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# Analysis of learning behavior and pattern of online learners on a MOOC platform

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**ABSTRACT:** Understanding a learner in an online environment can ensure success of an online course. The present study determines learning behavior and learning pattern among learners on the MOOC platform established for running an online course offered at ICAR-National Academy of Agricultural Research Management (NAARM), Hyderabad, India. The demographic description and significant difference between learning patterns of the learners on MOOC according to their subject domain were analyzed by using Moodle LMS (Learning Management System). The learner group was found to comprise in majority as males or doctorate degree holders and from agriculture domain. Most of the learners were found to be passive who were frequently engaging in the course in terms of learning behavior which indicates their way of participating in the course. Majority of the learners had moderate interest and seriousness to learn the subject. With regard to course participation which is measured in course log-in patterns, learners with subject domains like Engineering and Agribusiness Management and Agriculture and Veterinary streams had similarity in course participation. Among the weekly participation, there was a significant increase in course participation towards course ending irrespective of subject domains which indicates the participants' urge to complete the course for certification. The key observations found through the study can be of paramount importance in designing a successful MOOC with better completion rates.

**Key words:** Massive Open Online Courses, learning behavior, learning pattern, Learning Management System

Massive Open Online Courses (MOOCs) are freely accessible online courses for distance learners who have internet access (Tucker *et al.,* 2014). This offers increasing opportunities for acquiring skills and the courses are provided in an online environment with many features that vary from previous approaches to digital education. In recent years, there has been an increase in demand for MOOCs and more people found that it is a cheap way to learn new skills and boost their employability (Alraimi *et al.,* 2015; Christensen *et al.,* 2013). It allows individual learners to self-regulate their learning, deciding where, how and what content they associated with (Hood *et al.,* 2015). According to Mukala *et al.* (2015), good (distinction and normal) learners perform better than unsuccessful learners, since they obey the videos and submit quizzes in a more structured way. Knowing that the way that learners follow videos may have a significant effect on their final success is of utmost importance in organizing the course material and overall course structure. MOOCs attract a number of learners, each with varying interests and previous experience. Online courses provide rich, real-time data for the learners' learning to understand and develop. These also aimed at open participation, access across the internet, free distribution, elimination of financial, cultural and geographical barriers to participation. The majority of the learners who participated in MOOCs interact selectively with a portion of the content of the course (Anderson *et al.,* 2014; Breslow *et al.,*2013; Evans *et al.,* 2016; Ho *et al.,* 2015;Kizilcec *et al.,* 2013;Perna *et al.,* 2014; Seaton *et al.,* 2014). In a typical MOOC platform, learners can not only access speech videos, assignments and examinations, but also use learning tools, such as online discussion forums and wiki, for participating in peer-to peer interactions. In this way MOOC has become the main choice of online learning for millions of people worldwide. (Wen *et al.,* 2019).

The opportunity of accessing high quality courseware content within such platforms, while eliminating the burden of educational, financial and geographical obstacles has led to a rapid growth in participant numbers (Al-Shabandar *et al.,* 2018). It also has the opportunity to access evaluations of courses (e.g. assignments and quizzes), review learning goals and results with other participants (e.g. through an online forum) (Tucker *et al.,* 2014). The educational staff creates group discussions in all MOOC sites to promote and engage learners in discussions. Learners that are interested to participate in forums and quizzes may be presented to suggest levels of involvement (Spyropoulou *et al.,* 2014; Wang *et al.,* 2015). A small fee may be required at the end of certain MOOC courses to grant a certificate for active learners to complete the course. In the present study, learning behavior is operationalized as learners' participation in the course in terms of watching course content, downloading PPT, study material and questions about self-assessment, engaging in the group discussion, uploading assignments and attempting quizzes. Similarly, learning pattern is conceptualized as a coherent whole of learning behavior that typically employs the learners, their learning values, and motivation, a whole that distinguishes them in a given period. This is an organizing process in which the interrelationship between cognitive, affective, and regulative learning events, learning beliefs and motives for learning are unified (Vermunt and Donche, 2017).The joint efforts of academia and industry have led to the recent development of multiple MOOC platforms, such as Coursera, Udacity, Edx, and XuetangX, to adequately address diverse learning needs and cater to service learners by providing thousands of well-designed online courses (Wen *et al.,* 2019). Likewise, MOOCs platform called SWAYAM is developed in India to promote online learning in all subject areas. The time has come to understand the learners' actions related to various subject domains in the Indian context.

