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Evaluation of a UPOU MOOC using Biggs' 3P Model: Process Variable Result

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Abstract: Since 2012, the University of the Philippines Open University (UPOU), following its mission of providing greater access to quality education and Republic Act 10650 (Open Distance Learning Law), has been offering Massive Open Online Courses, or MOOCs (Almodiel et al., 2020). However, evaluation of MOOCs must be done to ensure that learners are receiving quality education. This study follows the MOOC Quality Guidelines' framework using Biggs' (1993) 3P Model by the Commonwealth of Learning (2016). For this research, the August 2022 MOOC "Artificial Intelligence for Quality Assurance in Education" was assessed for quality assurance. It was evaluated in terms of selected metrics from the Biggs' 3P Model, with this paper presenting the results of evaluating the **learning process** as a process variable. The process variable in this study refers to discussion forum posts made by the learner after every module. Only the posts made by learners who had given their consent for the study were analyzed using the Linguistic Inquiry and Word Count (LIWC) in three dimensions: analytic, clout, and dictionary words. With a total of 70 participants—42 male and 28 female—results showed a high percentage of engagement and quality of the posts from its analytics (66%-76%) and dictionary words (81%-87%), with average frequency (42%-55%) under the clout dimension. Evaluation of the MOOC will help provide best practices in offering MOOCS, thereby contributing to society as an open university in providing quality education for all. Results on the presage and product variables will be discussed in separate papers.

Keywords: MOOC Evaluation, Biggs' 3P Model, Sentiment Analysis, Quality Assurance, LIWC

INTRODUCTION

Background of the Study

Massive Open Online Courses, or MOOCs, are online platforms characterized by its fundamental characteristic of being open: enrollment is free to anyone who has access to the internet, and learning pace is dictated by the user; participatory: learners may interact with their fellow learners and instructor and participate in the various learning activities prepared; and distributed: knowledge sharing is encouraged to foster creative thinking in its participants—all leading to courses being offered around the world with no limit as to who may register and enroll in a course (Baturay, 2015). In a nutshell, MOOCs can be called "complete courses consisting of educational content, assessments, peer-to-peer tutoring, and/or some limited tutoring by academics" (Jansen et al., 2017).

The University of the Philippines Open University (UPOU) is one such institution that offers MOOCs in its own Moodle-based platform called MODeL, short for Massive and Open Distance e-Learning. Having pioneered the offering of MOOCs in the Philippines from the year 2012, UPOU has since then continued to offer online courses on various topics depending on its targeted stakeholders and relevance to the current situation, as per the university's mission of providing wider access to quality education and in support of the Republic Act 10650 - Open Distance Learning Law (Almodiel et al., 2020).

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While UPOU strives to ensure that the MOOCs offered are still answering to the quality education of UPOU's mission, there are still issues that its MOOCs face today. Among those identified were low course completion rates, lack of student support, reliable assessment methods, and plagiarism and cheating (Librero, 2020.) These prevailing issues are the reason why MOOCs must undergo quality assurance and be evaluated to ensure that learners are still receiving quality education.

In this research, Biggs' 3P Model of Student Learning (1993) will be used within the context of MOOCs. This model developed by John Biggs assumes that learning outcomes are influenced by several factors within that learning environment affecting each other (Barattucci, 2017). The 3P Model considers three groups of variables: presage variables, which are the *resources and factors* of the learning environment; process variables, meaning the *processes and actions* related to the presage variables; and product variables, relating to the *outcomes* of the learning process (Commonwealth of Learning, 2016). Under the MOOCs context of this research, the *presage variables* will focus on the *learners*, the *process variables* on the *learning process*, and the *product variables* on *enjoyment and self-satisfaction* and *completion/retention and certification rates*. This paper focuses on presenting the evaluation of the *process variable* on the *learning process.*

REVIEW OF LITERATURE

The 3P Model developed by John Biggs has greatly influenced the teaching and learning assessment systems being used today (Barattucci, 2017). According to an analysis done by Kember et al. (2020), the 3P Model was developed emphasizing the students' approaches to learning (SAL) paradigm. The model, as mentioned previously, assumes that learning outcomes are determined by several factors interacting with one another and therefore requires not only effectiveness and good quality but also compatibility of the components (Barattucci, 2017).

