College Students' Behavior Initiative, Psychological Availability, and Innovation and Entrepreneurship: The Mediating Effect of Interest Orientation

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Abstract—The features of college students' initiative character and psychological availability can generate great influence on their Innovative and Entrepreneurship (I&E). Relevant existing studies paid insufficient attention on the interest orientation management of college students' I&E from the perspective of I&E education, and few of them viewed the problems of the behavior initiative and psychological availability of college students' I&E from the perspective of individual student. To fill in these research blanks, this paper aims to analyze the relationship among behavior initiative, psychological availability, and I&E interest orientation of college students. At first, based on the evaluation data of the behavior initiative and psychological availability features of college students' I&E, tags of their I&E behavior were created, and the behavior preferences of their I&E were predicted based on the machine learning algorithm. Then, the prediction results of I&E interest were tested using the mediating effect method, and it's found that when behavior initiative and psychological availability features affect college students' I&E performance, interest orientation plays a mediating role in the process. The experiment verified the effectiveness of the proposed prediction model and gave the analysis results of the mediating effect.

Keywords—behavior initiative, psychological availability, innovation and entrepreneurship (I&E), interest orientation, mediating effect, prediction

1 Introduction

Initiative character can greatly affect a college student's I&E since the generation of such I&E behavior requires one to actively seek for new knowledge and technology, manage time and formulate plans, and take more active actions to plunge into I&E activities [1–9]. At the individual level, college students need to have a controllable and safe feeling over the I&E process, and hold a satisfactory feeling towards the I&E results, and only on this basis, will they take active actions to carry out the I&E behavior [10–18]. Therefore, it is of great value to study the relationship among behavior initiative, psychological availability, and I&E interest orientation of college students.

Existing I&E training paths are not complete enough, so efforts should be made to instruct college students to hold on to their I&E goals, cultivate their I&E spirit and morality, and train their I&E ability [19–23]. Scholar Wang [24] optimized the I&E training paths of college students based on Internet technology, and proved via practice that the optimized paths could well enhance their I&E ability, they can act as a guidance for college students' I&E and realize the development of ideological and political education in colleges and universities. Loh et al. [25] introduced an innovation and design program implemented by the National University of Singapore, which aims to provide design and I&E education for solving multidisciplinary problems in real world. Vision of this program is to cultivate graduates with an entrepreneurial mindset and realize learning programs via experience-based teams, including design thinking, innovation framework, prototype, and testing, etc., which lays a foundation for employer enterprises. Rivera et al. [26] investigated the relationship among gender, school year, and the knowledge and experience level of the I&E activities of teachers and students through data statistics and analysis, and developed two online evaluations to measure the impact, limitation, and advantage of students' interest, knowledge, and participation. Maheswaran [27] elaborated on a teacher-led project implemented successfully over the past three years in San Jose of California in the United States, the project targeted at promoting experiential and interactive learning in the entrepreneurial environment, the innovative experience-based learning method and its results were given in the paper, including student demonstrations, project samples, and some activities during the experiential and entrepreneurial education. Khurana and Dutta [28] employed insights of relational sociology and scenario-based and process-based entrepreneurial learning to discuss how to transform potential entrepreneurship in the drone industry of the United State to the emerging entrepreneurship, their study revealed the contour of the innovative ecosystem presented in the emerging drone industry.

After carefully reviewing and analyzing the existing research, it's found that relevant studies paid insufficient attention on the interest orientation management of college students' I&E from the perspective of I&E education, and few of them viewed the problems of the behavior initiative and psychological availability of college students' I&E from the perspective of individual student. To fill in these research blanks, this paper aims to analyze the relationship among behavior initiative, psychological availability, and I&E interest orientation of college students. In the second chapter, this paper created tags of college students' I&E behavior based on the evaluation data of their behavior initiative and psychological availability features, and predicted the behavior preferences of their I&E based on the machine learning algorithm. In the third chapter, the prediction results of college students' I&E interest were tested using the mediating effect method, and it's found that when behavior initiative and psychological availability affect college students' I&E performance, interest orientation plays a mediating role in the process. At last, experiment verified the effectiveness of the proposed prediction model and gave the analysis results of the mediating effect.

