Learners Expectations and Motivations using Content Analysis in a MOOC

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Abstract: The phenomenon of massive open online courses (MOOCs) has transformed the online educational delivery of courses around the world. There are several literature on MOOC publicity in the press, but little has been mentioned and discussed about the learner expectation and motivation. This paper investigates MOOC learner expectations and motivation from different perspectives. What they are hoping to achieve and how they prefer to learn. Firstly, we review existing literature bringing findings that correlate with learner expectations and motivation. We provide discussion from previously analysed research to review the relationship in expectation leading to motivation. Secondly, using the initial pilot investigation, we provide preliminary analysis of data from computing for teachers MOOC, run by the University of Warwick, UK hosted using Moodle platform. The first pilot study of CfT MOOC registered over 500 participants in 2013/2014. The CfT MOOC is of two main strands, programming and computing concepts delivered within the two modes of "traditional peer to peer support" which is free and "tutor supported" mode with real-time mostly by Google hangout and it is a paid mode. The focus in this paper is mainly on the activities and expectations of CfT MOOC participants. This paper explores the perspective of the learners' expectations and motivations to participate. The method we applied to retrieve the information was to use a survey about learner's knowledge, expectation and plans during the course in a text content. These preliminary content-based results were analysed to obtain the level of experience and desires of the participants. Finally, we discuss our preliminary findings on the expectations of the learners, and motivations of the learners measured using a qualitative content analysis analysed using statistical package for the social sciences (SPSS). The learners' expectations were classified into four categories according to their related theme. In the long run the research findings can be anticipated to inform further intervention by incorporating adaptivity as an effective model of MOOCs design.

Introduction

Motivation is revealed, as a factor of encouraging more participants in an online course because learners are given options to study in their area of interest. MOOC learners have shown different motivation beyond solely "utilitarian or learning goals" (Wang, 2014, Siemens, 2006). In a course where learners are not given options to navigate as the wish, these courses suffer motivation and lead to high dropout rate (Anderson, 2013, Carr, 2012, de Waard, 2011,Knox, 2012,Pappano, 2012). Majority of learners register for MOOC based on subjects they find interesting and familiar with. In this study of *CfT* MOOC, several participants already have their interest and expectations. A survey is conducted to acquire full understanding of the reasons for registering in the MOOC. Results show many expectations and motivation, which were the basis for these research findings evaluated using a content-based analysis.

Content analysis of data reduction is known as a key element of any qualitative analysis, hence the method respect the quality of the qualitative data (Cohen et al., 2007). Weber (1990) pointed out that content analysis is "a process by which the many words of texts are classified into much fewer categories". According to Flick (1998) the goal of content-based analysis is to reduce the material in different ways. The categories are normally obtained from "theoretical construct or areas of interest" planned ahead of the analysis. It is a "pre-ordinate categorization" rather than created from the actual data from respondents. However, these can be modified with reference to the empirical data according to Cohen et al., (2007).

This paper firstly, reviews literature relating to learners expectations and motivations in MOOCs. Secondly, preliminary data from the Computing for Teachers (CfT) MOOC pilot on learners' motivations and aspirations is then presented, discussion on the methods applied for the analysis. *CfT* Developed at the University of Warwick was run in two parallel modes "peer-supported" and "tutor-supported" modes. Finally, the expectation and motivation is measured using survey questions based on demographic were analysed to acquire the knowledge level of the participants. The survey empirical data was captured using online Google tool to collate the data for analysis using statistical package for the social sciences (SPSS) application. The data is further analysed with the popular content analysis methodology for text or word data analyses. In conclusion, we discuss issues arising from the findings and future research directions.

