frontiers | Frontiers in Education

TYPE Original Research
PUBLISHED 13 August 2025
DOI 10.3389/feduc.2025.1624827



OPEN ACCESS

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RECEIVED 09 May 2025
ACCEPTED 23 July 2025
PUBLISHED 13 August 2025

CITATION
Ma Y and Liu L (2025) HSNMF enables accurate and effective analysis for the college students' psychological health education data and student life data. *Front. Educ.* 10:1624827. doi: 10.3389/feduc.2025.1624827



# HSNMF enables accurate and effective analysis for the college students' psychological health education data and student life data

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**Introduction:** College students face different levels of anxiety, depression, and other psychological problems due to various factors such as academic stress, excess workload, and family responsibilities. The state of mind plays a crucial role in shaping individuals' daily behaviors and academic performance. To comprehensively analyze the psychological health status of college students and research domains related to psychological health education, it is urgently needed to develop effective tools and models.

**Methods:** In this study, we proposed a novel framework called hypergraph-induced semi-orthogonal nonnegative matrix factorization (HSNMF). By using this framework, we can effectively evaluate the college students' psychological health levels.

**Results:** We implemented the proposed algorithm on two real datasets, and the results showed that the proposed algorithm outperformed other competing methods. The identified research domains provided insights into psychological health education. We also implemented a depression-level classification task on the student life dataset. The results showed that the low-dimensional latent variables learned from HSNMF contained rich semantic information, further improving the performance of traditional machine learning models. Clustering and regression analyses performed on the student life dataset showed that the depression status of students was significantly correlated with their performance in class and social life, as indicated by variables such as "Number of friends ($p$-value $= 0.000598$)," "Gender ($p$-value $= 0.000034$)," and "Taking notes in class ($p$-value $= 0.03$)."

**Discussion:** The significance of student psychological health study is discussed.

KEYWORDS

**psychological health education, matrix factorization, hypergraph learning, data visualization, depress status association analysis**

## 1 Introduction

The psychological wellbeing of college students is of great significance because the state of mind plays a crucial role in shaping individuals' daily behaviors and academic performance, consequently affecting their learning outcomes and willingness to engage in educational activities (Jao et al., 2019). Accurately and timely assessing the psychological health status of students is crucial to ensure the smooth progress of their learning activities and serves as a basis for implementing intelligent psychological health education in colleges (Liu et al., 2020; Kontoangelos et al., 2020; Lu, 2022). The rapid accumulation of data on student education and student behavior provides us with an unprecedented opportunity to analyze the relationships between students' psychological health levels and their life behaviors.

Yi et al., established an association between risk behaviors and psychological health and physical activity using two-step clustering and regression analysis and found that a specific behavior cluster was significantly correlated with psychological health and physical activity (Yi et al., 2020). Opoku Asare et al., utilized smartphone data to analyze the relationships between human behaviors and depression, and identified some behavior markers related to depression (Opoku et al., 2021). Wang et al., conducted a Student Life study and found significant correlations among the following variables: lifecycle and stress, conversation, and activity (Wang et al., 2014). These studies have provided some valuable insights into students' psychological health problems; however, the clustering performance and extension of algorithms are poor, especially for high-dimensional sparse data analysis tasks.

Recently, non-negative matrix factorization (NMF)-based methods have attracted wide interests in data mining and visualization. Cai et al., proposed a graph regularized non-negative matrix factorization algorithm for data representation and clustering (Cai et al., 2010). Jiang et al., developed an NMF-based framework to analyze metagenomic data, and identified some canonical sample types (Jiang et al., 2012). Chavoshinejad et al., proposed an effective semi-supervised NMF algorithm to learn discriminative representations (Chavoshinejad et al., 2023). These studies have taken full advantages of NMF, and obtained the better part-based representation that can be used for data clustering and visualization. To the best of our knowledge, however, NMF-based methods are seldom used for the students' psychological health education data analysis and student life data analysis. Compared to other methods, the advantages of NMF lies in 2 folds: (1) It provides better explanation for many real-world problems. Specifically, NMF factories a non-negative data matrix $X \in R_{+}^{p\times n}$ into two low-rank factor matrices $W \in R_{+}^{p\times k}$ and $H \in R_{+}^{k\times n}$. For the entries in the coefficient matrix $H$, it presents the probability of one sample belonging to a certain cluster. However, for other clustering methods, such as spectral clustering and singular value decomposition (SVD), the factorized low rank matrices may contain negative elements, which are difficult to be viewed as probabilities. (2) NMF cannot only cluster rows in a data matrix, but also simultaneously groups columns in the data matrix. Hence, it can naturally capture associations between samples (students) and features (variables), and is further used to analyze the behaviors of the students.

In this study, we proposed a novel unsupervised learning framework called hypergraph-induced semi-orthogonal non-negative matrix factorization (HSNMF) to analyze the students' psychological health education data. HSNMF could evaluate their psychological health status. HSNMF is a versatile toolkit that enables data clustering and visualization and facilitates the analysis of the association between student depression levels and their daily behaviors. Unlike spectral clustering methods based on pairwise interaction relationships, HSNMF uses hypergraphs to encode the high-order interactions between more than two nodes. In addition, a semi-orthogonal constraint on the low-dimensional factor representation matrix ensures the uniqueness and interpretability of the solution. By implementing the HSNMF framework on two real students' psychological datasets, we demonstrated the effectiveness of HSNMF in identifying topic domains and student depression levels. HSNMF achieved superior performance in clustering and captured clear and meaningful clustering structures based on the learned similarity matrix. Figure 1 shows an overview of the proposed HSNMF framework.

