

Article | Received 22 April 2026; Revised 13 May 2026; Accepted 19 May 2026; Published 17 September 2026
<https://doi.org/10.55092/phess20260008>

Big data-enabled analysis of users' behavioral intention in AI-based job search services

Jiahao Zeng, Xiang Gong, Anxin Huang, Tianshi Tan and Lisha Ma*

School of Computer Science, Hunan First Normal University, Changsha 410205, China

* Correspondence author; E-mail: mls2460169412@163.com.

Abstract: With the core functions of accurate job-candidate matching and scene-based intelligent simulation, AI-based job search applications are transforming the traditional human resources market and are becoming a vital technological solution for alleviating structural employment issues and promoting high-quality employment. However, AI-based job search is currently in its infancy, facing issues such as users' cognitive bias and a lack of technical trust. To address these challenges, this study focuses on the popular topic of AI-based job search and proposes a multi-method fusion analysis framework. Firstly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed to rank and analyse the importance of the various factors influencing usage intention, clarifying the main factors. Secondly, factor analysis is employed to identify potential factors affecting users' willingness to use AI-based job search services. Finally, partial least squares path modeling (PLS-PM) is employed to study the relationships between the potential factors and to explore how each factor specifically influences users' willingness to use AI-based job search services. The results show that the top three important factors are data processing speed, the use of AI big models by people around them, and the accuracy of AI big model algorithms. The cumulative variance interpretation rate of the six extracted potential factors is 76.97%. Five influence paths were identified between the potential factors and willingness to use, indicating that the analysis framework constructed in this study can better explain users' willingness to use AI-based job search services. This is highly significant in terms of improving the users' experience of AI-based job search applications, optimizing product design, and promoting the application of AI technology in the field of job search.

Keywords: AI-based job search services; TOPSIS model; factor analysis; PLS-PM; users' acceptance intention.

1. Introduction

Breakthroughs in large language models such as GPT-4 and DeepSeek have revolutionized talent acquisition. According to CAICT, the market for AI-driven recruitment tools reached ¥28 billion in 2024, growing 47% year-on-year. Meanwhile, the MOHRSS reported a national skills gap of 22 million workers, juxtaposed with a 68% annual surge in AI-powered digital economy hiring.



Copyright©2026 by the authors. Published by ELSP. This work is licensed under Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium provided the original work is properly cited.

However, research on users' adoption of AI in job-seeking remains fragmented. Existing literature relies heavily on technology acceptance models and isolated case studies, lacking a unified theoretical framework. Notable gaps include: Ma *et al.* [1] identified perceived usefulness and privacy concerns via TAM but omitted generational effects. Qiang [2] applied TAM to campus delivery robots without cultural context. Xu *et al.* [3] analyzed AI-based job search requirements through web crawling and LDA modeling, but the sole use of Zhilian Recruitment data limits geographical generalizability. Liang *et al.* [4] verified the applicability of the ECM-ISC model in the context of job-seeking Apps, but failed to coordinate with TAM-based predictors. To address these gaps, this study employed a hybrid Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)-Factor analysis-Partial least squares path modeling (PLS-PM) approach to explore critical determinants of AI-based job search intention, model latent constructs, and quantify causal relationships.

2. Indicator system and data processing

2.1. Indicator system

In order to analyze the influencing factors of the willingness to use AI-based job search applications, this paper collected and sorted out relevant literature such as AI-based job search technology acceptance and users' behavior model [5]. A total of 16 indicators including technical performance indicators, social cognitive indicators, and functional auxiliary indicators were selected, as shown in Table 1.

Table 1. Indicators of users' influencing factors.

Indicator number	indicator content
factor1	Do you understand the application of AI big model in job search?
factor2	What do you think about the development status of AI big model in job search?
factor3	Do you think the AI model can help you in your job search process?
factor4	What is your willingness to use the AI model for job hunting?
factor5	Can AI models replace traditional interviews in hiring?
factor6	Would you continue using AI after using the AI big model for job hunting?
factor7	Data processing speed
factor8	The accuracy of AI big model algorithm
factor9	The use of AI big models by people around them
factor10	The industry has policy support for AI big model.
factor11	Generate personalized resumes
factor12	Write a cover letter
factor13	Provide interview question prediction and answer suggestions
factor14	Analyze the skills and experience required for the target position
factor15	Matching suitable job positions
factor16	Conduct simulated interview training

2.2. Data processing

Through validity screening, consistency auditing, missing value imputation, outlier distribution auditing, and normalization processes, 338 valid questionnaires were obtained, achieving an effective sample rate of 84.5%. The resulting standardized dataset was utilized for subsequent analysis of job-seeking service users' behavioral intentions.

