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PAPER

Students' Decisions in the Context of Social Network Learning Interaction

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ABSTRACT

In the context of globalization and technology-driven advancements in the 21st century, learning methods have undergone significant changes. The development of informatization education and social networking technology has facilitated the integration of learning into every aspect of daily life, extending beyond the confines of traditional classrooms. Students interact and cooperate with other learners on social media platforms, which provide them with rich learning resources. However, making the best choice from them has become a core issue. Although the evaluation and selection of learning resources on social networks have been extensively studied in the academic community, most of the studies have focused on the observable attributes of resources while neglecting the subjective perception and experiential attributes of students. This study aimed to investigate how students make learning decisions based on their expectations of learning energy efficiency in social network learning environments. The study also considered observable and experiential attributes of learning resources to provide more comprehensive and accurate references for learning decisions.

KEYWORDS

learning on social networks, selection of learning resources, expectation levels of learning energy efficiency, observable attributes, experiential attributes

1 INTRODUCTION

In the 21st century, driven by globalization and technology, learning has undergone profound changes [1–4]. With the continuous deepening of informatization education and the rapid popularization of social networking technology, traditional educational patterns have gradually shifted towards online forms. For students majoring in finance, this means that they also need to master new skills related to financial technology (FinTech) in addition to traditional financial knowledge. Instead of being limited to classrooms, learning has permeated every aspect of daily life [5, 6]. Students interact, communicate, and cooperate with other learners on various social networking platforms. This not only allows them to create new knowledge together

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but also helps them achieve personalized and self-directed learning goals. In such an environment, students are confronted with a learning ecosystem that offers a plethora of choices, particularly for those pursuing a finance major. These students are required to navigate through vast amounts of financial data and case studies, making important decisions along the way. How to make the best learning decisions among numerous resources has become a core issue in modern educational research [7–9].

Learning on social networks not only changes the form of learning but also brings unprecedented learning resources and opportunities to finance students [10, 11]. For example, they have access to the latest financial market dynamics and analysis tools on online platforms. However, this also brings up an issue: how do you find the most suitable learning resources among the vast amount available? The expectation levels of learning energy efficiency serve as a bridge that connects the anticipated impact and intrinsic motivation of students with the tangible benefits of learning resources [12–16]. By conducting in-depth research on the expectations and learning needs of students majoring in finance, we can gain a more accurate understanding and help them select learning resources in a more targeted manner.

Although the evaluation and selection of learning resources on social networks have been extensively studied in the academic community, most of the studies have focused on the observable attributes of resources while neglecting the subjective perception and experiential attributes of students [17–19]. For students majoring in finance, this means that they may place too much emphasis on the complexity of data and models when selecting learning resources, while neglecting the importance of practical applications and market insights. In addition, the current evaluation methods are not unified and standardized, which increases the confusion and challenges for students in the learning decision process.

The research content of this study can be divided into four main sections. First, the research question was clearly described, and a comprehensive research framework was established. Second, this study delved into the calculation method for students' perceptual learning energy efficiency based on observable attributes. Third, this study focused on experiential attributes and conducted a thorough analysis of their role in calculating the perceptual learning energy efficiency of students. Finally, based on the previous two parts, a brand-new calculation method for learning energy efficiency was proposed, and learning resources were systematically ranked accordingly. It is believed that this study not only provides students with more accurate learning decision-making references but also offers valuable strategic suggestions for educators and learning platforms.

2 PROBLEM DESCRIPTION AND RESEARCH FRAMEWORK

In the era of digital learning, students have access to a wealth of online learning resources. To predict the quality of resources, students often infer the values of their experiential attributes by relying on evaluations from their classmates who have already chosen the resources. In addition, students have certain expectations for the attributes and values of learning resources. When selecting resources, individuals establish their expectations for them. Therefore, considering the limited rational behavior of students, selecting the most ideal learning resources from their consideration set is an unresolved issue. This requires comprehensive consideration of observable and experiential attributes, as well as their expectation levels. Figure 1 illustrates the research framework for students' decision-making processes in social network learning interactions.

