RESEARCH ARTICLE

Badminton Skills Learning Model For China Colleges

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ABSTRACT

This research entitled badminton learning model uses research and development steps from Borg and Gall which consist of 10 steps of the Borg & Gall development research model was taken into consideration. The total number of respondents was 250 colleague student. The research subjects in the badminton learning model were 2nd semester students who chose the Badminton course, with details of 25 students in the small group trial, 75 students in the large group trial. In the effectiveness test, there were 75 students as the experimental group and 75 junior high school students as the control group. The following is an explanation of the research subject Based on the table above in the Equal variances assumed section, it is known that t-count = 8.656, df = 148, and p-value Sig. (2-tailed) = 0.000 < 0.05, so Ho is rejected and Ha is accepted, which means there is a difference in the average test results of the control group and the experimental group.

INTRODUCTION

One of the theoretical and practical courses that must be taken by undergraduate students of physical education study programmes is badminton (Perić et al., 2022). Badminton theory and practice courses are courses that are required to be followed because, this sport is one of the proud sports of the Chinese people which is very popular among the public (McGrath et al., 2019).

In badminton courses, the main competencies that must be achieved by students are knowledge, skills and affective competencies (Van den Berghe et al., 2020). Badminton game skills that must be mastered by students are the basic techniques of playing badminton (Rannaud Monany et al., 2022). Basic techniques in badminton include footwork, grip, lob, drive, service, and smash (Walton et al., 2021). Students have entered the motor development of the specialised movement phase (specialist), where this phase is very dependent on the previous phases, especially the development of the maturity of fundamental basic movement skills (Robertson et al., 2019). During the specialist phase, motion becomes a tool applied to a variety of complex movement activities for daily living, recreation, and sporting activities (Patrizia et al., 2019). It is a foundational period of increasingly refined stability, locomotor and manipulative skills, combined and developed for use in increasingly demanding situations (Bonavolontà et al., 2020). Despite having entered the specialisation phase, generally the basic movement skills of students are very diverse, therefore an effective badminton learning model is one that is developed at several levels of movement difficulty, both in type and intensity (Klostermann, 2019).

The learning process of badminton courses is carried out on the badminton court, so that learning time can be optimised for learning motion (Van Hooren et al., 2020). However, to be able to optimise the constructive cognitive and affective domains, the lecturer must have the right strategy (Walker et al., 2021). It will also provide efficiency in learning basic badminton techniques, because before going to the actual practice, students already have prior knowledge and visualisation of the movements to be

learned (Wójcik & Piekarczyk, 2020). Thus, it will be easier to perform the movements in question (Seidel-Marzi & Ragert, 2020). One of the efforts that can be made is to develop a varied, tiered badminton course learning model that is also equipped with interesting learning resources (von Schleinitz et al., 2021).

The three demands on students' cognitive capacity during learning are extraneous processing, essential processing and generative processing (Moran et al., 2021). The three instructional goals are to reduce irrelevant processing, manage essential processing, and encourage generative processing (Lindsay et al., 2023). Instructional messages of technology-based learning resources should be designed to guide appropriate cognitive processing during learning without overloading the learner's cognitive system (Bergauer et al., 2022). If in previous studies, badminton learning in tertiary institutions used more training approaches and printed textbooks, then in this study researchers developed a more varied learning model that was tiered and equipped with a model guidebook (Simpson et al., 2020). In addition to the form of learning using additional materials in the form of mulltimedia, the design of learning model items is also designed in stages and varied, so that each student can do it better and there are many choices (Crumbley et al., 2020).

2. METHODOLOGY

2.1. Characteristics of The Model Developed

The research targets will be students who take courses in badminton theory and practice. The model developed will later be adapted to the characteristics of learning in higher education and the product developed will be packaged in a guidebook for basic badminton technique learning models equipped with multimedia containing various variations of basic badminton technique learning patterns.

