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ORIGINAL ARTICLE

A Hybrid SEM-Neural Network Method for Identifying Influential Factors of Academic Motivation of Students Majoring in Traditional Chinese Medicine

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Abstract

Introduction: The rapid advancement of learning platforms has greatly improved instruments for vocational English instruction and promoted autonomous learning. To follow the trend, educational participants (faculty, teacher, peer, and student) must change their management policies, attitudes, roles, and psychological condition.

Methods : This study used Carroll Model of School Learning to examine factors affecting student academic motivation from macro, meso, and micro perspectives. The model was validated using a multi-analytic approach using Structural Equation Modelling (SEM), and the results were used as inputs for a neural network model to predict acceptance factors. 336 Chinese TCM majors provided data.

Results: The results show that internal and external elements are crucial to developing an academic atmosphere that motivates pupils. It showed that Carroll's Model of School Learning could employ SEM's causal analysis and ANN's nonlinearity to produce more trustworthy academic motivation influencing factor analysis results.

Discussion: This study's unique methodology and findings will add to the literature on learning platform adoption in TCM education and give a novel conceptual framework from macro, meso, and micro perspectives. This will boost instructor, teacher, and student performance and academic success.

Keyword: Carroll Model of School Learning; Autonomous Learning Theory; Motivation Theory; Structural Equation Model; Artificial Neural Network

Introduction

The rapid growth of learning platforms has substantially improved vocational educational English instruction materials and self-directed learning methods. For vocational students who

balance school, work, and practical training, these platforms allow them to learn at their own pace and place (Josué et al., 2023). Technology has enabled autonomous learning models that meet individual learning needs, promoting self-sufficiency, information retrieval, language confidence, and successful learning methods (Pratiwi & Waluyo, 2023). Hierarchical learning test functions have improved as information technology in education has advanced, providing a better teaching experience tailored to each student (Pratiwi & Waluyo, 2023). This research examined micro perspectives and used intrinsic and extrinsic components in autonomous learning, a novel technique. Integrating intrinsic and extrinsic elements in autonomous learning modes across educational contexts has the potential to foster learner autonomy, motivation, and competence, but more research is needed to fully understand and optimize its implementation (Josué et al., 2023).

Carroll's Model of School Learning, which emphasizes learning time and instructional quality, can be used from macro, meso, and micro perspectives to study student motivation. Large-scale school culture affects student academic motivation. Students are motivated to learn in an optimistic and supportive educational environment with cooperative peers, supporting staff, and abundant resources (Y. Wang, 2023). This method emphasizes the importance of giving students enough time to learn, which can be helped by flexible learning schedules and extended learning opportunities. The model also emphasizes the importance of high-quality teaching, which can be reinforced at the institutional level by investing in teacher training and development to prepare educators to deliver effective instruction (Gaines, 1973). Meso-level interactions between students, instructors, and peers are crucial. Effective educational practices can boost academic motivation by promoting teacher-student and peer interactions, as seen in technical faculties (Isha & Hashim, 2023). Self-esteem, psychological need, and emotional intelligence affect academic motivation at the micro level. These factors affect academic achievement directly and indirectly, with academic motivation having a major influence (Isha & Hashim, 2023). This study created a new conceptual framework with three analytical levels: macro (school culture created by institutional support), meso (teacher-peer interactions), and micro (self-esteem and psychological needs). The framework was built upon Carroll's Model of School Learning.

Structural Equation Modeling (SEM) is a sophisticated statistical tool for testing causal hypotheses between observable and latent variables. It is useful in educational research for understanding complex phenomena like academic motivation (Jobst et al., 2023). SEM can be used to study and assess how internal and external factors affect student motivation when predicting academic acceptance factors. Simulate variables like instruction quality, student attitudes, and campus facilities to understand their direct and indirect effects on educational attainment (Fariyanda, 2023). Previous studies examined linear elements that boost student academic motivation. In this study, the use of Structural Equation Modeling (SEM) and Artificial Neural Networks (ANN) in educational research represented a significant methodological advance, allowing for a more in-depth and efficient study of academic motivation and its influences. This comprehensive methodology improved understanding of student motivation and provided more reliable and practical insights for educators and policymakers. The utilization of SEM-ANN is consistent with its growing use in psychology, education, and management to build and test complex theoretical models. This study specifically examined the correlation between linear and nonlinear relationships and acquired more precise data about the improvement of students' academic motivation.

Significance

The purpose of this study was to use a model to determine the essential elements of the Carroll Model of School Learning, specifically autonomous learning, with the intent to improve students' academic motivation and their pursuit of academic success. The study conducted a comprehensive analysis using SEM-ANN to examine the correlations between the Carroll Model of School Learning and academic motivation, as well as the relationship between autonomous learning and academic motivation. The objective was to identify various factors at the micro, meso, and macro levels that influenced the creation of an academic environment conducive to students' motivation and learning (Isha &

Hashim, 2023). The research conducted on the Academic Motivation Model has made substantial contributions to the field by improving our comprehension of its conceptualization and evaluation.

Literature Review

Carroll Model of School Learning

In his comprehensive Carroll Model of School Learning, John B. Carroll emphasizes the importance of time and other instructional aspects in learning effectiveness. This approach indicates that learning is determined by time spent versus time needed. It emphasizes the importance of learning opportunities and student determination for educational success (Essa & Mojarad, 2020). The notion has been used in many educational settings to overcome learning challenges. The Dick and Carrey model follows Carroll's principles. It has improved Indonesian language learning by making it more engaging and adjustable to students' preferences (Magdalena et al., 2023). Elementary school students' integrated theme learning and civics education have improved greatly using the Discovery Learning paradigm, which encourages autonomous exploration and information discovery. Active learning and academic performance enhance with this paradigm, as shown in several research (Rahmadhani et al., 2020). For non-traditional learning environments like art museums, Carroll's model has been updated to integrate social and cognitive features to connect educational experiences with school curricula and improve student learning (Magdalena et al., 2023). Studies using structural equation modeling have revealed that cognitive abilities like processing speed and memory affect reading decoding skills. This confirms Carroll's focus on cognitive aspects and learning outcomes (Essa & Mojarad, 2020). The Carroll Model of School Learning uses time, high-quality instruction, and flexible learning environments to understand and improve educational attainment.

