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Understanding Learner Behaviour in Online Courses through Learning Analytics

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Building an effective online course requires an understanding of learning analytics. The study assumes significance in the COVID 19 pandemic situation as there is a sudden surge in online courses. Analysis of the online course using the data generated from the Moodle Learning Management System (LMS), Google Forms and Google Analytics was carried out to understand the tenants of an effective online course. About 515 learners participated in the initial pre-training needs & expectations' survey and 472 learners gave feedback at the end, apart from the real-time data generated from LMS and Google Analytics during the course period. This case study analysed online learning behaviour and the supporting learning environment and suggest critical factors to be at the centre stage in the design and development of online courses; leads to the improved online learning experience and thus the quality of education. User needs, quality of resources and effectiveness of online courses are equally important in taking further online courses.

Keywords: Learning analytics; learning behaviour; perceptions; Google analytics.

1. INTRODUCTION

The online courses have gained popularity over the last decade and are currently surging ahead in the pandemic situation of COVID 19. The premier higher educational institutions are providing quality education through blended approaches i.e. traditional as well as online education either synchronously or asynchronously. These online courses are offered as Web-based Learning, Webinars and Virtual Classrooms, Video-based Learning, Collaborative Learning, Custom eLearning, Mobile Learning etc. The Massive Open Online Courses (MOOCs) are a new model for online courses that have quickly gained interest and support among universities in recent years.

Availability of quality and voluminous data and advancements in computing techniques and availability of analytical tools [1] necessitated research on understanding the learning behaviours. These studies focused on data that involved students' online learning behaviours, study performance, demographics and course selection information. Also considered intervention practices to improve students' study performance, offering personalised feedback and improving student retention which led to improved productivity and effectiveness in learning and teaching [2]. Learning Analytics is going to play an important role in the field of education in future [3] and they become part of the classroom evaluation process [4] helps to understand in-depth learners' activity, for improving the online learning experience. The personalized metacognitive feedback based on learning analytics [5] and performance through prescriptive learning dashboards as instructional aid [6] improves students' engagement in an online course. However, learners' needs and expected outcomes determine their engagement in different activities over the Learning Management System which is reflected in the learning behaviours. The activity-based learning behaviours viz. trajectory behaviour, social behaviour, resource learning behaviour, evaluation and reflection behaviour are influenced by subjective thinking and also limited by the environment [7], apart from the learners' engagement, assessment methodologies, learners' motivation etc. [8]. Despite these, the major drawback in online courses is a significant drop in completion rates. The organisations/practitioners need to understand the implications of the learning analytics research in online learning environments and which helps to design and develop the online courses. Orientation towards monitoring/analysis and prediction/intervention, learning behaviour and learning level data has received much attention in analysing the online learning behaviour [9]. The paradox between quantum leap in online courses and the effectiveness of the online courses needs to be understood thoroughly to improve the quality and relevance of online courses. This necessitates a case study by employing appropriate tools that capture online learning behaviour. With this background, an attempt is made in this study to understand the online learning behaviour and associated changes for enhancing the quality of online learning.

2. METHODOLOGY

The case study is an intensive study of a single unit to understand a larger class of (similar) units [10]. This provides an opportunity to gain a deep holistic view of the research problem and may facilitate describing, understanding and explaining a research problem or situation. This study was conducted in the lines of the six-stage case study process and integrated additional relevant guidelines from the wider methodological literature [11,12]. The case study was carried out with the participants of MOOCs on Dynamics of Teaching-Learning organised by ICAR National Academy of Agricultural Research Management and with prior ethical approval. The pre-training needs/expectations at the beginning of the course and the feedback at the end of the course i.e. after one month, are captured through a google form which contained the items on the profile of participants, online learning environment (interest, duration, effective platform etc.), preferences for MOOCs, temporal changes in perceptions concerning expectations and outcome; perceived effectiveness of internet connectivity, preferred modes of engagement and formats for delivery of content, use of social media, quality of resources etc.

