product sentiment evaluation model On the basis of a BP neural network and an refined D-S evidence theory, achieving an organic integration of user sentiment perception and expert recommendations. The model effectively identifies the priority of improvements for key design elements and outputs a comprehensive sentiment index, providing quantitative evidence for product forward design. Current research still faces limitations such as limited data scale and the influence of expert preferences. Future work could incorporate methods like multimodal data and graph neural networks to further enhance the model's generalization and expressive capabilities.

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