A large number of learner registrations attract huge open online courses, but recent studies have shown that only a small fraction of these learners complete their courses. Thus, learners' dropout rates are big deterrent to MOOCs growth and progress. To reduce dropout rates, the comprehension of the learners' behavior as a course progresses is crucial. In an online world, identifying and assessing learner participation in the course as typical classroom courses where involvement can be measured in person is difficult. The participation of the learner includes online learner activity on the course website, interaction with other learners/ staff in discussion groups, completion of quizzes/ assignments. Such variations exacerbate the question of evaluating the engagement of learners (Ramesh *et al.,* 2013). Therefore, the need of the study is to explore the learning behavior and pattern of the learners in MOOC which evolve the learners' high engagement to course. The analyses of learning behavior and pattern presented in this study go some way to providing greater insights into learners' activity in MOOCs.

## REVIEW OF LITERATURE

Santos *et al.* (2014) examined the learning patterns of the learners in MOOCs and found that the learners who engaged more in courses have higher chance of completing the course. A better learning outcome was demonstrated by those learners who regularly interacted, discussed, exchanged and collaborated with others. Their research also showed that those who commented regularly in the discussion forum would pass the course at a higher pace. Qin *et al.* (2019) analyzed the learning behavior of 1,388 undergraduates in the online advanced mathematics course of the online platform named 'Erya'. They concluded that the lack of positive interaction between teachers and learners can affect learners' enthusiasm for learning and learners' learning outcomes. They also suggested that analysis of learning behaviour may leads to improvement in academic performance in the MOOCs.
Luo *et al.* (2018) stated that the learning behaviors include watching videos, completing exercises, participating in discussions and taking quizzes. It was found that the behavioral characteristics of watching videos were very close for all types of learners because passers did not watch enough videos, which indicate that most of passers already mast knowledge of the course. So, online courses are used to help them in learning.

Wen *et al.* (2019) revealed that the learners often exhibit similar learning behaviors on several consecutive days, like the learning status of a learner on the next day was a considerable likelihood of being similar to the learning status of the learner on the previous day.
Anderson *et al.* (2014) examined that how the degree of involvement and participation of the learners associated with the final grade of the learners, which explains the course certification. They found that the key characteristic of high-grade achiever was that during the course, they visited several lecture videos. Kizilcec *et al.* (2013) described four prototypical patterns of learning in a MOOC consisting of watching videos and taking quizzes. Such trends were as learners who completed the bulk of the evaluation, learners who participated primarily in watching videos, learners who evaluated at the beginning of the course, and learners who watched videos only one or two evaluation times.

Lan and Hew (2020) revealed that the MOOC learners' behavior engagement with higher frequency of posting forum messages, motivation with more eager to gain a certificate and being involved in the MOOC platform, psychological needs with perception of competence and cognitive engagement lead to successfully complete the course. Furthermore, their study suggested that satisfaction of MOOC participants' psychological needs through MOOC design could improve all aspects of their engagement in the course.

