The ABC of MOOCs: Affect and Its Inter-Play with Behavior and Cognition

Shazia Afzal*, Bikram Sengupta*, Munira Syed†, Nitesh Chawla†, G. Alex Ambrose† and Malolan Chetlur*
*IBM Research, India, Email:{shaafzal,bsengupt,mchetlur}@in.ibm.com
†University of Notre Dame, Email:{munira.syed.6,nchawla,gambrose}@nd.edu

***Abstract*—We report on a study of affective states of learners in a Massive Open Online Course (MOOC) and the inter-play of Affect, Behavior and Cognition at various stages of the course. Affect is measured through a series of self-reports from learners at strategic time posts during the period of study. Behavior is characterized in terms of a learners' engagement, interactivity, impatience and reflectivity, which constitute a set of novel high-level features derived from the clickstream of learner interactions. Cognition is evaluated from the performance of learners on assessments that are part of the course. We discover that learners in the MOOC experience multiple as well as mixed emotions as they go through the course, which we handle using the psychological dimensions of arousal and valence. This results in a set of emotional quadrants, whose co-occurrence analysis reveals a strong association with cognition and specific behavioral characteristics demonstrated by the learner. These results advance our understanding of the experience of MOOC learners to a more holistic level across the key dimensions of affect, behavior and cognition. They also have important implications for the design of the next generation MOOCs that can potentially leverage affect and behavior-aware interventions to drive greater personalization and eventually, improved learning outcomes.**

1. Introduction

Affect is related to cognitive, motivational and behavioral processes and is considered as an key determinant for successful learning gains [1], [2]. It is therefore crucial to have access to and ensure the emotional well-being of learners for targeted and timely feedback as well as for mitigation of affect states deemed obstructive towards learning [3]. This becomes even more critical in a self-paced learning experience as offered by traditional MOOCs. MOOCs in the present form is a typical example of a self-regulated learning model where the learner is in complete charge of the pace and strategy of learning [4]. The value in participation and performance therefore depends entirely on the motivation of the learner and the significance attributed to the content for personal goals and expectations. While it is difficult to control for people experimenting with a MOOC one can certainly aim to make the learning experience richer and more effective for learners in general. A practical strategy would be to investigate learner engagement and behavior patterns to understand the nature of interaction and overall experience. Affect forms an indispensable part of this experience and its evaluation a critical variable in the design of an adaptive and personalized MOOC learning experience.

In this work, we report on a study of affective states of learners in a MOOC and the inter-play of Affect, Behavior and Cognition at various stages of the course. The MOOC we study is an introductory course on Statistics offered on the EDX platform. We investigate and report on the following Research Questions in this paper:

RQ1: *What affective states do learners go through while taking a MOOC? How stable are these states over time, and which transitions across states are more (or less) likely?*

RQ2: *Are there any significant relationships between a learners' reported affect, observed behavior and cognition?*

We find that learners in the MOOC experience multiple as well as mixed emotions as they go through the course. Learners also have a higher likelihood of persisting in the same emotional state (or quadrant) across course segments than transitioning to a different state. Co-occurrence analysis reveals a strong association between the affect, observed video behaviors and the learning outcomes. Learners expressing negative emotions are associated with low performance. In terms of learner behavior, high interactivity is not necessarily associated with desirable outcomes and skipping portions of videos is not necessarily bad. Our results have significant implications for the design of the next generation MOOCs as they can provide the foundation for affect and behavior-aware interventions that drive greater adaptivity and personalization and eventually improved learning outcomes. While we see this work as novel within the space of MOOCs, there exist earlier efforts to study affect transitions [1], [5], [6], [7] and the inter-relations between affect, behavior, and learning outcomes [8], [9], [10] although mainly in the context of ITSs.

The paper is organized as follows: Section 2 introduces the MOOC we investigate in this paper and describes our study design. Section 3 reports on our findings on learner affective states and transitions. Section 4 discusses the relationships observed between affect and learner behavior and cognition. Section 5 summarizes the findings of the study and its implications, while Section 6 concludes the paper by discussing current limitations and directions of future work.

2. Course Structure / Study Design

This work is based on an introductory course on Statistics offered on the EDX platform as a traditional MOOC.