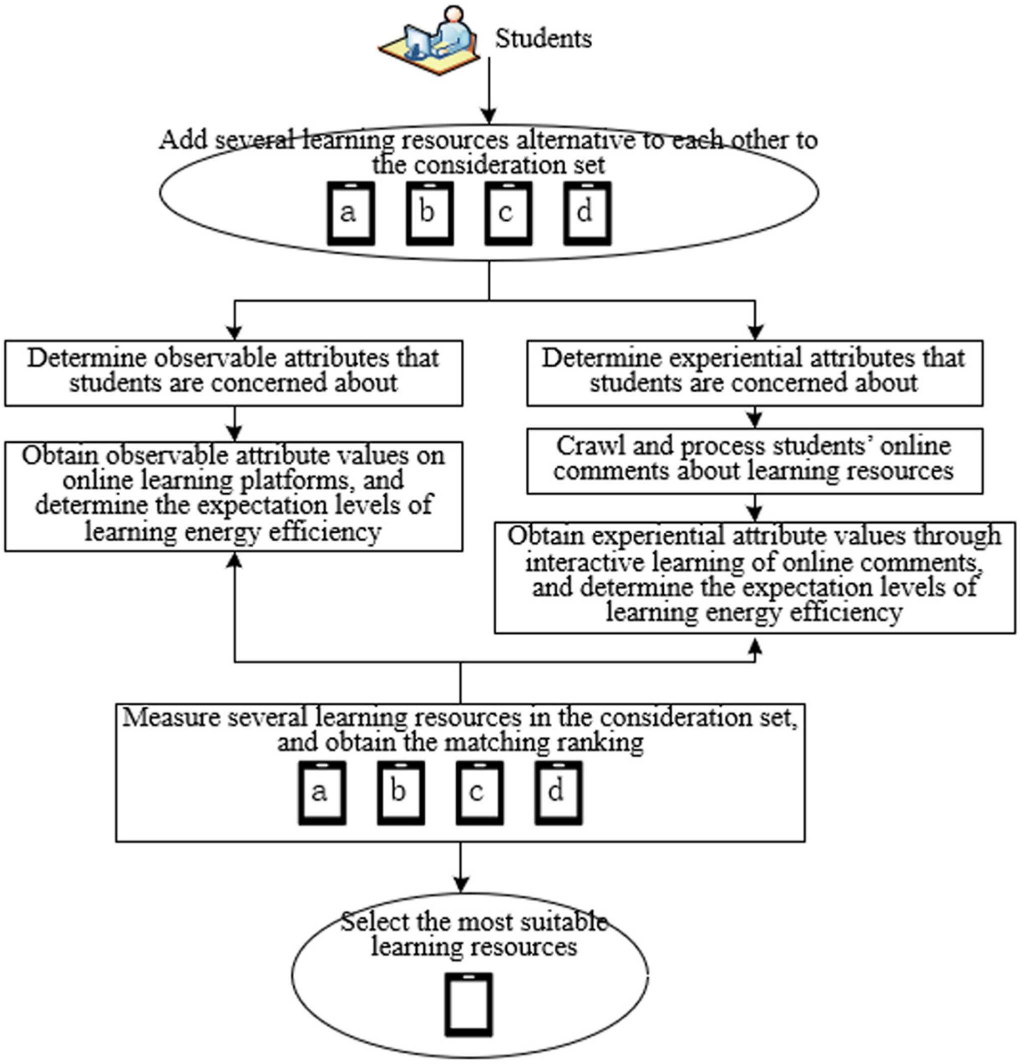

Fig. 1. Research framework of students' learning decision problem in social network learning interaction

In the context of selecting online learning resources described in this study, observable attributes refer to the information that students directly observe or obtain before accessing or using learning resources. These attributes include resource description (such as titles and introductions of videos), content form (such as videos, texts, interactive experiments, and multimedia), duration (such as the length of videos or the number of words in articles), author's qualifications (such as the lecturer's background, experiences, and awards), release date (indicating how new the resources are), organizations to which the resources belong (such as universities, educational institutions, or online platforms), and preview content (such as the first few minutes of videos or the beginning of texts). Students usually cannot evaluate or experience experiential attributes unless they have the opportunity to use or access learning resources. These resources include content quality (such as the depth, breadth, and accuracy of courses), teaching methods (such as the clarity of explanations, the rationality of examples, and the logicality of the course structure), interactivity (such as the presence of interactive elements such as Q&A and quizzes), learning effect (such as the degree of. knowledge mastery achieved by students after using the resources), user experience (such as the operation smoothness of platform operation and the loading speed of resources), evaluations from classmates (such as feedback and ratings from students who have already used the resources), and applicable groups (such as whether the resources are suitable for beginners, intermediate, or advanced learners).

When students select online learning resources, they initially make preliminary choices based on observable attributes. This is because these attributes quickly provide basic information about the resources. However, students began to focus on experiential attributes when they further considered the selection of resources. They obtained these experiential attributes by deeply understanding the feedback from their classmates who had used the resources or by trying them out. Experiential attributes typically provide a more accurate reflection of the true quality and impact of resources.

