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IDENTIFYING BEHAVIORAL PATTERNS IN MOOC VIDEO ENGAGEMENT USING CLUSTERING APPROACH

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Abstract

Videos are the core components of MOOCs for delivering course content and teaching the core concepts effectively. While the literature provides strong and consistent evidence regarding the link between video engagement and the success in MOOCs, the research on video engagement behavior is still emerging and in demand of further research. This research aims to contribute to the literature by identifying behavioral patterns of video engagement in a MOOC and reveal the association of these patterns with success and failure. In particular, we employed basic video engagement metrics with an attempt to identify clusters of behavioral patterns that can be applied across different contexts. Acknowledging that students may exhibit diverse engagement behaviors across study sessions, a session-level clustering analysis was performed, differently from previous research. After applying K-Means clustering algorithm, three clusters of behavioral patterns were identified: static viewing (the most predominant behavior), in which students viewed videos with minimal interactions; engaged viewing, involving high frequency of play and pause events; and focused viewing (the least frequent pattern), which involved mainly seeking the video for specific information. While video sessions with static viewing were very common among both high and low achieving students, most engaged-viewing sessions or focused-viewing sessions consistently belonged to the successful students. In addition, successful students were found to demonstrate multiple viewing behaviors, suggesting their effort in using several strategies while watching videos. Based on the findings, the paper discusses implications for the design of MOOCs and other online learning platforms that support video-based learning.

Keywords: massive open online course; video analytics; clustering; video-based learning.

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MOOC VİDEO ETKİLEŞİMİNDEKİ DAVRANIŞ ÖRÜNTÜLERİNİN KÜMELEME YAKLAŞIMI İLE BELİRLENMESİ

Öz

Videolar, ders içeriğini iletmek ve temel kavramları etkili bir şekilde öğretmek için kitlesel açık çevrimiçi derslerin önemli bileşenlerinden biridir. Literatür, video izleme ile bu kitlesel derslerdeki öğrencilerin başarısı arasındaki bağlantı konusunda güçlü ve tutarlı bulgular sunsa da video analitikleri hala gelişmekte olan bir alan olup, video izleme davranışı üzerine daha fazla araştırmaya ihtiyaç vardır. Bu araştırma, bir kitlesel açık çevrimiçi dersindeki video izleme aktivitelerindeki davranışsal desenleri tanımlayarak bu desenlerin başarı ve başarısızlıkla ilişkisini ortaya çıkarmayı amaçlamaktadır. Özellikle farklı bağlamlarda kullanılabilmesi ve uygulanabilmesi amacıyla, temel ve yaygınlaştırılabilir video izleme metrikleri kullanılmıştır. Öğrencilerin bir öğrenme oturumu süresince farklı video izleme davranışları gösterebileceği kabul edilerek, önceki araştırmalardan farklı olarak kümeleme analizi öğrenci değil oturum düzeyinde gerçekleştirilmiştir. Her oturum, öğrencinin belirli bir zaman dilimindeki etkileşimlerini yansıtır ve bu, öğrencinin genel davranışından ziyade belirli bir oturumdaki davranışını daha doğru bir şekilde analiz etmemizi sağlar. K-Means kümeleme algoritması ile analiz gerçekleştirilmiş ve üç davranışsal desen kümesi ortaya çıkmıştır: statik görüntüleme (en yaygın davranış), öğrencilerin minimum etkileşimle videoları izlediği durum; katılımlı görüntüleme, oynatma ve duraklama olaylarının sık olduğu durum ve odaklı görüntüleme (en az rastlanan desen), özellikle belirli bir bilgiyi arama durumu. Statik görüntülemenin hâkim olduğu video oturumları hem başarılı hem de başarısız öğrenciler arasında yaygın olarak gözlemlenmiştir. Ancak katılımlı görüntüleme ve odaklı görüntüleme oturumları ise en çok başarılı öğrenciler tarafından sergilenmiştir. Ayrıca başarılı öğrencilerin birden fazla görüntüleme davranışı sergilediği saptanmıştır. Bu bulgu, öğrencilerin videoları izlerken çeşitli sayıda strateji uygulama çabalarını göstermektedir. Bulgulara dayalı olarak, video tabanlı öğrenmeyi destekleyen diğer çevrimiçi öğrenme platformlarının tasarımı için pratik öneriler paylaşılmıştır.

Anahtar Kelimeler: kitlesel açık çevrimiçi ders; video analitikleri; kümeleme; video tabanlı öğrenme.