Pireva *et al.* (2015) concluded that the digital platforms were used not only as an added benefit on the technology platform to facilitate the conventional learning process, but also for networking, combining, and distance learning. They've contrasted Moodle, Atutor and Claroline as open source and Blackboard and Fronter as commercial ones on five platforms. Participants for MOOCs favored Moodle among the LMS. Participants also acknowledged that it is difficult to say that any given platform meets all of the a learners' criteria and is a solution to all learning needs. Blagojević and Milošević (2015) concluded that there are variations in EDX and Moodle MOOC capabilities and stated that both systems support large open online courses, but the individual segments vary in terms of instructor features and use. Moodle MOOC offers the ability to coordinate group events, through wikis and workshops. EdX offers participants the possibility of collaborative activities via the wiki, and more participants are also expected to work together through virtual labs. Nevertheless, as opposed to edX, exports of these data offer more options within Moodle MOOC in terms of different formats in which the reports are delivered. Both systems provide visualization of the tests.

Kizilcec Halawa (2015) stated that approximately 84% of the learners said they did not have enough time for the course. They also suggested that they were easily distracted from the course, indicating that resource management techniques may have obstructed their engagement. Gender differences emerged in the use of multiple self-regulated learning courses, in which women in particular were more likely to seek support than men, as compared to prior work (Basol and Balgalmis, 2016; Liou and Kuo, 2014; Yukselturk and Top, 2013). Numerous studies have found variation in the engagement and achievement of learners in MOOCs among themselves. Empirical work has linked variability in course activity and achievement with specific variations in the demographic and personal context of the learner (Evans *et al.,* 2016; Guo and Reinecke, 2014; Hansen and Reich, 2015; Kizilcec and Halawa 2015).

It may be noted that there are not much investigations done on MOOC concerning agriculture and its allied domains in comparison with other domains. Hence, the present study was taken up to study learning behavior and pattern in MOOCs with the following objectives:

1. To study the demographic characteristics of learners
2. To study the learning behavior of learners
3. To study the comparative login or learning pattern between subject domain learners

## MATERIALS AND METHODS

### Participation in the MOOC

A month-long MOOC on Teaching Excellence with the purpose of honing the teaching skills of working and aspirant teachers was offered during November 2018 through Moodle LMS. Moodle LMS is a non-commercial e-learning platform which is highly used by the people and this platform is easy to use and work with for a new user. The number of learners who enrolled in the MOOC course was 1192. The course content consisted of video lectures, reading material, PowerPoint presentations, discussion forums, and assignments. During the course period, participation in discussion and assignment submission was mandatory for the certification. The learner's learning pattern as well as performance was evaluated by participating in the discussion forums, assignment submission, and quiz. If the learners wanted to receive a certificate for completing the course, they needed to complete the quiz, complete at least two assignments, and participate at least twice in the required discussion forums. If learners wanted to receive a certificate for participation only, they needed to complete any one activity from the quiz, assignment, and discussion.

### Data Source, Sampling Technique and Analysis

During the MOOC course period, data pertaining to learner activities was been collected from data logs of LMS. Since, there is no control on the number of learners in each subject domain, a stratified simple random sampling technique with proportional allocation was used for extracting a specific sample size for the data analysis. A stratified random sampling with proportional allocation involves dividing the entire population into homogeneous groups called strata. A random sample from each stratum was taken in a number proportional to the stratum's size when compared to the population. These subsets of the strata are then pooled to form a random sample. The sample size is determined as below:

$$\text{Sample size of the strata} = \frac{\text{Sample Size}}{\text{population size}} \text{ x stratum size}$$

Considering a total sample size of 250 out of a total MOOC learner population size of 1192, the sample size for each domain worked out as follows:

**Table 1: Description of sample size based on the subject domain**

| Sl. No. | Subject Domain | Strata | Sample Size |
|---|---|---|---|
| 1. | Agriculture | 796 | 167 |
| 2. | Veterinary | 217 | 46 |
| 3. | Agribusiness Management and Engineering | 90 | 19 |
| 4. | Education | 89 | 18 |
| | Total | 1192 | 250 |

Descriptive analysis including frequency and percentage were carried out and a sample mean-difference test was conducted to compare learning pattern in terms of login activities in the different subject domains. ANOVA with a Post hoc test was used to determine the significant difference in the group means of learners' weekly login pattern for each subject domain.