Autonomous Learning Theory

Self-regulation, critical thinking, and adaptability to changing surroundings are stressed in autonomous learning theory. This strategy is useful in economics and foreign language courses, where professionals must write and speak clearly. Autonomous learning improves vocabulary, pronunciation, and text composition using internet resources, interactive exercises, and multimedia (Ariebowo, 2021). Activity theory in English as a Foreign Language (EFL) settings shows that autonomous learning includes social interactions and cooperation. Organized electronic learning platforms improve student autonomy in this notion (Ariebowo, 2021). Intelligent systems and neural network topologies like the ARTIR model enable autonomous learning by learning and adapting to new inputs. It helps students learn and apply independently. Higher education prioritizes autonomous learning competencies to satisfy the demand for people who can independently acquire and apply knowledge, skills, and talents in dynamic professional situations (Chyzhykova, 2022). In conclusion, autonomous learning theory uses many educational methods, technology tools, and cognitive models to allow students to independently manage their educational pathways and meet their area's criteria.

Motivation Theory

Motivation theory includes many concepts and frameworks that explain why people act a certain way. It affects education, professional development, and organizational management. The Motivational Theory of Life-Span Development (MTLSD) emphasizes personal motivation and career education, emphasizing how people actively promote lifelong improvement through goals and separation (Borkowski & Thorpe, 2023). Teachers, especially those in training, must understand motivation theory to inspire and motivate students. However, theoretical comprehension and practical implementation often differ (Schürmann et al., 2021). Wayne Wu and Bence Nanay's philosophical explanations of motivation have been criticized for failing to explain motivated mental states. The predictive processing (PP) architecture addresses action initiation, guidance, and control, offering a promising alternative (Schürmann et al., 2021). Engineering educators must understand motivation theory to design courses that suit students' diverse motivations and improve learning (Sullivan & Brennan, 2019). These perspectives highlight motivation theory's complexity and importance in human growth, education, organizational management, and more.

Conceptual Framework and Hypothesis Development

The Carroll Model of School Learning, developed by John B. Carroll, emphasizes the importance of macro, meso, and micro factors that affect educational results. The macro learning environment depends on institutional support. The macro context refers to cultural and societal values that shape school goals and organization, which affects teachers' material and practices (Richter & Dragano, 2018). Teachers and peers are important at the meso level. Based on student demographics, social and psychological learning environment, and teacher credentials, schools offer different educational and developmental opportunities (Richter & Dragano, 2018). Individual perseverance and psychological needs are significant at the microscopic level. Carroll's approach suggests that rewards may enhance students' time spent on a subject, but not their learning speed or extent. Effective learning requires intrinsic motivation and psychological needs (Millman et al., 1983). The Carrel Model of School Learning uses macro institutional support, meso-level teacher and peer relationships, and micro-level psychological needs to understand and improve educational outcomes, which affect career prospects. This study's conceptual framework was illustrated in Figure 1.

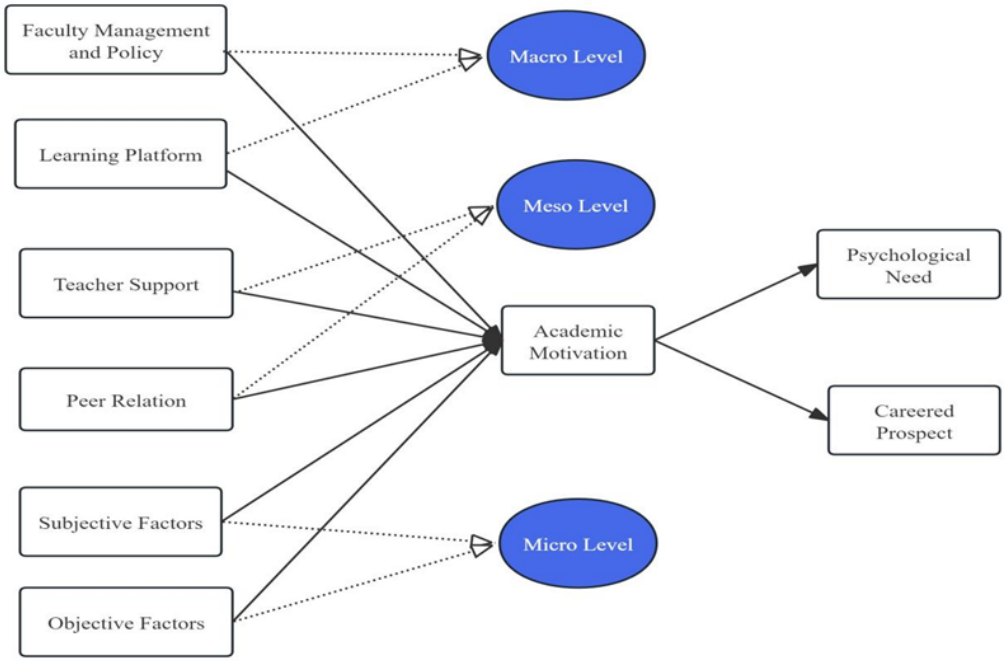

Fig. 1 Conceptual Framework

The relationship between the Carrel Model of School Learning and Motivation Theory

