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Article

VIEWER LEARNING PATTERNS AND ENGAGEMENT BEHAVIORS IN ONLINE EDUCATIONAL CONTENT CONSUMPTION: AN EMPIRICAL ANALYSIS WITH K-MEANS CLUSTER PROFILING AND SPEARMAN CORRELATION OF COMPLETION DETERMINANTS

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Abstract: This study analyzes the learning habits and engagement activities of users of online courses and examines the aspects of content design that are most influential in predicting the rate of course completion. A survey collected responses from 72 users and covered 58 variables related to demographics, content consumption, course participation, and learning satisfaction. K-Means clustering (k=3) was applied on the participants' 28 behavior-related variables that pertained to course content, learning preferences, and course participation, and resulted in the identification of three empirical learner personas: Highly Engaged Achievers (Cluster A, n=10), Moderate Learners (Cluster B, n=59), and Disengaged Passive Learners (Cluster C, n=3). The separation of the clusters was confirmed by a Principal Component Analysis that described two dimensions that captured 38.2% of the variance. Spearman rank-order correlations confirmed that the strongest associations with learning satisfaction were completing practice exercises prior to taking the assessments ($\rho=0.399$, $p<0.001$), Reflection on Real-Life Application ($\rho=0.385$, $p<0.001$), and maintaining motivation through challenges ($\rho=0.379$, $p<0.001$). The weekly study time had the strongest overall association with learning satisfaction ($\rho=0.436$, $p<0.001$). A dropout rate of 61% was attributed mainly to online participants' work/study conflicts (72.2%) and poor time management skills (61.1%). The study proposes, supported by the study findings, content design ideas for each identified learner cluster.

Keywords: online learning, course completion, K-Means clustering, Spearman correlation, learner personas, engagement behaviors, e-learning design, dropout

1. Introduction

The variety of online learning platforms such as Coursera, Udemy, SWAYAM, LinkedIn Learning, etc. has made education more accessible to more people. This has lead to simultaneous enrollment surges and course completion paradoxes. Self-paced digital courses and MOOCs reportedly have completion rates of 5-15%, indicating that there may be a disparity between how online courses are designed and how individuals learn.

The main problem is not motivational but is more a problem of behavior and design. Learners engagement in any sort of video or interactive learning content, structuring learning behaviors as well as the response to assessments are all affected by the decisions made with the design of the course by the instructors and platform builders. It is essential to understand the variation in learner behavior in order to design the course content in such a way that the users are engaged to the end of the course.

The purpose of this study is to identify the viewing and learning behavior patterns of consumers of online educational content, and to determine the course design features (video length, presence of interactive elements, and time gate release) that impact course completion rates.

1.1 Research Objectives

- Identify and describe the behaviors and demographics of the sample population.
- Apply K-Means clustering in order to identify learner personas.

- Use Spearman rank-order correlations in order to determine the relationships between behavior and learning outcomes.
- Identify barriers to course completion and determine their frequency.
- Provide design suggestions based on course completion for the various learner personas.

1.2 Significance of the Study

This study will be useful to e-learning developers and corporate and academic L&D professionals interested in designing more effective digital learning solutions. Through the application of quantitative analytics, clustering and correlation, on primary survey data, this study goes beyond the descriptive approach to learner segmentation and provides a more substantive framework.

2. LITERATURE REVIEW

2.1 Dropout and Completion in Online Learning

Course non-completion has been studied extensively since the rise of MOOCs. (Kizilcec et al., 2013) identified four behavioral archetypes in MOOC populations - completing, auditing, disengaging, and sampling - establishing that dropout is not a uniform event but a reflection of heterogeneous motivational and behavioral profiles. (Tinto, 1975) model of student departure, adapted for online contexts, highlights the combined role of academic integration and social belonging in retention. Self-Determination Theory (Ryan & Deci, 2000a) provides a motivational lens, identifying intrinsic motivation - curiosity, personal growth, and autonomy - as the primary driver of persistence.