Literature Review

When to Conduct Survey in a MOOC

This survey is done drawing experience of the qualitative survey conducted by Edinburgh MOOC (MOOCs@Edinburgh, 2013). The CfT evaluation was based on over 500 registered participants. The survey was conducted during and after the first course delivered in 2013/2014. According to Edinburgh MOOC report, they conducted their survey based on 6 exit, one per course and each comprised 15 standardized questions. *CfT* conducted demographic information based on survey respondents by incorporating and comparing the course specific standardized questions. Edinburgh conducted their survey within the first few months of the program across the 6 surveys (Lane, 2013). They recorded 15,210 responses, which approximately shows 4.9% of the total enrolment and 9.2% of active participants. As observed in Edinburgh MOOC, the survey revealed that most participants about 96% were interested in learning more about the subject area. Similar expectations was observed amongst *CfT* participants which revealed majority of respondents' reasons for participating in the MOOC was to learn new computing curriculum. It also seems likely the respondent's initial education background might not be computer science as also their main reason for registering was "to learn more about the subject" (MOOCs@Edinburgh, 2013, Macleod, 2015). The majority of the learners of *CfT* were teachers of computer science. They all desired to have their expectations met after the course. There are some degrees of similar expectations amongst the learners. The majority of the participants were from the U.K. and few from outside the UK. The teachers' goals were to gain more computing knowledge in order to deliver to their students. CfT MOOC observed much higher level of commitments from the teachers and professionals. As observed in Edinburgh report, majority of the people who enrolled in the MOOCs had low rate of engagement, which reflect a passive participation rate in some areas of the program (MOOCs@Edinburg, 2013). Davis et al., (2014) claimed they grouped their survey questionnaire on the following themes: The first section was to obtain basic details about the learners, the second focuses on the level of education, third was to know their motivation, and how many MOOC they had participated in, experiences and tools applied, and lastly their reasons for participating and leaving if that was the case.

Learners' Motivation

Learners' motivation to register and participate in a course is significant to MOOCs providers (Davis et al., 2014). Yuan et al., (2013) however mentioned some factors that influences learners' motivation to learn such as future benefit, personal development, challenges, and fun. Belanger, et al., (2013), claimed "the survey conducted by researchers at Duke University show that student motivation typically fell into one of four categories" namely:

- *"To support lifelong learning or gain an understanding of the subject matter, with no particular expectations for completion or achievement,*
- *For fun, entertainment, social experience and stimulation,*
- *Convenience, often in conjunction with barriers to traditional education options,*
- *To experience or explore online education".*

However, during the pre-course entry survey, majority of the participants selected fun and enjoyment as the most important reasons for enrolling into the course (about 95%). As the course progresses, participants make an informed decision whether to further into higher education. At the end of the course, a post-course survey was carried out; this then reveals that most learners have general interest in the course topics (Yuan et al., 2013, Belanger et al., 2013). Some authors such as Williams et al., (2011), Dabbagh et al., (2012), and Redecker et al., (2010) observed that learners demand to learn collaboratively through social media as a means of motivation. Forums have been acclaimed as a form of motivation for learners to derive their aspirations according to (Onah et al., 2014b, Onah et al., 2015).

Learner Analytics

One way to identify learners' expectations and motivations online is through ***learner analytics.*** De Liddo et al., (2011) analysed a learner analytics dataset to shed light on an individual or group learning patterns, and learners' activities in the course at different stages (Breslow et al., 2013) or their ability to proceed to the end successfully or fail and dropout (Barber et al., 2012). According to Kizilcec et al., (2013), these learner analytics presented method of classifying MOOC learners by grouping into levels of engagement. Course completion rate has been one of the most discussed metrics in any MOOC according to Wang (2014). However, this learning outcome was as a result of the construct of learner motivation. Several motivation theorists have argued that mastering learning goals intrinsic motivation (Deci et al., 1985, Elliot et al., 1994, Heyman et al., 1992). Ryan and Deci (2000) established that intrinsic motivation means executing learning activity out of inherent interests, while extrinsic motivation intends to gain separate outcome. Keller et al., (2004) argued that distance e-learning students are faced with motivational challenges being that they have to study independently in several cases. It is also observed that high dropout rates are inherent in distance e-learning (Pardos et al., 2013). With the above observation, suggestions shows that educational enhancement is either a happy moment for the participants in MOOC or otherwise (Davis et al., 2014).