# 2 Materials and methods

## 2.1 Datasets and data preprocessing

The college students' psychological health education dataset downloaded from China national knowledge infrastructure (CNKI, https://www.cnki.net), consisted of 865 articles. The terms "college students' psychological" and "education" were used as retrieve articles based on the Chinese social sciences citation Index (CSSCI), the Chinese science citation database (CSCD) and the Chinese core journal criterion of PKU. The time range was set between 1994 and 2024. We excluded the articles that were irrelevant to the current research or not an original research article (e.g., reviews, newsletters, or conference reports). Finally, 676 articles with bibliographic data including titles, keywords, authors and publish data were retained, and then these data were imported into the Bibliographic items co-occurrence matrix builder (Bicomb) software (Guo et al., 2015; Li and Cheng, 2021). Via Bicomb we extracted keywords from these articles, and generated a term-document matrix and a term-term co-occurrence matrix that were used to conduct downstream analysis tasks.

The student life dataset downloaded from Kaggle site (https://www.kaggle.com/datasets) comprised survey results from 100 computer science students. Demographic data, depression status, and performance variables, such as academic performance, taking notes in class, and presentation frequency, were collected. These variables have been measured before this study and are publicly accessibly (https://www.kaggle.com/datasets).

For the college students' psychological health education dataset, we implemented statistical analysis on keywords that appeared in each record, and obtained keyword rankings, in which high frequency indicated close attentions on the corresponding field. Keywords that occurred <2 times across all records were removed. For student life dataset, the Python toolkit package Scikit-learn was used to transform numerical variables and categorical variables.

## 2.2 Construction of hypergraph

Different from traditional graph where an edge can only connect to two nodes, in hypergraph an edge can connect more than two nodes. This mechanism of hypergraph effectively handles with information loss problem. For example, to group a set of articles into different topics, the common practice is to first construct a pairwise interaction network (simple graph) where two nodes are linked with an edge if there is at least one common author writes them, and then graph clustering method is implemented on this graph to obtain the final cluster assignments (Zhou et al., 2006).