The model is utilized in studies as a framework due to its integrative nature that ensures all factors contribute to a student's learning process so that a greater understanding of how their identified factors influence each other can be reached (Kanashiro et al., 2020; Song, 2018; Allison, 2021). It has been used in the context of MOOCs, K-12 computing education, examining psychological pathways, and even simply to synthesize papers of healthcare professionals (Song, 2018; Allison, 2021; Ganotice & Chan, 2019; Crowther et al., 2020).

While studies acknowledge that the 3P Model can be criticized as outdated, oversimplified, and certainly not the only model that can be used to understand educational context, it also appears to be the "most prominent learning model in higher education" (Kanashiro et al., 2020; Allison, 2021).

On Evaluating Learning Processes: Sentiment Analysis on Discussion Forums

One of the main forms of student engagement in MOOCs is discussion forums. Discussion forums are important due to their capacity to provide asynchronous communication throughout the entirety of the course, which not only encourages interaction but also helps students build a learning community among themselves (Wong et al., 2015).

Active participation in the discussion forums provides peer interaction and enhances the learning process they undergo, which in turn leads to better grades and higher completion rates (Tseng, 2016). This is further supported by a study done by Andres et al. (2018) that utilized the MOOC Replication Framework (MORF) to compare research questions in MOOCs from multiple MOOC data sets, which revealed that among the data analyzed, those who are more active in the discussion forum, such as posting and replying frequently, are more likely to complete the course.

To further understand the engagement happening in discussion forums, sentiment analysis is important to predict student attrition and understand the learners' thoughts of the course. Sentiment analysis is an approach that uses natural language processing (NLP), text analysis, and computational techniques to classify sentiment from reviews or any type of text (Hussein, 2018).

While there is no clear approach to sentiment analysis within the context of MOOCs, Moreno-Marcos et al. (2018) suggest that the first step towards sentiment analysis in MOOCs is identifying if forum messages are positive or negative. Their study used SentiWordNet for the sentiment analysis and Leave-One-Out cross validation for the evaluation of the results, which was focused on determining whether the learners' sentiments are positive or negative and its trends for the duration of the course. Results showed that positive messages peaked at the start of the course, which gradually decreased, and negative messages took over near the end of the deadline for the final project.

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Their study had taken inspiration from the one conducted by Chaplot et al. (2015) using a lexicon-based approach using SentiWordNet 3.0 as the knowledge resource, which has been designed for sentiment analysis and opinion mining applications. Their study focused on identifying students that may drop out based on their sentiment score, assisted by the neural network used to predict the student attrition.

Other studies utilized different sentiment analysis approaches, such as Wen et al. (2014), which used collective sentiment analysis to explore the relation between opinions expressed by learners and their dropout rate, then utilized survival analysis to examine how the learners' sentiment predicted their continued participation in the discussion forum.

In 2020, Lundqvist utilized VADER (Valence Aware Dictionary for Sentiment Reasoning), which produced four sentiment scores: positivity, negativity, neutrality, and a compound score, the latter of which was used in the study. Later, the score was calculated using Algorithmia.com, and the results of the study revealed that there is a connection between the sentiment in direct feedback and posts, as well as that non-target participants can create contradictory results in the analysis.

Moore (2019) used the Linguistic Inquiry Word Count (LIWC) tool for analyzing, which uses dictionaries to categorize and quantify language used in text and calculate the percentage of words within defined categories. The results of their study revealed that there were more engagement and substantive posts in self-paced MOOC forums.