## RESULTS AND DISCUSSION

Out of 1192 learners, 482 successfully completed the course, out of 482 learners 267 have got completion certificate and 215 have got participation certificate based on their learning pattern and level of performance in the course. The learner data was thoroughly analyzed to understand their learning patterns and background.

### Demographic Information

This section explained demographic information such as Gender, Education, Subject Domain of the learners.

**Table 2.Demographic information of the learners/ participants in MOOC**

| Sl. No. | . Demographic Information | Frequency (F) | Percentage (%) |
|---|---|---|---|
| **1.** | **Gender** | | |
| | Male | 188 | 75.2 |
| | Female | 62 | 24.8 |
| **2.** | **Educational Qualification** | | |
| | Bachler degree | 4 | 1.6 |
| | Master degree | 98 | 39.2 |
| | Doctoral degree | 148 | 59.2 |
| **3.** | **Subject Domain** | | |
| | Agribusiness Management | 8 | 3.2 |
| | Education | 18 | 7.2 |
| | Engineering | 11 | 4.4 |
| | Veterinary | 46 | 18.4 |
| | Agriculture | 167 | 66.8 |

The result concluded that there is a major participant from males, which is almost three times than of females. As shown in Table 2, the majority of the learners (59.2%) have done a doctorate in various subject domains, followed by 39.2% of the learners who have done master in various subject domains such as agriculture, veterinary science, education, technology, philosophy and agribusiness management. Only 1.6% of the learners have done an undergraduate degree in various subject domains. Since the learners were either students in higher education or academicians and administrators, it was expected to have a higher ratio in MOOC experience. This observation is in consonance with that of Guo and Reinecke (2014) who observed that majority of learners were post graduates in a MOOC offered on the edX platform. Generally, a massive number of learners register in MOOC for every different course and those learners belong to the various subject domain. Hence, the analysis was done to categorize learners according to the subject domain. The result indicates that the majority of learners (66.8%) were from the agriculture domain, followed by 18.4% from veterinary, 7.2% from education, 4.4% from engineering and 3.2% from agribusiness management.

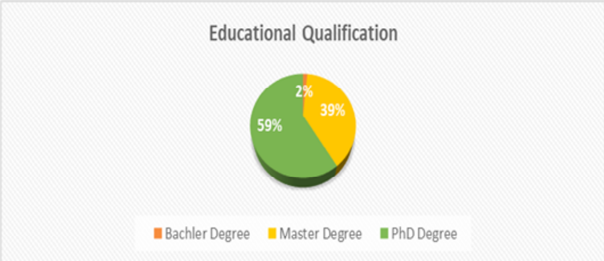


**Figure 1: Distribution of the learners according to their educational qualification**

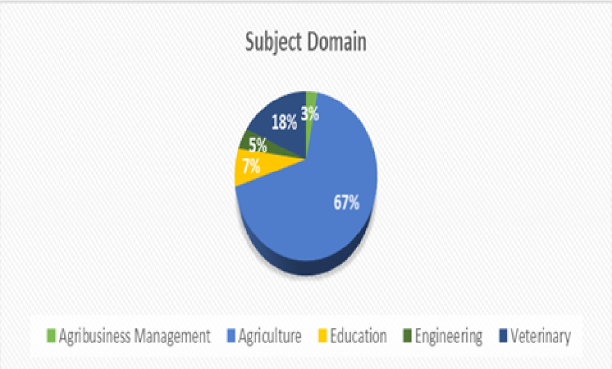


**Figure 2: Distribution of the learners according to their subject domain**

### Learning Behavior of the learners

In this section, learners learning activities were investigated based on the login patterns in MOOC during the course period.