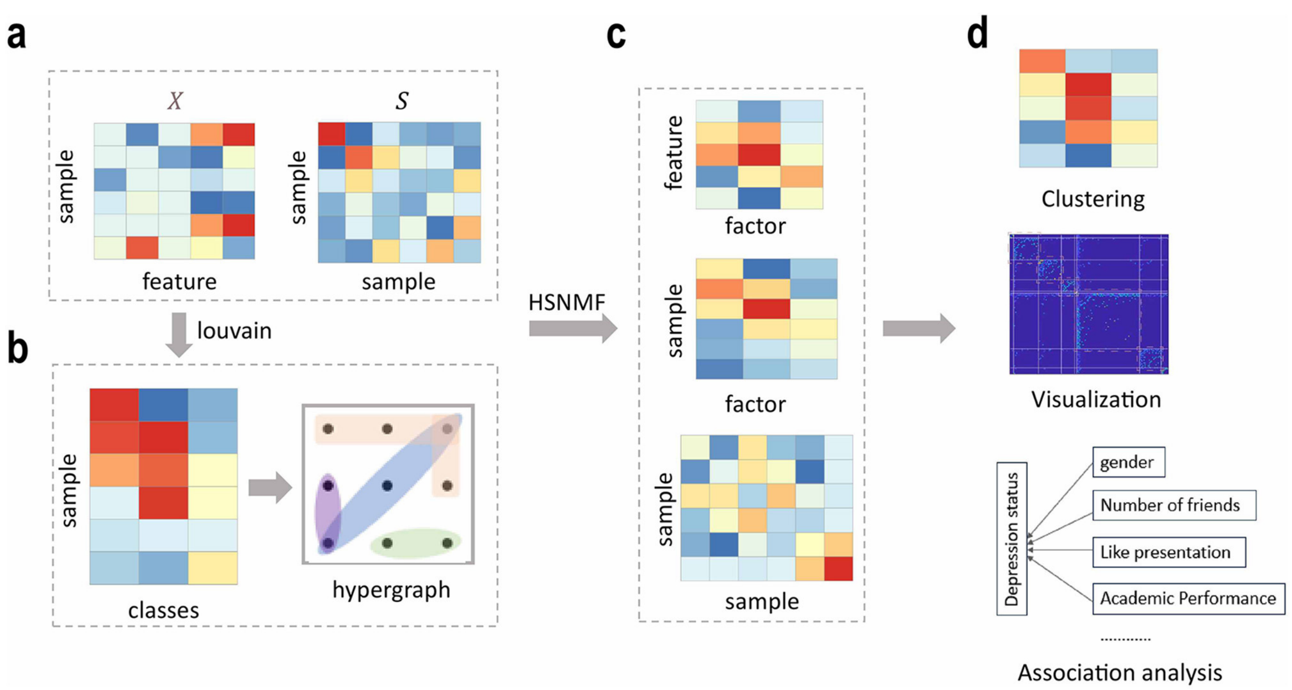



FIGURE 1
The flowchart of HSNMF. HSNMF is developed for analyzing students' psychological data. **(a)** The original data matrix $X$ and sample-sample similarity matrix $S$ that were used as inputs of HSNMF. **(b)** Hypergraph construction based the initially sample clustering matrix obtained by louvain algorithm. **(c)** The outputs of HSNMF, including the low-dimensional factor representation matrices $W$, $H$, and the consensus sample-sample similarity matrix $S$. **(d)** Based on the outputs of HSNMF, downstream analysis tasks can be implemented, including clustering, data visualization, and association analysis between depression status and students' behaviors.

However, the graph constructing strategy above obviously ignore some useful information when the same author contributes more than two articles. Such unexpected lost information is important to clustering or knowledge findings.

A natural approach to address information loss issue is to use hypergraph to organize data relationships. Figure 2 gives an illustrative example to construct hypergraph. Given the weighted hypergraph $G = (V, E, W)$, where $V$ is the set of nodes and $E$ denotes the of hyperedges. For each hyperedge $e$, we used $w(e)$ to represent its weight. In this manuscript, the gaussian kernel function is used to compute the weights of hyperedges. The incidence matrix $P \in R^{|V| \times |E|}$ corresponding to $G$ with entry $p(v, e)$ is defined as follows:

$$p(v, e) = \begin{cases} 1, & if\ v \in e, \\ 0, & if\ v \notin e. \end{cases} \tag{1}$$

where $|V|$ and $|E|$ represent the number of nodes and hyperedges, respectively. The degree of node $v$ is defined as $d(v) = \sum_{e \in E} w(e)p(v, e)$. The degree of hyperedge $e$ is defined as $\delta(e) = \sum_{v \in V} p(v, e)$. Let $D_v$ and $D_e$ denote degree matrices of nodes and hyperedges, respectively. The hypergraph Laplacian matrix $L_{hg}$ can be defined as follows:

$$L_{hg} = D_v - PWD_e^{-1}P^T. \tag{2}$$

Note that in this manuscript we used Louvain community detection algorithm (Blondel et al., 2008) instead of $k$-nearest neighbors (KNN) to generate hyperedges, i.e., each cluster represents a hyperedge. By using this strategy, noisy information or outliers are filtered out to some extent. The hypergraph captures the high-order interaction among nodes. The hypergraph regularization can be defined as follows:

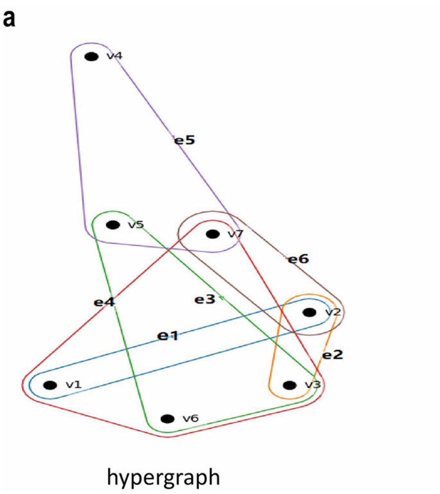
$$O(H) = \frac{1}{2} \sum_{e \in E} \sum_{(i,j) \in e} \frac{w(e)}{\delta(e)} \|H_i - H_j\|_F^2 = Tr\left(H^T L_{hg} H\right). \tag{3}$$

Here, $H$ denotes the low-dimensional representation matrix of nodes.

Next, we will introduce the proposed HSNMF algorithm by integrating hypergraph into this objective.

## 2.3 HSNMF model

To identify the college students' psychological health education research topics, we introduce hypergraph induced semi-orthogonal non-negative matrix factorization (HSNMF) model. Let $X \in R_+^{p \times n}$ denote the original data matrix, HSNMF aims to learn two low-dimensional representation matrices $W \in R_+^{p \times k}$ (basis matrix) and $H \in R_+^{k \times n}$ (coefficient matrix), and a feature similarity matrix $S \in R_+^{p \times p}$, where $p$, $n$ denote the numbers of features and samples, respectively. $k \ll min(p, n)$ is the rank of




b

| | $e_1$ | $e_2$ | $e_3$ | $e_4$ | $e_5$ | $e_6$ |
|---|---|---|---|---|---|---|
| $v_1$ | 1 | 0 | 0 | 1 | 0 | 0 |
| $v_2$ | 1 | 1 | 0 | 0 | 0 | 1 |
| $v_3$ | 0 | 1 | 1 | 1 | 0 | 0 |
| $v_4$ | 0 | 0 | 0 | 0 | 1 | 0 |
| $v_5$ | 0 | 0 | 1 | 0 | 1 | 0 |
| $v_6$ | 0 | 0 | 1 | 1 | 0 | 0 |
| $v_7$ | 0 | 0 | 0 | 1 | 1 | 1 |