2.2 Engagement and Learning Outcomes

Research on educational dropout has proliferated in the aftermath of the establishment of MOOCs. (Kizilcec et al., 2013) analyzed the dropout problem in view of four different behavioral types in MOOCs, namely: course completing, course auditing, course disengaging, and course sampling. According to this analysis, dropout is not a monolithic event but a heterogeneous motivational and behavioral problem. (Tinto, 1975) framework on educational dropout, when applied to the virtual context, emphasizes the combined effect of academic integration and social belonging on the problem of educational retention. (Ryan & Deci, 2000b) Self-Determination Theory offers an explanation of the motivational problem, where curiosity, personal development, and autonomy are treated as factors of intrinsic motivation and persistence.

2.3 Content Design Factors

(Guo et al., 2014), examined engagement data on edX and found that videos longer than 6 minutes caused an increased drop-off rate from viewers. They suggested micro-segmentation should be a design standard. (Mayer, 2008), developed the Cognitive Theory of Multimedia Learning. He said that videos that are segmented and designed with pacing and example are more efficient. Embedded quizzes or branching scenarios are interactive components that promote metacognitive thinking and retention. Flexible release schedules increase accessibility; however, they are linked to procrastination when soft deadlines are not present ((Zhang et al., 2006), (Adesope et al., 2017)).

2.4 Learner Clustering in Educational Research

K-means clustering has been previously utilized on learner data to identify behavioral segments. MOOC interaction data were analyzed by (Mouri & Rani, 2026) to identify learner profiles that are active, passive, or potentially drop-out. (Lust et al., 2013), utilized cluster analysis to uncover patterns of tool usage in blended learning. Those with high tool usage clusters also had a positive impact on learning outcomes. This study attempts to apply the same approach to a primary survey and will utilize clustering of self-reported behavior on a 28-item scale.

3. RESEARCH METHODOLOGY

3.1 Research Design

Data collection occurred between December 2025 and January 2026 and adopted a cross-sectional research design. Participants completed an online survey with 58 close-ended, semi-structured questions that utilized a Likert scale. Questions were organized thematically into six groups.

3.2 Sample and Sampling Strategy

A sample of 72 respondents was purposefully selected to capture people who have previously or currently participate in online learning. The sample was primarily urban, Indian, and students, all of which are representative of the population of interest of digital learning in the Indian context.

3.3 Analytical Framework

Three methods were used to analyze the data collected from the survey.

- Descriptive Statistics - Included Frequency distributions, percentage breakdowns, and means for all survey items.
- K-Means Cluster Analysis - Used a 28-feature matrix that encompassed content-viewing and active participation as well as learning style variables. The features were clustered after standardization via Z-score normalization. Optimal k was found by computing and comparing silhouette scores within k=2 to k=6. The k=3 grouping had the highest silhouette score (0.097) when compared to k=4, k=5, and k=6 groupings, which had silhouette scores of 0.076, 0.092, and 0.092, respectively. Other methods confirmed the resulting clusters (e.g., visually scatter plotted in 2D from PCA).
- Spearman Rank-Order Correlations - Used to find which of the behavioral variables had statistically significant ($p<0.05$) correlations with scores of learning outcomes.

k (Clusters)	Within-Cluster Inertia	Silhouette Score	Interpretability
2	1742.5	0.170	Too coarse - only 2 segments
3 ✓ Selected	1588.3	0.097	Best balance of parsimony and interpretability
4	1497.8	0.072	Marginal gain; overlapping segments
5	1375.2	0.092	Complex; limited practical distinction
6	1317.8	0.076	Over-segmented for n=72 sample

Table 1: K-Selection Analysis - Inertia and Silhouette Scores

4. SAMPLE PROFILE AND DESCRIPTIVE FINDINGS

4.1 Demographic Profile

The final sample consisted of 72 subjects (50% male, 50% female). The average age was 27.7 years, with 40.3% of the sample in the age range of 23-30 years, 31.9% in the age range of 18-22 years, and 26.4% in the age range of 31-50 years. 55.6% were from Mumbai, and 15.3% were from Sangli. The largest group of respondents were Postgraduates at 40.3%, the next group were Graduates (26.4%), and then Undergraduates (23.6%). 62.5% were students, and 33.3% were working professionals.