3. Construction of an AI-based job search intention model based on multi-model fusion

3.1. Ranking AI-based job search intention factors using the TOPSIS model

As a validated multicriteria decision analysis model, TOPSIS [6] offers a robust framework for evaluating alternatives against positive/negative ideal solutions. By quantifying relative similarity to optimal outcomes, it enables systematic comparison and ranking. Known for computational efficiency and discriminant validity, TOPSIS is widely used in complex decision scenarios across disciplines. This study applied TOPSIS to identify and prioritize key factors influencing AI-based job search intention, isolating critical variables for subsequent analysis [7]. The methodology proceeds as:

(1) This study used 338 validated questionnaires as evaluation units ($n = 338$), with 16 predefined influencing factors (factor1–16) as evaluation criteria ($m = 16$). All indicators are operationalized as benefit-type variables, where higher values signify stronger positive impacts on users' behavioral intention to adopt AI job-search services. The decision matrix X is constructed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

where X_{ij} represents the value of the j -th influencing factor ($j = 1, 2, \dots, 16$) in the i -th questionnaire ($i = 1, 2, \dots, 338$).

(2) Take the maximum value of each column in X as the positive ideal solution X^+ and the minimum value as the negative ideal solution X^- , and determine the positive and negative ideal solutions as:

$$\begin{aligned} X^+ &= \{\max x_{ij} \mid i = 1, 2, \dots, m\} = [x_1^+, x_2^+, \dots, x_m^+] \\ X^- &= \{\min x_{ij} \mid i = 1, 2, \dots, m\} = [x_1^-, x_2^-, \dots, x_m^-] \end{aligned} \quad (2)$$

where $X_j^+ = \max\{X_{1j}, X_{2j}, \dots, X_{nj}\}$, $X_j^- = \min\{X_{1j}, X_{2j}, \dots, X_{nj}\}$, $j = 1, 2, \dots, 16$.

(3) The weighted Euclidean distance between the evaluation object X_{ij} and the ideal solution X^+ and X^- is calculated as follows:

$$\begin{aligned} D_j^+ &= \sqrt{\sum_{i=1}^m (x_{ij} - x_i^+)^2} \\ D_j^- &= \sqrt{\sum_{i=1}^m (x_{ij} - x_i^-)^2} \end{aligned} \quad (3)$$

where D_j^+ represents the difference between the evaluation object corresponding to the i -th questionnaire and the positive ideal solution, reflecting its deviation from the optimal state; D_j^- represents the distance between the evaluation object and the negative ideal solution, showing its

difference from the worst state.

(4) Calculate the relative proximity of the evaluation object X_{ij} :

$$S_j = \frac{D_j^-}{D_j^+ + D_j^-} \quad (4)$$

The value of S_j spans from 0 to 1. A value near 1 indicates the evaluation object (i -th questionnaire) aligns closely with the positive ideal solution, implying stronger positive effects of corresponding factors on user intention. Conversely, approaching 0 reflects proximity to the negative ideal, signaling weaker influence.

3.2. Research on the influencing factors of willingness to use based on factor analysis

Using TOPSIS-identified factors, factor analysis explored latent constructs affecting AI job-search adoption. As a multivariate cornerstone [8], it reveals variable intercorrelations and reduces dimensionality by condensing variables into latent factors capturing distinct variances [9].

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + \varepsilon_1 \\ X_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + \varepsilon_2 \\ \cdots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m + \varepsilon_p \end{cases} \quad (5)$$

where the original variables X_1, X_2, X_p are the 16 influencing factors determined in the first part, F_1, F_2, F_m are unobservable variables, $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p$ are special factors, and a_{ij} is the factor loading, representing the load of the i -th variable on the j -th common factor, reflecting the degree of correlation between the i -th variable and the j -th common factor.