2 Prediction of college students' I&E interest

College students are independent individuals with different experiences and personalities, and they have their own ideological and behavior preferences in I&E. Based on the evaluation data of the behavior initiative and psychological availability features of college students' I&E, this paper created tags for college students' I&E behavior, and predicted their preferences in I&E behavior based on machine learning algorithm.

In this paper, tags of college students' I&E behavior are composed of initiative behavior content and psychological weight, and one thing should be noted is that these tags vary constantly with time. When the weight Q_{SL} of a tag on a college student's I&E behavior is lower than the preset threshold, then the tag should be removed from the student. Assuming: ω represents the decay factor; Q_B represents the weight of behavior tag, then there is:

$$Q_{SL} = Q_B * \omega \tag{1}$$

Psychological weight is usually represented by the value of *TF-IDF* (term frequency–inverse document frequency), formulas for calculating the keyword frequency and inverse document frequency of college students' entrepreneurial psychology are given below:

$$TF_{ij} = \frac{m_{ij}}{\sum_l m_{l,j}} \tag{2}$$

$$IDF_i = log \frac{|E|}{|\{j : p_i \in e_j\}|} \tag{3}$$

To create tags of college students' I&E behavior, at first, the tag types should be determined and the tags need to be standardized. Assuming: V represents the value after standardization, and U represents the value before standardization, then the formula of standardization is:

$$V = \left| \frac{U - U_{min}}{U_{max} - U_{min}} \right| \tag{4}$$

After all tags were created, they were classified, and the students' behavior features were described in detail.

College students' I&E interest is often uncertain and prone to the influence of their families, schools, and the society. This paper only took subjective factors into consideration, and attributes such as the perception of new things, the reflection of personal value, the improvement of management ability, the joy of career achievement, and the achievement of other people's expectations were taken as measures of college students' I&E interest, see Figure 1 for details.

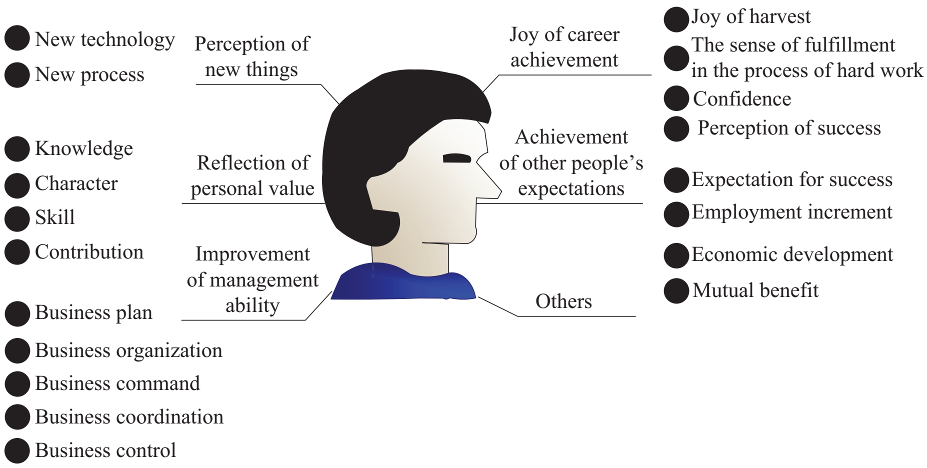

Fig. 1. Important attributes of college students' I&E interest

Assuming: $(a_1,a_2,a_3,\ldots a_m)$ represents the attribute features of college student i; $G(.)$ represents the function to be learnt by the model, and this function is a mapping of the determined attribute features and I&E interest of college student, then the prediction problem of college students' I&E interest could be expressed by Formula 5:

$$\hat{b}_{ij} = G(a_1, a_2, a_3, \ldots a_m), j \in DS_i \tag{5}$$

In this way, the prediction problem in this paper was converted to a problem of searching for the relationship between m a (values) and b (values); assuming $maxA$ and $maxB$ represent the maximum and minimum values of attribute feature vector A of the college student, the value range is $[L, H]$, then the normalization of A is given by Formula 6:

$$a_{norm} = \frac{(H-L)*(a-\min A)}{\max A - \min A} \tag{6}$$

Then above normalization processing can effectively reduce the number of model iterations and shorten the training time.