The Carroll Model of School Learning, which prioritizes a methodical and organizes approach to teaching and learning, overlaps considerably with numerous motivation theories, emphasizing the complex connection between structured educational practices and student motivation. The structured approach of the Carrel Model can increase motivation by establishing explicit goals and expectations. This is in line with goal orientation theories, which proposes that students are more motivated when they have precise and achievable targets (Bușu & Popescu, 2018). The Carrel Model prioritizes systematic education and ongoing evaluation to effectively discover and foster students' intrinsic motivation. This is achieved through consistent feedback and many opportunities for self-improvement (Astuti, 2020). Moreover, the crucial role of teachers in cultivating motivation is paramount. Educators who possess a deep understanding of motivation theories have the ability to establish a learning atmosphere that nurtures and amplifies student motivation. This is vital for the successful execution of the Carrel Model (Schürmann et al., 2021). The correlation among student motivation, socioemotional abilities, and school performance emphasizes the significance of a supportive and organized learning environment, as emphasized by the Carrel Model, in fostering overall student welfare and academic achievement (Chiappetta-Santana et al., 2022). The beliefs and interactions

of teachers with students, along with the classroom environment, have a substantial impact on the development of students' personal learning goals and the promotion of a mastery learning orientation (Chiappetta-Santana et al., 2022). Ultimately, the Carrel Model of School Learning and motivation theories are intricately linked, as the organized methodology of the Carrel Model creates a favorable setting for cultivating student motivation, hence improving learning results and overall educational achievement (Astuti, 2020; Bușu & Popescu, 2018; Chiappetta-Santana et al., 2022; Schürmann et al., 2021).

Hypothesis 1: There is a significant relationship between faculty management and academic motivation of students majoring in TCM.

Hypothesis 2: There is a significant relationship between learning platform and academic motivation of students majoring in TCM.

Hypothesis 3: There is a significant relationship between teacher support and academic motivation of students majoring in TCM.

Hypothesis 4: There is a significant relationship between peer relations and academic motivation of students majoring in TCM.

The relationship between the Autonomous Learning Theory and Motivation Theory

Autonomous Learning emphasizes student responsibility for learning. This includes choosing materials and strategies and assessing their progress. It fosters self-control and self-regulation (Ariebowo, 2021). Regulated motivation hurts subjective occupational well-being in professional settings, while autonomous motivation helps. It's important to meet psychological needs for autonomy, competence, and relatedness (Ariebowo, 2021). Motivation Theory's Self-Determination Theory (SDT) classifies motivation as intrinsic or extrinsic. Intrinsic motivation, linked to autonomous learning, prioritizes self-improvement and enjoyment (Rubic & Matijević, 2019). Self-Determination Theory (SDT) classifies motivation as intrinsic or extrinsic. Intrinsic motivation, linked to autonomous learning, prioritizes personal improvement and self-fulfillment (Rubic & Matijević, 2019). In summary, the interaction between Autonomous Learning Theory and Motivation Theory highlights the crucial importance of both objective elements, such as the learning environment and goal-setting, and subjective elements, such as personal motivation and psychological needs, in promoting effective and self-regulated learning.

Hypothesis 5: There is a significant relationship between autonomous learning (subjective factors) and academic motivation of students majoring in TCM.

Hypothesis 6: There is a significant relationship between autonomous learning (objective factors) and academic motivation of students majoring in TCM.

Research Methodology

This study was conducted in higher education institutes in China. Therefore, the study was carried out during the first quarter of 2024. The present study's sample was chosen from the target population using Stratified Sampling methods. Stratified sampling is a reliable and commonly employed technique in research that guarantees an accurate representation of the target population by splitting it into several subgroups or strata depending on certain features. This approach is especially efficient in decreasing variability within strata, therefore improving the accuracy of the estimates (Haron, 2022). 400 students in total participated in this research, among which the majority of students were female and the rest of students were male. All participants were over the age of 18 excluding the minors. Ultimately, 336 students filled in questionnaires. The 84 percent response rate obtained is typical for cross-sectional studies. Researchers must still consider the potential biases and limitations inherent in the cross-sectional design to ensure the validity and reliability of their findings, despite the fact that the 84 percent response rate is typical and suggests excellent participation (Ramke et al., 2018). Although SEM-ANN analysis provides substantial benefits in the capture of intricate relationships, it is imperative that researchers maintain a minimum sample size of 200 to ensure the reliability and validity of their findings, as evidenced by numerous studies and systematic reviews in the field (Leong et al., 2023).

Subjectivity and prejudice were prominent issues in behavioral research. To address this issue, preventative measures were taken, including protecting the confidentiality of respondent data and completing the analysis using SPSS. In addition, after collecting data, we

utilized Harman's single-factor test to examine standard procedure bias. When the variation for the first factor surpasses fifty percent, there is a problem with data bias (Baumgartner et al., 2021). After doing the analysis in SPSS, we obtained a variance of less than 25%, indicating that there was no bias in the sample responses.

The research utilized a questionnaire titled "Academic Motivation Questionnaire". The questionnaire (81 items) was comprised of four parts: respondents' personal information (5 items), the motivation (17 items), autonomous learning (15 items) and Carrel Model of School Learning (44 items). The motivation scale adopted items from motivation scale developed by Esra Kizilay and colleagues (Hiğde & Aktamış, 2022). 15 items of autonomous learning were from Gülgün Afacan Adanır's study (Han et al., 2021). Carrel Model of School Learning scale takes into account the role of social learning theory, as evidenced by the Role Model Preferences Scale of Imam Hatip Secondary School pupils (Algur & Kaya, 2021). To accomplish the objective of this investigation, which was to predict the antecedents of academic motivation through the use of linear and non-linear relationships, PLS-SEM and ANN were implemented to generate evidence regarding the target sample's feedback concerning the enhancement of students' academic motivation. The scale was ranked from firmly agree (5) to strongly disagree (1) on a five-point Likert scale.

Data Analysis and Results

This section consists of two steps for analyzing causal and nonlinear interactions. The initial stage entails evaluating the measurement model and the structural model. The second phase involved analyzing non-linear relationships using the Artificial Neural Network (ANN) approach.

Analysis of the Path Model Results of the Partial Least Squares Structural Equation Modeling.

This study utilized the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to examine the causal relationships. The examination of measurement involved examining both the convergent validity and the discriminant validity. Convergent validity can be assessed using composite reliability (CR), factor loading, and average variance extracted (AVE). Table 1 displayed the outcomes of convergent validity.