Content Analysis

Content analysis is the process of summarizing and reporting written important content of any data. According to some authors (Flick, 1998, Mayring, 2004, Krippendorp, 2004) who define content analysis as a systematic procedure for the rigorous analysis, investigation and 'verification of the contents of a written data'. They infer it is "a research technique for making replicable and valid inferences from texts", to context of their usage. Content analysis is often applied in analyzing large quantities of text. Cohen et al., (2007) pointed out that it is "facilitated by the systematic, rule-governed nature of content analysis". Krippendorp (2004) mentioned it is an "unobtrusive technique", also it is such that "one can observe without being observed" (Robson, 1993). Content analysis focuses on the meaning in the context of the data, and in a systematic order of the use of codes and categories (Mayring, 2004). However, as the data are in texts formats, there are needs for verification through re-analysis and there is also the possibility of replication. Content analysis is largely used as a device for extracting numerical data from word-based data (Cohen, 2007). Indeed Anderson and Arsenault (1998) argued that it described " relative frequency" and the significant of certain topics to evaluate bias, prejudice in the content materials.

Methodology

This research intends to expand understanding of *CfT* MOOC by analysing how the participant's expectations and motivations correlates towards course completion. The preliminary survey data was distributed to over 500 registered participants at the beginning of the course. At the end of the course the data were measured on the responses. The data evaluation was done using a methodology called content analysis.

Description of the Method

Research methods in education described content analysis as acquire texts, analyses, reduces and interrogates into summary using both "pre-existing categories and emergent themes in order to generate or test a theory" (Cohen et al., 2007). They mentioned that "it uses systematic, replicable, observable and rule-govern forms of analysis in a theory dependent system" for application of the categories.

Ezzy (2002) argued that content analysis uses texts and the categories to be used during the analysis, review, code and placed the code into categories. Then counts and log text occurrences, the codes and categories. Then statistical analysis and quantitative methods are applied to the data results.

CfT Participants' Expectations

The classifications was categorised into four themes. The criteria for selecting these themes were made from the most popular and related expectations of the learners. We then classified how closely related the expectations matches the four themes as follows:

1. *Learn how to deliver new computing curriculum*
2. *Expanding computing knowledge*
3. *Learn more about programming*
4. *Improve programming skills*

Learn How to Deliver New Computing Curriculum: Here in this category learners desire to acquire enough experience and knowledge to deliver the new computing concepts introduced by the U.K. government to educate KS3, KS4 in schools. Majority of the learners are young and registered to learn the fundamentals of computing to be able to deliver the new computing syllabus. The learners in this category were here to gain an insight on how to deliver the new computing curriculum courses in A-levels. Learners in the category also aspire to gain a qualification to teach new computer science concepts in schools. There were some head of schools participating in the CfT MOOC in order to refresh their knowledge on the new computing curriculum to apply the teaching concepts to their schools. Some participants aspire to develop understanding the concepts of teaching computing in schools. Some basically wish to develop their knowledge to support non-computing teachers in their schools.

Expanding Computing Knowledge: In this category participants wished to expand their computing knowledge to be able to teach the concepts in colleges. Learners in this category also desire to have a solid introduction to computing concepts and advance their teaching skills. While other learners wished to have confidence in teaching computing.

Learn More About Programming: In this category, learners aspired to learn basic Python programming language to be able to teach in schools. Participants aspired also to have a solid knowledge on programming concepts in Python and how to apply it in their teaching. Most of the learners wish to apply the knowledge to teach Python programming to KS3 and KS4 levels.

Improve programming skills: This category shows participants who are already knowledgeable in programming and wanted to extend to programming in Python. They already had basic knowledge and foundation into programming so they wanted to improve their skills to teach programming better. The learners aspired to advance their knowledge of computing programming. Several participants in this category desire to have a deeper understanding of Python programming added to their other programming language skills.

Demographics of CfT Learners' Expectations

At the launch of the course, there was a survey conducted to over 500 registered participants in *CfT* MOOC. There were continuing enrolments of participants in the course after the survey was sent to participants. According to Zimmerman, et al., (2001), a MOOC relies on the decision of learners to control their learning technique and motivation. Barnard-Brak et al., (2010), however, mentioned that motivation is an essential part of self-regulated learning processes. Intrinsic motivation helps in performing learning tasks and improves learning performance (Barnard-Brak et al., 2010, Lane, 2013). CfT conducted brief preliminary analysis on gender expectations. The demographics in this research will be conducted on the male and female expectation categories.

