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Problem-Based Learning Application Research in Logistics Simulation Software Course Teaching

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Abstract: Intelligent logistics is the current trend of industry development, and for the cultivation of logistics talents in universities, courses related to the Internet of Things need to be added. Therefore, the research on the application of problem-based learning (PBL) in the teaching of logistics practical simulation software courses is a topic worth exploring. This study utilizes commonly used software in logistics courses to implement problem-based learning teaching method in the classroom for students. Observing students' learning situation and obtaining feedback on problem-based learning teaching method is of substantial help to students' learning.

1. Introduction

The rapid development of the Internet has provided a good environment for the development of enterprise e-commerce. With the fierce commercial competition in the online market, enterprises urgently need logistics professionals. In order to meet the development needs of online marketing talents in society, various vocational schools have started to set up relevant majors and courses. Online teaching is a course that combines theory and practice for the education of logistics courses. The teaching and training objectives of the course can provide simulation and simulation learning opportunities for the cultivation of students' knowledge, skills, and abilities.

2. Literature Review

2.1 Intelligent logistics

In the management and practice of modern logistics facilities and equipment, intelligent information software and hardware are indispensable [1]. The application of Programmable Logic Controller (PLC) in automated logistics equipment can be said to be indispensable. The application of intelligent robots is a key element in forming intelligent logistics [2].Therefore, understanding the development trend of PLC technology and its application in the logistics equipment industry is of great significance for the intelligent improvement of logistics equipment, as well as for the operation and development of enterprises[3,4]

2.2 Problem based learning (PBL)

Problem based learning (PBL) is an educational method that takes students as the main body. The core of PBL learning is the teaching centered concept of identifying the knowledge points of the course through joint participation and discussion among student groups. In traditional education, most students adopt a teaching style learning mode, which makes it difficult to stimulate their creativity and potential. PBL will transform students from passive learners to active learners. Traditional teaching methods mainly focus on teachers' teaching of theoretical knowledge, ignoring students' subjective initiative. The entire classroom teaching is teacher centered, and students only passively accept knowledge. The learning activities of students in the classroom result in less participation and low interactivity, and there are very few practical activities that can be operated with their hands. Students have low interest in learning. Through problem-based learning and PBL learning methods, combined with network simulation teaching, the teaching knowledge points are specifically applied in PBL teaching for experimental verification. The teaching process includes main steps such as teaching preparation, problem setting, group discussion, presentation, summary and evaluation [5].

2.3 FlexSim

FlexSim software is an object-oriented simulation software similar to a Windows interface. It can be used in many industries, such as manufacturing, material handling, and office workflow planning. After explaining the usage functions in the classroom, the software can use the highly similar 3D virtual reality environment to create scenarios set in the practical classroom. Flexsim can provide operations, processes, and dynamic system simulation solutions for operators and decision-makers. Flexsim can conduct experimental testing, system evaluation, and visual simulation modeling. The software has the ability to integrate C++object oriented functionality. Super powerful 3D virtual reality or 3D animation. The biggest advantage of software for users is its intuitive and easy to understand user interface, with diverse simulation scenarios.[6].

2.4 Anylogic

AnyLogic is a programming and visualization simulation software and the first tool to introduce UML language into the field of model simulation. AnyLogic can effectively perform data calculations, systematic language exercises, and simulation modeling. For system dynamics, multi-agent systems, hybrid system modeling, and process simulation design can generate interactive reactions in the correlation design between processes and visual images. The software application fields include logistics, supply chain, manufacturing industry, pedestrian traffic simulation, pedestrian evacuation, urban planning and architectural design, urban development ecological environment, business processes, service systems, emergency management, GIS navigation information, port and airport construction, etc.[7]

3. Research method

This article adopts experimental research methods using logistics equipment simulation software, and selects students from Huai'an University as experimental subjects to set up experimental courses to observe students' reactions and preferences during learning. After the teaching experiment, questionnaire surveys, interviews, and self-assessment were conducted on the experimental class students to understand their attitudes towards PBL teaching. This experiment uses software such as FlexSim and Anylogic to combine textbook theory for practical course teaching. This questionnaire adopts the Likert 5-point scale, with a minimum score of 1 and a maximum score of 5.