The CR values, which must transcend the barrier of 0.70, were determined to be dependable for all variables. This was evidenced by several investigations where CR values exceeded this standard, such as the facility variable with a CR of 0.858 (Fithri et al., 2024). The factor loadings, which represent the correlation between indicators and their underlying variables, were carefully examined. Loadings above 0.50 were considered acceptable. In a study on the political socialization of youth, 42 out of 51 items demonstrated loadings above 0.50, indicating substantial correlations with their respective underlying variables (Memon et al., 2021). The AVE, which should ideally exceed 0.50 to ensure convergent validity, was also evaluated (Fithri et al., 2024). The following table 1 demonstrated that all loading factors were greater than 0.7. Furthermore, the values of CR and AVE exceeded 0.70 and 0.5, respectively. The values of Cronbach's alpha were all above 0.7. All the indicators demonstrated that all constructs met the criteria for convergent validity.

Table 1: Convergent Validity

Items	Loading	Cronbach's alpha	CR	AVE
Carrel Model of School Learning				
LP 1	0.746	0.947	0.948	0.576
LP 10	0.774			
LP 11	0.769			
LP 12	0.771			
LP 13	0.770			
LP 14	0.762			
LP 15	0.746			

LP 2	0.728			
LP 3	0.764			
LP 4	0.784			
LP 5	0.782			
LP 6	0.736			
LP 7	0.760			
LP 8	0.724			
LP 9	0.768			
TS 1	0.787	0.932	0.932	0.571
TS 10	0.741			
TS 11	0.758			
TS 12	0.752			
TS 2	0.714			
TS 3	0.774			
TS 4	0.763			
TS 5	0.782			
TS 6	0.723			
TS 7	0.743			
TS 8	0.758			
TS 9	0.769			
PR 1	0.786	0.914	0.916	0.594
PR 2	0.769			
PR 3	0.794			
PR 4	0.765			
PR 5	0.767			
PR 6	0.767			
PR 7	0.767			
PR 8	0.726			
PR 9	0.791			
FM 1	0.796	0.907	0.908	0.607
FM 2	0.768			
FM 3	0.788			
FM 4	0.795			
FM 5	0.759			
FM 6	0.779			
FM 7	0.777			
FM 8	0.769			
Autonomous Learning Theory				
SF 1	0.771	0.900	0.901	0.626
SF 2	0.798			
SF 3	0.815			
SF 4	0.810			
SF 5	0.748			
SF 6	0.803			
SF 7	0.789			
OF 1	0.763	0.916	0.916	0.629
OF 2	0.791			
OF 3	0.783			
OF 4	0.788			
OF 5	0.821			

OF 6	0.794			
OF 7	0.780			
OF 8	0.823			
Motivation Theory				
CP 1	0.802	0.897	0.897	0.617
CP 2	0.807			
CP 3	0.795			
CP 4	0.779			
CP 5	0.775			
CP 6	0.787			
CP 7	0.753			
PN 1	0.772	0.925	0.925	0.596
PN 10	0.787			
PN 2	0.733			
PN 3	0.760			
PN 4	0.761			
PN 5	0.775			
PN 6	0.755			
PN 7	0.794			
PN 8	0.811			
PN 9	0.772			
Note: LP: Learning Platform, TS: Teacher Support, PR: Peer relation, FM: Faculty Management, SF: Subjective Factors, OF: Objective Factors, CP: Careered Prospect, PN: Psychological Need				

This study adopted the Fornell-Larcker method to investigate the discriminant validity. The discriminant validity had been assessed using Fornell-Larcker's criterion. Fornell-Larcker's criterion assesses discriminant validity by comparing the square root of the average variance extracted (AVE) for each construct with the correlations between the components. Discriminant validity is demonstrated if the square root of the average variance extracted (AVE) for each construct exceeds the correlations with other constructs (Fithri et al., 2024). The data calculated by Smartpls exhibited discriminant validity, as indicated by the square root of the average variance retrieved from each dimension being greater than the absolute value of the correlation coefficient it had with other dimensions.

Assessment of Structural Model

Evaluation of the structural model was employed to illustrate the causal connections between all constructs. Using a bootstrapping method, we employed hypothesis testing to determine the statistical significance. Bootstrapping technique was configured to use 5000 bootstrap samples. Bootstrapping in regression analysis might yield more precise and enlightening outcomes compared to conventional approaches, particularly when confronted with intricate data distributions (Farag, 2023). Figure 2 and Table 2 provided an explanation of the evaluation of the structural model.

Table 2 and Figure 2 provided evidence that supported the acceptance of all hypotheses. Furthermore, this study revealed compelling findings that could make a valuable contribution to the existing body of literature and aid practitioners in addressing the challenges associated with the improvement of TCM major students' academic motivation by faculty and teachers. PLS-SEM techniques were used to examine causal linkages and validate the given hypotheses. However, this technique was not capable of analyzing non-linear relationships. Thus, artificial intelligence analysis has been employed to confirm the results of the PLS-SEM and ascertain the presence of non-linear correlations, as elaborated in the subsequent discussion.