Male Expectations: These expectation categories were collected on 328 male responses. These categories were designed using popular Google doc to capture the data in Excel. The data was analysed using content analysis methodology. Further analysis was done on the categorised data using Statistical Package for the Social Sciences (SPSS). It has been indicated from the analysis that 54% male wish to learn how to deliver the new computing curriculum, 22% wish to expand their computing knowledge, and 13% desire to learn more about programming, finally 11% aspired to improve upon their programming skills (as shown in Figure 1). The mean percentage observed within the four categories analysed was 25%. The other important demographic evaluation was the age analysis. We wanted to observe what age range desired to acquired more knowledge within the study. The result shows that ages of the male participants reveals 4% was under 25 years, 33% was in the range 25-43 which shows the highest respondents, 29% was in range 35-44, 24% was in range 45-54, 9% was observed in age range 55-64 and finally over 65 had the least of 1%. These reflect younger male participants from age range 25-44 aspired more in the CfT MOOC program while the older participants in age range 55-65 aspired less.

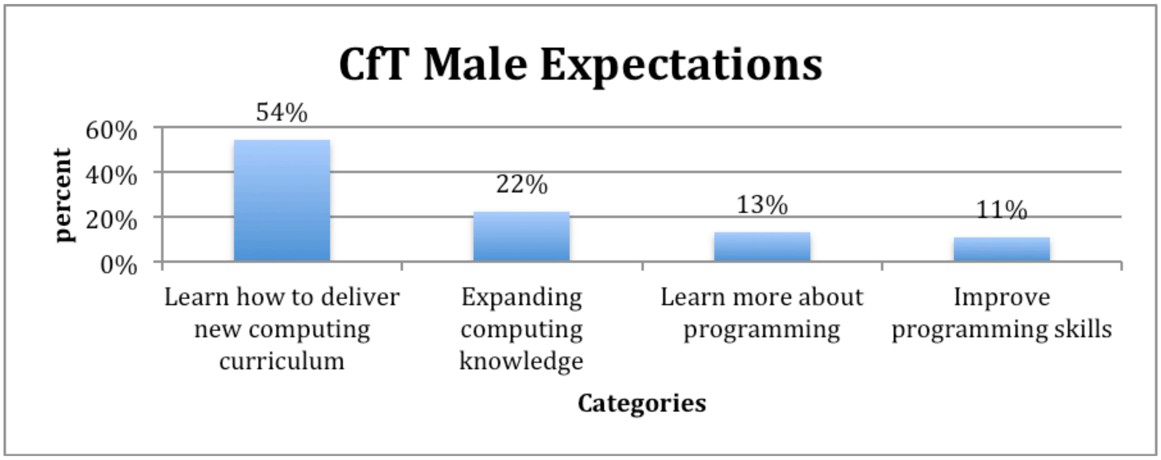

Figure 1. Shows the percentage of male expectation categories

Female Expectations: The classification was based on 228 registered female participants. As discussed in the male category, it has been observed that 50% of female desired to learn how to deliver the new computing curriculum in schools, 26% aspired to expand their computing knowledge, 11% wanted to learn more about programming, and finally 12% aspired to improve their programming skills (as shown in Figure 2). The average percentage of the female categories was 25% same as male. This revealed a close margin between male and female expectations. In the aspect of the female age range, we observed 1% was under 25 years, 25% was observed around 25-34 years, age range 35-44 showed 31%, 45-54 shows 33% which was revealed as the highest. Also as observed in the male categories, we discovered similar percentage expectations categorised in the age range 55-64 which was 9% and the over 65 which was observed to be 1%. These reflect middle age female participants in the range 35-54 aspired to gain more in the CfT MOOC program while there was a drop in the younger female participants, and the older female participants.