Basic framework of the prediction model is a time-series convolutional neural network, as shown in Figure 2. The model unified the input and output time steps of all hidden layers, namely, $SQ(ae,ak,ac,\ldots am) = SQ(be,B1\}Bc\}\ldots bm)$. To ensure the integrity of history behavior data, the model introduced the causal convolution, that is, the data source is the data generated at time moment p and before time moment p; B_p represents the output result that can only be generated before p; in the model, assuming: the bottom layer a and the top layer B respectively represent the input sequence and the output sequence; l_i represents the convolution kernel size of the i-th layer; s_j represents the convolution step size of the j-th layer, then the formula below calculates the receptive field of the upper layer:

$$SG_i = SG_{i-1} + (l_i - 1)\prod_{j=1}^{i-1} r_j \tag{7}$$

Compared with recurrent neural networks, causal convolutional models usually have higher training efficiency due to their structural advantages. Causal convolution makes the value of b_p predicted based on sequence $\{a_1, a_2, \ldots a_p\}$ closer to the true value of t, the formula below gives the expression of causal convolution:

$$t(a) = \prod_{p=1}^{P} t(a_p \mid a_1, \cdots, a_{p-1}) \tag{8}$$

To reduce the dependence of time series on history information, this paper introduced the dilated causal convolution to expand the receptive field of convolution, as shown in Figure 3. Assuming: *DI* represents the dilation coefficient *e*; *ST* represents the moving step size; *KE-SI* represents the length of convolution window 1-*D*; *PA* represents the filled length, then the calculation formula of the output result of dilated causal convolution is:

$$F_{out} = \left[\frac{F_{in} + 2 * PA[0] - DI[0] * (KE\_SI[0] - 1) - 1}{ST[0]} \right] \tag{9}$$

The calculation formula of *PA* is:

$$PA = (KE\_SI - 1) * DI \tag{10}$$

When *KE-SI*=2, there is *PA* = *DA*. The college student I&E interest prediction model proposed in this paper cannot directly process the time series data of behavior initiative evaluation, psychological availability evaluation, and student basic attribute evaluation, the above time series data were spliced into a matrix for processing, see Figure 4. A comprehensive data table describing college students' I&E interest was formed by connecting two tables in the database. In this way, this paper converted the problem of predicting college students' I&E interest into a sequence prediction event problem that can be solved by the proposed deep neural network model.

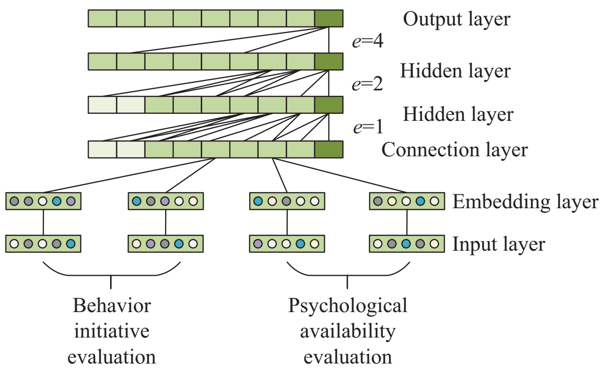

Fig. 2. Structure of the prediction model

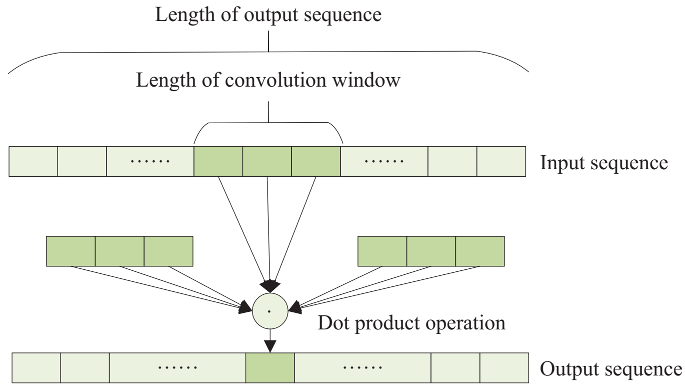

Fig. 3. Schematic diagram of dilated causal convolution

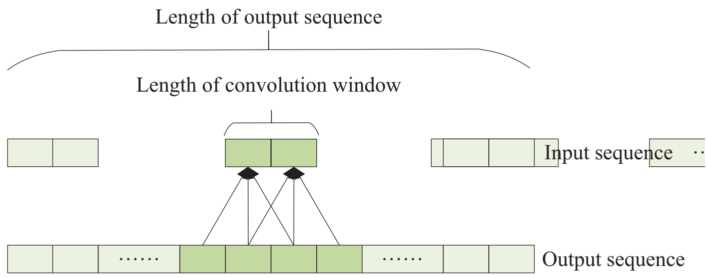

Fig. 4. Subsequence in the time series convolutional network

3 Test on the mediating effect of interest orientation

In order to further determine the role of interest orientation as mediating variable when behavior initiative and psychological availability exert an impact on college students' I&E performance, this strictly applied the mediating effect test method based on the prediction results of college students' I&E interest.