978-1-5386-0563-9/17/$31.00 ©2017 IEEE

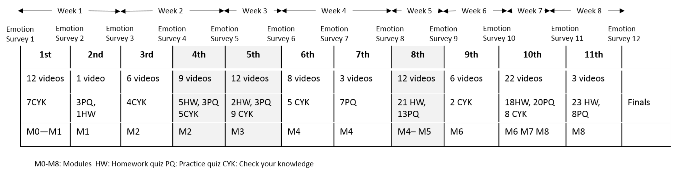

Figure 1. Course Structure and Segments for analysis

The course comprised of eight modules plus a final ninth module consisting of assessment of the overall course. The demographic information of the students was not collected during the course so the data used for analysis in this paper does not contain any personally identifiable information. The MOOC had a total enrollment of 24,279 students from across 183 countries. However, only about 15,000 students had any activity recorded in the beginning two weeks. There was a significant dropout of students in the initial two weeks to approximately 8000 by third week to just about 1200 students who continued in the course until module 8. In this paper, we included only those students who accessed the course content in module order, participated in the self-reported emotion surveys at least once and completed the emotion self-reports in time order. This resulted in data from 5057 students (4167 dropped out before module 8, 890 completed until last module).

As part of the course design, a total of 12 periodic emotion surveys were conducted wherein students were asked to self-report on their current emotional state voluntarily. Compared to sensor-based affect detection methods, self-report is an efficient methodology for capturing the subjective emotional experience of learners, is technically easier to deploy at scale (as in a MOOC) and has high face validity. The number and placement of these surveys was designed to balance the need to collect a learners' affect data at regular periodicity while not imposing too much burden on the learner or not coming across as overly intrusive. In each survey, a student was asked to categorize their affect state by selecting at least two emotions from a pre-selected list of fifteen emotions. The list of emotions were derived from previous studies on learning-centric emotions [2] and some that were considered relevant to a MOOC setting e.g. Isolation. The final list of emotions consisted of: *anger, anxiety, boredom, confusion, contentment, disappointment, enjoyment, frustration, hope, hopelessness, isolation, pride, relief, sadness, and shame*. No specific definition of these emotions was provided to students as these are commonly used in everyday language and therefore intuitively familiar.

The 12 emotions surveys formed eleven segments of learning activities (as shown in Figure 1). While we included all emotion surveys to study affect distributions and their transitions, we selected only the fourth, fifth and eighth segments to study the relation between affect, behavior and cognition as these had learning activities and emotion self-report in temporal proximity for correlating affect, behavior (video related) and cognition (from home work quiz) related information.

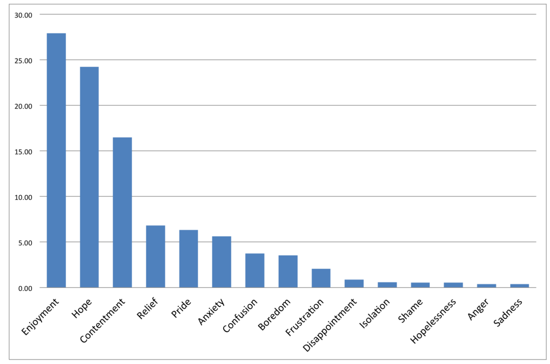

Figure 2. Distribution of reported emotions across all surveys

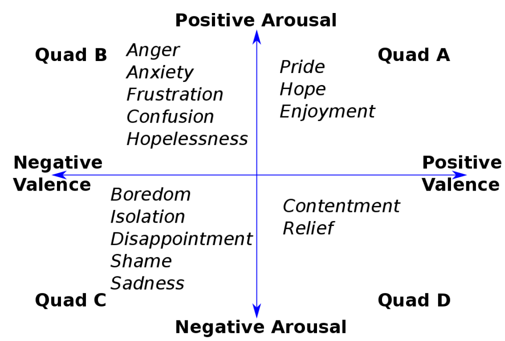

Figure 3. Learning emotions grouped into quadrants using ANEW [11]

3. Findings / Affect

This section addresses the first research question RQ1 in Section 1 based on our findings with respect to learners' affect and its transitions over the course of the MOOC. Figure 2 shows the distribution of learner reported emotions aggregated across all surveys in the course. The Y axis shows % of surveys where a given emotion (on X-axis) was reported. The raw emotions reported in the surveys demonstrate the breadth of affect states experienced by learners. There is also a clear skew towards the positive affect states of Enjoyment, Hope and Contentment, followed by Relief and Pride. Amongst the reported negative emotions, Anxiety is prominent, followed by Confusion, Boredom, Frustration and Disappointment while the remaining negative emotions (Isolation, Shame, Hopelessness, Anger and Sadness) constitute a long tail. Interestingly, we observed that emotions reported together were sometimes of opposite polarity e.g. Hope and Anxiety. About 5% of responders selected more than three emotions at once.