3.1. Analysis of students' learning reactions

After statistical analysis, the survey after PBL teaching practice class found that: Question 1: The acceptance rate of students' response to the effectiveness of using PBL teaching is 88%. Question 2: The satisfaction rate of students with this classroom teaching under the PBL teaching method is 79.6%. Question 3: The proportion of students who feel a sense of achievement in learning under this PBL teaching method is 85.1%. Question 4: 84.2% of students are able to adapt to the PBL teaching method for this course. Question 5: Through this period of learning, 87% of students believe that PBL is helpful in understanding and applying the knowledge of this course. Question 6: Compared to traditional teaching methods, 86% of students hope to use PBL teaching methods in this course in their future studies. Question 7: During the learning process, 86.1% of students believe that creating problem situations is helpful for their learning. Question 8: Compared with traditional teaching methods, 89.8% of students believe that the PBL teaching method in this course has learning effectiveness.Question 9: In the process of analyzing the problem, 86.1% of students believe that group cooperation, discussion, and communication are helpful for their learning. Question 10: 87.1% of students benefit from the presentation and summary of their achievements after solving the problem. Question 11: What major gains do students feel have been brought by PBL teaching method.(1) 40% of students believe that their abilities in knowledge acquisition, information processing, and utilization have improved.(2) 40% of students have an awareness of active learning and have improved their ability to learn independently. The reliability analysis of the questionnaire showed that cronbach's Alpha was 0.81, and the effective sample size was 108, with an average of 4.19 or above, and a standard deviation between 0.678 and 0.754 in Table1.

Table 1: Average and standard deviation

Questions	average	standard deviation
Question 1	4.333	0.669
Question 2	4.194	0.754
Question 3	4.333	0.723
Question 4	4.314	0.731
Question 5	4.268	0.678
Question 6	4.324	0.708
Question 7	4.361	0.662
Question 8	4.333	0.710
Question 9	4.324	0.694

3.2 Correlation Analysis of PBL Teaching Curriculum Indicators

We will encode the teaching course indicators, including a) acceptance, b) satisfaction, c) adaptability, d) understanding and application, e) continued adoption, f) creation of problem scenarios, g) learning effectiveness, h) collaborative discussion and exchange, i) presentation and summary of results. After Pearson correlation comparative analysis, it was found that acceptance, satisfaction, adaptability, understanding and application, continued use, creating problem scenarios, learning effectiveness, collaborative discussion and communication, and achievement display and summary all have a correlation of more than 0.5. Especially in terms of acceptance, satisfaction, adaptability, understanding and application, continued use, and creating problem situations, the correlation between these six indicators is greater than 0.7 or above. The PBL method has shown significant effectiveness in experimental teaching, with high student acceptance and good learning outcomes. The detailed data is explained in Table 2.

Table 2: Pearson correlation analysis

	a	b	c	d	e	f	g	h	i
a	1	0.814**	0.791**	0.755**	0.798**	0.736**	0.674**	0.629**	0.589**
b	0.814**	1	0.770**	0.701**	0.739**	0.668*	0.700**	0.558**	0.518**
c	0.791**	0.770**	1	0.753**	0.730**	0.699**	0.702**	0.600**	0.601**
d	0.791**	0.770**	1	0.753**	0.730**	0.699**	0.702**	0.600**	0.601**
e	0.789**	0.737**	0.730**	0.789**	1	0.751**	0.677**	0.647**	0.666**
f	0.736**	0.668**	0.699**	0.757**	0.751*	1	0.645**	0.749**	0.715**
g	0.674**	0.700**	0.702**	0.689**	0.677**	0.665**	1	0.755**	0.678**
h	0.629**	0.558**	0.600**	0.659**	0.647**	0.749**	0.755**	1	0.764**
i	0.589**	0.538**	0.601**	0.661**	0.666**	0.715**	0.678**	0.764**	1

Note: The significance of the correlation in the above table reaches p<0.01, represented by * *

3.3 Construction of Structural Equation Model

The construction of the structural equation model is shown in Table 3, which shows the factor load coefficient table of the model, including potential variables, analysis items, non-standard load coefficients, z-test results, etc. Generally speaking, the measured variables are represented by p-values through significance testing, and the (P<0.05) table shows high significance. In the table, the p-value is represented by *. The p-values of question2 and question3 in Factor1 are significantly higher. The p-values of question5 and question6 in Factor2 are significantly higher. The p-values of question8 and question9 in Factor3 are significantly higher.