Incidence matrix

FIGURE 2
An illustrative example for hypergraph organization. **(a)** Hyperedges contains more than two nodes in hypergraph. $v_i$ denotes $i$th nodes, $e_j$ denotes $j$th hyperedge. **(b)** The incidence matrix of hypergraph. The entry $(v_i, e_j)$ is set to be 1 when $v_i$ belongs to $e_j$, and 0 otherwise.

factorized matrix. The objective function of HSNMF can be written as follows:

$$\min_{W,\,H,\,S} J = \|X - WH\|_F^2 + \frac{\alpha}{2}\left\|S - WW^T\right\|_F^2 + \beta tr\left(W^T L_{hg} W\right) + \frac{\gamma}{2}\left\|W^T W - I\right\|_F^2. \quad (4)$$
$$\text{s.t.} W,\ H,\ S,\ \alpha,\ \beta,\ \gamma\ \geq 0,\ S\mathbf{1}{=}\mathbf{1}.$$

where $I$ is identity matrix, $\mathbf{1}$ is a column vector with all its elements to be 1s. $S$ is the learned feature similarity matrix that can be used for clustering and data visualization. $\alpha$, $\beta$ and $\gamma$ are hyperparameters to be tuned. We will discuss how to select their values in the later section.

In the object of HSNMF, the first term, $\|X - WH\|_F^2$, is standard non-negative matrix factorization (NMF) loss function for student psychological education or student life data. The second term, $\left\|S - WW^T\right\|_F^2$, is a consensus graph factorization strategy which regularizes kernel $WW^T$ toward a consensus graph $S$, and generating a meaningful factorization. Through iterative training, the first two terms in Equation 4 can learned the low-dimensional representation for samples and features, however, the high-order relationships among nodes may be ignored. For example, the depression level of student may be correlated to the mixed effects of academic pressure, numerous work, and family responsibilities (Opoku et al., 2021; Wang et al., 2014). Hence, modeling high-order interactions among variables with hypergraph is important to mine the latent feature associations. Therefore, we include the third term, $tr\left(W^T L_{hg} W\right)$, in HSNMF model. The fourth term, $\left\|W^T W - I\right\|_F^2$, encourages $W$ to be column-orthogonal. One of the advantages is the uniqueness and interpretability of solution $W$. The term, $S\mathbf{1}{=}\mathbf{1}$, is a constraint term on $S$ that enforces each row of $S$ to have summation close to 1.

Unlike other clustering methods based on spectral graph theory including spectral clustering and its variants which used the eigenvectors corresponding to large eigenvalues to conduct clustering (White and Smyth, 2005; Ng et al., 2001; Law et al., 2017), HSNMF adopts hypergraph Laplacian to explore the complicated interaction relationships among variables. The low-dimensional factor matrices obtained from HSNMF own stronger representation ability. In addition, orthogonal constraints on basis matrix $W$ leads to better clustering solution and interpretability: the columns in $W$ will tend to be sparse. The optimization algorithm of HSNMF is presented in the next subsection.

## 2.4 Optimization of HSNMF model

The optimal problem of objective function (Equation 4) can be divided into three sub-problems and can be solved alternately.

### 2.4.1 Fixing *W* and *S*, updating *H*

For $H$, the constrained optimization problem of Equation 4 can be solved easily by multiplicative update rule as traditional NMF did (Lee and Seung, 2000, 1999). Based on trace operation, Equation 4 can be rewritten as follows:

$$L = tr\left(X^T X - 2X^T WH + H^T W^T WH\right) + \frac{\alpha}{2} tr\left(S^T S - 2S^T WW^T + WW^T WW^T\right) + \beta tr\left(W^T L_{hg} W\right) + \frac{\gamma}{2} tr(W^T WW^T W - 2W^T W + I^2). \quad (5)$$

We only consider the terms related to $H$, and introduced Lagrange multiplier $\Phi^{(1)}$ to solve the optimal problem. Taking the partial derivatives of $L$ with respect to $H$ gives:

$$\frac{\partial L}{\partial H} = -2W^T X + 2W^T WH + \Phi^{(1)}. \quad (6)$$

Using KKT condition, we can obtain the following updating rule for $H$:

$$H_{ij} \longleftarrow H_{ij}\frac{\left(W^{T}X\right)_{ij}}{\left(W^{T}WH\right)_{ij}}. \tag{7}$$

### 2.4.2 Fixing $H$ and $S$, updating $W$

Similarly, we can obtain the updating rule for $W$:

$$W_{ij} \longleftarrow W_{ij}\frac{\left(XH^{T}+\alpha S^{T}W+\beta L_{hg}^{-}W+\gamma W\right)_{ij}}{\left(WHH^{T}+\alpha WW^{T}W+\beta L_{hg}^{+}W+\gamma WW^{T}W\right)_{ij}}. \tag{8}$$

where $L_{hg}^{+}=(L_{hg}+abs(L_{hg}))/2$, $L_{hg}^{-}=(abs\left(L_{hg}\right)-\ L_{hg})/2$.