3.1. Emotion Quadrants and Trajectories

To deal with the multiple emotion states and their skewed distribution in our analyses, we adopted a principled approach to group related emotions in accordance with the well-established psychological dimensions of valence (positive and negative) and arousal (activating and deactivating). Using the valence and arousal values for individual emotions from the Affective Norms of English Words [11],

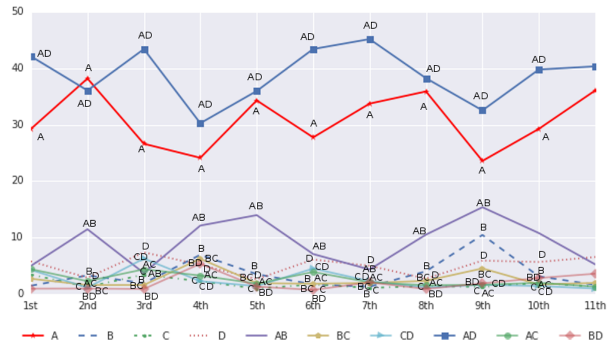

Figure 4. Trajectories of affect quadrants across the course

we grouped the self-reports into four quadrants based on positive/negative valence and high/low arousal values. The resultant quadrants and emotions they comprise are shown in Figure 3. Quadrant A consists of Enjoyment, Hope and Pride, Quadrant B of Anger, Anxiety, Confusion, Frustration and Hopelessness, Quadrant C of Boredom, Disappointment, Isolation, Shame and Sadness; while Quadrant D includes Contentment and Relief.

Interestingly, this membership broadly maps onto Pekrun's categorization of academic emotions as positive activating (Quad A), negative activating (Quad B), negative deactivating (Quad C) and positive deactivating (Quad D). Only the emotions Shame and Hopelessness exchange their positions when compared with Pekrun's categorization but since the incidence of both is very low in our dataset ($< 1\%$) it does not have any significant impact on our results. So while reducing the complexity of analyzing 15 different emotions expressed by the learners in various combinations, these quadrants also have a theoretical basis in their effects and outcomes to be clustered together. Pekrun for example associates each quadrant with the use of specific learning strategies and learning effects [12]. One can think of developing affect adaptation strategies on similar lines.

When learners reported more than one emotion at a time, these were often close enough to map to the same quadrant. However, at times, these were drawn from different quadrants. We grouped such self-reports according to their membership across combinatory quadrants like AB, AC, and so on along a hypothetical third dimension. The combinations of more than two quadrants had negligible occurrence ($< 1\%$) which is why we consider only Quadrants A, B, C, D, AB, BC, CD, AD, AC and BD for further analysis in the paper.

Figure 4 shows the longitudinal trajectory of these emotion quadrants over the successive segments of the course, aggregated from the reports of all learners. Quadrants A, AB and AD showed the highest percentage distribution across all the surveys implying that emotions in these quadrants are most frequently occurring irrespective of the position within the course. The pre-dominance of positive emotions is similar to findings in ITS where students report Enjoyment or Flow most frequently (e.g. see [1] and [5]). The occurrence of negative states as in Quadrants B and C follow similar

TABLE 1. TRANSITION LIKELIHOOD VALUES AT P$<$ 0.0001

Quadrants	A	B	C	D	AB	BC	CD	AD	AC	BD	Do	F-score
A	**0.27**	-0.01	0.00	-0.01	-0.02	-0.01	-0.01	**-0.16**	0.00	-0.01	0.00	44.98
B	**-0.14**	0.15	0.01	0.01	0.05	0.06	0.03	**-0.16**	0.02	0.03	0.06	8.06
C	-0.03	0.10	**0.21**	0.04	-0.03	0.13	0.04	**-0.30**	0.07	-0.01	0.09	7.65
D	**-0.12**	0.02	0.02	**0.18**	-0.01	0.00	0.03	**-0.13**	0.00	0.02	**0.12**	10.18
AB	**-0.10**	0.03	0.00	-0.01	**0.17**	0.02	0.00	**-0.16**	0.00	0.01	0.01	22.57
BC	**-0.17**	0.08	0.03	0.01	0.00	**0.19**	0.03	**-0.17**	0.01	0.04	0.07	12.24
CD	**-0.23**	0.03	0.07	0.05	-0.03	0.04	**0.20**	-0.05	0.08	0.08	0.02	7.20
AD	**-0.11**	-0.01	0.00	0.00	-0.02	-0.01	0.00	**0.24**	-0.01	0.00	-0.03	93.07
AC	-0.05	-0.01	0.05	-0.01	0.00	0.06	0.04	**-0.14**	0.12	0.05	0.01	5.95
BD	**-0.14**	0.06	0.10	0.06	0.09	0.03	0.03	0.00	0.03	0.17	0.07	2.84