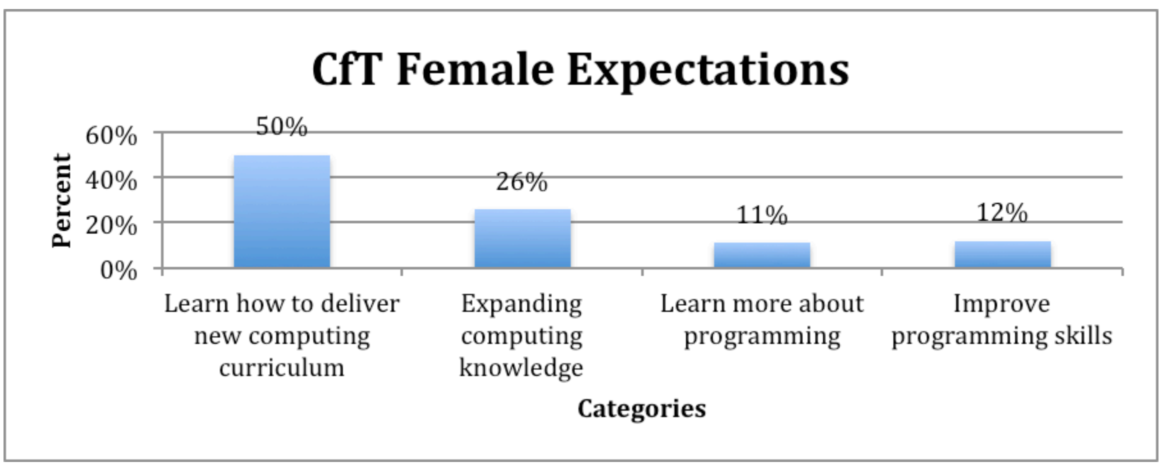

Figure 2. Shows the percentage of female expectation categories

CfT Survey Analysis

For the learners' motivations, an online survey was conducted to acquire information about their experiences and expectations in participating in *CfT* MOOC, looking in depth to obtain the reasons why

learners register and observing their behaviours in *CfT* MOOC. The survey was conducted to investigate if the learners' expectations were met and how they became motivated with their study patterns. According to Edinburgh report in response to one of their survey questions "Did you feel you got what you wanted from the course?" 45% agreed yes completely, 32% agreed yes, the course met their expectations, 21% to some extent and finally 2% said no (MOOCs@Edinburgh, 2013). CfT incorporated similar questions in the survey conducted during the course progression.
Figure 3 revealed the question; 'I know a lot about computer programming and concepts'. This showed 44.12% of neutral respondents, 20.80% agreed and 23.15% disagreed. Although learners with different expectations responded to the question, this will enable us measure level of computer programming.

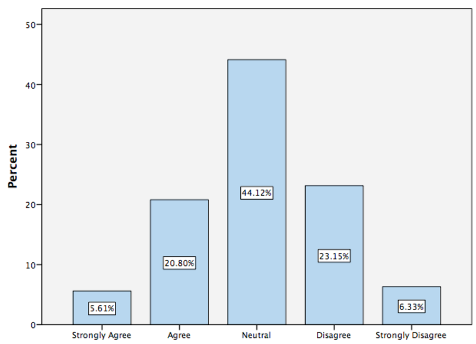

Figure 3. I know a lot about computer programming and concepts

Figure 4 shows the respondents to the question 'I know a lot about teaching others', obviously reveals the program was developed to support teachers to be efficient in their teaching due to the percentage responses received, this revealed 42.50% agreed, 35.08% strongly agreed and 1.99% disagreed.

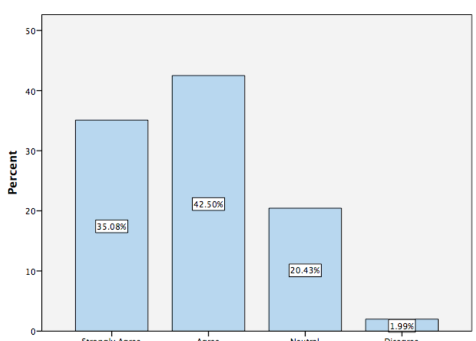

Figure 4. I know a lot about teaching others

Figure 5, however, indicated that the majority of participants have several online learning experiences. This revealed 21.70% strongly agreed, 42.13% agreed to the survey question 'I am very familiar with online learning' and 6.87% disagreed.