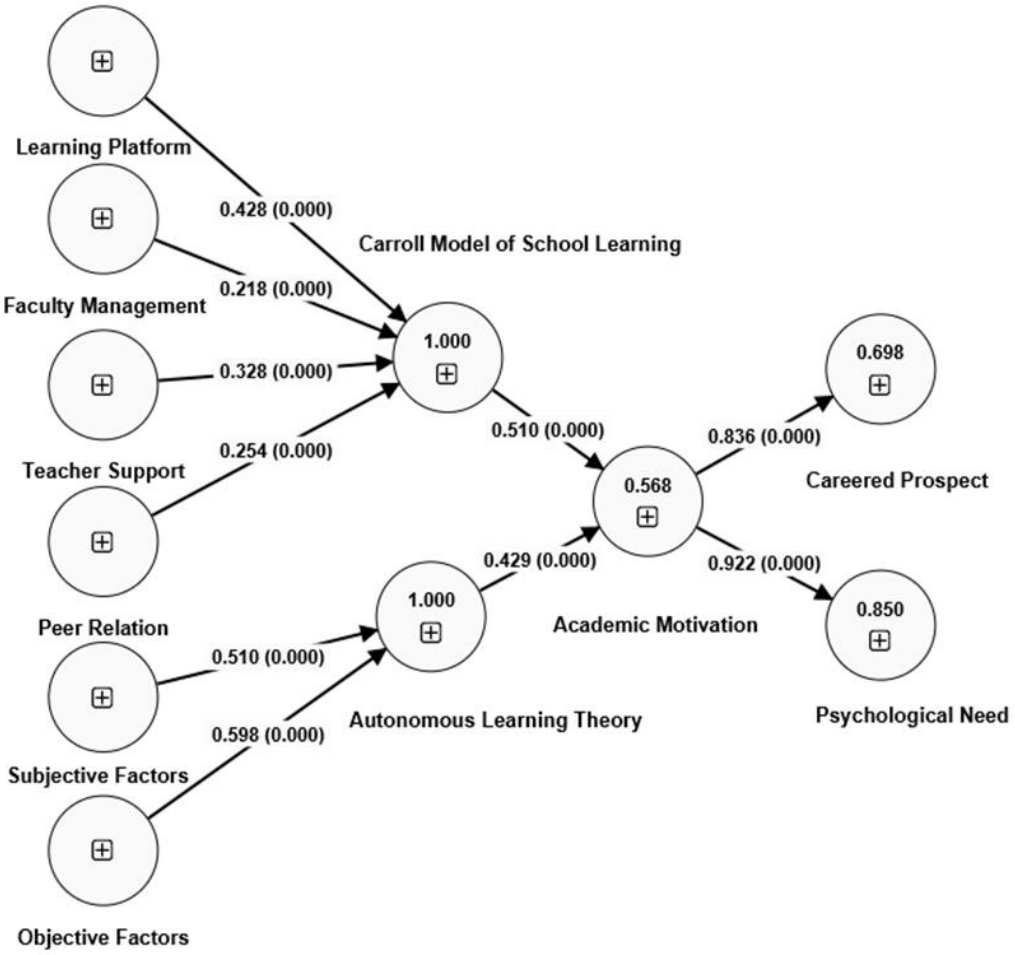

Fig. 2 Assessment of Structural Model

Table 2: Path Coefficients and Hypotheses Testing

Direct and Indirect Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Results
Academic Motivation -> Careered Prospect	0.836	0.835	0.019	44.197	0.000	Supported
Academic Motivation -> Psychological Need	0.922	0.922	0.008	120.924	0.000	Supported
Autonomous Learning Theory -> Academic Motivation	0.429	0.430	0.036	11.812	0.000	Supported
Carroll Model of School Learning -> Academic Motivation	0.510	0.511	0.034	14.896	0.000	Supported

Faculty Management -> Carroll Model of School Learning	0.218	0.218	0.011	19.637	0.000	Supported
Learning Platform -> Carroll Model of School Learning	0.428	0.427	0.016	26.063	0.000	Supported
Objective Factors -> Autonomous Learning Theory	0.598	0.598	0.018	33.817	0.000	Supported
Peer Relation -> Carroll Model of School Learning	0.254	0.254	0.012	21.223	0.000	Supported
Subjective Factors -> Autonomous Learning Theory	0.510	0.510	0.018	28.949	0.000	Supported
Teacher Support -> Carroll Model of School Learning	0.328	0.328	0.016	20.646	0.000	Supported

Artificial Neural Network

Several research used Artificial Neural Networks (ANN) to identify elements that boost student academic motivation. Ping-yu Liu examined college students' English learning data using an ANN algorithm (Liu, 2022). The results showed that curriculum design, teaching methods, and teacher-student interaction affect negative English learning motivation (Liu, 2022). Many fields use Artificial Neural Networks (ANNs) because they can process complex, non-linear data and make accurate predictions. ANNs effectively identify linear and nonlinear correlations among variables, yielding accurate results (Liu, 2022).

In artificial neural network (ANN) analysis, each neuron computes its output by considering the number of stimulations received from an input vector, x. The weights connecting input component-i to hidden neuron-j are denoted as Wji, whereas the weights connecting hidden neuron-j to output neuron-k are represented as Vkj. The actual input neuron is determined by the weighted sum of its inputs and the output of the neuron (yi). To be more precise, for the j-th hidden neuron (Liu, 2022).

(1)

$$net_j^h = \sum_{i=1}^{N} W_{ji} x_i \text{ and } Y_i = f(net_j^h)$$

For the k-th output neuron:

(2)

$$net_k^0 = \sum_{j=1}^{J+1} V_{kj}\, y_j \; and \; o_k = f(net_k^0)$$

Equation (3) demonstrates the sigmoid function's response, which is influenced by the parameter ƛ, allowing for the regulation of the function's steepness. Therefore, by following the training technique for a particular input pattern, the outputs that are acceptable will be generated to align with the desired response of each neuron d_k. Subsequently, the weights will be adjusted in order to minimize the mistake and propagate the next pattern. The output layer weights *V* will be calculated using the weight adjustment formula described in equation (4), while the hidden layer weights *W* will be computed using equation (5). The term "o_{pk}" represents the desired output of a neuron, while "o_{pk}" represents the actual output of neuron-k for a certain input pattern-p. The weights will undergo continual modification in this technique until the sum of squared errors is minimized using equation (6)(Roodschild et al., 2020):

(3)

$$f(\,net\,) = \frac{1}{1 + e^{-\lambda\, net}}$$

(4)

$$V_{kj}(t+1) = v_{kj}(t) + c\lambda(d_k - o_k)\, o_k(1 - o_k)\, y_i(t)$$

(5)

$$W_{ji}(t+1) = W_{ji}(t) + c\lambda^2\, y_j(1 - y_j) x_i\,(t)\Big(\sum_{k=1}^{k}(\,d_k - o_k)\, o_k(1 - o_k)\, V_{kj}\Big)$$

(6)

$$SSE = \frac{1}{2P}\sum_{p=1}^{p}\sum_{k=1}^{k} \quad (d_{pk} - o_{pk})^2$$

We employed multilayer perceptrons with a "feed-forward back-propagation" algorithm. In this approach, the influential predictors identified through PLS path analysis were utilized as input neurons. Additionally, a sigmoid function was implemented to activate both the output and hidden layers. Table 3 displayed the Root Mean Square Error (RMSE) values obtained using tenfold cross-validation.