patterns of decreasing frequency. It should be noted that B, C and BC are interesting quadrants from the perspective of interventions during learning as they feature only negative emotions that may have a detrimental effect on learning.

3.2. Emotion Quadrant Transition Likelihoods

Recent studies have analyzed the affective trajectories of critical learning relevant emotions like boredom, flow, confusion, frustration, delight, and surprise. These concur in their findings that learners generally tend to persist in the same affective state [1], [5], [6], [7]. Following this line of enquiry in exploring the emotional transitions of learners, we investigated the transition likelihoods of the learners in our dataset across the different quadrants. To compare with previous work, we compute D'Mello et al. [1] as the transition likelihood for affective transition analysis according to the following formula where C is Current and N is Next:

$$L(C \rightarrow N) = (Pr(N \mid C) - Pr(N)) \;/\; (1 - Pr(N)) \quad (1)$$

The Transition likelihood, L, computes the probability that a transition between two affective states (C$\rightarrow$ N) will occur. The formula accounts for the base frequency of the Next affect state in assessing the likelihood of a particular transition. The denominator normalizes scores between infinity and 1. Therefore, an L value equal to 1 translates to emotion Next always following the Current emotion; an L value equal to zero means the likelihood of Current transitioning to Next is equal to chance while an L value lower than zero indicates the transition to be less than chance.

Here the transitions are computed for each state for each student (total no. of transitions = 25239) and then averaged in order to find the transition likelihood from one quadrant to another. The mean values of L are then compared in a series of ANOVAs to determine whether the differences are statistically significant. The transition likelihood values for quadrants A through BD are shown in Table 1. The rows in Table 1 represent the Current affect quadrant while the columns represent the Next quadrants. Specifically, each row i of the table indicates the transition likelihoods of quadrant at i to each of the quadrants represented in columns A through to J. ANOVAs indicated significant variation among the transitions at $p < 0.0001$. Significantly meaningful transitions were determined using Tukey post hoc tests and are highlighted in Table 1. The main observations from the transition analysis are:

- State-to-State transitions along the diagonal are all significant except B-B, AC-AC and BD-BD. This indicates that learners have a higher likelihood to persist in the same emotion quadrant than to transition to a different one.
- The transition to B-B is not significant as revealed through post hoc comparisons. B consists of emotions like Confusion, Frustration and Anxiety that are more spontaneous emotions and therefore may have not be as likely to persist as emotions in some of the other quadrants. At the same time, it should be noted that the transition likelihood of B to A and D that are positive quadrants is significantly below chance meaning that learners go into complex emotional orientations after B and not necessarily into a completely positive state.
- Similarly, AC-AC and BD-BD feature emotions from diagonally opposite quadrants making it unlikely to be a stable state.
- The column on Dropout shows the likelihood of each quadrant transitioning into student dropout from the course. Only D appears to be significantly related with Dropout. This is interesting because D has satisfactory but deactivating emotions like Contentment and Relief and could imply a sort of positive dropout wherein the learners have satisfactorily achieved their goals or expectations from course and hence do not continue further.
- With the exception of C and AC, the transition likelihood of any quadrant to A seems to be statistically significantly below chance. Similarly, the transition likelihood to AD from any state except CD and BD is also significantly below chance. This is interesting because both A and AD have the highest distributions across the course also supported by the statistically significant transition likelihood of A-A (0.27) and AD-AD (0.24). This seems to imply that A and AD are the most stable states and that students generally tend to be in positive emotional orientation during the course.

