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Development of Adaptive MOOCs to Support Personalized Learning: Mixed Method Analysis

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ABSTRACT

This study aims to explain the development of adaptive MOOCs that support personalized learning. This study was designed with a mixed method design of sequential explanatory type at the association level. Quantitative analysis used confirmatory factor analysis (CFA) (n = 110) and was deepened with qualitative analysis of the Miles and Huberman model. Quantitatively measured domains include accessibility, learning curriculum, competence, motivation, satisfaction, efficacy, and self-study. The domain was used as a reference for qualitative data mining through focus group discussions (FGD) involving lecturers and doctoral students (n = 25). The analysis results show that the curriculum domain and one of the motivational indicators should be removed because it did not meet the requirements after bootstrapping. The second running algorithm showed all valid and reliable variables. Some domains that significantly affect MOOC user satisfaction are efficacy, competence, and motivation. R square results showed 37% influenced by motivation, accessibility, efficacy, and self-study, and the rest influenced by other variables. In the qualitative analysis, 19 subcodes were found that were included in the three main codes. In conclusion, there is new information in the accessibility domain that expands quantitative data, including information on MOOCs, marketing traps, regulation, and dropouts. Meanwhile, what strengthens and deepens quantitative data is found in the information on metacognitive and personalized coding that strengthens the domain of efficiency, the domain of competence, which is strengthened by content, mentoring collaboration, and motivation reinforced by coding the user's motivations and goals.

Keywords*:* adaptive, metacognitive, mixed method, MOOC, personalized

INTRODUCTION

Technology is evolving so quickly and broadly in the field of education. Today, Anyone has access to data and information on the internet. As of January 2022, there were 4.95 billion internet users worldwide [1]. Even Indonesia was once ranked as having the sixth-highest global internet usage rate [2]. This demonstrates how the internet's promise for education in Indonesia can address the country's limited educational access and educational inequality. MOOCs as a substitute for internet-based learning that offers convenience, accessibility, and a variety of course topics. Even UNESCO underlined that in order to answer the rhetoric of "education for all" [3], [4].

The MOOC was first introduced by Dave Cormier, who is the Manager of Web Communication and Innovations at the University of Prince Edward Island, and his friend Bryan Alexander who is a senior researcher at the National Institute for Technology in Liberal Education, in an open course organized by George Siemens (Associate Director, Technology Enhanced Knowledge Research Institute at Athabasca University) and Stephen Downes (Senior Researcher at The National Research Council, Canada). At that time, they created a course entitled "*Connectivism and Connective Knowledge"* which was attended by 25 Extended Education students at the University of Manitoba plus 2300 students from the general public who took the course online and free of charge [5]. The

inherent characteristics of MOOCs are openness, participatory, and distributive [6].

The use of MOOCs in Indonesia is growing quite rapidly. Based on the survey results [7] out of 1023 respondents (56.11%) had heard the term MOOC/Online Learning Class, but most of them. (78.30%) have never tried it. Among those who have participated in MOOCs, the lion's share (57.5%) have ever followed foreign language learning. Many respondents welcomed the idea of alternative learning materials that have not been provided in various MOOCs, such as taxation for the self-employed and freelance workers (51.90%) and the study of traditional Indonesian arts (48.39%). Even at the University level, an academic environment filled with practitioners, only a few have organized MOOCs.

Predictable MOOC user satisfaction is influenced by system quality, user attitudes, and course quality [8]–[10]. In addition to satisfaction, the success of a MOOC is also influenced by Self Regulated Learning [8]–[12]. Some studies noted that student learning independence was one of its main controls was metacognitive [8]. However, how a MOOC can achieve these two things is still being researched. In this study, we saw the need for a MOOC that is adaptive to user conditions.

Previous research that has a relation with this research is Radford's research with a mixed method that quantitatively shows that workers who use MOOCs can be a representation of workers who are always motivated and learn to develop themselves quite large, but after a more in-depth study qualitatively shows that employers will still consider the quality of MOOCs that their workers follow if they want to be assessed as one of the parts Work Performance [14].