The sensitivity study revealed that 80% of the variability in macro, meso and micro influencing factors to improve students' academic motivation can be anticipated by the input neurons. The sensitivity analysis, as shown in Table 4, determined the normalized significance (NI) of all input neurons. This was done by dividing the mean importance by the maximum importance and expressing it as a percentage.

Table 3: RMSE Values

Input Neurons: FM, LP, TS, PR, CP, PN							
Output Nodes: MT							
Neural Network	**Training**			**Testing**			
	N	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**Total**
1	296	60.112	.408	40	9.132	.513	336
2	301	73.438	.490	35	6.878	.402	336

3	290	67.839	.469	46	15.584	.512	336
4	308	68.268	.445	28	3.231	.426	336
5	299	65.639	.441	37	9.140	.343	336
6	294	74.161	.506	42	5.742	.283	336
7	308	66.803	.435	28	5.915	.325	336
8	293	63.468	.435	43	8.698	.331	336
9	298	81.202	.547	38	7.790	.495	336
10	302	67.457	.448	34	8.618	.627	336
Mean		68.839	0.462		8.073	0.426	
SD		6.009	0.041		3.239	0.109	

Note: FM: Faculty Management, LP: Learning Platform, OF: Objective Factors, PR: Peer Relation, MT: Motivation Theory, SF: Subjective Factors, TS: Teacher Support

The predictive accuracy of the ANN model was measured using the Root Mean Square of Error (RMSE). As indicated, the RMSE Mean-values for training and testing were 0.462 and 0.426, respectively. The small and similar RMSE mean values showed that ANN method for the model could recommend high prediction accuracy. The results also indicated that the derived models were highly reliable in capturing the relationships between the significant predictors and the output variables (Almeida et al., 2023). The artificial neural network (ANN) model exhibited strong prediction accuracy, as seen by the root mean square error (RMSE) mean values of 0.462 for training and 0.426 for testing. These results suggest that the model has little overfitting and possesses robust generalization capabilities (Almeida et al., 2023).

Table 4: Sensitivity Analysis with Normalized Importance

	Relative Importance					
Neural Network	**SF**	**OF**	**FM**	**LP**	**TS**	**PR**
1	.190	.229	.167	.042	.155	.217
2	.246	.183	.128	.087	.173	.183
3	.214	.175	.160	.127	.155	.169
4	.190	.213	.203	.094	.143	.157
5	.202	.217	.187	.071	.070	.253
6	.180	.155	.174	.101	.157	.233
7	.202	.188	.280	.069	.107	.154
8	.222	.203	.104	.113	.218	.140
9	.200	.171	.176	.058	.063	.332
10	.282	.109	.231	.145	.151	.082
Mean relative importance	.311	.146	.067	.128	.103	.245
Normalized importance (%)	100.0%	47.1%	21.5%	41.0%	33.2%	78.6%

Note: FM: Faculty Management, LP: Learning Platform, OF: Objective Factors, PR: Peer Relation, SF: Subjective Factors, TS: Teacher Support

In addition, the sensitivity analysis was computed by utilizing the mean relevance of all predictors in determining a significant outcome variable. The normalized relative relevance of each predictor in the model was calculated by dividing the relative importance of each predictor by the predictor with the highest importance (Zhang & Tchetgen Tchetgen, 2022). The above Table 4 illustrated the average and normalized importance of each predictor. Sensitivity analysis was engaged to assess the contribution of each variable in the enhancement of motivation (Zhang & Tchetgen Tchetgen, 2022). Normalized importance was calculated according to the percentage depending on the relative importance fraction of each input neuron section to examine the greatest relative importance for the performance model (Zhang & Tchetgen Tchetgen, 2022). The results revealed that SF was relatively the most significant predictor of students' academic motivation followed by PR, OF, LP, TS and FM.

Discussion

Using a dual-stage PLS-SEM and ANN model, this study examined Traditional Chinese Medicine majors' motivation. This study also examined macro, meso, and micro factors through the lenses of autonomous learning theory, motivation theory, and Carroll Model of School Learning to determine if they positively affected students' academic motivation. This was highlighted by researching Chinese vocational college students specializing in Traditional Chinese Medicine and their responses to learning English with a platform. Macro (faculty management and learning platform), meso (teacher support and peer interactions), micro (subjective and objective elements), and academic motivation (psychological need and career potential) were correlated in the study. Additionally, the academic motivation model was created. The important variables identified by the Smart PLS analysis were utilized to enhance the neural network analysis. Artificial Neural Networks (ANNs) have demonstrated considerable potential in estimating parameters for different statistical and mechanistic models, providing notable enhancements in computational efficiency and accuracy compared to conventional approaches (Almeida et al., 2023). The parameter estimates calculated by ANN demonstrated that the hidden neuron of H(1:1) for the students' motivation model was the most contributing factor. A goodness-of-fit index was captured in the following equation to determine the ANN model predictions: $\boldsymbol{R^2 = 1 - \frac{RMSE}{S_y^2}}$ where ($\boldsymbol{S_y^2}$) was the variance of the preferred output according to the average (SSE) in the testing process. The results showed 99.3% of students' academic motivation model was predicted by the ANN model. Similarly, Lau et al. (2019) demonstrated the efficacy of neural network models in predicting students' performance, attaining a prediction accuracy of 84.8% by utilizing a model with 11 input variables and two layers of hidden neurons, which was trained using the Levenberg–Marquardt algorithm. The input part consisted of six distinct and significant parameters derived from the SEM. In contrast, the output section consisted of a single output variable, specifically the adoption of Carroll Model of School Learning, as shown in Figure 3.