a. Target

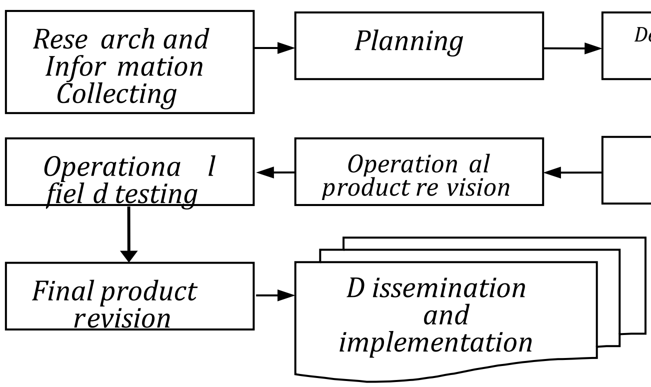
The main target of this research is students who choose Badminton courses. It is hoped that the characteristics of the training model developed can be used as a guide and reference for lecturers in carrying out learning innovations so that the learning process runs effectively, efficiently, and is interesting and enjoyable.

b. Research Subjects

The research subjects in the badminton learning model were 2nd semester students who chose the Badminton course, with details of 25 students in the small group trial, 75 students in the large group trial. In the effectiveness test, there were 75 students as the experimental group and 75 junior high school students as the control group. The following is an explanation of the research subject

2.2. Instrument development

The model creation steps that researchers use refer to the Borg & Gall model. Here are the steps in Borg & Gall:



Picture 1
Model Borg & Gall and Gal, Meredith D 4th Edition (New York; Logman Inc, 2003)

2.3. Characteristic Learning Model

In this research, the characteristics of the model created are rock climbing learning models for students. This means making various forms of rock climbing learning activities. This learning model will be compiled and made as well as possible so that later it will produce a product that can be a guide and guide for lecturers, students and rock climbing clubs.

The characteristics of the learning model created can increase the motivation of lecturers, students and stakeholders in undergoing the learning process.

1. Effectiveness, meaning that the rock climbing learning model can facilitate students and lecturers in providing rock climbing learning.

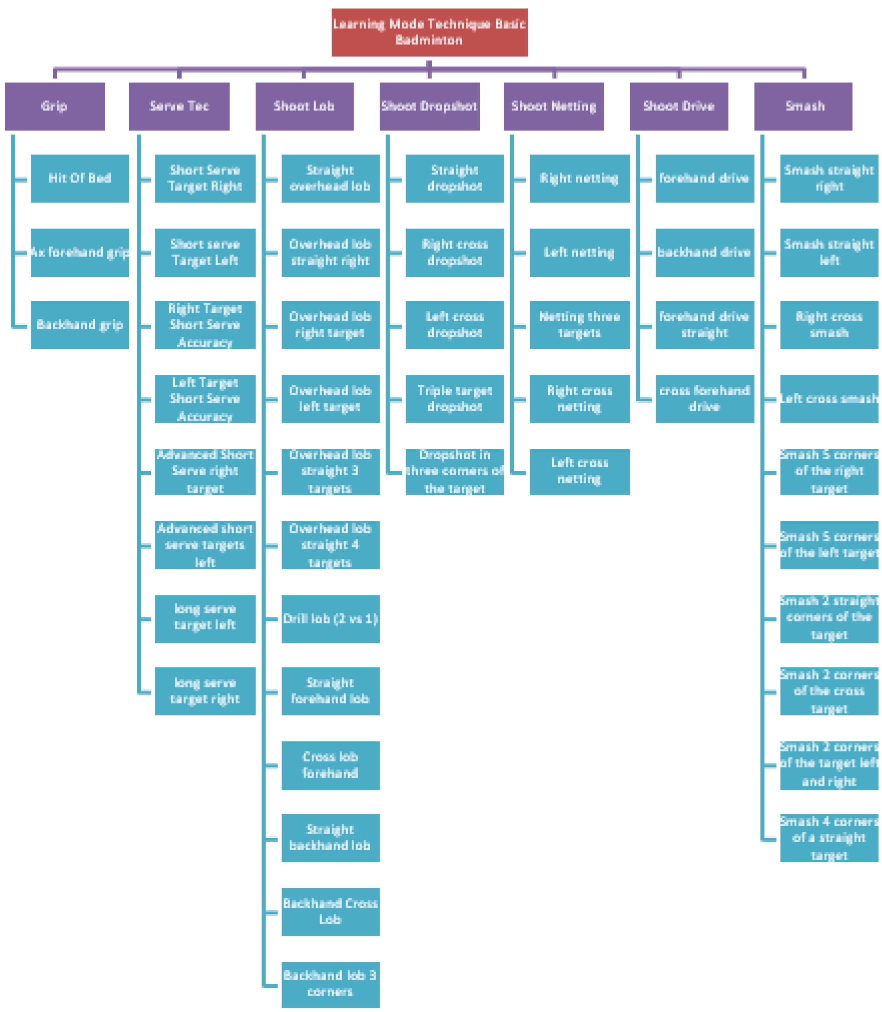
2. Efficient, meaning that the learning process is very efficient because in addition to improving students' rock climbing skills, it also enriches insights in the formation of movements and techniques.