Table 3: Construction of Structural Equation Model

factors	variable	Non-standard load factor	Standardized load factor	z	S.E	P
Factor1	Question1	1	0.921	-	-	-
	Question2	1.067	0.873	13.958	0.076	0.000***
	Question3	1.024	0.874	13.983	0.073	0.000***
Factor2	Question4	1	0.886	-	-	-
	Question5	0.927	0.886	13.373	0.069	0.000***
	Question6	0.943	0.864	12.653	0.075	0.000***
Factor3	Question7	1	0.853	-	-	-
	Question8	1.11	0.882	11.699	0.095	0.000***
	Question9	1.031	0.837	10.787	0.096	0.000***

3.4 Path coefficient

The regression coefficients of path nodes can be understood as the least squares method of univariate linear regression. Usually, it is only necessary to observe the P-value and standardized path coefficient to determine whether the path (X ->Y) has a direct linear impact. According to the significance test analysis (P<0.05), whether there is an impact relationship between model variables. If there is significance, it indicates an influence relationship between variables. Standardized path coefficients can be used for in-depth analysis. Based on pairing factor 1->factor 2, the significance P-value is 0.000 * * *, which is significant at the level of significance. Therefore, this path is effective with an impact coefficient of 0.934. Based on pairing factor 2->factor 3, the significance P-value is 0.000 * * *, and this path is effective at the significance level with an impact coefficient of 0.889. This indicates that factor 1 (willingness to learn) has an impact on factor 2 (acquisition of learning skills), while factor 2 (acquisition of learning skills) also has an impact on factor 3 (team collaboration), as shown in Table 4.

Table 4: Path coefficient analysis

Factor (latent variable)	Analysis item (explicit variable)	Non standardized coefficient	Standardized Coefficient	Standard error	z	p
Factor1	Factor2	0.982	0.934	0.079	12.487	0.000***
Factor2	Factor3	0.774	0.889	0.077	10.113	0.000***

Note: * * *, * *, * represent significance levels of 1%, 5%, and 10%, respectively

3.5 Model fitting indicators

In structural equation analysis, chi square and degrees of freedom are mainly used to compare the differences between multiple models. The smaller the chi square value of the model data, the better. The simpler the model, the more degrees of freedom it has. On the contrary, the more complex the model, the lower its degree of freedom. GFI (goodness of fit index): Mainly used to test the model's fit to sample observations using judgment coefficients and regression standard deviations. The value range of GFI is from 0 to 1, and the closer it is to 0, the worse the fit. The GFI value of this study is 0.955. CFI ≥ 0.9 indicates that the model in this study fits well. RMSEA (root mean square of approximation error): Typically, RMSEA is below 0.08 (smaller is better). The RMSEA value in this study is 0.081. RMR (Root Mean Square Residual): This indicator measures the degree of fit of the model by measuring the average residual between predicted and observed correlations. If the RMR is less than 0.1, it is considered that the model fits well. The RMR value of this study is 0.017. CFI (Comparison Fit Index): When comparing hypothetical models and independent models, the value of this index is between 0 and 1. The closer CFI is to 0, the worse the fit, and the closer it is to 1, the better the fit. Usually, if the CFI is ≥ 0.9, it is considered that the model fits well. The CFI value of this study is 0.981. The larger the values of NNFI and CFI, the better, and the better the fitting model performs. In this study, the NNFI (non standard fitting coefficient) value is 0.972. The CFI (Comparative Fit Index) value of this study is 0.981. All data is shown in Table 5.

Table 5: Model fitting indicators

χ^2	df	P	Chi square ratio	GFI	RMSEA	RMR	CFI	NFI	NNFI
-	-	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
42.705	25.000	0.015**	1.708	0.955	0.081	0.017	0.981	0.955	0.972

4. Conclusion

The results of correlation analysis and structural equation analysis. Discovering that PBL teaching can motivate students to actively learn in experimental teaching activities. From this study, it was found that students' learning attitudes affect their willingness to learn. Especially since logistics courses have entered the era of intelligence, university logistics courses should be adjusted according to the times and current situation. Only by combining theory with practice can students effectively learn and learn how to apply it. This has practical assistance in training logistics professionals. This viewpoint has also been confirmed in the field investigation and validation work of this study. With the support of theory, combined with on-site operations and practice, students can increase their interest in learning and actively participate in classroom activities, thus applying what they have learned.

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References

[1] Zou, X. (2023) Intelligent logistics facilities and equipment. Electronic Industry Press.

[2] Yang, Y. T. (2023) Make logistics equipment more intelligent and personalized. Small and medium-sized enterprises in China.

[3] Xi, C. B. (2022) Application and Development of PLC in the Intelligent Development of Logistics Equipment. Logistics Technology and Applications.

[4] Wang, X. L. (2022) Application and Development Trends of Intelligent Logistics Equipment. Logistics Equipment

[5] Barbara, J. D. (2008) Problem-based learning in physics: Making connections with the real world. AIP Conference Proceedings. 399(1): 557-565

[6] Yu, S. Z. and Chen, J. (2018) FlexSim simulation modeling and analysis. Northeast University Press.

[7] Guo, X. P., Yang, X. Wang, Y. Y. (2020) Anylogic Modeling and Simulation. Central South University Press.