The results of transition likelihood in general correlate with previous research in affect transitions about the persistence of emotional states albeit at a longer time frame. Therefore the fact that learners tend to stay in a particular affect orientation across multiple interactions with learning content often spaced over weeks is an important finding. Also, our findings on transition trajectories and likelihoods of emotion quadrants are novel as opposed to transitions among individual emotions. Finally, it is worthwhile to note that this is perhaps the first formal study exploring affect transitions occurring in a self-paced learning environment as MOOCs as against previous studies that have been conducted in a one-one setting in intelligent learning environments.

4. Inter-Play of Affect, Behavior, Cognition

In this section, we study the relationship between a learners' affect, behavior and cognition in the MOOC in order to address the second research question RQ2. We begin by explaining how we model a learners' behavior from raw video clickstream data and cognition from assessment performance.

4.1. Behavior

The interaction behavior of learners can be characterized using clickstream analysis on the digital trail of their MOOC activities. Analysis of this data can be used to study and uncover patterns of interest that may correlate with higher level categories of interest [8], [13], [14]. While most work in interaction data analysis has focused on prediction of performance and dropout rates, only recently has affect received some focus. The motivation is to explore whether certain behavioral patterns are associated with affect states so that a learner model can be built for eventual affect prediction using clickstream data. In our analysis we attempt to investigate precisely this aspect through a set of measures derived from the raw clickstream events while watching lecture videos.

For a specific video content, there can be multiple viewing sessions. The behavior metrics for a video are obtained from the behavior metrics of its individual sessions. The lecture videos are split into segments to measure the portions accessed. In our experiments, the video segments are of length 10 seconds.

Impatient: For a specific video content and video session, the impatience score of a learner is the fraction of video segments not yet watched with respect to the total number of segments in the video and considering segments watched in past sessions. The Impatience score of a video and group of videos is the average of impatience scores across all viewing sessions and individual videos in the group respectively.

Reflective: For a specific video content and video session, the reflective score is the fraction of video segments rewatched during the current session with respect to the total number of segments in the video and considering segments watched in past sessions. The Reflective score of a video and group of videos is the average of reflective scores across all viewing sessions and videos in the group respectively.

Interactive: For a specific video content and video session, interactivity is the ratio of the total number of events generated in the session to the total session duration in seconds. All browser generated events like play, pause, stop, etc. captured in the clickstream data are considered as interactivity events. Interactivity of a video and group of videos is the average of interactivity across all viewing sessions and videos in the group respectively.

Engaged: For a specific video content and video session, engagement is measured as the ratio of viewing session duration to the length of the video content. The Engagement score of a video and group of videos is the average of engagement scores across all viewing sessions and videos in the group respectively. In the case of overall engagement score, engagement with all videos within a group is considered irrespective of being watched by the learner or not. Therefore, overall engagement score decreases for students when they do not watch all videos within a group.

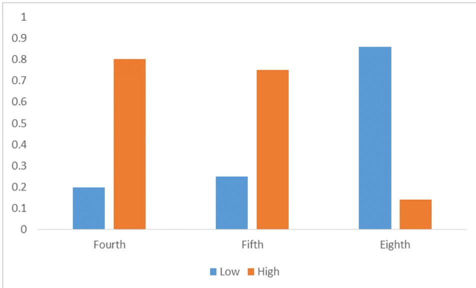

Figure 5. Distribution of performance levels in the segments

The number of forward / rewind events are accounted for as part of a learners overall Interactivity. We consciously avoided using the number of fast forward events as a measure of Impatience and the number of rewind events as a measure of Reflectivity (since many learners close a session early or re-watch in a new session).

4.2. Cognition

We measure cognition as an outcome of learning tested via performance on assessments. The MOOC data set had three sets of assessments: (i) check your knowledge (CYK) with multiple retry option after every video lecture, (ii) practice problems and (iii) homework problems. For the current analysis, we considered the performance scores in only the homework problems as the level of cognition achieved. In our analysis, CYK and practice problems are not considered while measuring cognition as CYK allowed multiple retries while both these assessments were not proximal to emotion surveys when compared to homework problems.

The overall performance in home work problems was above average and therefore, we chose a higher threshold for expected outcome and categorized the students having more than 75% of correct answers in the quiz as HIGH and LOW otherwise. For a group of homework assessments within a time period, similar threshold of 75% of correct answers was considered as cognition level of HIGH. Figure 5 shows the distribution of performance level among the students within individual time periods. It is evident that homework problems in the 4th and 5th time periods had higher performance achievement while the 8th time period had very few students (30%) achieving the HIGH performance band.