In the test, the set independent variable $FE_{i,p}$ contains behavior initiative feature $BIC_{i,p}$ (reflecting whether the *i*-th college students' I&E behavior tag has reflected his/her behavior initiative feature at time moment *p*) and psychological availability feature $PAC_{i,p}$ (reflecting whether the *i*-th college students' I&E behavior tag has reflected his/her psychological availability feature at time moment *p*). Control variable $CON_{i,p}$ contains *IEP* (I&E performance in the market); $IEIN_{i,p}$ (I&E input of the *i*-th college student at time moment *p*); $IEIC_{i,p}$ (I&E cost of the *i*-th college student at time moment *p*). Mediating variables include $IEA_{i,p}$ (the *i*-th college student's attention degree on I&E at time moment *p*) and $IEI_{i,p}$ (the *i*-th college student's I&E input degree at time moment *p*). Dependent variable $B_{i,p}$ contains $GAD_{i,p}$ (the achievement degree of the *i*-th college student's I&E goal at time moment *p*), $RC_{i,p}$ (the concentration degree of I&E resources of the i-th college student at time moment p), $BCV_{i,p}$ (the value created by the I&E behavior of the i-th college student at time moment p), and $BFD_{i,p}$ (the frequency and degree of the I&E behavior of the i-th college student at time moment p).

In the test, the coefficient d in the following formula was checked to verify Hypothesis F_1: The tags of college students' I&E behavior reflect their behavior initiative and psychological availability features and can trigger I&E interest in them.

$$B_{i,p} = dFE_{i,p} + \omega CON_{i,p} + \sigma_{1(i,p)} \tag{11}$$

Then, the coefficient γ in Formula 12 representing the I&E attention path was verified, and the coefficient y in Formula 13 was verified as well. If the verification result of coefficient d is significant and at the same time, the verification results of coefficients γ and y are both significant, then the mediating effect of the mediating variable could be considered as significant. If the verification result of coefficient d' in Formula 13 is not significant, then the mediating effect of the mediating variable can be regarded as a complete mediating effect, which could verify Hypothesis F_2: The tags of college students' I&E behavior reflect their behavior initiative and psychological availability features, they could exert an impact on the I&E performance of college students by affecting their I&E interest; Hypothesis F_3 was verified as well: The behavior initiative and psychological availability features can arouse the attention of college students in I&E and ultimately exert an impact on their I&E performance by affecting related indexes such as the completion degree of I&E goals.

$$IEA_{i,p} = \gamma FE_{i,p} + \omega CON_{i,p} + \sigma_{i,p} \tag{12}$$

$$B_{i,p} = d' FE_{i,p} + yIEA_{i,p} + \omega CON_{i,p} + \sigma_{i,p} \tag{13}$$

At last, the coefficient γ in Formula 14 representing the path of I&E input was verified, and coefficient y in Formula 15 was verified as well, if the verification result of coefficient d in Formula 11 is significant, and at the same time the verification results of coefficient γ and y in Formulas 14 and 15 are significant, then the mediating effect of the mediating variable can be regarded as significant. If the verification result of coefficient d' in Formula 15 is not significant, then the mediating effect of the mediating variable can be regarded as a complete mediating effect, which could verify Hypothesis F_4: College students' behavior initiative and psychological availability features can exert an impact on the I&E behavior of college students by affecting their I&E input, and the effect is mainly acted on related indexes such as the concentration degree of I&E resources and the value created by I&E behavior, etc.

$$IEI_{i,p} = \gamma FE_{i,p} + \omega CON_{i,p} + \sigma_{i,p} \tag{14}$$

$$B_{i,p} = d' FE_{i,p} + yIEI_{i,p} + \omega CON_{i,p} + \sigma_{i,p} \tag{15}$$

To ensure not to confuse the two paths of I&E attention degree and input degree of the mediating variable, when the model performs fitting on one path, the other path of the mediating variable was taken as the control variable to perform verification, and the confusing paths between the two paths need to be checked for robustness.