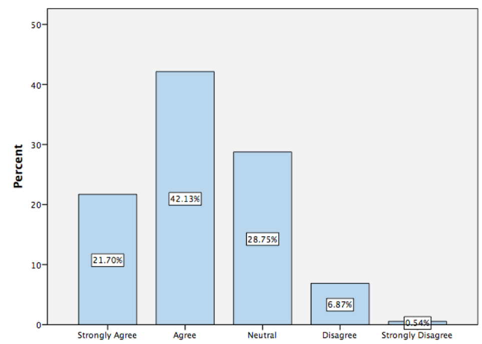

Figure 5. I am very familiar with online learning

Figure 6 reveals participants that learned well when information were represented graphically. The survey showed 42.50% agreed and 2.89% disagreed. This analysis revealed more people will prefer to study when the study material have graphs, charts, diagramatic representation of concepts.

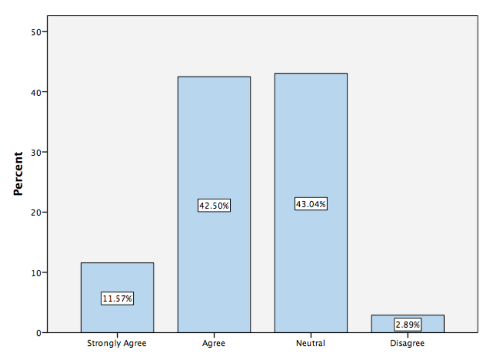

Figure 6. I learn best when information is depicted visually

The survey question in figure 7 revealed participants who learn better when information is heard or spoken. The analysis showed 25.50% agreed and 15.01% disagreed.

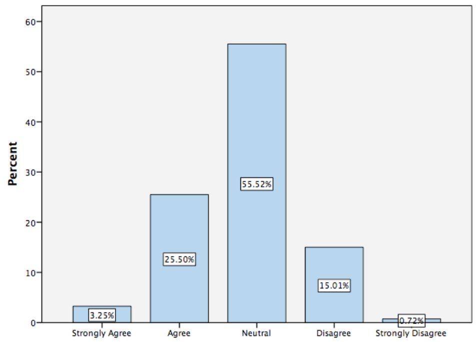

Figure 7. I learn best when information is heard or spoken

Some participants preferred to 'learn when information is displayed in words' as revealed in figure 8. This showed 33.27% agreed and 6.15% disagreed.

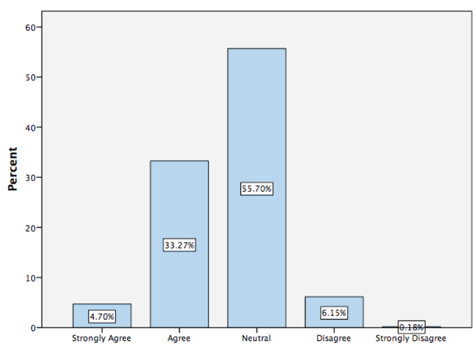

Figure 8. I learn best when information is displayed as words

In another survey question, participants responses to the question 'I learn best through watching or doing an activity' indicated 30.74% strongly agreed, 44.85% agreed, 0.54% diagreed and 0.18% strongly disagreed as illustrated in figure 9.

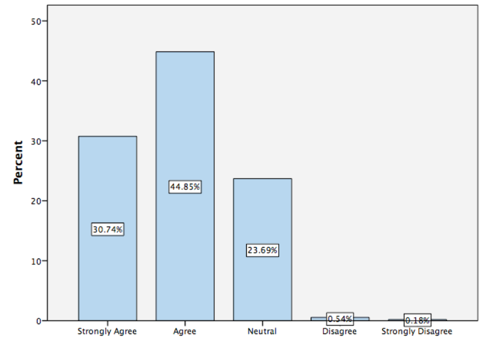

Figure 9. I learn best through watching or doing an activity

Figure 10 revealed 18.99% agreed and 16.09% disagreed for the survey question ' I prefer to learn in groups or with other people'. This analysis did not reveal much collaboration in the study.