Variable	Category	n	%
Gender	Male	36	50.0%
	Female	36	50.0%
Age Group	18–22 years	23	31.9%
	23–30 years	29	40.3%
	31–50 years	19	26.4%
	51+ years	1	1.4%
Education	Undergraduate	17	23.6%
	Graduate	19	26.4%
	Postgraduate	29	40.3%
	Ph.D / Doctorate	7	9.7%
Occupation	Student	45	62.5%
	Working Professional	24	33.3%
	Other	3	4.2%

Table 2: Demographic Profile of Respondents

4.2 Online Learning Background

Udemy and Coursera were used together by 19.4% of respondents. Udemy and Coursera together was followed by Coursera (15.3%) and SWAYAM (8.3%). Sites for online learning were used by the majority (59.7%) for longer than six months. 45.8% study online for less than 2 hours a week, 43.1% for 2 - 5 hours a week, and only 11.1% for more than 5 hours

4.3 Dropout and Completion Behavior

The documented dropout rate was 61.1 % with 31.9% being a one-time dropout, 23.6% dropping out 2-3 times, and 4.2% dropping out more than 3 times. The rest, 38.9%, claimed to have never dropped out. The three main reasons for dropping out were lack of time (44.4% of dropouts), lost interest (38.9%), and not meeting expectations (38.9%). The main reason for dropping out being 'lost interest' suggests the presence of poor dropout structural design quality and poor design relevance.

5. K-MEANS CLUSTER ANALYSIS: LEARNER PERSONAS

5.1 Analytical Setup

In this study, K-Means clustering was applied (k=3, random_state=42, n_init=20) to a behavioral matrix (28 standardized features) that was developed from three behavioral dimensions: content viewing (6 items, 5-point frequency scale), learning style (6 items, 5-point frequency scale), and active participation (16 items, 4-point agreement scale). These dimensions were measured with respect to all the 72 study participants. Z-score normalization was applied before clustering to prevent scale-dominance bias.

For two-dimensional representation, PCA was implemented, where PC1 and PC2 accounted for 25.9% and 12.3% of total variance, respectively, summing to 38.2% of the total. PCA space showed clear separation of three clusters, validating the k=3 solution, where Cluster A was in the high engagement area (PCA1 centroid = +4.78), Cluster B was at the origin (PCA1 = −0.40), and Cluster C was in the low engagement area (PCA1 = −7.97).

5.2 Cluster Profiles

Dimension	Cluster A: Engaged Achievers (n=10)	Cluster B: Moderate Learners (n=59)	Cluster C: Passive Learners (n=3)
Sample Share	13.9%	81.9%	4.2%
Avg. Content Viewing Score (1-5)	3.05	3.12	2.78
Avg. Learning Style Score (1-5)	4.35	3.45	2.50
Avg. Participation Score (1-4)	3.71	2.86	1.50
Mean Outcome Score (1-4)	3.50 (Good–Excellent)	2.68 (Average–Good)	2.33 (Average)
Mean Weekly Hours	2.50 (2–5 hrs band)	1.59 (< 2 hrs band)	1.00 (< 2 hrs band)
Dropout Never (%)	70.0%	35.6%	33.3%
Top Completion Style	Steady (60%)	Mixed	Casual (67%)
PCA1 Centroid	+4.78	−0.40	−7.97

Table 3: K-Means Cluster Profile Summary

5.3 Cluster Interpretation

Cluster A - This cluster's respondents are called Highly Engaged Achievers (n=10, 13.9%). This group demonstrated the highest engagement scores (participation, mean=3.71/4.0; alignment, mean=4.35/5.0). All 10 members completed all the courses at or faster than the estimated pace, 70% of the group never dropped out. Group members dedicated more than the standard ~2.5 hours a week (mean study time ~ 2.5 hrs/week), preferred study scheduling that included practical study exercises coupled with real-world examples (Study Scheduling, mean=4.2/5.), and participated actively in forums and other supplementary materials. The mean engagement outcome score of this group was 3.50 (between Good and Excellent). It seems this group consists of people that are highly self motivated and/or possibly working professionals, since many of the participants demonstrated clear career related engagement with the study content.