Using the Linguistic Inquiry Word Count as a Sentiment Analysis Software

The Linguistic Inquiry Word Count, or LIWC, as previously mentioned, is software for analyzing word use. LIWC primarily determines how often people use various word categories from a variety of text, referred to as "target words," and produces numerical frequency values of the content differentiated by various categories such as cognitive processes and emotion words (Pennebaker et al., 2015). Some of the content that has used LIWC is from blogs, emails, conversations, novels, and even social media such as Facebook, Twitter, and Yelp reviews (LIWC, 2022).

The LIWC-22 version used for this study has four summary measures: analytical thinking, clout, authenticity, and emotional tone. For this paper, the focus is placed on analytical thinking and clout, with the addition of the dictionary word dimension, similar to what Moore (2019) had done. As this study used the discussion forum posts made by learners, these three dimensions were picked to best analyze the texts based on the percentage of engagement and quality of the target words.

Analytical thinking, or analytic, is a dimension focused on the "degree to which people use words that suggest formal, logical, and hierarchical thinking patterns" (LIWC, 2022). A high percentage under the analytic dimension suggests high reasoning skills used by the learner and more substantive quality of posts.

The clout dimension refers to the "confidence or leadership that people display through their writing and talking" (LIWC, 2022). It also denotes the level of confidence and certainty, which would mean that a high percentage of clout should lead to positive cognitive processing.

Lastly, the dimension of dictionary words indicates the number of notable words used per text. Moore (2019) found that this dimension is positively associated with cognitive processing, which reflects a level of language complexity. Therefore, the higher the number of dictionary words used, the higher the engagement and quality of the posts being analyzed.

THEORETICAL FRAMEWORK

Biggs' 3P Model consists of three groups of variables: presage variables, process variables, and product variables. As seen in Figure 1 below, these variables are interconnected with each other, as all factors contribute to a student's learning process.

In this research, as visualized in Figure 2 below, the presage variables are identified to be the learners, the process variables will focus on the learning process, and enjoyment and self-satisfaction.

The focus of this paper is the process variable, meaning the discussion forum posts made by the learners. These posts are created after every module, answering the question posed by the MOOC coordinator that serves as a learning summary at the end of the module. The questions raised aim to foster creative thinking and engage discussion among the students regarding what they have learned for each module.