### 2.4.3 Fixing $W$ and $H$, updating $S$

$$S_{ij} \longleftarrow S_{ij}\frac{\left(\alpha WW^{T}+\vartheta \mathbf{1}_{n\times n}\right)_{ij}}{\left(\alpha S+\vartheta S\mathbf{1}_{n\times n}\right)_{ij}}. \tag{9}$$

## 2.5 Parameter selection

In HSNMF, there are three parameters $\alpha$, $\beta$ and $\gamma$ that need to be determined. First, we used NNDSVD (Boutsidis and Gallopoulos, 2008) to solved the optimization problem $\|X-WH\|_F^2$ and obtain the initial solutions $\widehat{W}$ and $\widehat{H}$. Second, we used Ochiai coefficients (Vancraeynest et al., 2024; Kalgotra et al., 2020) to set the initial value $\widehat{S}$ of $S$. Finally, $\alpha$, $\beta$ and $\gamma$ are set as:

$$\alpha=\left\|X-\widehat{W}\widehat{H}\right\|_F^2/\left(\left\|\widehat{S}-\widehat{W}\widehat{W}^{T}\right\|_F^2\right), \tag{10}$$

$$\beta=\left\|X-\widehat{W}\widehat{H}\right\|_F^2/\left(tr(\widehat{W}^{T}L_{hg}W)\right), \tag{11}$$

$$\gamma=\left\|X-\widehat{W}\widehat{H}\right\|_F^2/\left(\left\|\widehat{W}^{T}W-I\right\|_F^2\right). \tag{12}$$

Noting that for the sake of fairness we adopted parameter selection rules defined in Equations 10–12 across all the experiments. The ablation experiments in the following subsection also demonstrated the effectiveness of the objection of HSNMF algorithm.

## 2.6 Evaluation metrics

Unsupervised clustering metric silhouette coefficient (Kaufman and Rousseeuw, 2009), Calinski-Harabasz index (CHI; José-García and Gómez-Flores, 2023; Caliński and Harabasz, 1974), and Davies-Bouldin index (DBI; José-García and Gómez-Flores, 2023; Davies and Bouldin, 1979) are used to evaluate the performance of the clustering methods.

Let $a\left(i\right)$ denote the average distance of data point $i$ to all other data within the same cluster with $i$, and $b\left(i\right)$ denote the average distance of $i$ to all data points to the neighboring cluster, i.e., the smallest average distance to the cluster of $i$. The silhouette coefficient for data point $i$ is defined as:

$$sil\left(i\right)=\begin{cases}1-\frac{a(i)}{b(i)}, & if\ a\left(i\right)<b\left(i\right)\\ 0, & if\ a\left(i\right)=b\left(i\right)\\ \frac{b(i)}{a(i)}-1, & if\ a\left(i\right)>b\left(i\right).\end{cases} \tag{13}$$

High silhouette score indicates good clustering performance. The average values of silhouette scores of all the data points are reported.

Let $n$, $k$ denote the number of data points and clusters, respectively, the CHI is defined as follows:

$$CHI=\frac{\sum_{i=1}^{k}n_i\left\|c_i-c\right\|^2/(k-1)}{\sum_{i=1}^{k}\sum_{x\in C_i}\left\|x-c_i\right\|^2/(n-k)}. \tag{14}$$

where $n_i$ is the number of data points belonging to $i$th cluster, $C_i$ is the data set belonging to $i$th cluster, $c_i$ is the centroid of $i$th cluster, $c$ is the centroid of all data points.

The DBI is defined as follows:

$$DBI=\frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\left(\frac{S_i+S_j}{d\left(c_i,c_j\right)}\right), \tag{15}$$

$$S_i=\frac{1}{\left|C_i\right|}\sum_{x\in C_i}d\left(x,\ c_i\right). \tag{16}$$

where $\left|C_i\right|$ denotes the number of data points in $C_i$, $d\left(x,\ c_i\right)$ denotes the distance between $x$ and $c_i$.

# 3 Results and discussion

## 3.1 HSNMF achieves superior performance on the college students' psychological health education dataset

In the college students' psychology health education dataset, we used the term-document matrix and the term-term co-occurrence matrix as inputs for HSNMF, and obtained the low-dimensional representation matrices $W$, $H$ and a similarity matrix $S$. Clustering and data visualization were implemented using $S$. We compared the HSNMF algorithm with other competing methods, including NMF (Lee and Seung, 2000, 1999), spectral clustering (SC; White and Smyth, 2005; Jia et al., 2014), and symmetric non-negative matrix factorization (SNMF; Kuang et al., 2012; Ma et al., 2020), for the topic analysis of students' psychological health research. For SC, we first constructed similarity matrix with the cosine function, and then implemented spectral clustering on the similarity matrix. For HSNMF, we first constructed a $k$-nearest neighbor (KNN) graph based on the learned similarity matrix $S$, and then implemented Louvain clustering on the KNN graph.

The clustering performance evaluated by CHI, DBI and silhouette scores are presented in Figure 3.