3.3. Establishment of the PLS-PM for potential factors of use intention

Based on factor analysis, this study established causal links between six determinants (comprehensive auxiliary capacity, EP, technology substitution cognition, technical infrastructure & policy environment, cognitive proficiency, SI) and adoption propensity [10]. By specifying influence mechanisms, it holistically explains the processes. The PLS-PM structural equation [11] is in Equation (6).

$$\alpha = \lambda_\alpha \beta + \varepsilon_\alpha \quad (6)$$

The main calculation steps of the PLS-PM model are three steps:

(1) The predictive value of the potential factors corresponding to each group of indicators according to the Formula (7).

$$\gamma_i^{t+1} = f_i^{t+1} \sum_{j=1}^k \pi_{ij}^t X_{ij} \quad (7)$$

where γ_i is the value of the latent variable. After t iterations, its external estimated vector γ_i^{t+1} is obtained. f_i^{t+1} and π_{ij} are the weights of scalar and influencing factor variables respectively.

(2) The weight between each influencing factor and its potential factors is obtained as:

$$X_{ij} = \pi^{t+1} \gamma_i^{t+1} + \varepsilon_{X_{ij}}^{t+1} \quad (8)$$

where X_{ij} is the influencing factor variable (from 16 influencing factors indicators, $j = 1, 2, \dots, 16$), and

π^{t+1} is the weight.

(3) The loading matrix and the path coefficients (γ) of the influencing factor variables were calculated using ordinary least squares (OLS) regression analysis of data on six potential influencing factors and 16 influencing factor indicators.

4. Results and discussion

The experiment was completed under the Windows 11 system. The configuration of the experimental computer is as follows: Intel (R) Core (TM) i5–8265U CPU @ 1.60 GHz 1.80 GHz, 8 GB RAM, 271G SSD solid-state drive. The software platform is Python 3.12. Its extensive libraries facilitate efficient data processing, streamlined dimensionality reduction, variable relationship exploration, and model path construction, enhancing modeling efficiency and accuracy.

4.1. Ranking results of influencing factors on the willingness to use AI in job hunting

Sixteen influencing factors of usage intention from the questionnaire were selected. The evaluation data were the values transformed from the user's satisfaction with each factor through data preprocessing. The importance scores of each influencing factor were obtained and ranked using TOPSIS, as shown in Figure 1.

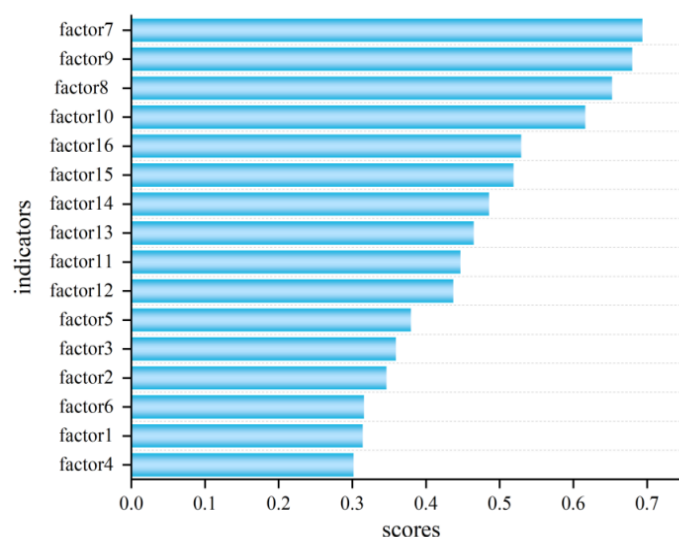


Figure 1. TOPSIS influencing factor scores.

As can be seen from Figure 1, the top three in terms of importance are factor 7 (data processing speed), factor 9 (the use of the AI large model by people around), and factor 8 (the accuracy of the AI large model algorithm). Take them as important research factors for subsequent factor analysis.

4.2. Analysis results of influencing factors of willingness to use

Before factor analysis, KMO and Bartlett sphericity tests need to be conducted. The test results show that the KMO coefficient is equal to 0.847, and the p -value of Bartlett sphericity test is 0.000, indicating that it is highly suitable for factor analysis.