Let $L = \{1, 2, ..., l\}$; $B = \{1, 2, ..., l\}$; $O = \{O_1, O_2, ..., O_l\}$ be the consideration set of alternative learning resources; $P_i O_u$ be the u-th alternative learning resource; $V = \{V_1, V_2, ..., V_b\}$ be the attribute set of learning resources; V_k be the attributes of the k-th learning resource; $V^P = \{V_1, V_2, ..., V_{b1}\}$ and $V^R = \{V_{b1+1}, V_{b1+2}, ..., V_b\}$ be the subsets of V; V^P be the set of observable attributes; V^R be the set of experiential attributes, with $V^P \cup V^R = V$; $V^P = \{1, 2, ..., b_1\}$; $V^R = \{b_1 + m, b_1 + 2, ..., b\}$, with $B^P \cup B^R = B$; $q = (q_1, q_2, ..., q_b)$ be the weights of learning resource attributes; q_k be the weight or importance of V_k, with $\sum_{k=1}^{b} q_k = 1\ (0 \le q_k \le 1, k \in B)$.

Let $A = [a_{uk}]_{l \times bu}$ be the decision matrix of observable attributes; a_{uk} be the values of attributes V_k of learning resources O_u. Before selecting learning resources, students obtained the values of a_{uk} through the description of learning resource attributes, with $u \in L$ and $k \in B^P$.

Students typically choose the most suitable learning resources by establishing expectations for the attributes of the resource. For observable attributes, students usually expressed their expectations for learning energy efficiency in the following three forms:

Expectation type 1: Students expected that a_{uk} should preferably not exceed their expected values r_k for attributes V.

Expectation type 2: Students expected that a_{uk} should preferably not be lower than r_k'.

Expectation type 3: Students expected that a_{uk} should preferably be within the range of $r_k^- = \left[r_k^m, r_k^i\right]$, with $r_k^i > r_k^m$.

Let $W = \left[w_{uk}^n\right]_{l \times (b-b1)}$ be the decision matrix of experiential attributes; w_{uk}^n be the values of experiential attributes V_k of learning resources O_u; $SO_u = \{SO_u^1, SO_u^2, \ldots, SO_u^{ju}\}$ be classmates' evaluation set of learning resources; SO_u^y be the y-th evaluation of learning resources O_u.

After collecting learning resources from online learning platforms and reviewing evaluations made by students, this study analyzed the evaluation content and extracted the experiential attribute values. After obtaining students' expectation levels for different attributes of learning resources through questionnaire surveys or in-depth interviews, this study quantified the levels of expectation and transformed them into measurable indexes. A decision model for resource selection was constructed based on the values of observable and experiential attributes, as well as the expectations of students. Considering the limited rational behavior of students, the decision model was optimized and corrected. Finally, the decision model was used to select the most ideal learning resources from the set of resources being considered by students. The selection results were used to verify the degree of match between the actual effect and students' expectations.

3 CALCULATING PERCEPTUAL LEARNING ENERGY EFFICIENCY OF STUDENTS FOR OBSERVABLE ATTRIBUTES

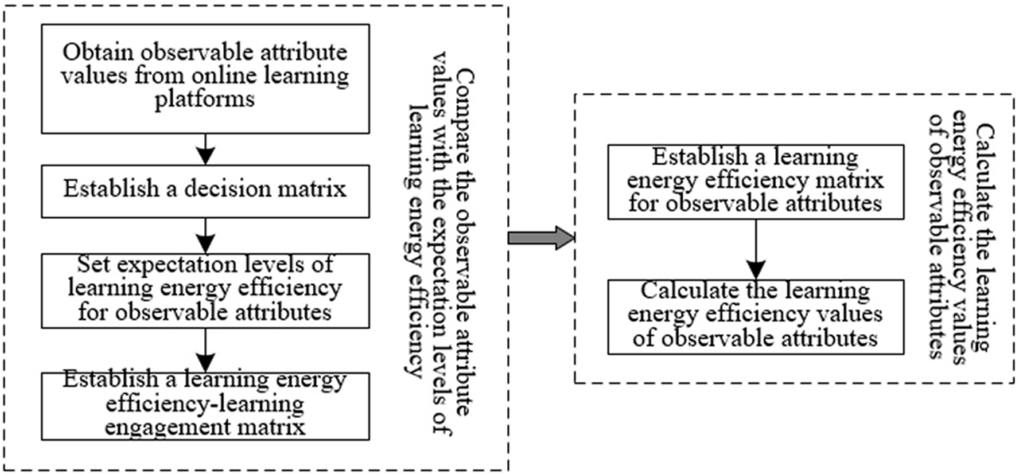

Fig. 2. Observable attribute processing framework for students' learning decisions

In an online learning environment with numerous learning resources, students first need to select resources. Calculation of learning energy efficiency based on observable attributes provides students with a fast and intuitive reference, helping them quickly find potential suitable candidates in massive resources. Meanwhile, observable attributes provide relatively objective and consistent information because they are directly displayed as features outside of the resources. By calculating the energy efficiency of learning based on these attributes, students obtained a relatively objective evaluation of learning resources, reducing the risk of interference from subjective factors. Figure 2 illustrates the framework for processing observable attributes in order to make learning decisions for students.