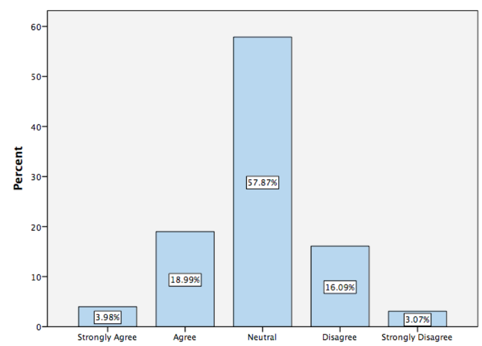

Figure 10. I prefer to learn in groups or with other people

Figure 11 illustrated participants who preferred to work all by themselves and use self study. This indicated that 32.73% agreed to the survey question ' I prefer to work alone and use self-study'.

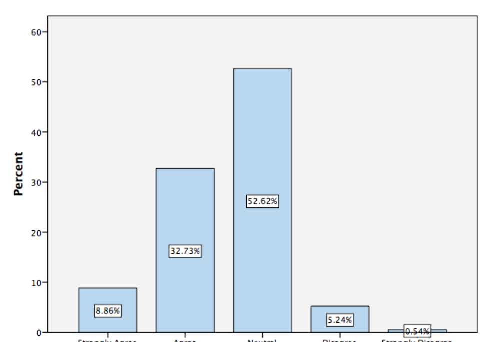

Figure 11. I prefer to work alone and use self-study

In summary, age has an effect on how participants learn best. This was indicated in the *CfT* survey analysis as revealing high performance recorded within the youthful age range. Also majority of the participants prefered to be neutral in their responses as observed in the survey questions analysed.

Preliminary Contribution

MOOC learners represents vast online learning community with diverse motivational interest (Kizilcec et al., 2013, Pardos et al., 2013, Veeramachaneni et al., 2013). The low completion rate in MOOC is as a result of lack of enthusiasm in the course engagement to motivate learners toward participation. However, some issues of low completion rates in MOOC might not been that the learners are not motivated to participate, but as claimed by Onah et al., (2014a) some of the learners are engaging with the course at their own pace. In this new innovative context, MOOC completion rate can be related to learners expectations and motivations are imperative to understanding learner's goals (Wang, 2014). CfT survey analysis indicated that better performance in the course expectation and motivation was observed in the young generation as compared to the older participants.

The preliminary results indicated how *CfT* expectation and motivation can increase correlation with course completion and participation. By understanding the expectation and motivation of a learner, this can help educators and course developers to create adaptible courses profoundly to the learners interest and achievable goals. Our survey reveals the importance of expectation and motivation to supporting better learning and participations. As course developers and instructors considering learners expectation and motivation before creating and developing learning management system (LMS), then we predict the high dropout rates talked about in MOOC will be reducing due to the encouragement learners will receive from their motivation to complete the course, thus completion rate will be high. Future intervention is proposed to develop a learning management system suitable to the learning preferences of an individual learner expectation.

Conclusions & Further Work

MOOC has rapidly evolved in terms of popularity in the delivery of online educational contents. Despite these massive hype of attention, they are new to distance and online learning. MOOC have encountered drastic dropout rates as described in (Onah et al., 2014a) from learners, which make the system to be difficult to reconcile with. This paper has considered looking into the expectation and motivation of learners of computing for teachers MOOC. CfT MOOC reveals most of the learners were participating to acquire more knowledge on how to deliver computing concepts and programming in schools. This research discusses learner expectations as a factor of motivation to each individual learner who studied based on their knowledge and experience. Several learners participated in the course for specific reasons, in the situation where goals are not achieved, this leads to dropout from the course (Onah et al., 2014a).

The participants' expectations and analysis presented in this paper reflect the motivation observed from the over 500 registered learners in *CfT* MOOCs. The expectations were classified into four categories using content analysis method, according to themes related to individual expectations. The selection was logically allocated to the right theme suitable for each expectation. The method for conducting the content analysis of the expectations follows certain patterns of survey to capture the motivation for participating. The survey evaluation reveals that majority of the participants are already teaching GCSE computing (about 41.2%), and 36.6% aspired in their planned preferences to advance their knowledge of teaching GCSE computing after completion. The research indicated the effect of the age range in the performance expectation and motivation within the course. This revealed youger participants of both genders male (25 - 54) and female (35 - 54) where rated in the analysis as high in participation. Further work is needed to investigate learners' motivation and preferences to different learning patterns. We intend to uncover aspect of course adaptivity for MOOC instruction so as to inspire effective learner participation.

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