Google Analytics is also preferred as it provides time-series data and comes with the guarantee of Google technology [13]. The Google Analytics, integrated with eLearning platform (https://elearning.naarm.org.in/) built on MOODLE environment, provided the data about age groupings, internet access (browsers, device-based internet usage), channel grouping, online traffic, session duration, bounce rates, page views etc.

Descriptive statistics were used for the analysis of the data. The paired t-test was used to compare the pre and post knowledge scores of the MOOCs participants. About 515 learners responded to the initial pre-training needs & expectations' survey and 472 learners gave feedback at the end. The participants of the survey included young and aspiring in-service faculty of various Universities with an ambition to become effective teachers/managers of teaching. About 69 per cent of the participants were males and 31 per cent females. The maximum number of participants (51%) had the highest qualification as PhD, followed by Post Graduation (45%) and Graduation (4 %). The majority of the participants (54.26%) belonged to the agriculture stream and the remaining from the non-agriculture stream (45.76%) which included Engineering, Arts, Science, Management and other domains. The majority of the registered users belonged to the 25-34 years age group (47.39%) followed by 18-24 years (17.36%), 35-44 years(14.17%), 45-54 years' groups (9.39%) and above 65 years (3.54%) etc. Online courses are more preferred by the young group of 25-34 years.

3. RESULTS AND DISCUSSION

The present study analysed different parameters of changes in levels of perception, online learning behaviour and performance etc.

3.1 Learners' Perceptions

3.1.1 Preferences for online courses

About seventy per cent of the participants opted for the online course as it is having relevance to the job followed by their interest (58.47 %). Other reasons attributed were the career progression and brand value of ICAR-NAARM. In professional higher educational institutions, a mechanism for developing the teaching skills, especially at entry-level, is seldom available. These MOOCs attracted mainly young faculty who are either in the initial stages of their career or yet to start a career in the teaching profession (postgraduate and doctoral students) (Fig. 1).

3.1.2 Changes in expected and actual outcomes

The expectations (at the beginning) and the outcome (at the end) were captured on 10 items - convenience of learning, flexible learning, improved quality of learning resources, learning from peers and others, strengthening of networking, provision for earning a certificate from home, enrichment in knowledge, development of skills, a favourable attitude and motivation to teach effectively etc. A considerable change was observed among users' perceptions over time (four weeks). A significant and positive change of up to ten per cent was observed on items viz. favourable attitude, flexible learning, the convenience of learning and provision for earning a certificate from home at the end of the course, over the expectations (Fig. 2). However, the remaining items viz. motivation to teach effectively, improved quality of learning resources, development of skills, strengthening of networking and learning from peers and other resources had high expectations which were not converted into positive outcomes. The expectations and the outcome on five parameters i.e. flexible learning, improved quality of learning resources, enrichment in knowledge, motivation to teach effectively and favourable attitude were almost matching. Academic analytics and educational data mining are enabling gathering, analysing, and presenting student data, which sooner or later faculty have to use in the course design and as evidence for implementing new assessments and lines of communication between instructors and students. For those who practice the scholarship of teaching and learning, the concepts of academic analytics, data mining in higher education, and course management system audits and the data generated is very much useful [14]. The course design considered the needs and expectations of users, topics modified based on the needs, content developed in user desired formats. The Moodle LMS is integrated with an assessment tool (online test) to assess the performance before and after the administration of the course.

3.1.3 Online Learning Behaviour

a) Access to Digital Devices

The availability and accessibility of online learning devices, platforms, connectivity, tools etc., play a significant role in online learning. The devices used to access the learning resources were tracked and analysed through the embedded Google Analytics in the learning management system. The preferred devices and the actual usage of devices were significantly different among MOOC learners. The preferred tools and accessed tools for MOOCs are indicated in Fig. 3. Most of the users preferred desktop (89.30 %), mobile (10.30 %) and tablet (0.40 %) for course access.