3.1 Calculation of learning energy efficiency and learning engagement

For the three types of expectations proposed earlier in this study, their learning energy efficiency and learning engagement were calculated using the methods described below.

For expectation type 1, when students' expectation levels r_k were considered as a reference point, the functional relationship between learning energy efficiency and learning engagement was obtained as follows:

$$D_{uk} = r'_k - a_{uk}, u \in L, k \in B^P \tag{1}$$

For expectation type 2, when students' expectation levels r'_k were considered as a reference point, the functional relationship between learning energy efficiency and learning engagement was obtained as follows:

$$D_{uk} = a_{uk} - r'_k, u \in L, k \in B^P \tag{2}$$

For expectation type 3, when students' expectation levels r'_k were considered as a reference point, the functional relationship between learning energy efficiency and learning engagement was obtained as follows:

$$D_{uk} = \begin{cases} 0, r_k^m \le a_{uk} \le r_k^i \\ a_{uk} - r_j^m, a_{uk} < r_k^m \\ r_k^i - a_{uk}, a_{uk} > r_k^i \end{cases}, u \in L, k \in B^P \tag{3}$$

For Equations 1–3, D_{uk} represented students' learning energy efficiency values in case of $D_{uk} > 0$, and represented their learning engagement values in case of $D_{uk} < 0$. Therefore, the learning energy efficiency-learning engagement matrix $D = [D_{uk}]_{l \times bu}$ was established based on these equations.

3.2 Calculating the learning energy efficiency values for observable attributes

The energy efficiency value of each learning resource attribute was calculated, enabling students to have a clear understanding of each attribute. For example, in a video tutorial, students clearly understood the impact of different factors, such as content quality, teaching methods, and interactivity, on the overall learning experience. Different students may attach more importance to specific attributes. By calculating the energy efficiency values for all attributes, students were able to select learning resources that best matched their preferences and needs. The energy efficiency values of attributes V_k of learning resources O_u were calculated using the following equation:

$$C_{uk} = \begin{cases} \left(D_{uk}\right)^{\beta}, D_{uk} \ge 0 \\ -\eta\left(-D_{uk}\right)^{\beta}, D_{uk} < 0 \end{cases}, u \in L, k \in B^P \tag{4}$$

where, β and α are students' attitudes towards both learning energy efficiency and learning engagement, with $0 \le \beta$ and $\alpha \le 1$; η is students' aversion degree of learning engagement, with $\eta > 1$. The learning energy efficiency matrix $C = [C_{uk}]_{l \times bu}$ needed to be normalized to $C' = [C'_{uk}]_{l \times bu}$ using the following equations:

$$C'_k = \frac{C_{uk}}{C_k^{MAX}}, u \in L, k \in B^P \tag{5}$$

$$C_k^{MAX} = \underset{u \in L}{MAX}\left\{\left|C_{uk}\right|\right\}, k \in B^P \tag{6}$$

For students, the overall learning energy efficiency value provides them with a concise and intuitive evaluation index, making it more convenient for them to select learning resources. For online learning platforms, value serves as an important criterion for ranking and recommending resources. Resources with higher values are more likely to be recommended to students, thereby enhancing their learning outcomes and satisfaction. Based on the above analysis, the overall learning energy efficiency values I_u^P of O_u for observable attributes were further calculated using a simple weighting method as follows:

$$I_u^P = \sum_{k=1}^{b_1} q_k C'_{uk}, u \in L \tag{7}$$

4 CALCULATING PERCEPTUAL LEARNING ENERGY EFFICIENCY OF STUDENTS FOR EXPERIENTIAL ATTRIBUTES

4.1 Perception update of experiential attributes

If students' post-learning perception of learning resources O_u with experiential attributes V_k obeyed a normal distribution, i.e. $w_{uk}^{\sim} \sim B(w_{uk}, \delta_{uk}^2)$. Let w_{uk} be the average value of experiential attributes V_k of learning resources O_u, and δ_{uk} be the difference of all students in post-learning perception of experiential attributes V_k of learning resources O_u. Students and their classmates usually have a certain understanding of learning resources before making a decision to select them, which may be influenced by teachers' recommendations. Therefore, it is assumed that all students have the same preconceived notion perception of learning resources. Let $w_{uk}^{\sim s}$ be the prior beliefs shared by all students regarding the experiential attributes V_k of learning resources O_u. It is assumed that $w_{uk}^{\sim s}$ also obeys a normal distribution, i.e. $w_{uk}^{\sim s} \sim BB(w_{uk}^s, (\delta_{uk}^s)^2)$, with $u \in L$ and $k \in B^R$.