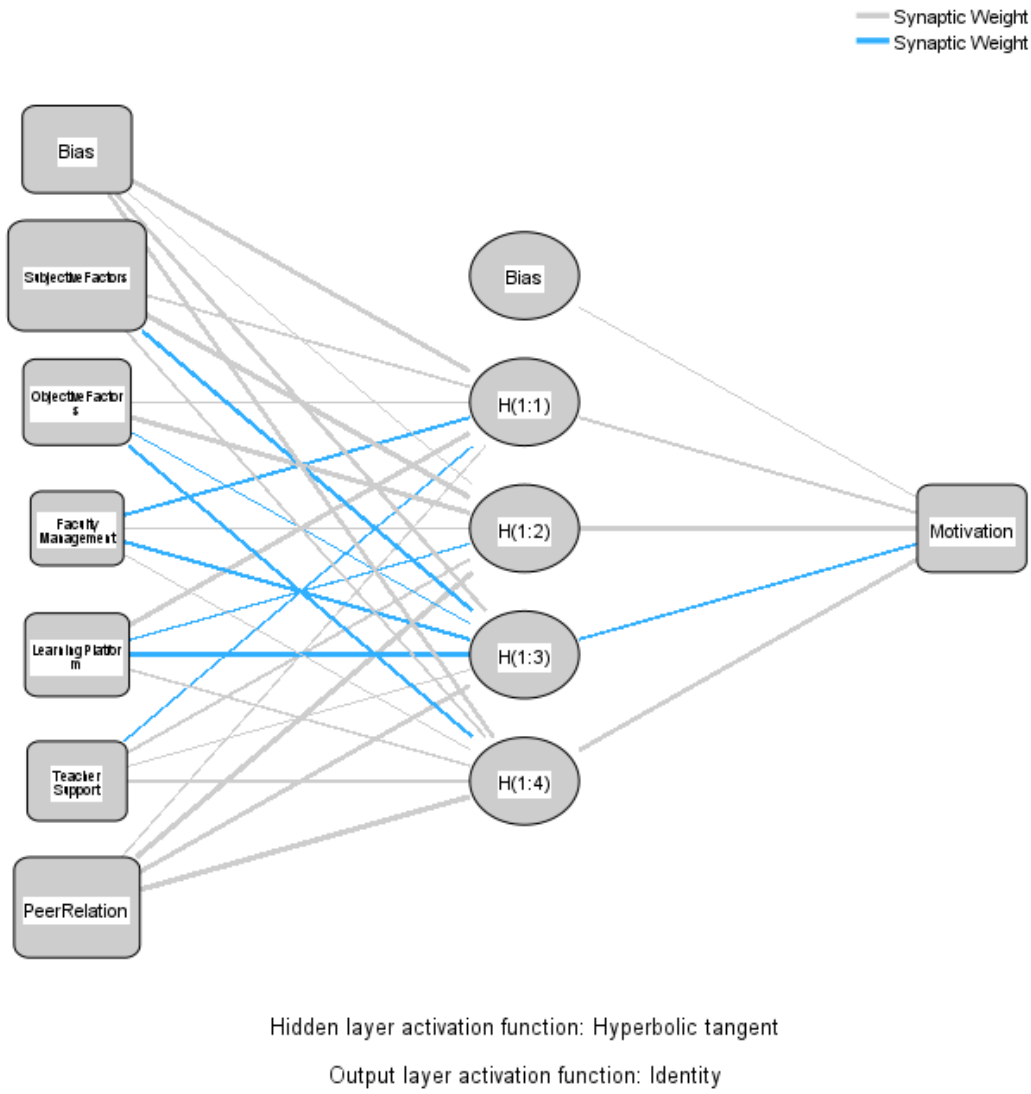

Fig. 3 Total Contribution of Hidden Layer

Theoretical Implications

Most research evaluate intrinsic, extrinsic, subjective, or objective aspects. Seth Sunu and David Baidoo-Anu found that pupils with a favorable academic self-concept are more intrinsically driven and perform better. Individuals are driven by intrinsic rewards and satisfaction. Oğuzhan Çelik's study (Çelik, 2024) found that parental autonomy support and psychological requirements significantly impact intrinsic and extrinsic drive. The study stresses that parental autonomy support increases psychological needs satisfaction and motivation. Objective factors like educational institutions' physical and social environments affect motivation. To fully understand and improve academic motivation, Thu Tran Thi Le and Son Nguyen Duc recommend incorporating many theories and considering autonomy, cultural, economic, and political contexts (Saeedi et al., 2021). However, this study investigated factors at the macro, meso, and micro levels and developed a novel academic motivation model by incorporating the Carroll Model of School Learning, autonomous learning theory, and motivation theory.

SmartPLS has been utilized to study academic motivation and its linear relationships in most studies. SmartPLS works well with complex models and little samples (Khilda & Usman, 2020). Khilda Iqmaulia and Osly Usman used SmartPLS to study how needs, rewards, interests, and learning contexts affect learning motivation. Their findings support the idea that these factors promote academic motivation (Khilda & Usman, 2020). Shahbaz Sharif and colleagues used SmartPLS to study academic supports' effects on MTL and TOT. The study found that organizational, supervisor, and peer support affect TOT. They also found that MTL and MTT mediated this connection (Sharif et al., 2023).

These research showed that SmartPLS was essential for understanding academic motivation's linear correlations and affecting elements across educational environments. The study employed a combination of two-phase Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) techniques, as well as both linear and nonlinear analysis, to investigate the correlation between the Carroll Model of School Learning, autonomous learning theory, and academic motivation theory.