A scree plot was constructed based on each indicator and its corresponding eigenvalue, as shown in Figure 2. The number of factors at the point where the broken line transitions abruptly from a steep to a flat trend serves as the reference for factor extraction. To ensure the extracted factors capture sufficient information, six common factors were ultimately selected. Additionally, the data in this study were subjected to varimax rotation, which maximizes the factor loadings of each construct to simplify factor interpretation. The variance explanation rates of each common factor for willingness to use are presented in Table 2.

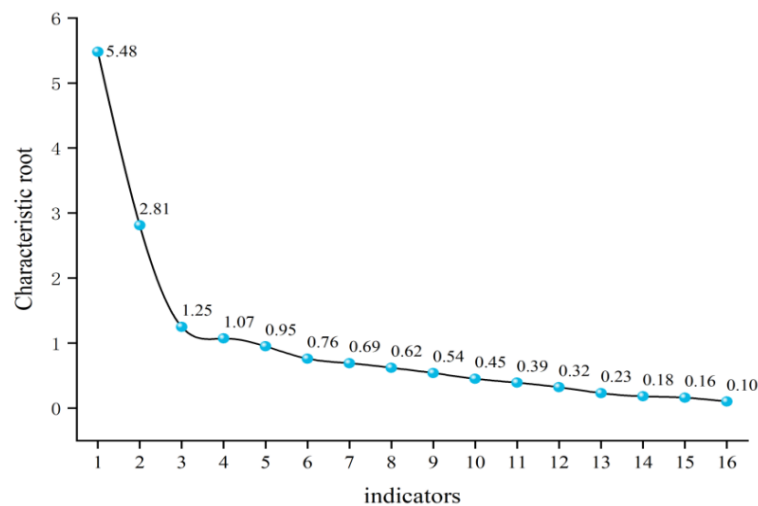


Figure 2. The scree plot.

Table 2. Variance interpretation rate.

Factor	Characteristic root	Variance explained before rotation (%)		Variance explained after rotation (%)	
		Single	Accumulation	Single	Accumulation
1	5.480	34.252	34.252	29.419	29.419
2	2.807	17.545	51.797	15.294	44.713
3	1.248	7.800	59.597	10.106	54.819
4	1.069	6.680	66.278	9.373	64.192
5	0.946	5.915	72.193	6.468	70.660
6	0.765	4.779	76.972	6.311	76.972

As shown in Table 2, the variances explained by the six factors selected via the scree plot after rotation are 29.419%, 15.294%, 10.106%, 9.373%, 6.468%, and 6.311%, respectively. The cumulative variance explained after rotation is 76.972%, indicating that the model captures 76.972% of the information and demonstrates a high level of fidelity in reconstructing the original data, thus clearly presenting the evaluation data of the influencing factors.

As shown in Table 3: (1) CSC reveals users' heavy reliance on AI tools for critical job-search phases. Their automated precision boosts efficiency while increasing platform retention and satisfaction. (2) EP demonstrates users' endorsements, yet negative speed loading reveals latency-induced dissatisfaction, establishing it as a key evaluation criterion. (3) TSDP reveals users' skepticism toward AI as interview replacements, with current technology perceived as inferior to traditional methods' efficacy. (4) TIPE embodies users' dual demands for AI-Based job search tools: they require both accurate and reliable underlying technology and industry policy support. (5) CL highlights that users' unfamiliarity with the functions of AI-Based job search tools hinders their willingness to try them.

(6) SI demonstrates strong peer adoption effects of AI systems, with high factor loadings corroborated by TOPSIS analysis, confirming their disproportionate impact on usage intention. These six factors collectively shape users' utilization, evaluation, and selection of AI-Based job search tools.

Table 3. Results of factor analysis for 16 influencing factors.