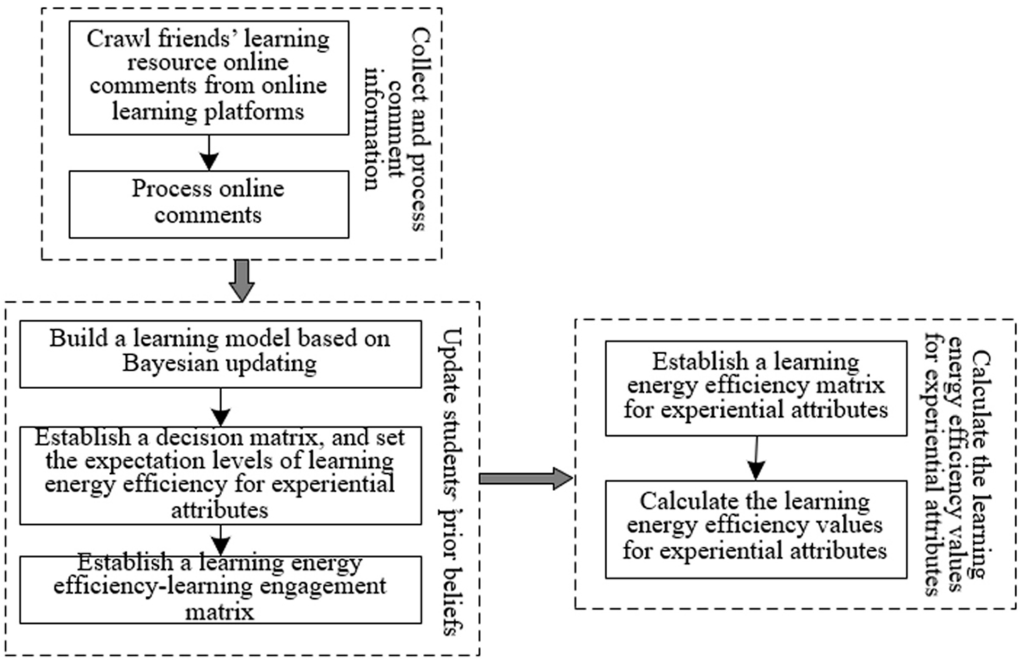

Fig. 3. Experiential attribute processing framework for students' learning decisions

Figure 3 illustrates the framework for processing experiential attributes in students' learning decisions. Before making a decision on resource selection, students typically browse evaluations of alternative learning resources made by their classmates on online learning platforms. This allows them to infer the experiential attribute values of the learning resources and update their prior beliefs to posterior ones through the learning process. The posterior beliefs of students also followed a normal distribution, i.e., $w_{uk}^{\sim n} \sim BB(w_{uk}^{n}, (\delta_{uk}^{n})^2)$. Let $J_u = \{j_{u(b1+1)}, j_{u(b1+2)}, \ldots, j_{ub}\}$ be the set of comments for each type of experiential attribute.

Based on the Bayesian updating criterion, this study constructed the following learning model that updated students' prior beliefs:

$$w_{uk}^{n} = \frac{(\delta_{uk})^2}{j_{uk}(\delta_{uk}^{s})^2 + (\delta_{uk})^2} w_{uk}^{s} + \frac{j_{uk}(\delta_{uk}^{s})^2}{j_{uk}(\delta_{uk}^{s})^2 + (\delta_{uk})^2} w_{uk}, u \in L, k \in B^R \tag{8}$$

$$(\delta_{uk}^{s})^2 = \frac{(\delta_{uk}^{s})^2 (\delta_{uk})^2}{(\delta_{uk}^{s})^2 + (\delta_{uk})^2}, u \in L, k \in B^R \tag{9}$$

Let $w_{uk}^{s} = 0$. Variance F_{uk} represented classmates' perceptual difference of experiential attributes V_k of learning resources O_u, because the average rating value E_{uk} represented the actual post-perception. Equation 8 was updated as follows:

$$w_{uk}^{n} = \frac{j_{uk}(\delta_{uk}^{s})^2}{j_{uk}(\delta_{uk}^{s})^2 + F_{uk}} E_{uk}, u \in L, g = k \in B^R \tag{10}$$