As shown in Figure 3, HSNMF achieved the best performance on the college students' psychological health education dataset in terms of CHI, DBI and silhouette scores. NMF achieves the second-best performance in terms of CHI. SC also performed well in terms of silhouette score. The results demonstrate that the

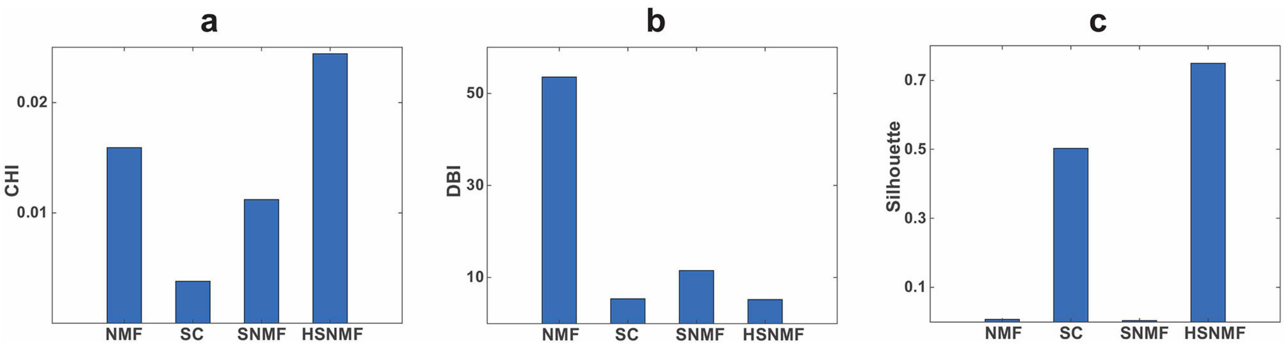



FIGURE 3
Comparison of clustering performance in the college students' psychological health education data. **(a)** Assessment of clustering performance in terms of CHI. **(b)** Assessment of clustering performance in terms of DBI. **(c)** Assessment of clustering performance in terms of the averaged silhouette scores. These three unsupervised metrics were computed based on the original term-document matrix and cluster results obtain from each method. For CHI and silhouette score metrics, high values indicate good clustering performance. For DBI, The smaller the values of the DBI, the better the performance of the algorithms.

proposed HSNMF algorithm is effective on students' psychological health education dataset. One of the possible reasons is that the introducing hypergraph regularization term and the semi-orthogonal constraints on the low-dimensional representation $W$ into the HSNMF objective function.

## 3.2 Ablation study

We further validate the effectiveness of HSNMF via ablation experiments. We set $\alpha$, $\beta$ and $\gamma$ to 0 in turn. When $\alpha = 0$, the values of CHI and DBI were 2.7e-5 and 45.87, respectively. When $\beta = 0$, the values of CHI and DBI were 0.0075 and 17.51, respectively. When $\gamma = 0$, the values of CHI and DBI were 0.0082 and 19.05, respectively, and the averaged silhouette score was 0.7206. The results demonstrate that the effectiveness of introducing the hypergraph regularization term, consensus graph factorization strategy, and semi-orthogonal constraints on the columns of $W$ into the object of the HSNMF algorithm.

## 3.3 HSNMF facilitates visualization for topic terms of psychological health education fields

HSNMF can not only be used to cluster, but also be used to data visualization. Based on the learned the low-dimensional factor matrix $W$, the term similarity matrix $S$, and the clustering indices of all terms, we implemented visualization analysis, and the term clusters were represented in Figures 4a, b. We can see that the learned the low-dimensional factor matrix $W$ and similarity matrix $S$ had clear clustering structures. The terms in pink box in the figure consist of research topics related to psychological health education. As Figure 4 shown, $W$ and $S$ had consistent clustering structures in some topics.

We conducted further investigation into the five topics and found that they primarily focused on the following several fields: 1) Psychological health problem, including psychological characteristics, psychological capital, and psychological stress. 2) Psychological health education and teaching, including psychological health education for college students, teaching reform, psychological counseling, art education, curriculum system, moral education, frustration education. 3) Strategy and service system, including growth path, student psychological health services, and education strategy.

## 3.4 HSNMF identified the latent associations between depression levels and student class behavior

We further validated the performance of HSNMF on student life dataset. Figures 5a, b show the visualization results for the original data matrix and the learned low-dimensional factor matrix $W$ (the averaged silhouette score equals 0.9128). We can see that the individuals with different depression levels show the clearly clustering structure (Figure 5b). Additional analysis was conducted on the factor matrices $W$ and $H$, where we inspected the rows of $H$ with the large entries, and identified several features related to student depression status. The experimental results showed that three kinds of behaviors including "Academic performance," "Taking note in class" and "Number of friends" were related to student depression status (depression). "Gender," "Taking note in class" and "Like presentation" are related to student depression status (sometimes depression).

Next, we implemented an association analysis between depression levels and student class behaviors based on student life data. Logistic regression analysis (LogisticRegression function in Sklearn package) was implemented to measure the associations between student depression level and behavior variables. The regression coefficients for features "Number of friends," "Gender" and "Taking note in class" are $-1.32$ ($p$-value $= 0.000598$), $-0.97$($p$-value $= 0.000034$) and $-0.27$($p$-value $= 0.03$), respectively. The results indicate that students' depression level is significantly correlated to their class performance and social communication strength (number of friends).