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Figure 1

Biggs' 3P Model of Student Learning

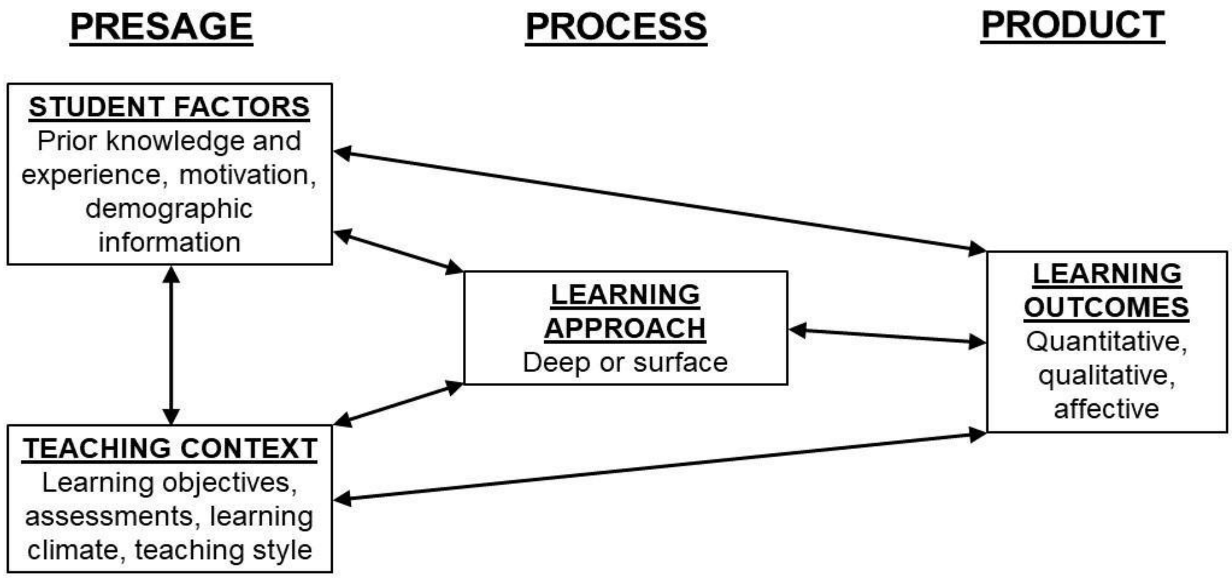
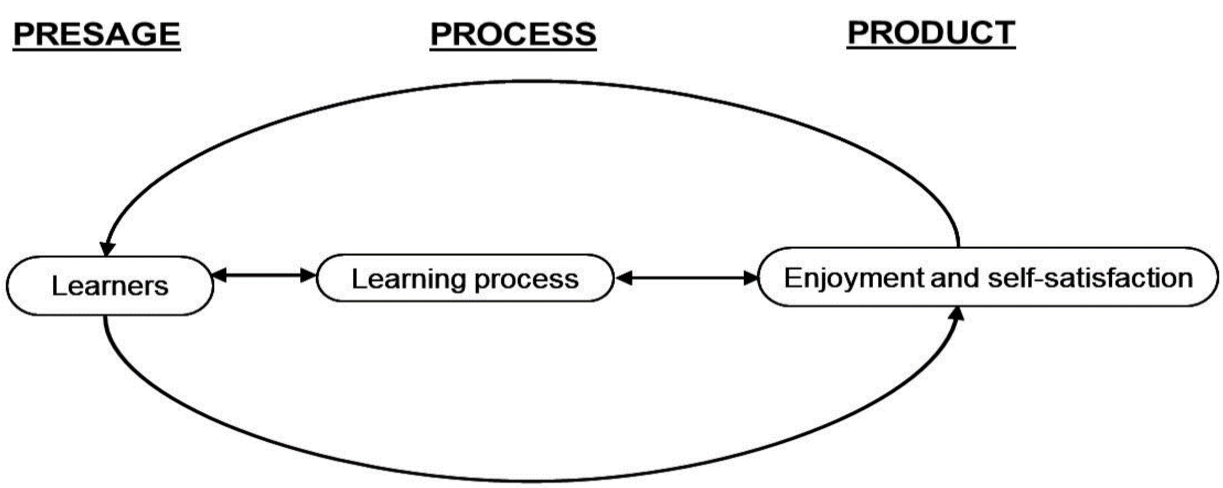


Figure 2

Adapted Framework of Biggs' 3P Model



Statement of the Problem

There is a need to regularly evaluate MOOCs offered by any institution for quality assurance and for continuous improvement. Moreover, established instruments are not regularly used for evaluation. This research attempts to fill in these gaps by using selected metrics from the Biggs' 3P Model to provide an instrument that can be used for regular MOOC evaluation. Through regular MOOC evaluation, quality assurance of MOOCs can be better ensured.

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Objectives of the Study

This paper aims to evaluate the Artificial Intelligence for Quality Assurance in Education MOOC discussion forum posts using the Linguistic Inquiry and Word Count analysis software.

Specifically, it aims to:

1. Analyze the discussion forum posts based on the gender of the learners;
2. Evaluate the discussion forum posts based on the dictionary words dimension;
3. Evaluate the discussion forum posts based on the analytic dimension;
4. Evaluate the discussion forum posts based on the clout dimension; and
5. Assess the correlation among the three dimensions.