Based on the above analysis, the decision matrix $W = [w_{uk}^{n}]_{l\times(b-b1)}$ of experiential attributes was constructed after determining students' posterior perception of learning resources. Similar to observable attributes, students usually also establish expected values for experiential attributes. However, it was usually expected by students that the larger the values of experiential attributes, the better. Therefore, similar to the processing of observable attributes, the learning energy efficiency or learning engagement of students for experiential attributes V_k of learning resources O_u is expressed as:

$$M_{uk} = w_{uk}^{s} - r_k', u \in L, k \in B^R \tag{11}$$

In the above equation, M_{uk} represents students' learning energy efficiency in case of $M_{uk} > 0$, and their learning engagement when $M_{uk} < 0$. The matrix $M = [M_{uk}]_{l\times(b-b1)}$ was constructed to measure the learning energy efficiency and learning engagement matrix for experiential attributes.

4.2 Calculating the learning energy efficiency values for experiential attributes

Students had varying psychological responses to learning about energy efficiency and engaging in the learning process. Based on prospect theory, the values of students' learning energy efficiency for experiential attributes V_k of learning resources O_u were calculated using the following equation:

$$T_{uk} = \begin{cases} (M_{uk})^{\beta}, M_{uk} \geq 0 \\ -\eta(-M_{uk})^{\alpha}, M_{uk} < 0 \end{cases}, u \in M, k \in B^R \tag{12}$$

After adopting the same values of β, α and η as observable attributes, a learning energy efficiency value matrix $T = [T_{uk}]_{l\times(b-b1)}$ was further constructed for experiential attributes. The matrix $T = [T_{uk}]_{l\times(b-b1)}$ was normalized to $T' = [T_{uk}']_{l\times(b-b1)}$ using the following equations:

$$T_{uk}' = \frac{T_{uk}}{T_k^{MAX}}, u \in L, k \in B^R \tag{13}$$

$$T_k^{MAX} = \underset{u \in L}{MAX}\left\{\left|T_{uk}\right|\right\}, k \in B^R \tag{14}$$

Furthermore, the comprehensive learning energy efficiency value I_u^R of O_u for experiential attributes was calculated based on the simple weighting method using the following equation:

$$I_u^R = \sum_{k=b_1+1}^{b} q_k T'_{uk}, u \in L \tag{15}$$

5 CALCULATING THE COMPREHENSIVE PERCEPTUAL LEARNING ENERGY EFFICIENCY OF STUDENTS AND RANKING OF LEARNING RESOURCES

Combined with the analysis in the previous two sections, the overall learning energy efficiency value of learning resources was calculated by summing the learning energy efficiency values of observable and experiential attributes. The overall learning energy efficiency value of learning resources O_u for students was calculated using the following equation:

$$I_u = I_u^P + I_u^R, u \in L \tag{16}$$

Learning resources in the consideration set were ranked using the method described above. The higher value of the learning energy efficiency value I_u indicated that students were more satisfied with the learning resources O_u, which resulted in a better learning outcome.

6 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Observable attribute values and students' learning energy efficiency expectation levels

Attributes		Resource Description	Content Form	Duration	Author's Qualifications
Learning resources	1	8.9	6.1	9.8	3.2
	2	3.6	5.7	8.5	2.2
	3	6.8	6.0	6	5
Learning energy efficiency expectations of students		Preferably within [6, 10]	Preferably within [5, 10]	Preferably within [5, 10]	Preferably within [4, 10]
Attributes		Release date	Organization to which the resource belongs	Preview content	
Learning resources	1	4	2.5	5.5	
	2	5	5.5	7	
	3	1	6	8.7	
Learning energy efficiency expectations of students		Preferably not more than three months	Preferably within [5, 10]	Preferably within [6, 10]	

Table 1 displays the measurable attribute values and students' levels of expectation regarding learning energy efficiency. It can be seen from the table that the resource description, content form, and author's qualifications for learning resource 1 are excellent. However, the duration, release date, organization to which the resource belongs, and preview content do not fully meet the expectations of students. The organization to which the resource belongs, the preview content, and the duration of learning resource 2 are good. However, the resource description and author's qualifications are lower than the expectations of students. Resource description, content form, duration, author's qualifications, the organization to which the resource belongs, as well as the preview content of learning resource 3, meet or exceed the expectations of students. However, the release date falls below the expectations of students. Overall, learning resource 3 performs the best, with most attributes meeting or exceeding the expectations of students for learning energy efficiency. Learning resource 1 has outstanding performance in certain core attributes but falls short of meeting expectations in some other areas. Learning resource 2 performs well in some areas but is slightly lacking in other important aspects. Therefore, students should make decisions based on the attributes that they value the most when selecting learning resources. If importance is placed on the freshness and preview content of resources, learning resource 3 may be the best choice. If more importance is attached to the author's qualifications and the form of the content, learning resource 1 is also a good option.