4.3. Co-occurrence Analysis

We analyze the association between quadrants and the set of behavior and performance measures using the Lift metric. Lift is a data mining technique used to learn association rules by taking antecedent-consequent pairs (X, Y) and computing the support from data by taking the ratio P(X and Y) / P(X) * P(Y). Lift scores greater than 1 are considered an indication of occurrence more frequently than that expected by chance. Lift scores were computed between the emotion quadrants and the behavior and cognition features for all the three course segments (4th, 5th and 8th). Taking $p < 0.0001$, the significant associations that appear in all the three segments are shown in Table 2. In addition, we computed the Lift for individual emotions against the behavior and cognition metrics. These are discussed in relation with the findings of Table 2.

TABLE 2. CO-OCCURRENCE OF QUADRANTS, BEHAVIOR & COGNITION

Qs	Interactive	Reflective	Impatient	Engaged	Cognition
A				X	
B	X				Low
C	X				
D			X		High
AB					Low
AD		X			High

We find that learners in Quadrant A are associated with high engagement. Individually, Enjoyment within Quadrant A is associated with both high engagement and high performance. Quadrant B comprises of crucial emotions like Confusion, Frustration and Anxiety, and these show an association with low performance but also high interactivity. Quadrant C comprises of negative deactivating emotions and is probably the most undesirable state in terms of its impact on learning. Boredom, a frequent emotion within Quadrant C, shows association with both interactivity and impatience. While one would expect a strong association with low performance here, we find that this occurs only in 2 out of 3 segments. Quadrant D is associated with impatience and high performance. The combination of impatient behavior together with performance is an interesting relationship that could be examined further. Quadrant AB is a combination of individual emotions from Quadrant A and B. Our results show that Quadrant AB co-occurs with low performance. Moreover, Engagement feature associated with Quadrant A is absent in Quadrant AB. Quadrant AD, consisting of emotions from Quadrant A and D, is associated with Reflective behavior and higher performance.

There are few interesting observations from the co-occurrence analysis using the Lift metric. Learners with emotions from only the positive quadrants, D and AD, are associated with high performance. Individual emotions Hope and Pride from Quadrant A and AD are also found to be Reflective, indicating they access portions of the video lectures multiple times when compared to learners from other quadrants. Being Engaged with the content is observed in Quadrant A and this indicates learners engage with the content more often when they are in a positive emotional state. Quadrants with negative emotions (B, C and AB) are not associated with Engaged and Reflective behavior. Quadrants B and AB are associated with low performance. Confusion, an individual emotion from Quadrant B is associated with low performance.

5. Summary of Findings

Our investigation into RQ1 reveals that the learners experienced a wide range of emotions in course of the MOOC. While these emotions are predominantly positive in nature, learners often experience multiple emotions at the same time, and even emotions of opposite valence and/or arousal. Learners have a higher likelihood of persisting in the same emotional state (or quadrant) across course segments than transitioning to a different state. The only exceptions seem to be states dealing with spontaneous emotions (quadrant B) or with emotions drawn from diagonally opposite quadrants. Finally, the statistical likelihood of a learner transitioning to the dominant positive quadrants (from most of the negative or mixed quadrants) seems significantly below chance. This indicates that additional interventions may need to be designed to motivate learners in sub-optimal affect states and shift their trajectories in a positive direction.

Our analyses into RQ2 reveals that there exist statistically significant relations between the affect, observed video behaviors and the learning outcomes. Learners in Quadrant A are engaged with the video lectures, and learners in Quadrant D and AD are associated with high performance. On the other hand, learners expressing negative emotions with positive arousal (emotional states in Quadrant B and AB) are associated with low performance. Also, students in the negative affect states, residing in Quadrants B and C exhibit high interactivity. Overall, Interactivity is not necessarily good and Impatience is not necessarily bad, and these need to be understood in the context of the learners' affect orientation and other behavioral traits to determine whether there is a risk of poor performance outcome. The co-occurrence of affect quadrants with behavioral features validates our initial goal of defining conceptual metrics in order to capture the learning traits of learners based on their video watching activity. As emotional states are complex, the quadrant representation of multiple/co-occurring emotions, as proposed here, can serve as a proxy to study and explore their relation with behavior and performance. This has the potential to design newer and simpler form of affect sensing and appropriate learning interventions when multiple emotions co-occur.