Learners' average login to the MOOC describes their daily activities in the MOOC such as course video viewing, participation in the discussion forum, downloading PowerPoint presentations, reading materials and self-assessment questions. Types of learners have been found out by learners' average login value with categorization into three categories namely Active, Moderate and Passive learners. As given in Table 3, the majority of the learners (79.6%) had fallen under passive types of learners with criteria of average login value d" 30. It could be concluded that Passive learners were those who were periodically visiting the course which is measured by their course log pattern. About 19.2% of the learners had fallen under Moderate types of learners with average login between 30-60. It indicates the learning pattern of the learners who were regularly visiting the course and completed all the requirements for certification. The least number of the learners (1.2%) had fallen under Active types of learners with criteria of average login value >60. Active types of learners were those who have shown their excellent performance in the course in terms of course activities like watching video lectures, discussion fora & assignment submission and completed the course requirement of certification.

Kahan *et al.* (2017) had identified seven types of learners' learning behavior in MOOCs in which Tasters and the Downloaders presented low levels of engagement in the course. The Disengages were moderately engaged in the course. The online and offline engagers, the moderately social engagers, and the social engagershad shown high levels of engagement in the course. Tseng *et al.* (2016) were revealed three kind of MOOC learners in their study andgiven name as active, passive, and bystander. Active learners were those who submitted assignments on time, frequently watched lecture videos, shown higher completion rate and better grade in the course. Active learners were completing assignments were more often among than passive learners and bystanders. These findings addressed the classification of learners learning behavior in MOOCs which is relevant to the present study.

**Table 3: Distribution of the learners according to their login pattern in MOOC**

| Sl. No. | Type of learners | Criteria of average login value | Frequency (F) | Percentage (%) |
|---|---|---|---|---|
| 1. | Active | >60 | 3 | 1.2 |
| 2. | Moderate | 30-60 | 48 | 19.2 |
| 3. | Passive | <30 | 199 | 79.6 |
| | Total | | 250 | 100 |

**Experimental result: Comparison between the subject domain learners with their learning patterns**

**Analysis of Paired sample t-Test for learning on MOOC**

The agriculture, veterinary, agribusiness management, engineering and education subject domain learners' login or learning pattern was calculated in MOOC. The paired sample t-test technique was used for comparing the means of the agriculture and veterinary domain learner's learning pattern which includes weekly average login in MOOC. The result of the paired sample t-test is displayed in Table 4.

**Hypothesis:**

**H0:** There is no significant difference in mean of weekly average login between agriculture and veterinary domain learners and between agribusiness management, engineering and education domain learners

**H1:** There is a significant difference in mean of weekly average login between agriculture and veterinary domain learners and between agribusiness management, engineering and education domain learners

The results have shown for agriculture and veterinary domain learners' average login the calculated t-value and

**Table 4: Paired sample t-test for weekly average login pattern between agriculture and veterinary domain learners**

| | | Paired Difference | | | | | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Std. Deviation | SE Mean | 95% Confidence Interval of the difference | | | | |
| | | | | | Lower | Upper | | | |
| Pair 1 | Average login agriculture –veterinary | 1.59 | 1.97 | 0.98 | -1.54 | 4.73 | 1.61 | 3 | $0.205^{NS}$ |
| Pair 2 | Average login agribusiness management, engineering – education | -20.66 | 12.42 | 6.21 | -40.43 | -0.89 | -3.32 | 3 | $0.045^{*}$ |

***Significant at 5% level, NS= Non-significant**

P-value were 1.613 & 0.205 and for agribusiness management, engineering and education domain learners' average login the calculated t-value and P-value were 3.32 and 0.045 respectively. The calculated P-value is greater than the alpha value 0.05, so it can be concluded that there was no significant difference between agriculture and veterinary subject domain learners' weekly average login pattern in MOOC. Whereas, the p-value is less than 0.05, there is a significant difference between ABM, engineering, and education domain learners' average login pattern. Agribusiness management, engineering domain learners had shown more active performance in terms of login pattern as compared to the education domain learners. Therefore, the null hypothesis is rejected and accepted the alternate hypothesis.