4 Experimental results and analysis

Figure 5 compares the prediction accuracy of college students' I&E interest based on some important attributes and all important attributes. In the figure, grey bars represent prediction results attained based on some important attributes, and the blue bars represent those attained based on all important attributes, obviously, the prediction accuracy based on some important attributes is lower than that based on all important attributes, which has verified that important attributes such as the perception of things, reflection of personal value, improvement of management ability, joy of career achievement, and achievement of other people's expectations all have certain impact on the prediction results of college students' I&E interest. In order to verify the validity of the constructed prediction model, this paper designed a comparative experiment for predicting the performance of four typical machine learning algorithms, including logistic regression, K-nearest neighbor, conventional BP neural network, and support vector machine (SVM), which were denoted as reference models 1, 2, 3, and 4, respectively. In this paper, 3/4 of the samples were taken as the training set, and 1/4 of the samples were taken as the test set. Figure 6 shows the prediction results of the I&E interest of college students with significant behavior initiative feature. Figure 7 shows the prediction results of the I&E interest of college students with significant psychological availability feature. For college students with behavior initiative feature or psychological availability feature, the proposed model outperformed the other models in terms of predicting the I&E interest of these students.

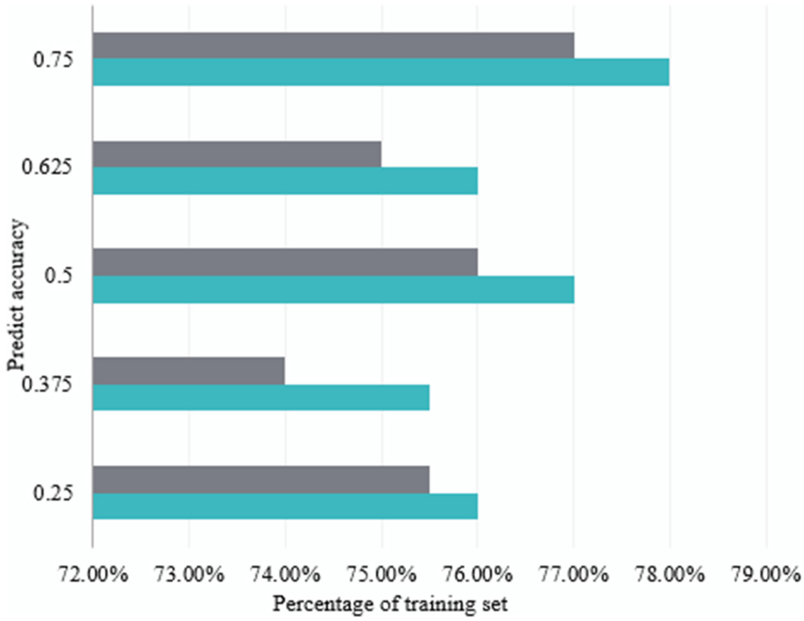

Fig. 5. Comparison of prediction accuracy of college students' I&E interest based on important attributes

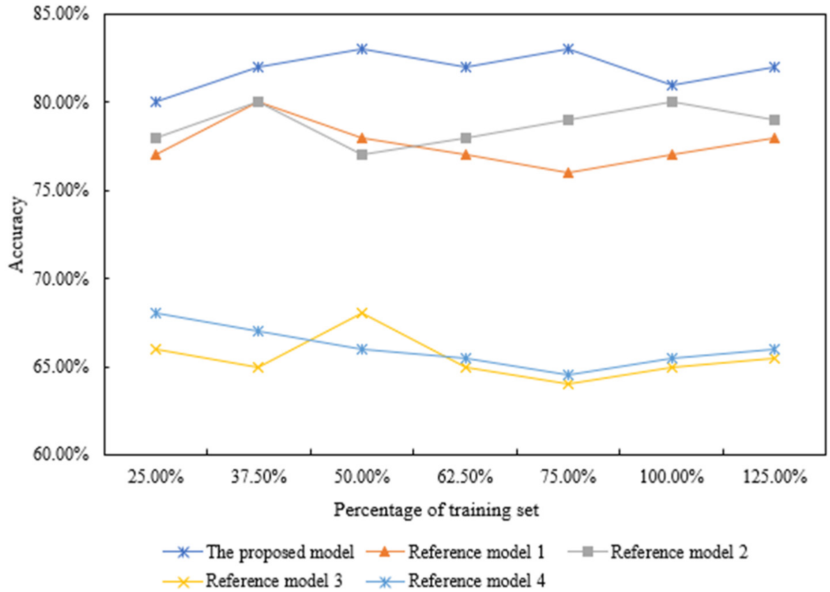

Fig. 6. Prediction results of the I&E interest of college student with obvious behavior initiative feature