Cluster B - This group is referred to as Moderate Learners (n=59, 81.9%). This was the largest group. Participation was scored as moderate (mean=2.86/4.0), and learning style and content viewing scores were mid-range (mean=3.45/5.0 and 3.12/5.0, respectively). Completion style was varied across all four types (steady, casual, binge, sprint), and 35.6% had never dropped out. The mean engagement outcome score of this group was 2.68 (Average–Good). The group was behaviorally heterogeneous, and moderately engaged active users of the platform, and as a result, the group was the most actionable for platform designers.

Cluster C - Passive Disengaged Learners (n=3, 4.2%): The smallest but most at-risk group. Participation scores reflected an almost total disengagement, with a low participation mean of 1.50/4.0. They have very low forum participation, attempt very few quizzes, show little interest in additional materials, and have no fixed study schedules (mean=1.0/5.0). They all study less than 2 hours a week, and the average outcome was 2.33 (Average). This group consists mainly of casual learners, with all participants working at, or below, the estimated pace. These learners have most likely enrolled to obtain the certificate for extrinsic reasons, and have no intrinsic interest in engagement.

6. SPEARMAN RANK-ORDER CORRELATION ANALYSIS

6.1 Weekly Study Time and Outcomes

The most significant of the predictors of learning outcomes was the time invested per week. This correlation was also the strongest (Spearman $\rho=0.436$, $p<0.001$). The participants in the study who invested more than 10 hours a week in learning showed an average score of 4.00 (Excellent), while the participants who invested 5-10 hours showed an average of 3.20, the participants who invested 2-5 hours an average of 2.87, and those who invested less than 2 hours an average of 2.52. The results also suggest a possible link with Deliberate Practice Theory (Ericsson et al., 1993). The results also indicate that, with the constraints imposed by the majority of the participants, the learning content must be designed in a way that provides the most value.

6.2 Participation Behaviors and Outcomes

Spearman correlations determined how the sixteen active participation behaviors correlated with the overall learning outcome scores. Eleven behaviors displayed significant positive correlations ($p<0.05$). The strongest predictors include:

Participation Behavior	Spearman ρ	p-value	Significance
Completing practice exercises before assessments	0.399	0.0005	***
Reflecting on real-world application of content	0.385	0.0008	***
Spending time on supplementary materials	0.379	0.0010	***
Remaining motivated through course difficulty	0.379	0.0010	***
Asking questions when concepts unclear	0.370	0.0014	**
Reviewing quiz results and learning from mistakes	0.311	0.0079	**
Setting personal deadlines for completion	0.327	0.0050	**
Dedicating uninterrupted study time	0.329	0.0047	**
Sharing learnings with other learners	0.312	0.0077	**
Participating in course discussion forums	0.273	0.0205	*
Checking for new content/updates regularly	0.269	0.0221	*

Table 4: Spearman Correlations - Participation Behaviors vs. Learning Outcomes (* p<0.05 ** p<0.01 *** p<0.001)

6.3 Content Viewing Behaviors and Outcomes

When considering the content viewing behaviors, rewatching difficult sections displayed a significant negative correlation ($p=0.027$, $\rho=-0.261$). This counterintuitive result indicates that rewatching sections is likely a compensation behavior to a learner's poor comprehension of the task. This suggests that the rewatching behavior relates to low initial learning, and not poor content engagement. Viewing behavior was the same across the board, and did not show significant correlations with outcomes, therefore participation behaviors will dominate viewing behaviors, and are much more important to the learning process.

The rapid viewing of videos had a mean score of 3.04 out of 5.0, and correlated negatively ($p=0.402$, $\rho=-0.100$) suggesting no correlation. Given that the outcome of rapid viewing of videos is very unlikely to be damaging, it suggests a neutral preference of convenience when viewing videos.