**Analysis of the learning pattern of agriculture and veterinary domain learners based on their gender**

A comparative analysis (Table 5) was carried out to determine a significant difference in the means of the agriculture and veterinary domain male and female learners' weekly average login in MOOC.

**Hypothesis:**

**H0**: There is no significant difference in mean of average login between the agriculture domain male and female learners and between veterinary domain male and female learners in MOOC

**H1**: There is a significant difference in mean of average login between the agriculture domain male and female learners and between veterinary domain male and female learners in MOOC

Results showed that the calculated t-value and p-value were -0.686 and 0. 542 respectively for the agriculture male and female learners. Along with this the calculated t-value and P-value were 0.771 and 0. 497 respectively for the veterinary male and female learners. By using the confidence interval of 95%, the alpha value is 0.05. Since the P-value is greater than 0.05, there is no evidence against the null hypothesis and the data appear to be consistent with the null hypothesis that there is no significant difference in means of agriculture and veterinary learner's gender-based average login in MOOC. Thus, it can be seen that the male and female learners from the agriculture and veterinary domain were showing similar course participation patterns in MOOCs.

**Analysis of variance with respective to MOOC parameters**

ANOVA test the equality of at least three or more group

**Table 5: Paired sample test for total login pattern by agriculture domain MOOC learners**

| | | Paired Difference | | | | | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Std. Deviation | SE Mean | 95% Confidence Interval of the difference | | | | |
| | | | | | Lower | Upper | | | |
| Pair 1 | Weekly Average login Agriculture Male- Female | -3.36 | 9.81 | 4.90 | -18.98 | 12.25 | -0.686 | 3 | 0.542$^{NS}$ |
| Pair 2 | Weekly average login Veterinary Male – Female | 7.80 | 20.24 | 10.12 | -24.40 | 40.01 | .771 | 3 | 0.497$^{NS}$ |

**NS= Non-significant**

**Table 6: ANOVA for comparison of weekly login in different groups**

| Source of Variation | Degrees of Freedom | Sum of Squares | Mean Sum of Squares | F value | Pr(>F) |
|---|---|---|---|---|---|
| **Agriculture Group** | | | | | |
| Login week | 3 | 397503 | 132501 | 52.28 | <0.001 |
| Replication | 116 | 1392446 | 8388 | 3.31 | <0.001 |
| **Veterinary Group** | | | | | |
| Login week | 3 | 94793 | 31598 | 15.319 | <0.001 |
| Replication | 45 | 354781 | 7884 | 3.822 | <0.001 |
| **Agribusiness Management & Engineering Group** | | | | | |
| Login week | 3 | 13291 | 4430 | 4.123 | 0.010 |
| Replication | 18 | 97728 | 5429 | 5.053 | <0.001 |
| **Education Group** | | | | | |
| Login week | 3 | 37543 | 12514 | 8.448 | <0.001 |
| Replication | 17 | 172581 | 10152 | 6.853 | <0.001 |

**Table 7: Post hoc test for all subject domain (Probabilities for comparison of individual means)**

| Result of Post Hoc Test | | | |
|---|---|---|---|
| **Agriculture** | | | |
| | Week 1 | Week 2 | Week3 |
| Week 2 | 0.575 | - | - |
| Week 3 | 0.069 | 0.209 | - |
| Week 4 | <0.001 | <0.001 | <0.001 |
| **Veterinary** | | | |
| | Week 1 | Week 2 | Week 3 |
| Week 2 | 0.57210 | - | - |
| Week 3 | 0.29380 | 0.62692 | - |
| Week 4 | <0.001 | <0.001 | 0.00036 |
| **Agribusiness Management & Engineering** | | | |
| | Week 1 | Week 2 | Week 3 |
| Week 2 | 0.583 | - | - |
| Week 3 | 0.479 | 0.873 | - |
| Week 4 | 0.021 | 0.076 | 0.106 |
| **Education** | | | |
| | Week 1 | Week 2 | Week 3 |
| Week 2 | 0.8625 | - | - |
| Week 3 | 0.5999 | 0.4858 | - |
| Week 4 | 0.0095 | 0.0059 | 0.0359 |

means, statistically significant results indicate that not all of the group means are equal. However, ANOVA results do not identify which particular differences between pairs of means are significant. ANOVA with factor replication was conducted to determine the significant difference between or within group means among each subject domain learners' no. of login in different weeks in MOOC. The obtained result has presented in Table 6.