Yasal İzinler: Bu araştırma kapsamında insan(lar)dan veri toplanmadığı için etik kurul iznine tabi değildir. Araştırmada tamamen kamuya açık bir veri seti kullanılmıştır ve herhangi bir şekilde ek veri toplanmamıştır.

Geniş Özet

Kitlesel Açık Çevrimiçi Dersler (KAÇD) eğitimciler ve öğrenciler için yeni bir öğrenme deneyimi çağını başlatmıştır. KAÇD'ler genellikle bölümlenmiş video dersler, çevrimiçi okuma materyalleri, tartışma forumları, sınavlar ve akran değerlendirmesine tabii ödevler içerir. Videolar, bu tip kitlesel derslerde, temel kavramları öğrencilere aktarmak için merkezi bir rol oynamaktadır. Araştırmalar, öğrencilerin KAÇD'lerde en fazla video içerikleri ile etkileşimde bulunduğunu göstermektedir (Kizilcec et al., 2013). Bu video etkileşimleri, oynama, duraklatma ve geri sarma gibi eylemleri içermekte (Glance et al., 2013) ve etkileşim verileri, bireysel öğrenme alışkanlıkları ve davranışları hakkında değerli içgörüler sağlayabilmektedir (Hu et al., 2020). Bu içgörüler sayesinde etkili pedagojik destek ve daha kişiselleştirilmiş ve etkili öğrenme deneyimleri sunmak mümkün olmaktadır.

Diğer taraftan, öğrencileri video etkileşimlerine göre tanımlamaya ve profil oluşturmaya yönelik yeterince araştırma bulunmamaktadır. Çeşitli çalışmalar, elde edilmesi zor etkileşim parametreleri ve ölçütler kullanarak birbirinden farklı öğrenci profillerini ortaya çıkarmıştır (Zhang et al., 2022). Ancak, bu durum literatürde belirgin bir tutarsızlığa neden olmuştur. Literatürde kullanılan etkileşim metrikleri belirli bir oynatıcıya özgü olabilmekte ve bu nedenle aynı metrikleri farklı bağlamlarda elde edilmesi ve kullanılması mümkün olamamaktadır (Yoon et al., 2021). Ayrıca, çoğu çalışma öğrencileri tüm video etkileşimine göre etiketlemekte ve farklı konu ve zorluk derecesine sahip oturumlardaki videoların davranışlara olan etkisini gözden kaçırmaktadır (Matcha et al., 2020). Diğer taraftan, başarılı ve başarısız öğrencilerin videolarla nasıl etkileşime girdiği konusunda sınırlı bilimsel bulgu bulunmaktadır (Yoon et al., 2021) ve akademik başarı ile video görüntüleme davranışları arasındaki karmaşık ilişkiyi keşfetmek için daha fazla araştırmaya ihtiyaç duyulmaktadır.

Literatürde belirtilen eksiklikleri ele almak amacıyla bu araştırma, video tabanlı öğrenme ortamlarında kolayca toplanabilecek temel video etkileşim metriklerini kullanarak video izleme sırasındaki genellenebilir davranışsal örüntüleri tanımlamayı hedeflemektedir. Araştırmada, öğrenci yerine oturum düzeyinde örüntüler incelenmiştir. Bunun nedeni, öğrencilerin izlenilen videonun konusu ve içeriği ile ilişkili olarak farklı video oturumlarında değişken davranışlar sergileyebilmesidir (Matcha et al., 2020),. Ayrıca KAÇD'lerdeki farklı video etkileşim tiplerini incelemeyi ve video etkileşim davranışları açısından başarılı ve başarısız öğrenciler arasındaki farklılıkları veya benzerlikleri araştırmayı amaçlamaktadır.