METHODS

This study used a mixed method design of sequential explanatory type. Merging on the sequential explanatory method is at the associative level [15]. Collecting data by purposive on MOOC users at Yogyakarta State University consisting of 110 lecturers and students. Data were analyzed using confirmatory factor analysis (CFA) using smartPLS 3. Furthermore, in-depth interviews were conducted in a Forum Group Discussion (FGD) with 25 lecturers and doctoral students who often take part in MOOCs from various platforms and have expertise in online learning. Our FGD qualitative data were analyzed using MAXQDA 2020. Analysis result using qualitative analysis of the Miles and Huberman model, which can be seen in the following figure 1:

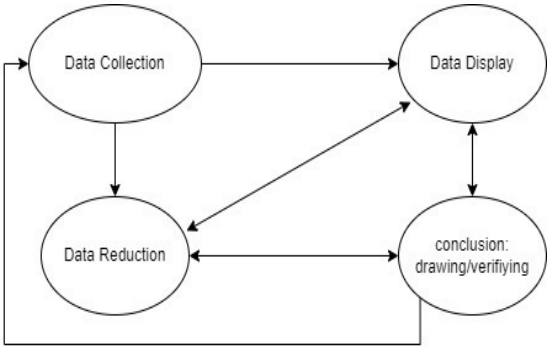

Figure 1. Miles and Huberman's qualitative analysis flow

Quantitative data were obtained by giving questionnaires to respondents online using google form with the following question structure:

Table 1. MOOC Domain and Indicators

Domain	MOOC Indicators	Item
Accessibility	• Information and interface sets are fully delivered, and nothing to hide (*perceivable*) • Interface components and menus (navigation) can be operated by the user (*operable*) • The information content and operation of the interface are understandable to the user (*understandable*) • Content that is reliable (valid) so that it can be interpreted by various users (*robust*)	11,12, 13,14

Domain	MOOC Indicators	Item
Learning curriculum	• MOOCs provide materials from various institutions and professionals • MOOCs support independent learning curriculum	15,16
Competence	• Users can know the objectives of the competence to be achieved before starting the material in the course • Information/material submitted in accordance with the objectives • The evaluation provided is appropriate to test the achievement of learning objectives • Users feel a good understanding of the courses followed	17,18, 19, 20
Motivation	• There is a mover from within the user to take the course (new knowledge) • There is encouragement from outside the user to take the course (certificate) • Giving direction to learning activities	21, 22, 23
Satisfaction	• The feedback instructor is quick and helpful • The media used is excellent and diverse • Explanations from instructors are well understood	24, 25, 26
Efficacy	• Trying to solve the problems and difficulties of the course being followed • Users are confident in the benefits and usability of the course when successfully completing it • Users have completed online learning with great hard work and persistence	27, 28, 29
Self-study	• Users can set the time to study • Choosing the material you want to know and the instructor • Users can monitor their own learning outcomes	30,31, 32

RESULT AND DISCUSSION

Based on the CFA test, the diagram can be found as follows:

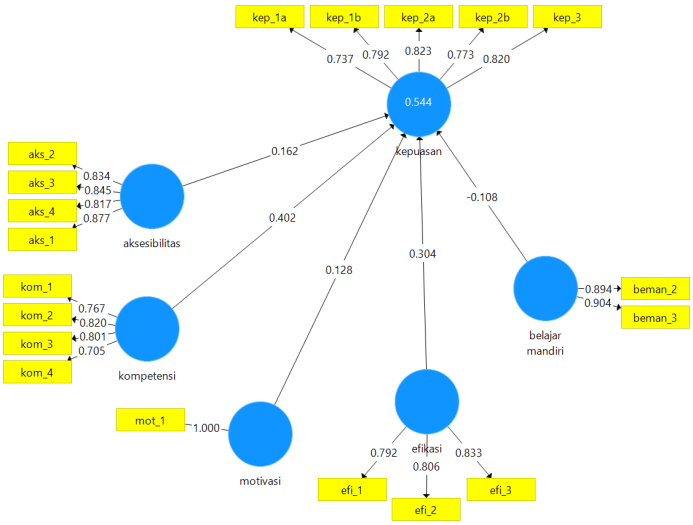

Figure 2. CFA Diagram

Table 2. Reliability and validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
accessibility	0.6006	0.6305	0.4937
independent learning	0.5298	0.6208	0.5611
efficacy	0.5131	0.5909	0.4562
satisfaction	0.5902	0.6194	0.4333
competency	0.5395	0.5951	0.4166
motivation	1.000	1.000	1.000

A. Confirmatory Factor Analysis

The following test results are the test results after bootstrapping on subsample 1000 with a significance level of 0.5 (one-tailed) so that the results of the inner model evaluation are obtained.