Table 2. Average value and variance of experiential attribute rating and students' learning energy efficiency expectation levels

Attributes	Content Quality			Teaching Methods			Interactivity			Learning Effect		
Learning resources	1	2	3	1	2	3	1	2	3	1	2	3
Average value	5.8	6.2	6.0	5.4	5.5	5.2	5.8	5.7	6.2	5.5	5.2	5.8
Variance	1.1	1.0	1.4	1.7	1.5	1.6	1.6	1.2	1.1	1.5	1.6	1.6
Number of comments	167	178	123	118	108	91	138	88	156	108	96	138
Learning energy efficiency expectations of students	Preferably within [6, 10]			Preferably within [5, 10]			Preferably within [5, 10]			Preferably within [5, 10]		
Attributes	User experience			Evaluations of classmates			Applicable groups					
Learning resources	1	2	3	1	2	3	1	2	3			
Average value	5.4	6.2	7.0	5.4	5.7	5.2	5.9	5.7	7.2			
Variance	1.2	1.0	1.5	1.6	1.1	1.6	1.5	1.2	1.4			
Number of comments	167	169	93	118	142	99	138	96	106			
Learning energy efficiency expectations of students	Preferably within [6, 10]			Preferably within [5, 10]			Preferably within [5, 10]					

Table 2 displays the mean value and variance of experiential attribute ratings and students' expectation levels of learning energy efficiency. It can be seen from the table that learning resource 1 meets or approaches students' expectations for energy efficiency in terms of interactivity, learning effectiveness, and applicable groups. However, it slightly falls short in other areas. Learning resource 2 has relatively good content quality, but it does not fully meet students' expectations in other areas, particularly in terms of learning effectiveness. Learning resource 3 performs well in terms of interactivity, user experience, and applicability to different groups, significantly surpassing other resources and meeting student' expectations for energy efficiency in learning. It also performs well in other attributes. Overall, learning resource 3 meets or exceeds students' expectations for energy efficiency in most areas and demonstrates exceptional overall performance. Learning resources 1 and 2 demonstrate strong performance in certain attributes, but they are somewhat lacking in other areas. Therefore, students should make decisions based on the attributes that they value the most when selecting learning resources. If importance is placed on interactivity, user experience, and applicable groups, learning resource 3 may be the best choice. If more importance is attached to content quality, learning resource 2 can be considered. Learning resources 1 is a well-rounded option with consistent performance in all aspects, making it a solid choice.

Table 3 displays the collinearity statistics for experiential attributes. It can be observed from the table that the majority of the experiential attributes do not show significant collinearity. This suggests that the variables have a relatively independent relationship and offer valuable information for the multiple regression model. Teaching methods and evaluations of classmates show high variance inflation factor (VIF) values in certain aspects. These high values may indicate a correlation between these variables and other variables, suggesting the need for further research or model adjustments. The user experience exhibits very low collinearity in all three aspects, which is highly significant. This suggests that it is a relatively independent variable and provides unique information for the model. Overall, most of these experiential attributes do not have serious issues with collinearity. However, special attention may need to be paid to "teaching methods" and "evaluations of classmates" when modeling.

Table 3. Collinearity statistics of experiential attributes

	Number of Submitted Ideas		Scores		Number of Obtained Votes	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
Content quality	0.721	1.389	0.499	2.143	0.819	1.325
Teaching methods	0.425	2.521	0.351	2.798	0.498	2.154
Interactivity	0.815	1.123	0.679	1.523	0.688	1.345
Learning effect	0.411	2.541	0.613	1.522	0.512	1.883
User experience	0.751	1.239	0.755	1.345	0.987	1.006
Evaluations of classmates	0.423	2.539	0.655	1.519	0.569	1.827
Applicable groups	0.772	1.259	0.721	1.339	0.901	1.098

Table 4 displays the results of the regression analysis. It can be seen from the table that content quality is an important positive influencing factor in all three types of learning. Energy efficiency expectations, meaning that high-quality content improves students' expectations for learning energy efficiency. Teaching methods can have a negative impact on Type 1, indicating that certain teaching methods may not be very effective for specific students. However, teaching methods have a positive impact on Types 2 and 3. The user experience is significantly negative across all types of expectations, which is an interesting finding that warrants further research and explanation. Evaluations of classmates have a negative impact on Type 1 students but have a positive impact on Types 2 and 3. This suggests that different types of students may have varying responses to evaluations from their classmates. All models perform well overall, but the Type 2 model has the highest degree of fit, indicating that it explains the most variation in the dependent variables. Overall, the models provide valuable information on energy efficiency expectations. However, they also indicate that students of different types may respond differently to various variables. This provides important guidance for educators, indicating that they may need to adopt different strategies to meet the needs of various students.