**Hypothesis**:

**H0**: All subject domain groups learners' learning pattern means are equal.

**H1**: All subject domain group learners' learning pattern means are not equal.

From Table 6, the result showed that the significance or P-value (< 0.001 for all groups except ABM & engineering group which is 0.010) is much smaller than the table value 0.05 for all subject domain group in terms of no. of login in different weeks. So, it can be concluded that there was a highly significant difference between the no. of logins in different weeks for the agriculture, veterinary, agribusiness management and engineering and education group. It means learners' participation in to course was varying in every week.This is great to know, but it is not clear which of the specific groups differed.

**Post hoc test for agriculture, veterinary, agribusiness management and engineering and education domains weekly login pattern (Probabilities for comparison of individual week means)**

Post hoc test is an integral part of ANOVA. Post hoc test used to explore differences between multiple groups means while controlling the experiment-wise error rate. Post hoc test ensures which particular group means is the statistically significant difference among all other groups. Post hoc test for multiple comparison with Least Significant Difference (LSD) was carried out with significance level 0.05 (5%). From Table 9 the calculated significance value is very less than significance level 0.05 for agriculture, veterinary, and education group no. of login in different weeks. So, it could be concluded that there is a significant difference between the no. of logins in week 4 and the number of logins in week 1, 2 and 3 are on par. Whereas, agribusiness management group shows a significant difference between only no. of logins in week 4 and week 1 and all others are on par. It means learners have more actively participated in MOOC at the timing of course ending may be with the purpose of getting certificate.

## CONCLUSION

In this study, the learning behavior of the learners and their learning pattern in terms of login activities were calculated to determine the subject-domain based learning pattern in the MOOC platform. Stratified simple random sampling with proportional allocation was carried out for the study. In this study, first described the demographic characteristic of the learners and learning behavior in MOOC. Then, the paired sample t-test was employed to find out significant differences in the learning patterns of the learners based on their subject domain. The findings of this study revealed that the majority of the learners were male, doctorate degree holders and from the agriculture subject domain. It may conclude that the male learners were highly aware of the course and interested to participate in MOOC and agriculture domain learners were highly enrolled in the MOOC as compared to all other subject domain learners. Most of the learners fall under the passive types of learners with their learning behavior which indicates their way of participating in the course. The majority of the learners were falling under moderate types of learners which indicates their interest to learn and seriousness about the course.

Paired sample t-test results indicated that there was no significant difference between the login pattern of agriculture and veterinary subject domain learners.

However, there was a significant difference between ABM, engineering, and education domain learners' login patterns. It concluded that the agriculture and veterinary domain learners have similar learning patterns in MOOC. Whereas, agribusiness management and engineering domain learners were performing well with login pattern as compared to education domain learners. Likewise, there was a similar learning pattern in MOOC by the male and female learners of the agriculture and veterinary subject domain. ANOVA with factor replication result revealed that there is a highly significant difference in group means for all subject domains in terms of no. of login in different weeks. Post hoc test results indicated that there is a significant difference between the no. of logins in week four and other weeks for the agriculture, veterinary, and education group. Whereas, there is a significant difference between only no. of logins in week four and week one and all others are on par for agribusiness management & engineering group. The findings of this study contribute to a better understanding of learners' learning behavior and pattern in MOOCs. The learning behavior and pattern of learners are likely to prove the richest for improving the quality of learning and the learning environment.

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