Table 3. T Statistic

	T Statistics (|O/STDEV|)	P Values
accesibility → satisfaction	1.628	0.052
Self-learning → satisfaction	1.123	0.090972
efficacy→ satisfaction	3.168	0.001
competence → satisfaction	3.832	0.000
motivation → satisfaction	1.820	0.034

Based on table 3, it appears that the value of t-loading for accessibility and self-study is still below 1.96, so only efficacy, competence, and motivation have a significant effect on user satisfaction. The findings of this self-study are similar to other studies that show that self-regulated cannot improve MOOC performance [16].

Table 4. R Square

	R Square	R Square Adjusted
Satisfaction	0.377778	0.3625

Based on table 4 shows that the R square value is 0.377778, which means that the influence of motivation, accessibility, efficacy, and self-study on satisfaction is 37%, and other variables influence the rest.

Table 5. Model fit

	Saturated Model	Estimated Model
SRMR	0.080	0.080
d_ULS	1.212	1.212
d_G	0.38125	0.38125
Chi-Square	340.491	340.491
NFI	0.4875	0.4875
rms Theta	0.129167	

Based on table 5, the model gives a theta value = 0.129; since the value is close to zero, it is called fit.

B. Qualitative Analysis

To strengthen the results of the CFA analysis, an in-depth analysis was carried out, which was initiated by reducing data from the results of the FGD interview. Data reduction is carried out by looking for coding on the interview results during the FGD. Furthermore, the coding results are visualized in a word cloud (Figure 3) and conceptual framework. Qualitative analysis shows some interesting new findings for more in-depth study. We processed the FGD qualitative data using MAXQDA 2020. The results of the discussion resulted in coding in the form of:

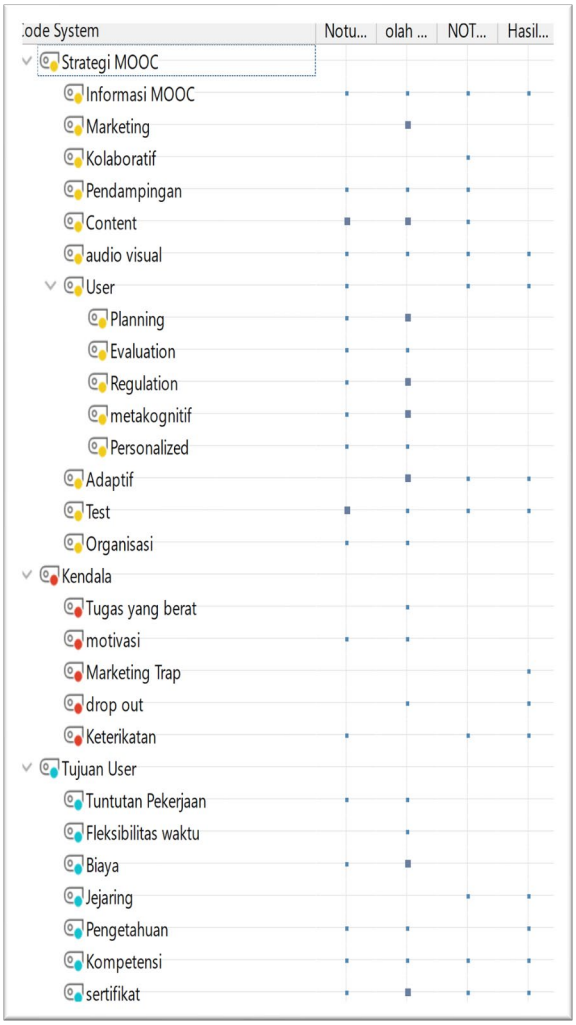

Figure 3. *Coding from FGD*

Table 6. Segments with Code

	Frequency	Percentage
Content	23	13.86
Test	18	10.84
Regulation	13	7.83
Planning	11	6.63
Adaptif	11	6.63
Pendampingan	11	6.63
Audio Visual	10	6.02
User	9	5.42
Evaluation	8	4.82
metakognitif	8	4.82
Informasi MOOC	7	4.22
Marketing	7	4.22
Organisasi	6	3.61
Personalized	5	3.01
drop out	5	3.01
Marketing Trap	4	2.41
motivasi	3	1.81
Keterikatan	3	1.81
Kolaboratif	2	1.20
Tugas yang berat	2	1.20
Strategi MOOC	0	0.00
Kendala	0	0.00
Tujuan User	0	0.00
TOTAL	166	100.00