Bu çalışmada, bir KAÇD'ye katılan katılımcıların etkileşim günlüklerinden oluşan anonim bir veri kümesi kullanılmıştır. Halka açık bir kaynaktan alınan veriler, kullanıcı adı, oturum_id'si, eylem, nesne ve zaman gibi sütunları içeren 285.120 satır içermektedir. Bu satırların her biri, öğrencilerin sistemle gerçekleştirdiği ayrı bir etkileşimi temsil etmektedir. KAÇD'yi başarıyla tamamlayan öğrenciler "0" (n=214), başaramayan öğrenciler ise "1" (n=593) olarak etiketlenmiştir. Video etkileşimlerine odaklanmak için veri kümesi, video etkileşiminin önemli göstergeleri olan duraklatma, oynatma ve arama gibi eylemleri içerecek şekilde filtrelenmiştir. Her öğrencinin bir oturum sırasında belirli bir videoyla etkileşimi ayrı olarak ele alınmıştır. Örneğin bir öğrenci Y videosuyla oynat-duraklat-oynat şeklinde ve Z videosuyla oynat-ara-ara-duraklat-oynat şeklinde etkileşime girdiyse iki ayrı oturum oluşturulmuştur. Bu süreç, her bir alt oturum için video etkileşim göstergelerini içeren 6.656 satırlık bir veri seti oluşmasını sağlamıştır. Veri analizi, k-means kümeleme algoritması kullanılarak gerçekleştirilmiştir. Kümeleme analizinde, oturum bazında oynatma (play), duraklatma (pause), ve video içi arama (seek) metrikleri kullanılmıştır.

Kümeleme analizi sonucunda üç küme ortaya çıkmıştır. Birinci küme, çoğunluğu oluşturmaktadır (%80,66) ve "statik görüntüleme" olarak adlandırılmıştır. Bu kümedeki oturumlarda, öğrencilerin video etkileşimi diğer kümelere göre daha düşük seviyede kalmıştır. Ortalama olarak videolar 2,44 kez oynatılmış, 2,01 kez duraklatılmış ve yalnızca 0,54 kez video içinde arama yapılmıştır. "Etkileşimli görüntüleme" olarak adlandırılan ikinci kümedeki (%13,60) oturumlarda, kümesindeki oturumlarda, öğrenciler videolarla diğer kümelere göre daha yüksek etkileşim göstermiştir. Ortalama olarak, videolar 12.31 kere oynatılmış ve 10.86 kere duraklatılmıştır ve bu değerler tüm kümeler içinde en yüksektir. Diğer taraftan bu kümedeki oturumlarda ortalamada 3.01 kere videolar içinde arama yapılmıştır. Bu davranışlar, öğrencilerin video içeriğiyle daha fazla etkileşimde bulunduğunu ve içerikten daha fazla faydalandığını göstermektedir. Üçüncü küme ise en az oturumu içeren (%5,74) ve "odaklanmış görüntüleme" olarak adlandırılan gruptur. Bu kümedeki oturumlarda ortalama video duraklatma (4,05) ve oynatma (8,68) sayıları, etkileşimli görüntüleme kümesine göre düşük, statik görüntüleme kümesine göre ise yüksektir. Video içinde arama sayısı (13,59) ise diğer kümelere kıyasla oldukça yüksektir. Bu bulgular, bu kümedeki oturumlarda öğrencilerin videoları hem oynatma hem de aktif olarak arama eğiliminde olduğunu gösteriyor. Bu davranışlar, öğrencilerin belirli içerikle yoğun bir şekilde ilgilendiğini ve içeriği derinlemesine incelediğini göstermektedir.

Her kümedeki video izleme davranışını daha derinlemesine anlamak amacıyla video etkileşim göstergeleri arasındaki ilişkiler incelenmiştir. Sonuçlara göre, tüm kümelerde oynatma ve duraklama sayıları arasında pozitif bir korelasyon ortaya çıkmıştır. Bu korelasyon ilişkisi özellikle 1. ve 2. kümelerde güçlü olmasına rağmen, 1. kümedeki (statik görüntüleme) oturumlarda oynatma ve duraklatma sayıları çok daha düşük olarak belirlenmiştir. Buna karşılık, oturumların çoğu video içeriği arama davranışını içerdiğinden 3. kümede (odaklanmış görüntüleme) oynatma-duraklatma arasında daha zayıf bir korelasyon belirlenmiştir. Videoyu oynatma ve video içerisinde arama arasındaki ilişki zayıf ve de her bir kümde farklıdır. Ek olarak, en zayıf korelasyon arama-duraklatma sayıları arasında belirlenmiştir. Özellikle, 1. ve 3. kümelerdeki zayıf korelasyonlar, video içinde arama ve videoları duraklatma arasında çok anlamlı bir ilişki olmadığını ortaya koymuştur.