Practical Implications

This study utilized the dual stages PLS-SEM and ANN model to examine the implications for practitioners (faculty and teachers) in the field of educational psychology. The aim was to enhance the understanding and development of students' academic motivation. Fostered students' capacity for independent learning, promoted the natural and meaningful use of language, and established an optimal environment for language acquisition. This study examined the impact of educational interventions on college students' self-directed learning from a psychological teaching viewpoint. It aimed to identify effective teaching approaches and faculty management that could enhance college students' self-directed learning and academic motivation. As shown in a vocational college setting, psychological therapies and personalized education management dramatically lower student depression, which can tangentially improve the learning environment and promote self-directed learning (Çelik, 2024). Furthermore, students can overcome burnout and mood problems with the support of educational psychology therapies that emphasize moral development, emotional stability, and self-responsibility (Ying, 2023). This will create a more favorable learning environment.

This study integrated contemporary learning theory with the practical implementation of college English classroom instruction and proposed the implementation strategy of academic motivation model in college English teaching reform. The achievement goal orientation theory proposes that modifying teaching objectives, implementing positive evaluations, developing effective teaching methods, and supplementing teaching content can improve students' motivation and English proficiency, especially for those with limited language skills (Dong, 2023). This strategy held significant practical guidance for faculty and teaching staff in meeting the new management requirements. This resource was anticipated to offer significant assistance to college English instructors in the process of reforming basic education courses. Additionally, it offered valuable insights that might be applied to the teaching of other disciplines at the college level.

Research Limitation and Future Direction

Even though every hypothesis was accepted, there were certain constraints in this study that made it difficult to move further with this paper. Firstly, because during the process of collection data, the researcher were pursuing study in Malaysia which made it difficult to collect the data from the intended sample. Secondly, only data gathered from Shandong vocational education was used to analyze the model. Therefore, a number of barriers, including fund investment, infrastructure construction, and psychological adaption, hindered the growth of students' academic motivation in China and limited its adoption. The findings of this study should assist providers in focusing their efforts on aspects like faculty management, teacher support, learning platform construction and peer relation to improve students' academic motivation in China.

The following are some additional study directions that this work suggests. Firstly, we have suggested and evaluated a non-linear artificial neural network strategy for students' academic motivation in English learning. The research found all the positive macro, meso and micro influencing factors to improve students' academic motivation.

Future studies could look at other negative, mediating and moderating influencing factors. Second, there may be a positive or negative correlation between students' autonomous learning attitudes, Carroll Model of School Learning and the academic motivation. Furthermore, future research should conduct a study that took into account the individual's original family background and the level of parental support. This study employed Carroll Model of School learning, autonomous learning theory and motivation theory to establish the academic motivation model. Ultimately, the future study will explore the academic motivation

adopting social cognitive theory, constructivism theory and complexity theory.

Conclusion

Correlate macro, meso, and micro factors with student academic motivation. The proposed SEM-ANN approach can help designers map the influence of Carroll Model of School Learning and autonomous Learning on students' academic motivation. It also helps understand academic motivation elements and their relationships. SEM's causal analysis and ANN's nonlinearity help the SEM-ANN model overcome their constraints. The essay's main contributions:

(1) This study used a SEM-ANN model to determine and map the effects of faculty management, learning platform, teacher support, autonomous learning, and academic motivation on student involvement in learning. The effect path design and path coefficient revision phases of this methodology examine students' academic motivation.

(2) The improved route coefficients are calculated using the BP algorithm following the standard SEM to handle nonlinearity in variable interactions. SEM-ANN successfully uses SEM's causal analysis and ANN's nonlinear properties, so mitigating their limitations to a certain degree.

(3) The SEM model determines the topological configuration of the Artificial Neural Network (ANN). Structural Equation Modeling (SEM) can be used to build a predictive neural network model. A fully linked Artificial Neural Network (ANN) has unknown neuron importance in the hidden layers. Furthermore, the process of constructing a neural network model from data is frequently challenging.

We used the case study to demonstrate how SEM and ANN may better describe nonlinear relationships between variables. We also demonstrate that structural equation modeling (SEM) can create a neural network model with better predictive power than a fully linked network. As the measurement model and structural model get increasingly complicated, psychological construct interactions may be nonlinear. The suggested two-phased SEM-ANN method may efficiently reveal these relationships. This strategy can be employed in other domains, including product design, psychology, physiology, and education, in addition to its usage in the enhancement of students' academic motivation study.

The datasets generated by the survey research during and/or analyzed during the current study are available in the Shandong College of Traditional Chinese Medicine repository at https://jiaowuchu.sdctcm.edu.cn

The studies involving human participants were reviewed and approved by Shandong College of Traditional Chinese Medicine of ethics committee. Written informed consent to participate in this study was provided by the participants.

Conflict of Interest

The authors declare that there exists no competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Contributions of the Authors:

Shaoshuai Liang: Conceptualized the study and developed the research framework. Designed the data analysis approach using Structural Equation Modeling (SEM) and Artificial Neural Network techniques. Drafted the manuscript and contributed to the interpretation of the findings.

Qian Peng[+]: Conducted data collection and pre-processed the data. Assisted with the structural equation modeling analysis. Contributed to the formulation of the methodology section and the discussion of results.

Ting Wang: Conducted the literature review, providing the background and theoretical framework. Contributed to the design of the conceptual model. Assisted in drafting and reviewing the manuscript.

Yiwen Zhang: Analyzed the Artificial Neural Network aspect, particularly using SmartPLS and ANN methods. Contributed to the interpretation of the results related to identifying influential factors of academic motivation of students majoring in traditional Chinese medicine. Assisted in revising the manuscript.

Mingyu Yu and Jie Chen: Provided insight into the academic motivation of students majoring in traditional Chinese medicine. Assisted in the data collection process, particularly with expert

evaluations. Contributed to the manuscript's revision and the final proofreading.

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