But during course delivery, the participants used desktop (65.00 %), mobile (33.00 %) and tablet (1.38 %) to access MOOCs. Desktops were preferred over smartphones as the majority of participants were new to online courses. But later, the trend reversed in actual usage. The use of mobile phones increased due to the suitability of the content to the mobile environment and handy to use smartphones became available everywhere and at any time. A decline in usage of tablets across the globe was evident in this case study also. Regular feedback (85.44%), examinations (85.24%), assignments (81.75%), online interaction with course teachers (81.36%) discussion forums (76.50%) and offline interaction with course teachers (67.18%) were found to be the most preferred modes for online learners.

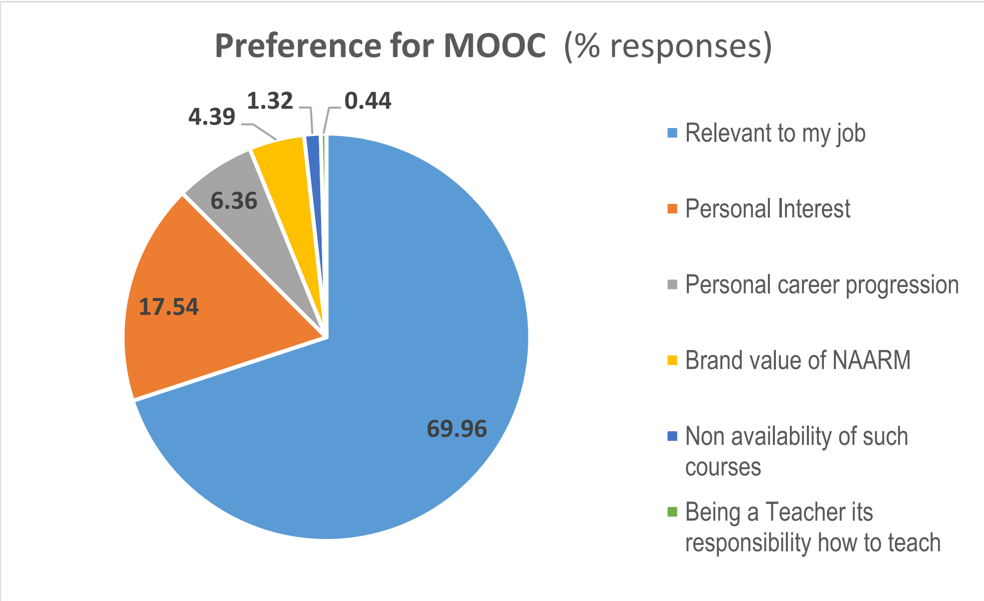

Fig. 1. Users' reasons for joining the MOOCs

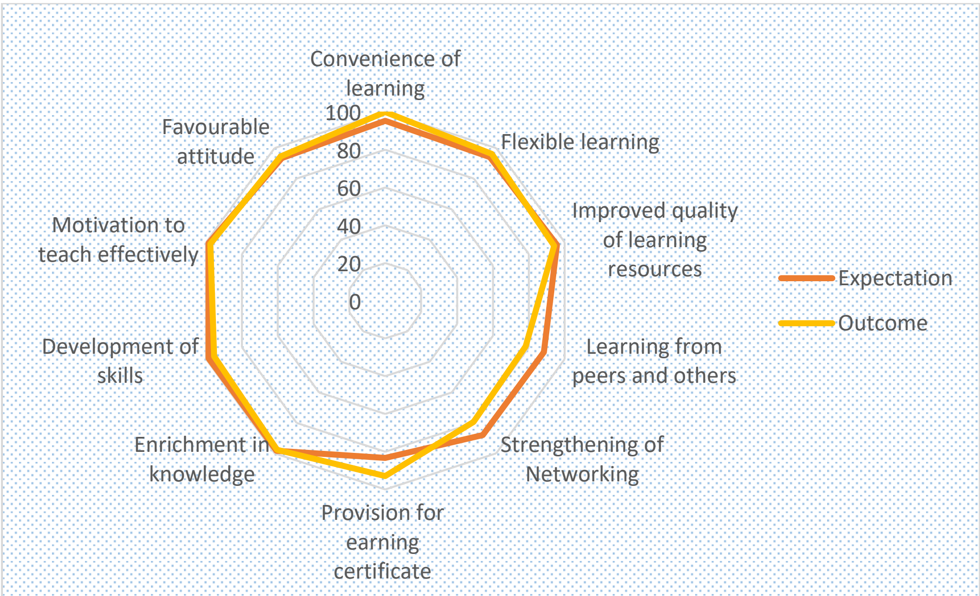

Fig. 2. Users' Expectations and Outcome from MOOCs

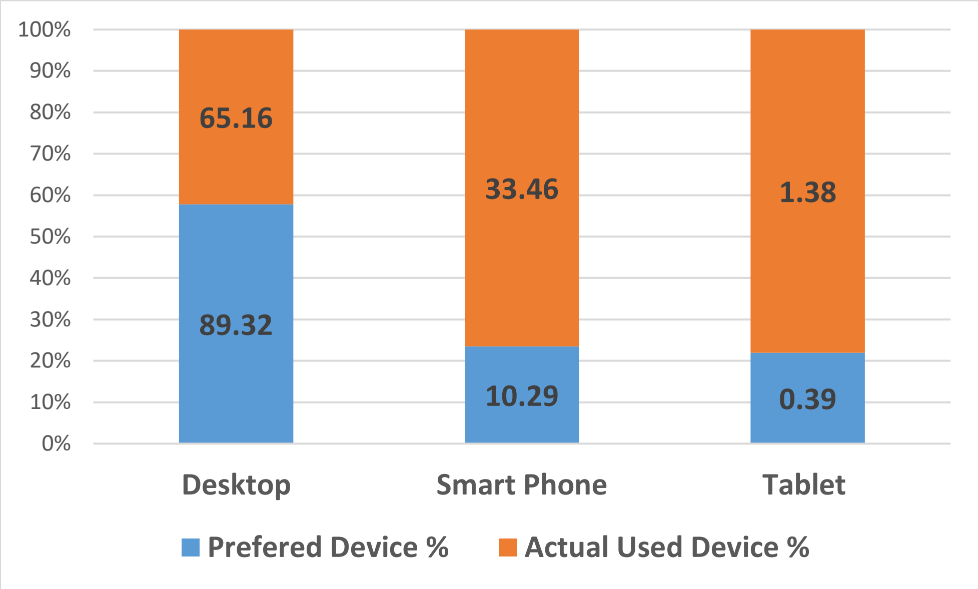

Fig. 3. Device utilization by Online Learners (%)

b) Variations in learners' engagement

The learners' engagement in the sessions and bounce rates for different age groups is presented in Fig. 4. About 47 per cent of the users were in the age group of 25-34 years and had the highest session participation (48%) with a high bounce rate of about 17 per cent. Whereas, the least bounce rate (3.7 %) was observed in the age group above 65 years. So, the online courses have attracted more the age group of 25-34 years, followed by 18-24 years and so on. Bounce rate is the users' single-page visits (Fig. 4) (users only visits on the first page and immediately leave from the entrance page) [15]. Higher participation in sessions leads to high course completion rates. With a few exceptions among Higher Education Institutions of four European Universities, the academic staff sees learning analytics as a tool to understand the learning activities and providing feedback to students which helps in adapting the curriculum to meet learners' needs. The academic staff had consistently low expectations and a desire to act based on data that shows students being at risk of failing or underperforming [16]. The expertise of teachers who are trained and practising the pedagogy for the more or less homogenous group in the face to face type of instruction, utilised in online course delivery. The study also points out the understanding the online learning behaviour such as users profile, LMS, choices/preferences, engagement, pedagogy, effectiveness etc. which focuses on the need for online pedagogical implications. A study conducted in Spain concluded that students perceive the video as a very useful element and are very satisfied with it, although they perceive it as complementary material to textual material. The performance results of students showed that videos can improve the chances of passing the subject [17].