7. BARRIERS TO COMPLETION AND CONTENT DESIGN IMPLICATIONS

7.1 Barrier Analysis

From a provided list, respondents identified the top three factors hindering their ability to complete coursework quickly. After grouping all the responses, work and study commitments represented the largest barrier, noted by 72.2% of respondents, followed by time management (61.1%), lack of motivation (40.3%), and lack of interaction or support (22.2%). Difficulty with content and issues with the technical platform represented barriers for 6.9% and 5.6% of the respondents, respectively. This suggests that barriers formed by cognitive and interface issues are relatively small, when compared to the structural or motivational barriers.

Barrier to Completion	Frequency (n)	% of Respondents	Cluster Most Affected
Work / Study Commitments	52	72.2%	B and C
Time Management Issues	44	61.1%	B and C
Lack of Motivation	29	40.3%	C primarily
Lack of Interaction / Support	16	22.2%	B and C
Content Difficulty Level	5	6.9%	B
Technical / Platform Issues	4	5.6%	All

Table 5: Barriers to Course Completion (Multiple Responses, n=72)

7.2 Design Recommendations by Cluster

Combining the cluster data and barriers data, the segmentation reveals the following for each cluster:

For Cluster A (Engaged Achievers): This group is well aligned with both engagement and outcomes. Course design for this cluster should include content that is more in-depth, supports collaborative work, and provides engagement with facilitators to design pathways for practical outcomes and certification of engagement.

For Cluster B (Moderate Learners): The majority of this group has time and study disruptions. This calls for learning design with segments that are 10-15 minutes in length, with automatic notifications for progress and completion, and soft deadlines. This group's limited engagement in forums suggests that passive social behavior may transform into more active behavior through gamified social nudges, such as a visible cohort progress to peers.

For Cluster C (Passive Learners): Engaging these high-risk learners means employing entirely different techniques. Typical content will need to be ultra-short (a maximum of five to seven minutes), use a high entertainment-to-information ratio, have low friction interactivity (click-only polls, embedded reflections), and be augmented by behaviorally triggered (for example, 7-day inactivity) motivational re-engagement email workflows. Onboarding tests, calibrated to learner goals, may also help to reduce 'lost interest' attrition by making content relevant from the very start.

8. LEARNING OUTCOME SATISFACTION ANALYSIS

8.1 Overall Outcome Ratings

Respondents rated their overall learning outcomes from online courses on a 4-point scale. The distribution was: Excellent (11.1%), Good (59.7%), Average (25.0%), and Below Average (4.2%), yielding a mean overall rating of

2.78/4.0. While broadly positive, the absence of Excellent ratings among Cluster B and C respondents underscores the unrealized potential of these segments under current content design conditions.

8.2 Outcome Satisfaction Dimensions

Rating of the 11 specific outcome dimensions was conducted on a 4-point scale. All items were rated in the 2.99-3.21 range, reflecting a moderate-to-positive agreement. The highest rated outcomes were acquisition of knowledge and skills, increase in confidence regarding the subject and the outcome of knowledge application to work/projects, all rated as 3.21. The outcome with the lowest score was retention of information from the previous modules, rated as 2.99. This indicates the presence of a structural deficit with respect to memory consolidation among the participants and can be attributed to the lack of adequate spaced repetition and retrieval practice in the design of the course.