Factor	Factor loadings						Communality	Common factors (Potential influencing factors)
	C-factor 1	C-factor 2	C-factor 3	C-factor 4	C-factor 5	C-factor 6		
factor 11	0.859	0.007	−0.245	0.056	−0.069	0.076	0.812	Comprehensive support capability (CSC)
factor 12	0.871	−0.018	−0.278	0.001	−0.039	0.069	0.843	
factor 13	0.883	−0.010	−0.215	0.124	0.037	0.031	0.844	
factor 14	0.866	−0.066	−0.021	0.132	0.036	0.069	0.779	
factor 15	0.863	−0.162	0.160	0.143	0.012	0.062	0.822	
factor 16	0.838	−0.100	0.209	0.290	0.013	−0.011	0.841	
factor 3	−0.057	0.597	0.369	−0.223	−0.226	0.047	0.598	Efficiency perception (EP)
factor 4	0.017	0.793	0.260	−0.176	0.144	0.045	0.751	
factor 6	−0.057	0.714	0.021	−0.148	0.248	−0.130	0.614	
factor 7	0.185	−0.753	0.074	−0.202	−0.026	0.230	0.701	Technical substitutability and development perception (TSDP)
factor 2	0.006	0.481	0.588	−0.270	0.092	0.030	0.659	
factor 5	−0.212	0.126	0.854	0.038	0.015	−0.116	0.806	
factor 8	0.318	−0.079	0.112	0.805	0.023	0.062	0.773	Technical infrastructure and policy environment (TIPE)
factor 10	0.159	−0.153	−0.236	0.686	−0.153	0.076	0.604	
factor 1	0.010	0.198	0.037	−0.097	0.923	−0.080	0.908	Cognitive level (CL)
factor 9	0.136	−0.167	−0.092	0.118	−0.088	0.941	0.962	Social Impact (SI)

4.3. Results of latent factors influence pathways

The PLS–PM model was constructed by using the six common factors obtained by factor analysis as latent variables and the corresponding influencing factors (factor1–16) in Table 1 as explicit variables. The results are visualized as shown in Figure 3.

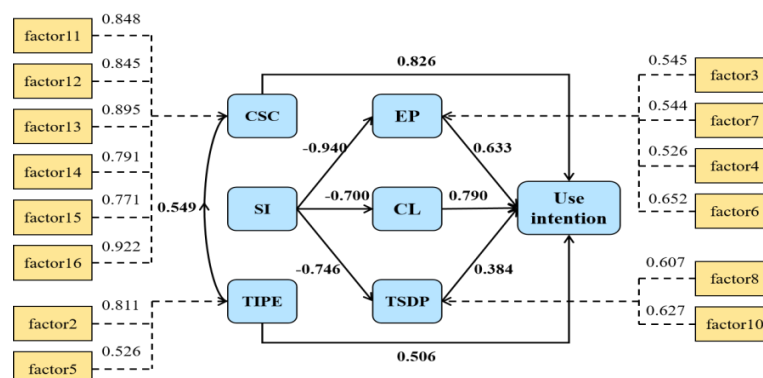


Figure 3. The result of PLS–PM.

The model was tested using five indices: p-value, chi-squared to degrees of freedom ratio (χ^2), root mean square error of approximation (RMSEA), comparative fit index (CFI), and non-normed fit index (NNFI). The results showed that $P = 0.00 < 0.05$, $\chi^2 = 1.71 < 3$, $RMSEA = 0.068 < 0.1$, $CFT = 0.949 > 0.9$, $NNFI = 0.932 > 0.9$, all meeting the evaluation criteria. This indicates that the PLS model for latent factors of usage intention has a good fit.

As shown in Figure 3, Among the potential factors: (1) The influence path of willingness to use is diverse, showing multi-level interaction characteristics. TIPE positively drives the willingness to use through direct and indirect dual paths. SI indirectly inhibits the willingness to use through three paths, and CSC, EP, TSDP, TIPE and CL all have a direct effect on the willingness to use. (2) CSC and CL are the core drivers, and SI is significantly inhibited. CSC ($\gamma = 0.826$) had the greatest positive impact on use intention, followed by CL ($\gamma = 0.79$) and EP ($\gamma = 0.633$). The cumulative γ value of SI through the three paths is -2.386 , which is the main negative factor. The direct effect of TSDP ($\gamma = 0.384$) is general.