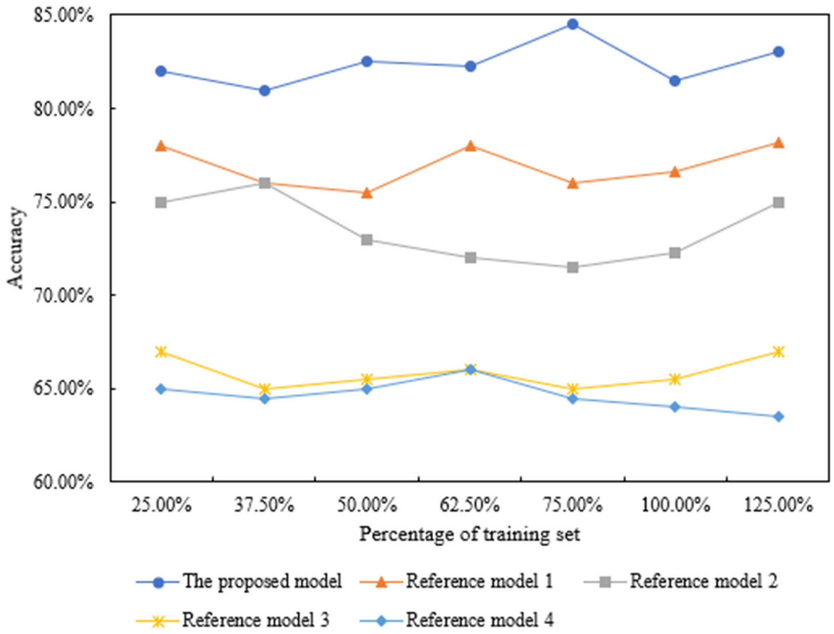

Fig. 7. Prediction results of the I&E interest of college student with obvious psychological availability feature

Table 1. Behavior initiative feature, psychological availability feature, I&E interest of college students, and achievement degree of I&E goals

	GAD	*IEA*	*GAD*
FE	0.025**	0.068*	0.051***
	(0.014)	(0.021)	(0.024)
IEP	1.326*	0.396***	1.635*
	(0.035)	(0.048)	(0.044)
IEIC	−0.058***	0.085*	0.062***
	(0.027)	(0.024)	(0.095)
IEIN	0.096	1.625***	0.017*
	(0.021)	(0.084)	(0.062)
IEI	0.074**	−0.027**	0.017**
	(0.023)	(0.062)	(0.011)
IEA			0.035*
			(0.069)
Adj-R2	0.369	0.214	0.348
F	1858.625	162.384	1623.582
N	79.685	74.516	77.516

Table 2. Behavior initiative feature, psychological availability feature, I&E interest of college students, and achievement degree of I&E goals

	RC	*IEA*	*RC*
FE	0.274**	0.061***	0.084**
	(0.026)	(0.051)	(0.062)
IEP	2.092*	0.314*	1.329*
	(0.128)	(0.041)	(0.134)
IEICi,p	−0.215**	−0.025***	−0.057***
	(0.037)	(0.017)	(0.021)
IEIN	4.192**	1.629*	1.528***
	(0.263)	(0.085)	(0.137)
IEI	−0.149**	−0.051**	−0.037*
	0.051	0.027	0.015
IEA			2.159**
			(0.048)
Adj-R2	0.216	0.274	0..561
F	241.168	148.514	815.431
N	74.519	75.491	75.419