A high bounce rate was observed in the 3rd week (16.13%), followed by the 2nd week (16.09%), 4th week(16.07%) and 1st week(15.57%). Bounce rates can be used to help determine the effectiveness or performance of an entry page at generating the interest of visitors. The high bounce rate in the third week may be due to the type and nature of the topics.

c) Google Analytics Channels

These are rule-based groupings based on traffic sources and by the default classified as *Paid Search* and *Direct*. This allows to quickly check the performance of each of the traffic channels. The traffic denotes the movement of a user to another domain, email, app, or any other channel to the e-learning platform. Every referral to a website also has a medium, which may be "organic" (unpaid search), "CPC" (cost per click, i.e. paid search), “referral” (referral), “email” (the name of a custom medium you have created), “none” (direct traffic has a medium of “none”). (https://support.google.com/analytics/answer/1033173?hl=en). The traffic data of Google Analytics are classified into three channels i.e. Direct, Organic search and Referral. During the one-month MOOC programme, four channels were utilised by users viz. Direct (58.43%), Organic Search (39.07%), Referral (2.46%) and Social (0.04%). However, the bounce rate was very high (46.43%) in referral channels than social, organic and direct channels (Table 1). This trend implied that, since the access to course content is through approved registration, the dedicated learners had only access to the content directly instead of referral mode, hence a low bounce rate in the direct channel (18.10%). The integral development of learners in their learning and knowledge construction process is the very objective of any educational institution, which is achieved through accompaniment and continuous monitoring of students. Monitoring of students/learners online is best possible through digital platforms such as Learning Management System. Integration of analytical tools such as Google Analytics allows access to learners’ fingerprints, generating a large volume of data, that analysis allows a deep way of understanding their behaviour. The online users were continuously monitored through the built-in discussion forum, assignments that enable cross-learning. Regular course updates through email etc. provided. The "referral" is like a recommendation from one website to another. Google Analytics helps to view these referrals, which then add to one’s understanding of how learners find your website and what they do once they get there. In the case of organic search, the bounce rate is less which may be due to less number of users or users who found the exact content. Therefore, the number of pages per session and the average duration is also more as compared to direct search and vice versa. Referral traffic can be a strong indicator for identifying external sources that are most valuable in helping MOOCs achieve their goals. An entry page with a low bounce rate means that the page effectively engages visitors to view more pages and continue deeper into the website. High bounce rates typically indicate that the eLearning platform is to be improved for attracting the continued interest of visitors.

Pages per session broadly gauge how compelling users find course content and the ease of access. On average, each trainee had an engagement of 13.59 pages per session which is a good sign of engagement in an educational context. It portrays that users were highly engaged and willing to explore more of the e-learning site. This is an excellent way of measuring interest and curiosity in the course (Table 1).