3. Variative, meaning that this rock climbing learning model has variations of learning that can make learning not boring.

4. Attractiveness, meaning that the rock climbing learning model can motivate lecturers and students in carrying out the learning process.

5. Target clients or target users in the research of making rock climbing learning models for students are students of physical education study programmes in China.

2.4. Badminthon Model Learning Design



Picture 2.
Badminthon Model Design

3. Data analysis and result

3.1. Data Analysis

The data in this research was obtained by experiencing, doing, asking, and observing. Data can be primary data and secondary data. Secondary data was obtained through analysis of various types of documents. Data sources are based on data collection techniques, including those obtained from respondents, the circumstances of certain things or events, the environment or place of research, photos and relevant documents.

The data obtained is in the form of quantitative and qualitative data. Quantitative data is used to analyze needs, product feasibility, and product effectiveness. Meanwhile, qualitative data is suggestions for improvements from experts for product improvement, as well as field notes during product trials. The instruments used in this research were questionnaires for needs analysis, expert evaluation questionnaires and model test questionnaires for students. The needs identification instrument in this research was prepared with the aim of obtaining data on lecturers' opinions regarding the models they have used or are currently using, and what kind of models they want. The small and large group trial instruments were prepared based on the evaluation concept of students who had carried out the model. Meanwhile, the test instrument to determine basic badminton technical skills uses the Badminton Assessment Plan: E 350 Assessment instrument developed by (Maguder, 2018). This shows that descriptive data shows that there are differences in the average badminton skill test results in the control group and the experimental group. Next, to determine whether the data is normally distributed, a data normality test will be carried out on the control and experimental groups as follows:

Descriptive Data of control and experimental groups

	Class	N	Mean	Std. Deviation	Std. Error Mean
Skore	Control	75	.2804	.07755	.00896
	Exsperiment	75	.3941	.08490	.00980

Tests of Normality

	Class	Kolmogorov-Smirnova			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Skor	kontrol	.150	75	.056	.744	75	.000
	eksperimen	.101	75	.065	.976	75	.161

Lilliefors Significance Correction

The results of the Kolmogorov-Smirnov normality test show a significance figure of more than 0.05. Thus, it can be concluded that the data from the control group and experimental group are normally distributed. Next, a homogeneity test will be carried out to determine whether a variant of the diversity of data from two groups is homogeneous (same) or heterogeneous (not the same). Homogeneous data is one of the requirements in the independent sample t-test. In this study, the homogeneous test was used to determine whether the posttest data for the control group and posttest data in the experimental group were homogeneous or not.

3.2. Result

Based on the implementation of all development steps that have been carried out by researchers, with the support of data and analysis of the data obtained, it can be concluded that:

1. This development research has produced development products in the form of learning tools for badminton theory and practice courses for universities, as well as a book on basic badminton technique variations consisting of 47 variations

2. The development product, in the form of a learning model for basic badminton technical skills, has been proven to be effective in improving the results of students' basic badminton technical skills which are better than the control group using learning media.

4. DISCUSSION

Recommendations related to the results of this research are as follows;

1. The results of this development research provide additional media that has multiple functions in badminton learning in particular.
2. The application of the results of this development research for lecturers has made the learning process easier and smoother, for students it has made the learning process easier and faster, especially mastering basic techniques. So that multi-directional learning interactions can be realized and support the achievement of learning objectives.
3. The results of this development research make it easier for students to learn because students can study anytime, anywhere without depending on the presence of the lecturer in face-to-face sessions in class.
4. The results of this research development have contributed to scientific thinking whose truth can be justified. So it is very possible for scientists and other researchers to develop badminton learning to make it more specific, interesting and useful.

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