Table 6: Learning Outcome Satisfaction - Dimension-Level Mean Scores by Cluster

Outcome Dimension	Mean Score (1-4)	Cluster A Mean	Cluster B Mean
Gained new knowledge and skills	3.21	3.80	3.10
Confidence in subject area increased	3.21	3.90	3.10
Applied knowledge in work/projects	3.21	3.80	3.12
Can explain concepts learned to others	3.19	3.80	3.08
Course improved professional performance	3.17	3.60	3.08
Can apply learning in practical situations	3.06	3.50	2.97
Course met stated learning objectives	3.04	3.60	2.95
Satisfied with learning progress	3.04	3.50	2.93
Course content matched expectations	3.04	3.50	2.95
Quiz scores reflect actual learning	3.03	3.40	2.95
Retained information from prev. modules	2.99	3.30	2.90

9. DISCUSSION

9.1 Key Insights from Cluster Analysis

K-Means analysis shows that, at least for this sample from urban India, the online learner population is a heterogeneous population. The dominant Cluster B (81.9%) captures the most learners and represents the large middle ground of moderate engagement, where learners are capable of better outcomes but are faced with structural issues and the lack of self-regulation characteristic of Cluster A. In light of that, it is relevant that Cluster A (the high-engagement segment) accounts for only 13.9% of the sample: only a small fraction of the learners is fully engaged under the current conditions of content design.

Although small at 4.2%, Cluster C presents a disproportionate threat to platform reputation and retention metrics. It is likely these learners are only participating to receive a completion certificate. This highlights an instance of learner and platform incentive misalignment. The SDT theory classifies such misalignment as a primary driver of dropout.

9.2 Implications of the Spearman Findings

The correlation analysis shows that learning outcomes improve by having learners adopt a number of metacognitive and application-based behaviors. These include practicing a skill prior to an assessment on that skill, reflecting upon the assessment's relevance to real-life experiences, and persisting through motivational challenges. Interestingly, these behaviors can easily be embedded in the design of learning content, such as including opportunities for practice before an assessment, reflective prompts, and discussions of practice-relevant workplace problems rather than assessment questions.

The negative relationship between rewatching and outcomes (ρ=−0.261) does not mean that rewatching is bad. Instead, rewatching is a remediation strategy that is primarily used by learners that did not do well. The intervention is meant to happen before rewatching, and that is meant to reduce the cognitive load that makes rewatching necessary. Better video production that enables learners to comprehend the material during the first viewing through the addition of worked examples and on-demand definitions would likely lessen the need for remediation through rewatching.

9.3 Alignment with Literature

(Guo et al., 2014) recommended videos that are short and have high information density. This study's preference for a fast playback (mean=3.04) and short study bursts (mean=3.36) supports that recommendation. Some recommendations based on Self-Determination Theory (SDT) are directly supported. The engagement categories in Cluster A (which are self-determined and, therefore, intrinsically motivated) and Cluster C (which are passive and extrinsically motivated) are directly supported by SDT. The cluster of correlations around reflective practice, self-testing, and application to the real world supports the recommendations of Pintrich and De Groot's metacognitive engagement framework (Pintrich & De Groot, 1990).

10. CONCLUSION

The behavioral landscape of digital education engagement was analyzed by employing K-Means cluster analysis and Spearman rank-order correlations using primary survey data collected from 72 online learners. Three distinct learner personas were identified. Engaged Achievers, who independently set deadlines, participate in practical activities, and achieve outcomes that are near-Excellent, are contrasted with the Moderate Learners, who are the majority, and respond to design nudges. Passive Learners are behaviorally disengaged and are at high risk of dropout.

The analysis shows learner outcomes are tied to certain consistent behaviors: doing practice exercises, engaging in reflection on the exercises, engaging in additional activities, and using time effectively and self-regulated. Fortunately, these behaviors are not reliant on the learner's self-control. Thoughtful planning of the course content has the potential to structure these behaviors. Evidence-based levers include micro-learning, embedded formative assessments, practical case studies, and socially-integrated progress features.

The 61.1% dropout rate reflects the absence of a major motivation crisis for learners (the content is not overly challenging), but rather an external constraint on the learners. This indicates a gap between how online learners typically structure their week and how most online courses are designed. This gap is a design problem, not a motivation problem, and the learner cluster profiles and correlations in this study provide information on how to address this gap.

With the clustering profiles, more research can be done to study the actual completion rates longitudinally for the same participants, and to validate and expand the cluster profiles to measure participants from a wider geographic area. Controlled studies can also be done to measure the actual impact specific course content design changes have on cluster-based completion rates.

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