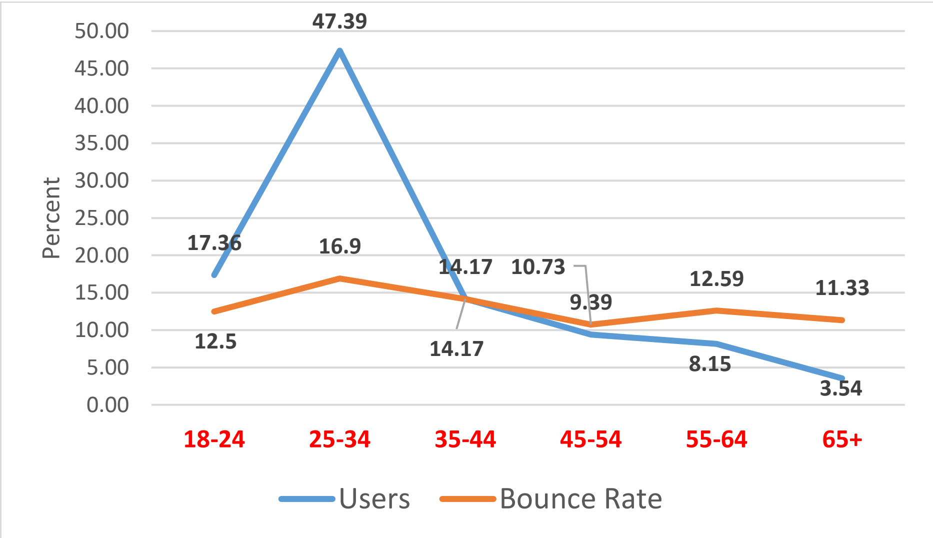

Fig. 4. User Engagement among age groups

Table 1. Channel wise sessions and bounce rates

S. N	Default Channel Grouping	Users	New Users	Sessions	Bounce Rate	Pages/ Session	Avg. Session Duration (sec)
1	Direct	1473 (58.43%)	1118	5789	18.10%	13.05	903.99
2	Organic Search	985 (39.07%)	548	5922	11.69%	14.08	1037.30
3	Referral	62 (2.46%)	45	84	46.43%	9.14	847.79
4	Social	1 (0.04%)	0	46	10.87%	26.96	949.52
	Total	2521	1711	11841	15.07%	13.59	970.44

d) Sustaining Interest

The week-wise traffic in terms of page views was also captured and analysed. Page views measure the total number of pages viewed, including repeated views of a single page. In Fig. 5, first week and last week page views were more as compared to remaining weeks which may be because participants explored more content during the starting of MOOCs. This means that the interest in learning is more and participants need to be more attentive towards completion of remaining modules, assignments and knowledge tests during last week. Sustaining uniform interest across all weeks is a major issue that can be addressed through more online engagement, interactivity, synchronous learning, discussion threads etc.

The session duration is the direct measure of users' engagement on the eLearning platform. The session times and the page views were directly proportional, which is depicted in Fig. 6. The page views significantly increased with an increase in session duration of more than 3 minutes. The more pronounced upward movement was noticed when the duration was about 30 minutes. It was found that a session duration of 11-30 seconds had fewer session times and page views as compared to other session duration Fig. 6.