In order to verify the influence of behavior initiative and psychological availability features on college students' I&E behavior and the mediating effect of I&E interest, this paper adopted the stepwise regression method to test the direct effect and mediating effect of four indexes of college students' I&E behavior, and the test results are given in Tables 1–4. According to the test results, in terms of the overall effect, behavior initiative and psychological availability features can cause significant changes in college students' I&E goal achievement degree, resource concentration degree, value created by I&E behavior, and I&E behavior frequency and degree. These findings had basically verified Hypothesis F_1: The tags of college students' I&E behavior reflect their behavior initiative and psychological availability features and can trigger I&E interest in them. According to the second and third columns in the tables, behavior initiative and psychological availability features can arouse significant changes in college students' interest in I&E, and affect their I&E behavior ultimately, which had verified Hypothesis F_2: The tags of college students' I&E behavior reflect their behavior initiative and psychological availability features, they could exert an impact on the I&E performance of college students by affecting their I&E interest.

Table 3. Behavior initiative feature, psychological availability feature, I&E interest of college students, and value created by I&E behavior

	BCV	*IEA*	*BCV*
FE	0.124**	0.085***	0.052**
	0.032	0.014	0.095
IEP	1.628*	0.316**	1.362***
	0.174	0.012	0.049
IEICi,p	−0.274***	−0.068***	−0.135*
	0.051	0.037	0.041
IEIN	2.194*	1.392***	1.068*
	0.138	0.042	0.025
IEI	−0.084***	−0.052*	0.049***
	0.037	0.037	0.037
IEA			1.854*
			0.051
Adj-R2	0.263	0.295	0.683
F	261.58	142.619	1418.627
N	75.412	77.382	77.691

According to the four tables, when behavior initiative feature and psychological availability feature are taken as explanatory variables and college students' I&E interest is taken as mediating variable, except for the index of the frequency and degree of I&E behavior, the other three dependent variables all have mediating effects, wherein the mediating effects on *GAD* (achievement degree of I&E goals), *RC* (concentration degree of I&E resources), and *BCV* (value created by I&E behavior) are partial mediating effect. By comparing the coefficient values in columns 1 and 3 of Table 1, Table 2, and Table 3, it can be seen that when behavior initiative and psychological availability features exert an impact on college students' I&E interest, the changes in the coefficients of the indexes are more obvious, indicating that the mediating effect is more significant, which had verified Hypothesis F_3: The behavior initiative and psychological availability features can arouse the attention of college students in I&E and ultimately exert an impact on their I&E performance by affecting related indexes such as the completion degree of I&E goals. This paper analyzed the reasons for these results. At first, behavior initiative and psychological availability features can directly affect the achievement of I&E goals, this is because college students with these features know the ability of themselves better, and the I&E goals they set fit their own conditions better. The two indexes of resource concentration degree and value created by I&E behavior could measure the I&E performance of college students, students with these two features have firmer I&E belief and stronger action power, and their input in I&E will be higher.

Table 4. Behavior initiative feature, psychological availability feature, I&E interest of college students, and frequency and degree of I&E behavior

	BFD	***IEA***	***BFD***
FE	0.025	0.091***	0.057
	0.062	0.052	0.036
IEP	9.847*	0.319**	9.145*
	0.136	0.058	0.162
IEICi,p	0.014	−0.068***	−0.014**
	0.062	0.016	0.062
IEIN	0.008	1.485**	0.035*
	0.052	0.062	0.126
IEI	0.136***	−0.048*	0.174***
	0.025	0.032	0.038
IEA			−0.062***
			0.024
Adj-R2	0.162	0.218	0.162
F	1777.625	141.62	1352.485
N	77.528	77.618	74.629

5 Conclusion

This paper analyzed the relationship between the behavior initiative and psychological availability features of college students and their I&E interest orientation. At first, tags of college students' I&E behavior were created based on the evaluation data of their behavior initiative and psychological availability features, and their I&E behavior preferences were predicted based on the machine learning algorithm. Then, according to the prediction results of I&E interest, this paper employed the mediating effect method to determine that when behavior initiative and psychological availability exert an impact on college students' I&E performance, interest orientation plays a mediating effect as a mediating variable. In the experiment, this paper compared the prediction accuracy of college students' I&E interest based on important attributes, and gave the prediction results of students with obvious behavior initiative and psychological availability features, the results suggested that the proposed model outperformed other models in terms of the prediction of students with these features. At last, the stepwise regression method was adopted to test the direct effect and mediating effect of four indexes of college students' I&E behavior, and the test results verified the four hypotheses proposed in the paper.

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