The results of the FGD with prospective users confirm that Adaptive MOOCs can answer market needs regarding implementing relevant MOOCs. This is reflected in several *strong relation words* regarding the items needed to create a MOOC. In the strategy aspect, content, audio-visual, and mentoring appear. These aspects are items that will be *treated* to produce adaptive MOOCs. Through metacognition, the content will be adjusted to the user's cognition level [17]. Through the same method, users will get different treatments based on identifying the level of knowledge from the initial *screening* process. Consequently, adaptive MOOCs will provide a variety of content and learning models to suit user-level needs. This includes content variations and tests such as audio-visual optimization. This is what makes the discussion about the content in the interview delivered very much by informants. Therefore, the need for a good MOOC strategy has been well facilitated in the MOOC adaptive plan.

In addition, in terms of constraints and objectives, adaptive MOOCs can respond to these needs. The problem of an overwhelming task is a major concern for adaptive MOOCs. The problem occurs because it needs to be in sync between the user's knowledge level and the content so that the user feels a task is too heavy. Meanwhile, in Manage adaptive MOOC, the process of identifying users via metacognition will be carried out to avoid the irrelevance of that level. In the end, users will get content and treatment according to their level of understanding. This will avoid the user's perspective on "too heavy a task". As for the objectives, Adaptive MOOC provides a diverse course experience according to needs [18], [19]. Users can choose whether they want to get knowledge only or along with a certificate. This option is provided with its own consequences; If it is enough to get knowledge without a certificate, you can follow it more cheaply or for free, but if you want a certificate, there needs to be a cost incurred. Adaptive MOOC prioritizes the appropriate choice for the user [20].

If we visualize it in a word cloud, it will appear in Figure 4 and Figure 5.

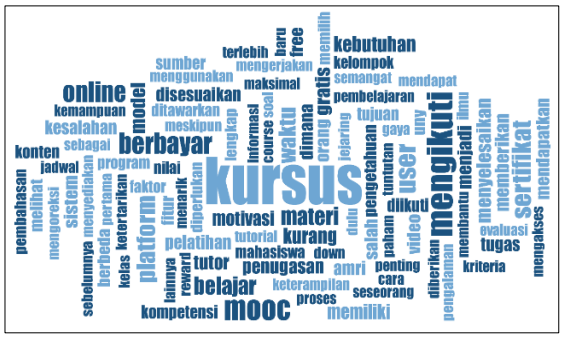

Figure 4. Words cloud from FGD

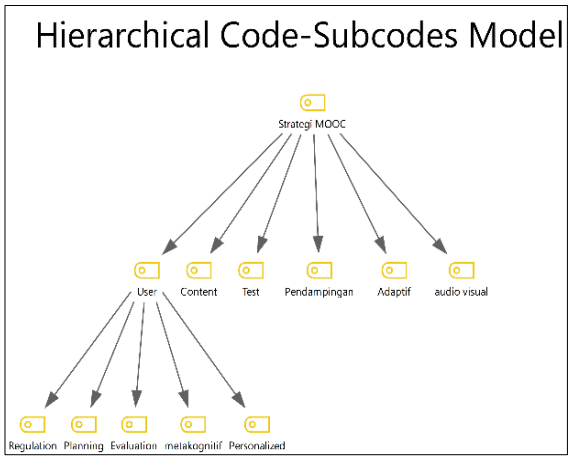

Figure 5. MOOC Model

Learning content in MOOCs has at least several forms that can be used (based on table 6), including:

1. Learning Video

Learning videos are explanations of material from the infrastructure to users consisting of sound and visuals. The visual presentation technique can be PowerPoint slides, direct explanations from the instructor with a half-body camera, and documentary video.

The video presented must certainly be packaged as well as possible. Sufficient lighting, keyword assignment, and some animations make it easier for users to understand.