Table 4. Regression analysis results

Variables	Dependent Variables		
	Type 1	Type 2	Type 3
Independent variables			
Constant term	–24.238*** (2.894)	–732.256*** (–3.268)	–225.568* (–1.789)
Content quality	0.946*** (81.351)	0.812*** (68.239)	0.478*** (25.361)
Teaching methods	–0.093*** (–6.238)	0.187*** (12.369)	0.375*** (14.236)
Interactivity	–0.038*** (–3.691)	–0.038*** (–3.756)	0.088*** (0.032)
Learning effect	0.228*** (14.268)	0.165*** (13.562)	0.225.139 (11.258)
User experience	–0.032** (–2.895)	–0.078*** (–8.364)	–0.132*** (–7.158)
Evaluations of classmates	–0.055*** (–4.561)	0.195*** (12.125)	0.487*** (14.143)
Applicable groups	–0.058*** (–3.226)	–0.066*** (–3.745)	0.092*** (0.059)
Adjusted R^2	0.8795	0.925	0.669
F	1835.524***	2639.521***	462.158***
DW	1.899	2.127	2.183
N	1325	1325	1325

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; the statistical value of corresponding coefficient y is shown in parentheses.

Table 5 presents the results of hypothesis testing for each category of learning energy efficiency expectations. It can be seen from the table that all factors of Type 1, excluding the learning effect, have a positive relationship with the students' expectations of learning energy efficiency. This suggests that students of this type prioritize content, interactivity, and evaluations from their classmates. For Type 2, while the expected relationship between teaching methods and interactivity is not supported, all other factors show a positive relationship with students' expectations of learning energy efficiency. For Type 3, although there is an expected interactivity, learning effect, and user experience, there is a negative relationship with learning energy efficiency expectations. However, the actual relationship is not supported. Other factors have a positive relationship with students' expectations for learning energy efficiency.

Table 5. Hypothesis testing results

Independent Variables	Hypotheses	Prediction Symbols	Results
Learning energy efficiency expectation type 1	A1	+	Support
	A2	+	Support
	A3	+	Support
	A4	−	Not support
	A5	+	Support
	A6	+	Support
	A7	+	Support
Learning energy efficiency expectation type 2	B1	+	Support
	B2	−	Not support
	B3	−	Not support
	B4	+	Support
	B5	+	Support
	B6	+	Support
	B7	+	Support
Learning energy efficiency expectation type 3	C1	+	Support
	C2	+	Support
	C3	−	Not support
	C4	−	Not support
	C5	−	Not support
	C6	+	Support
	C7	+	Support

7 CONCLUSION

This study discusses how students make decisions when faced with numerous learning resources in the context of social network learning interactions. Especially before selecting learning resources, students often rely on evaluations on online learning platforms to predict the experiential attribute values of those resources. By combining observable and experiential attributes with students' expectations of energy efficiency in learning, this study proposes a decision-making method that incorporates students' limited rational behavior. In addition, this study introduces a method for calculating the energy efficiency of perceptual learning in students, taking into account observable and experiential attributes. It also provides a comprehensive ranking of learning resources.

After conducting a collinearity analysis of experiential attributes, this study determined which variables had a relatively independent relationship and which ones required further investigation. A regression analysis of learning energy efficiency expectations revealed that the direction and extent of these expectations are affected by all independent variables, such as content quality and teaching methods.

Based on the established hypotheses, the test results showed that most factors had a positive relationship with students' expectations of learning energy efficiency. However, there were also some exceptions.

The empirical results showed that most factors, such as content quality, teaching methods, and interactivity, had a positive relationship with students' expectations of learning energy efficiency. However, there were also exceptions, which demonstrated the complexity and diversity of students. It is particularly noteworthy that experiential attributes, such as user experience and evaluations of classmates, have a critical impact on decision-making in specific situations.

Overall, this study provides important insights for online learning platforms, educators, and course designers. It emphasizes the significance of offering tailored learning resources for various types of students and uncovers the key factors that influence students' learning choices.

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