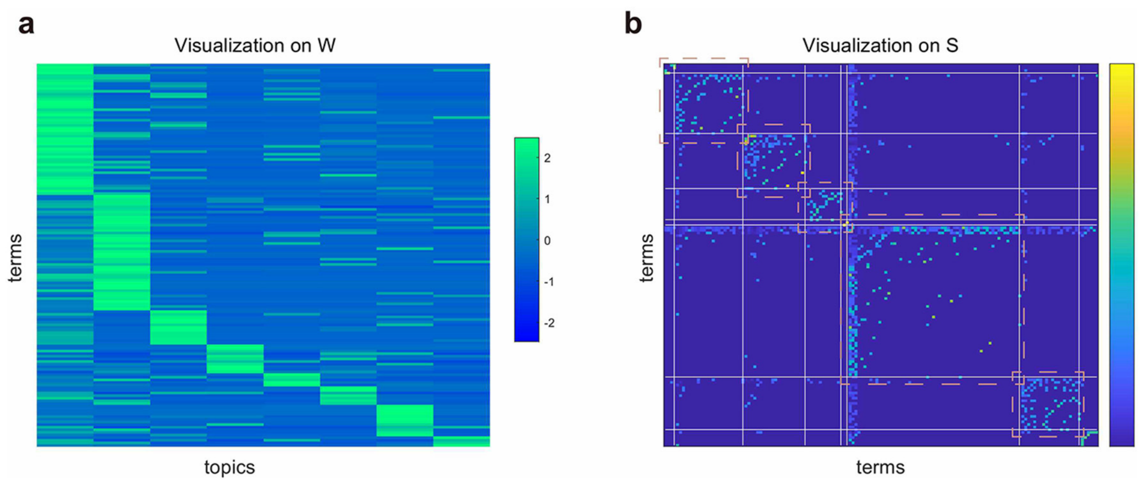



FIGURE 4
Visualization of terms in the psychological health education research fields. **(a)** Visualization on *W*. **(b)** Visualization on *S*. The ranges in pink boxes indicate five main research topics in the psychological health education research fields.