Table 7. Content Video Standard

Representation Mode	Standard
Picture	Resolution 16:9 minimum 20148 x 1152 pixels, the format can be in jpeg, png, bmp, or gif
Video	High Definition video is at least 720p; the image does not shake, and additional elements are sharp. 60% of courses are in video format
Sound quality	Clear, not noisy, avoid "ooo", "eh". Maximum music back sound -20db
Delivery by instructor	Neat and convincing appearance and full of confidence
Duration of lectures	6 – 20 minutes
Lesson structure	Structured according to the level of matter, we can use Bloom's taxonomy.
Reinforcement of learning	Strategies for providing quizzes, exercises, and tests
Promo video	Courses should include promo videos, be concise, concise, represent and reflect the course.
Format	Composition, shot size, screencast, slides, drawing board.
Support	16:9 video format attempted to be opened on a mobile device

2. Interactive Media

Interactive media is a medium capable of demanding user engagement on the material. It can build an attachment between a given material and user interaction and includes advanced instructor feedback.

3. Video Conference

Video conferences are the leading choice compared to the video recording material. This is because users can interact with the instructor, for example, with the rise hand feature. However, of course, there are disadvantages to using this feature, such as flexibility of learning schedules and interface interaction with video, such as playback.

4. Assignments

An assignment is a form of evaluation used to maintain a user's attachment to the course he is taking. This assignment is not positioned as a final test to see graduation but as a form of practice within the course.

5. Discussion and consultation room

The discussion room is one of the course's mandatory components. This feature gives users space to discuss with instructors and discussions between users.

Recognizing the personal user can include knowing the learning style of the prospective user, the initial understanding of the user, or also looking at the metacognition of the future user. This is very influential in the establishment of independence to learn from users. An online learning culture is (1) planning, (2) evaluation, (3) regulation, (4) metacognition, and (5) personalized learning.

Psychologically testing participants' readiness before entering the course will maximize the system's learning process. Developers can create courses that suit the user's learning style. In addition to learning styles, measuring the metacognitive of the user by looking at metacognitive knowledge and self-regulation, followed by the preparation of courses following the user's metacognitive

profile, will support differentiated learning. This will certainly be philosophically good for users. Because, after all, users have different characteristics [21], [22]. Consequently, developers in adaptive learning must put much effort into presenting different course models in each theme [23].

Every learner can see the achievement of learning objectives through written tests and product tests (outcomes). Developers are required to ensure the suitability of the test to the learning objectives. In learning at MOOC, users generally take exams to get a certificate. Although sometimes users skip the material and only take test sessions. So in making a test, it is necessary to consider the granting of a Certificate based on the user's time spent in the course and the lowest score limit to get a certificate [22], [24], [25].

C. Quantitative and qualitative analysis of relationships between variables

This analysis is carried out by interrelating quantitative and qualitative confirmatory factor analysis data contained in table 3 and qualitative data based on the influence of table 6 variables.

Table 8 shows that the new variables affecting MOOC user satisfaction are information on the MOOC platform and a marketing trap in promoting MOOCs. From a user perspective, self-regulation is needed, and dropout desires can affect MOOC user satisfaction. Several things show that metacognition, motivation, content, mentoring, and personalized are variables that strengthen and deeply affect the satisfaction of MOOC users.

CONCLUSION

In developing an adaptive MOOC, of course, paying attention to user needs is necessary. The results of the quantitative analysis show that the efficacy, motivation, and competence of both user and instructor competencies in online courses greatly influence user satisfaction. Although in quantitative analysis, accessibility does not have a significant effect, and qualitative analysis shows that one of the important things in a MOOC is clear information about the courses provided, such as the competency information offered, course fees, and course facilities.

Table 8. Interrelating between variables

	T-Stat.	Qualitative code	Explanation
Accessibility → satisfaction	1.628	Information MOOC Marketing trap	Expand quant. data
Self-learning → satisfaction	1.123	Regulation Drop out	Expand quant. data
efficacy → satisfaction	3.168	Metacognition Personalized	Deepening and strengthening
competence → satisfaction	3.832	Content Mentoring collaborative	Deepening and strengthening
motivation → satisfaction	1.820	Motivation User objectives	Deepening and strengthening

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