RESEARCH DESIGN & METHODS

For this research, the Artificial Intelligence for Quality Assurance in Education MOOC was assessed for quality assurance. It was evaluated in terms of selected metrics from the Biggs' 3P Model, specifically the learner-centric ones, in order to provide more focus for the research. It took one metric from each of the 3Ps. Specifically, it took the variable concerning **learners** for *presage dimensions,* **learning process** for *process variables,* and **enjoyment and self-satisfaction** for the *product variables*. These metrics have readily available instruments to use for evaluation.

For the process variable (learning process), sentiment analysis was used on the discussion forums. The goal of sentiment analysis for this research was to analyze if there were more engagement and substantive posts in the MOOC being evaluated (Moore, 2019) in order to further quantify the learners' learning processes. These discussion forums were available after every topic to generate dialogue among the learners. Descriptive statistics were used throughout the analysis.

The evaluation of the Artificial Intelligence for Quality Assurance in Education MOOC can provide insight on how MOOCs can be further improved based on variables like learners, learning processes, and enjoyment and self-satisfaction of the learners. This study's results would be able to provide recommendations for future MOOC offerings in UPOU and other institutions. This study addresses SDG 4, Quality Education, and falls under the UPOU flagship program QAlidad.

This study involved voluntary participants from the Artificial Intelligence for Quality Assurance in Education MOOC August 2022 class. As of 31 August 2022, 70 out of 205 enrolled students participated in the study. It should be noted that out of the 205 enrolled students, there were 50 students who did not complete any of the 33 Moodle activities and are considered to have dropped out of the course. Thus, 70 out of 155 active students resulted in 45.16% study participation.

The study focused on the discussion forum posts made by the learners, not including the replies they created on other posts. Some students were more inclined to simply reply to their fellow students instead of posting, which were not included for the sentiment analysis.

RESULTS AND DISCUSSION

The Artificial Intelligence for Quality Assurance in Education MOOC was composed of five modules, meaning five discussion forum, or DF posts were made by the learners. The questions answered by the learners per module are:

DF 1: What are the other applications of AI that you can think of?
DF 2: Can you identify the subprocesses that can be automated, even if it is by different AI systems?
DF 3: How can you exhibit fairness in the machine learning process for QA in Education?
DF 4: Can you give one example of an unethical AI? How can you address the ethical concerns surrounding it and turn it into an ethical AI system?
DF 5: What future AI projects used in QA for education can you propose to your institution?

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LIWC Results – Gender

Of the 155 learners, a total of 70 students gave permission for the study to analyze their discussion forum posts. Forty-two (60%) of the participants were male, while the remaining 28 (40%) were female. From the three dimensions, it was found that males had a higher (74.63%) mean percentage under the analytic dimension. Meanwhile, females have a higher percentage under both the clout (47.67%) and dictionary words (85.13%) dimensions.

Table 1

Gender statistics of the analytic, clout, and dictionary words dimension

GENDER	Analytic	Clout	Dictionary Words
Male	74.63	46.66	84.78
Female	67.38	47.67	85.13

These results would mean that males had more substantive quality of posts by using logical and analytical thinking patterns, while the females were more intuitive in their thinking patterns when creating their posts. On the other hand, females were more confident and certain in their posts, as well as having used more complex words, leading to more engaging and quality posts.

LIWC Results – Analytic

As discussed previously, the males mostly dominated the discussion forum posts under the analytic dimension. The females had a higher percentage under discussion forum 5 through a narrow margin, as seen in the table below.

Table 2

Mean percentage of discussion forums under the analytic dimension

GENDER	DF 1	DF 2	DF 3	DF 4	DF 5
Male	78.70	70.04	81.14	70.34	72.92
Female	66.39	61.75	69.11	66.58	73.09

Discussion Forum 3 had the highest percentage (81.14%) of analytic thinking among all the posts with the question of "*How can you exhibit fairness in the machine learning process for QA in Education?"*. The structure of the question prompted the learners to be more logical and explanatory in answers, as compared to the lowest percentage (70.04%) garnered by DF 2. While DF 2 was a close-ended question being "*Can you identify the subprocesses that can be automated even if it is by different AI systems?"*, the question did not encourage the learners to be engaging in their posts and mostly had simple answers.