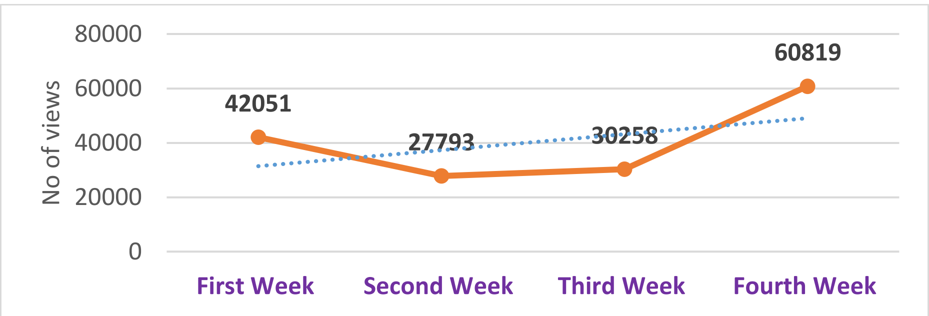

Fig. 5. Weekly traffic on Learning Management System

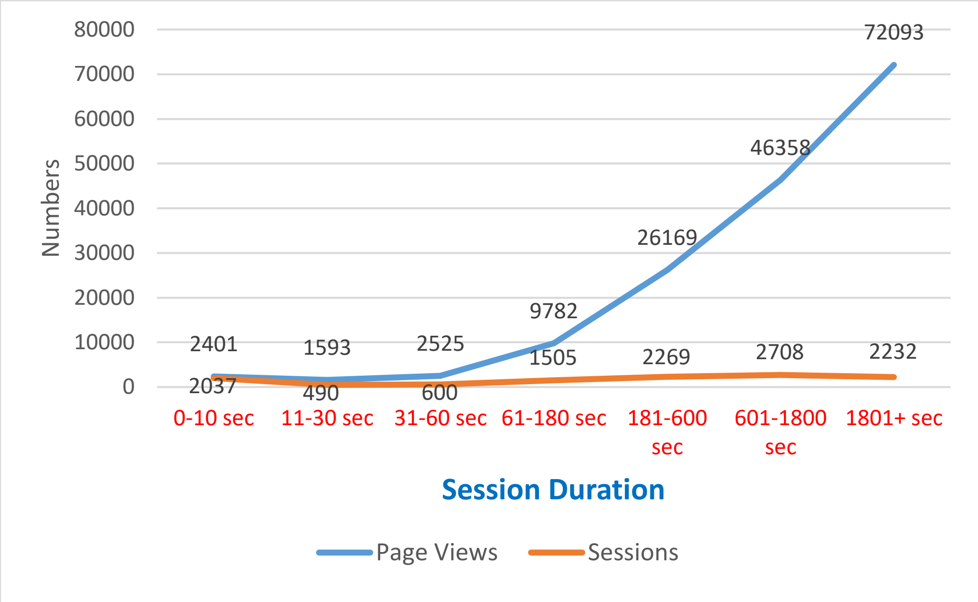

Fig. 6. Users Session times and Page views

Table 2. Paired t-Test for Pre and Post knowledge scores of MOOCs participant (n=157)

Parameter	Before MOOC	After MOOC
Mean	52.611	66.898
Variance	234.803	155.053
t statistic	1.65 (p-< 0.001)	

e) Learners Performance

The performance of 157 learners who attended both examinations i.e. pre-knowledge test and a post knowledge test were analysed using the paired t-test (Table 2). The results indicated a significant increase in the knowledge level of MOOCs users at a one per cent level. The average knowledge score of the participants increased from 52.61 to 66.89 after participating in the MOOC. In future, all online courses, are expected to have an online component to some extent. Integration of technology into formal education has become a necessity especially during the pandemics like COVID19. The MOOCs undoubtedly holds promise as the mode of knowledge acquisition and future capacity building as most of the MOOCs learners had sustained interest even after two years of participating in MOOCs. To increase its positive impact, technology has to be simple to motivate learners and evaluation methods have to be properly strengthened to suit different scenarios. Consideration of online education as a means of scholarly development, improvement of self-esteem, increasing competition among institutions, models that cope with declining public funding, development of a digital marketplace for global higher education etc. are some of the critical factors attributed to the promotion of MOOCs [18].

4. CONCLUSION

Learning analytics helps to understand learning paths and strategies to improve the learning management system continuously. This case study analysed user participation in MOOCs focussing on different aspects of learning behaviour, changes in the perceptions and actual situations and the effectiveness etc. The study identified the critical elements of an effective online course viz. learners' profile, online learning environment, preference for MOOCs, temporal changes in perceptions, access to digital devices for online learning, internet connectivity, learning management system, engagement of learners, online traffic dimensions, quality of resources learners' performance etc. Consideration of these factors in the design and development of online courses leads to the improved online learning experience and thus the quality of education. The experiences of the present case study point out the development of the user-friendly design of the Learning Management System, often missing in open-source software. However, the present study portrays future research in using the customised artificial intelligence and machine learning tools for better prediction models of learners' performance and retention rates. Support systems for the development of learning content suitable for different devices with features such as easy tracking and assessment, seamless delivery suitable etc. are very much essential in development.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by the personal efforts of the authors.

CONSENT

It is not applicable.

ETHICAL APPROVAL

The case study was carried out with the participants of MOOCs on Dynamics of Teaching-Learning organised by ICAR National Academy of Agricultural Research Management and with prior ethical approval

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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