Within each potential factor: (1) In the CSC dimension, the X values of all factors are more than 0.7, indicating that users are very concerned about the AI big model 's precise assistance ability to the core links of job search, reflecting the users' high demand for the whole process of job search assistance. (2) In the TSDP dimension, factor2 ($X = 0.811$) and factor5 ($X = 0.526$) show that users have ambivalence about AI substitutability, indicating that although the recognition of technology development is high, it may imply users' concerns. (3) In the EP dimension, the influence of the three factors of factor is not high, and factor7 is negatively correlated with EP. (4) In the TIPE dimension, factor10 ($X = 0.627$) and factor8 ($X = 0.607$) are the main drivers, indicating that policy endorsement and technical reliability are the basis of users' acceptance.

5. Conclusion

This study employs a three-part methodological framework: The TOPSIS was first used to screen out the top three primary factors from the raw data; the factor analysis then reduced all factors into six latent factors; and the PLS–PM model was developed to establish the path relationships between these latent factors and willingness to use, while quantifying the influence degrees of each path. The results show that data processing speed, the use of AI big models by people around them, and the accuracy of AI big model algorithms are key factors influencing willingness to use. Factor analysis identified six latent influencing factors, including CSC, EP, TSDP, TIPE, CL, SI. PLS–PM revealed complex influence paths on use intention, where CSC and CL exhibit strong direct effects, while social influence demonstrates a significant inhibitory role.

Declaration of Generative AI and AI-assisted Technologies

The authors did not use generative AI or AI-assisted technologies in the writing of this manuscript.

Acknowledgments

The authors would like to thank the anonymous reviewers and editors for their valuable comments and suggestions, which have greatly improved the quality of this paper. We also sincerely thank all

researchers who provided assistance and support during the present study. This work was supported in part by the Industry – University Cooperation Collaborative Education Project of the Ministry of Education (Grant No. 250703879185935) and in part by the Enterprise Technology Research Project (Grant No. 2025 – JSFW – 047).

Authors' contribution

Writing—original draft preparation, methodology, software and writing—review and editing, Jiahao Zeng; visualization, software and formal analysis, Xiang Gong; validation and visualization, Anxing Huang; data curation and validation, Tianshi Tan; writing—review and editing, Lisha Ma. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

References

- [1] Ma J, Mao C. Study on the influencing factors of users' acceptance and willingness to use ChatGPT. *Tech. Commun.* 2024, 16(17):118–124.
- [2] Strong. Research on the willingness to use campus express unmanned vehicles based on TAM model. *Logist. Technol.* 2024, 47(13):51–54,62.
- [3] Xu Z, Wen B, Xie M, Cai X. Research on AI job demand analysis based on big data technology. *Guangxi Sci.* 2021, 28(3):321–329.
- [4] Liang C, Yang J, Shao S, Zheng Y. Research on the impact of job-seeking app college students' willingness to continue to use. *Trade Fair Econ.* 2023, 15:116–119.
- [5] Liu X, Lu C, Xue H. Job seekers' acceptance of AI interviews and its influencing factors: a qualitative study based on a fair perspective. *Hum. Resour. Dev. China.* 2023, 40(3):117–130.
- [6] Yoon KP, Kim WK. The behavioral TOPSIS. *Expert Syst. Appl.* 2017, 89:266–272.
- [7] Zaman M, Ghani F, Khan A, Abdullah S, Khan F. Complex Fermatean fuzzy extended TOPSIS method and its applications in decision making. *Heliyon* 2023, 9(9):e19170.
- [8] He Y, Ning C, Yao P, Xia F, Hao Z. Analysis of the influencing factors of medical students' employment pressure in Jilin Province based on factor analysis. *Med. Soc.* 2021, 34(4):27–31.
- [9] Wang X, Wang W, Huang S, Yi H. A study on the comprehensive evaluation of academic journals based on indicator contraction method and improved factor analysis method. *Inf. Stud.: Theory Appl.* 2025, 48(3):92–98.
- [10] Schuberth F, Rademaker ME, Henseler J. Estimating and assessing second-order constructs using PLS-PM: the case of composites of composites. *Ind. Manag. Data Syst.* 2020, 120(12):2211–2241.
- [11] Wu T, Yang D, Jiang S. Research on the impact path of Sino-US trade frictions on China's financial security—Validation based on PLS model. *Int. Bus. Res.* 2020, 41(1):85–95.