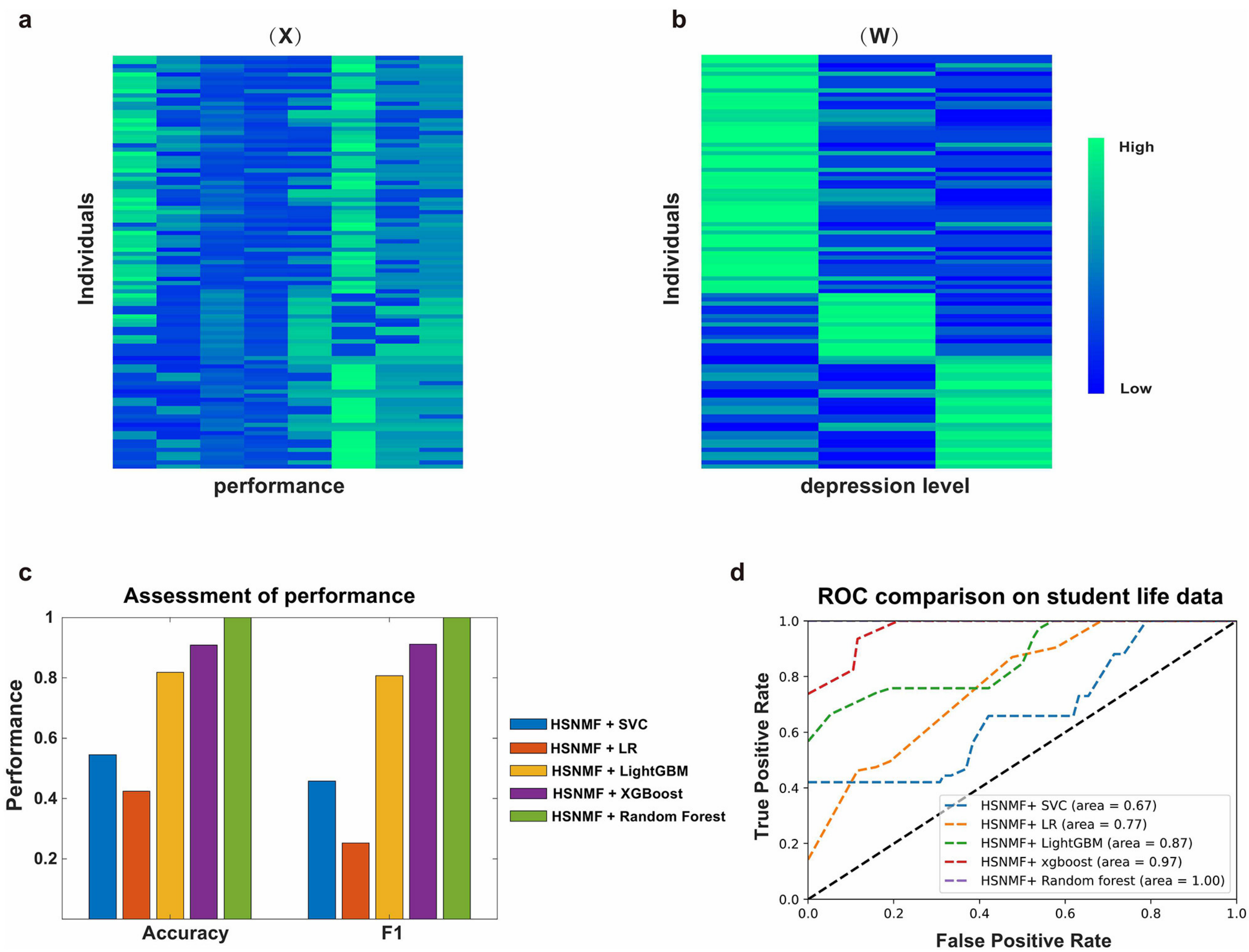



FIGURE 5
Analysis on student life data. **(a)** Visualization on the original student life dataset. Row represents the individual, and column represents the student behavior. **(b)** Visualization on the low-dimensional factor matrix *W*. Column represents the latent depression levels of students. **(c)** Performance assessment of different methods in terms of accuracy and f1 score. **(d)** Macro-average ROC curves of different methods.

HSNMF can not only be used for sample clustering, but also be used for classification. We further validate the effectiveness of HSNMF via cross-validation where the original data are divided into two parts. The one is used to train model, the other is used to test. The results were presented in Figures 5c, d. We can see that "HSNMF + random forest" achieves the best performance compared to other competing methods in terms of accuracy, F1, and AUC metrics. Different from random forest, we used the low-dimensional factor matrix $W$ obtained from HSNMF to train classification models, and obtain the better performance (random forest, accuracy 0.85). The results demonstrate that integrating HSNMF into the traditional machine learning algorithms can effectively improves the model's performance. One of the possible reasons is that the learned low-dimensional latent variable $W$ contain more semantic information that can guide the training process for more effective classification tasks.

Although HSNMF achieves better performance in terms of accuracy, F1, and AUC metrics, it still needs to be further validated in more student life data. In this manuscript, we aimed to develop a novel algorithm to analyze the students' behaviour, and explored the relationships between depression levels and student class behaviors. For other questions, such as population study and behavior variables measurement, they are beyond the scope of our research.

## 4 Conclusion

The rapid accumulation of student education data and student behavior data provides us an unprecedented chance to analyze the relationships between students' psychological health levels and their life behaviors. To this end, we proposed an effective analysis framework HSNMF, which utilizes hypergraph to learn the low-dimensional factor representation and sample-sample similarity matrix. One advantage of hypergraph lies that it can encode the high-order interaction relationships between objects, thus leading to better clustering qualities. Extensive experiments were implemented on two real datasets. The experimental results showed that the proposed HSNMF algorithm achieved the best performance compared to other competing methods. We also implemented depression level classification task on student life dataset by cross-validation experiments. The experimental results showed that integrating HSNMF into the traditional machine learning models can effectively improve their performance, which indicated that the low-dimensional latent variables learned from HSNMF may contain more semantic information. In terms of the versatileness of HSNMF, we can use it in various fields for different populations and purposes, such as informetric, knowledge graph, and so on.

Analysis on the college students' psychology health education data identified several meaningful topic domains, including psychological health problem, psychological health education and teaching, and the psychological teaching strategies and service system. Clustering analysis and regression analysis on the student life dataset showed student depression status is significantly correlated to their performance in class and social life, such as "Number of friends ($p$-value = 0.000598)," "Gender ($p$-value = 0.000034)" and "Taking note in class ($p$-value = 0.03)."

The college students' psychological health is one of the most important problems in current higher education. This study aimed to develop a novel framework to group students with various mental statuses into different clusters and further identify the latent associations between depression status and behavior variables based on the college student life data. The conclusions from association analysis help to shine a light on student life, and help teachers and parents to preliminarily assess the status of mental of the students in the college. So, some interventions can be timely adopted to improve the mental health of students.

The limitations of this study lie in: 1) for the college students' psychological health education data, we only analyzed the CNKI data source, other source including Web of Science, Scopus, Engineering Index (EI) were not included in the study. So, extensive data analysis based on different data sources is necessary to validate the generalization performance of HSNMF. 2) For student depression status analysis, more complicated interactions relationships between variables may exist. The interplay among these variables may be beyond the interaction between two variables, high-order interaction relationships may be ubiquitous in student behavior analysis. In this study, we used hypergraph to encode the high-order interactions, however, the association analysis was still based on the correlation between two variables.

The future directions of HSNMF framework mainly focus on the following aspects. 1) Identification of depression risk factors from health surveys and biomedicine data (Jamali et al., 2024). 2) Extending HSNMF to multi-modality student psychological health data, including psychological health survey, biomedicine image data, metagenomics data (Lai et al., 2022), microbiome data (Rong et al., 2019), and so on.

## Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://github.com/chonghua-1983/student_life_analysis.

## Author contributions

YM: Conceptualization, Methodology, Software, Writing – review & editing. LL: Data curation, Validation, Writing – original draft.

## Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by Hubei Provincial Key Project of Educational Science Planning "Research on the Construction and Measurement of Indicator System, and Improvement Strategies of the Aesthetic Education Integration Campus" [24GA095] and Hubei Superior and Distinctive Discipline Group of "New Energy Vehicle and Smart Transportation."

## Acknowledgments

The authors thank LetPub (https://www.letpub.com.cn) for its linguistic assistance during the preparation of this manuscript.

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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