LIWC Results – Clout

For the clout dimension, three out of the five discussion forum posts were dominated by the females, while the remaining two posts were where the males felt more confident in their answers.

Table 3

Mean percentage of discussion forums under the clout dimension

GENDER	DF 1	DF 2	DF 3	DF 4	DF 5
Male	46.12	47.58	43.88	41.82	53.89
Female	41.69	54.60	39.94	44.58	57.56

The DF question that inspired the learners the most (57.56%) to be more confident and certain in their answers was DF 5, "*What future AI projects used in QA for education can you propose to your institution?"* likely due to its nature of being a personal question. This allowed the learners to draw more from their own experiences and be confident, thus leading to a more positive cognitive processing structure in their posts. Comparatively, DF 3, which

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led to the highest analytic thinking, has the lowest percentage (43.88%) in the clout dimension, as the analytical answers given by the students did not inspire them to integrate their personal knowledge in their posts.

LIWC Results – Dictionary Words

Similar to the clout dimension, three out of five DF posts were dominated by the females in the dictionary words dimension. Overall, the percentages for the dictionary words were the highest of the three dimensions being analyzed, the lowest being 81.66% and the highest being 88.17%. Interestingly, the mentioned percentages were both the means from the male learners.

Table 4

Mean percentage of discussion forums under the dictionary words dimension

GENDER	DF 1	DF 2	DF 3	DF 4	DF 5
Male	85.57	83.19	81.66	85.32	88.17
Female	87.06	85.49	81.71	84.74	86.63

The highest mean percentage came from the DF 5, while the DF 3 had the lowest, mirroring the clout dimension results. With the learners confident in their thought processes, they used more complex words as they were more engaged in their discussions. This is in contrast to the analytic dimension, with DF 3 at its highest, as the logical answers given by the learners led to them using more direct and simple words to accurately answer the question.

CONCLUSION

The LIWC results of the discussion forum posts under the analytic, clout, and dictionary words dimensions were also analyzed with gender lenses. With a total of 70 participants in the study, posts were observed from 42 male (60%) learners and 28 female (40%) learners. Results showed that males had the highest percentage under the analytic dimension, while the females dominated the clout and dictionary words dimension. This meant that males leaned more to being logical and formal in their posts, while females tended to be more creative and use complex language as well as being more confident.

The analytic dimension had the highest percentage under DF 3, "*How can you exhibit fairness in the machine learning process for QA in Education?*", which had the lowest percentage for the clout and dictionary words dimension. This observation meant that the logical structure of the answers the learners gave did not inspire confidence in sharing personal knowledge as well as the use of much complex words.

On the other hand, there was a correlation between the clout and dictionary words dimension, both being similar in having DF 5 "*What future AI projects used in QA for education can you propose to your institution?*" garner the highest percentage for the two dimensions. Learners, being more confident and certain in their discussions, tend to use more complex words in their posts. The structure of the question also involved more personal knowledge/experience from the answers, compared to questions that required more logical answers.

In conclusion, discussion forum posts had a high percentage of engagement and quality from its analytic dimension if the question required more logically structured answers, which were also mostly garnered from the male learners, and higher engagement from the dictionary words and clout dimension if the question inspired the learners to share answers incorporating personal knowledge, which garnered its high percentage from the female learners.

RECOMMENDATIONS

As the study was limited to the gender demographic, it is recommended for future studies to analyze other demographics as well, such as educational attainment, to see how it correlates with the analyzed dimensions. Other studies can also focus on identifying the question structure to see which would create more discussion from the posts, whether it should be leaning more towards the analytic dimension or the clout and dictionary words dimension. The MOOC evaluated in the study was also more logical in nature; thus, the discussion forum posts were not analyzed

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based on its emotional tone. A study can be conducted to analyze emotions to correlate with the completion rates of the students, as well as their demographics.

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