6. Limitations and Future Work

There are a few limitations in our approach that we intend to address in future. We plan to conduct a pre-course survey of registrants to better understand their motivations or goals and see how that correlates with their affect, behavior and cognition as well as their drop-out/retention behavior. The demographic/cultural characteristics of learners may also influence affect or behavior; however, this information was not collected as part of the MOOC we studied, and we intend to cover this in future.

While video lecture viewing is the predominant learning activity, students also participate in discussion forum, surveys, etc., inclusion of which may improve our analysis. Our model of cognition is currently based on a simple performance threshold that results in two categories. Going forward, we intend to explore richer models that may involve finer categorizations and investigation into the nature and complexity of assessments.

Finally, the eventual goal of this research is to provide a foundation for designing personalized and timely interventions based on a well-informed view of a learners' affect, behavior and cognition. In future, we plan to design such an intervention framework for MOOC learners and evaluate its effectiveness in driving higher engagement, improved retention and performance.

References

[1] S. D'Mello, A. Graesser *et al.*, "Monitoring affective trajectories during complex learning," in *Proceedings of the Cognitive Science Society*, vol. 29, no. 29, 2007.

[2] R. Pekrun, T. Goetz, W. Titz, and R. P. Perry, "Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research," *Educational psychologist*, vol. 37, no. 2, pp. 91–105, 2002.

[3] M. Wosnitza and S. Volet, "Origin, direction and impact of emotions in social online learning," *Learning and instruction*, vol. 15, no. 5, pp. 449–464, 2005.

[4] K. OR̀egan, "Emotion and e-learning," *Journal of Asynchronous Learning Networks*, vol. 7, no. 3, pp. 78–92, 2003.

[5] R. J. L. McQuiggan, S. W. and J. C. Lester, "Affective transitions in narrative-centered learning environments," *Educational Technology & Society*, vol. 13, no. 1, pp. 40–53, 2010.

[6] R. S. d Baker, M. M. T. Rodrigo, and U. E. Xolocotzin, "The dynamics of affective transitions in simulation problem-solving environments," in *Intl. Conf. on Affective Computing and Intelligent Interaction*. Springer, 2007, pp. 666–677.

[7] M. M. T. Rodrigo, "Dynamics of student cognitive-affective transitions during a mathematics game," *Simulation & Gaming*, vol. 42, no. 1, pp. 85–99, 2011.

[8] C. G. Brinton, S. Buccapatnam, M. Chiang, and H. V. Poor, "Mining mooc clickstreams: On the relationship between learner video-watching behavior and performance," in *ACD Conference on Knowledge Dicrovery and Data Mining (SIGKDD)*, 2015.

[9] Z. A. Pardos, R. S. J. D. Baker, M. O. C. Z. San Pedro, S. M. Gowda, and S. M. Gowda, "Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes," in *Intl. Conf. on Learning Analytics and Knowledge*, ser. LAK '13. ACM, 2013, pp. 117–124.

[10] R. S. Baker, S. K. D'Mello, M. T. Rodrigo, and A. C. Graesser, "Better to be frustrated than bored: The incidence, persistence, and impact of learners cognitiveaffective states during interactions with three different computer-based learning environments," *Intl. Journal of Human-Computer Studies*, vol. 68, no. 4, pp. 223 – 241, 2010.

[11] M. Bradley and P. Lang, "Affective norms for english words (anew): Instruction manual and affective ratings," *Technical Report C-1, The Center for Research in Psychophysiology, University of Florida*, vol. 30, no. 1, pp. 25–36, 1999.

[12] R. Pekrun, T. Goetz, A. C. Frenzel, P. Barchfeld, and R. P. Perry, "Measuring emotions in students' learning and performance: The achievement emotions questionnaire (aeq)," *Contemporary educational psychology*, vol. 36, no. 1, pp. 36–48, 2011.

[13] T. Sinha, P. Jermann, N. Li, and P. Dillenbourg, "Your click decides your fate: Inferring information processing and attrition behavior from mooc video clickstream interactions," in *2014 Empirical Methods in Natural Language Processing Workshop on Modeling Large Scale Social Interaction in Massively Open Online Courses*, no. EPFL-TALK-202095, 2014.

[14] R. F. Kizilcec, C. Piech, and E. Schneider, "Deconstructing disengagement: analyzing learner subpopulations in massive open online courses," in *Intl. Conf. on Learning Analytics and Knowledge*. ACM, 2013, pp. 170–179.