Ayrıca bu çalışma, öğrencilerin başarı durumları (başarılı vs. başarısız) ile video izleme davranışları arasındaki ilişkiyi üç aşamada analiz etmiştir. İlk aşamada, her bir kümedeki oturum sayılarının başarı durumlarına göre öğrencilere dağılım oranı hesaplanmıştır Statik görüntüleme oturumlarının %54,83'ü başarılı, %45,17'si ise başarısız öğrencilere ait olduğu belirlenmiştir. Yani statik görüntülemede dağılım çok yakın çıkmıştır. Ancak iki öğrenci grubu arasındaki fark, daha fazla başarılı öğrencilerin katıldığı etkileşimli görüntüleme (%59'a karşı %41) ve odaklı görüntüleme (%61,78'e karşı %38,22) davranışlarında belirgin bir hal almıştır. İkinci aşamada, her iki başarı grubunda da her bir video davranışını en az bir kez gösteren öğrencilerin yüzdeleri hesaplanmıştır. Her iki gruptan da büyük bir çoğunluğu en az bir kez statik görüntüleme davranışını göstermiştir (%89,25 ve %87,86). Fakat etkileşimli görüntüleme (%49,07'ye karşı %21,59) ve odaklı görüntüleme (%36,92'ye karşı %11,47) davranışları, başarısız öğrencilerde başarılı öğrencilere kıyasla iki veya üç kat daha az gözlemlenmiştir. Üçüncü aşamada, birden fazla tip video görüntüleme davranışı gösteren öğrencilerin yüzdelerine odaklanılmıştır. Statik ve etkileşimli görüntüleme (%46,25'e karşı %19,56), statik ve odaklı görüntüleme (%33,64'e karşı %9,27) ve etkileşimli ve odaklı görüntüleme (%24,30'a karşı %5,05) davranışlarını gösterme oranlarında, her zaman başarılı öğrencilerin yüzdeleri daha yüksektir. Üç tip davranışı en az bir kere gösteren öğrenci sayılarına bakıldığında da, başarılı öğrenciler daha yüksek bir oran göstermiştir (%24,30'a karşı %5,06).

Bu araştırmanın bulguları, KAÇD'lerin ve video tabanlı öğrenmeyi destekleyen diğer çevrimiçi öğrenme platformlarının tasarımı için önemli çıkarımlara sahiptir. KAÇD öğrencileri çeşitli video katılım davranışları sergilemektedirler ve çevrimiçi öğrenme platformlarının tasarımı, video içeriğiyle etkili ve anlamlı etkileşimi teşvik edecek şekilde bu davranışları dikkate almalıdır. Videoları etkileşimli bir şekilde izlemeyi sağlayan müdahaleler, öğrencilerin videolardan öğrenme süreçlerinde olumlu bir etki yaratabilir ve öğrenmeyi arttırabilir. Örnek bir müdahale, bir video duraklatıldığında not almayı sağlayan bir video özelliği veya videoya ait alt metinlerin önemli bölümlerinin vurgulanmasını sağlayan ve öğrencilerin video içeriğine daha derin katılımını teşvik edecek bir özellik olabilir. Ayrıca, videolarda aktif arama yapmaya yönelik özellikler, odaklanmış izlemeyi ve video içeriğine daha derin katılımı teşvik etmede etkili olabilir. Örneğin, öğrencilerin belirli video bölümlerini ileride tekrar izlemek üzere işaretlemelerine olanak tanıyan bir yer imi özelliğinin uygulanması yararlı olabilir. Bu müdahale, önemli bilgilere daha hızlı erişimi teşvik edebilir ve genel öğrenme sonuçlarını iyileştirebilir. Bu çalışma, bir KAÇD'de videolarla doğru şekilde ilgilenmenin başarının önemli bir göstergesi olabileceğini gösterdiğinden, bu tür müdahaleler KAÇD katılımcılarının öğrenme deneyimlerini destekleyebilir ve daha yüksek başarıya yol açabilir.

Bu çalışmanın temel sınırlılığı bağlam hakkında bilgi eksikliğidir. Araştırmada, bir KAÇD'deki öğrenenlerin etkileşim günlüklerinden oluşan halka açık bir veri seti kullanılmıştır. Veriler anonimleştirildiğinden, genel kurs yapısı (örn. modül sayısı), pedagojik yaklaşım (örn. kişisel hıza karşı eğitmen liderliğinde) ve videoların özellikleri (süre, format, kalite vb.) bilinmemektedir. Bu faktörler öğrenci katılımını ve başarısını şekillendirmede kritik bir rol oynayabilir (Er et al, 2019; Lockyer ve diğerleri, 2013). Başarı düzeyleri öğrencilerin video izleme davranışlarıyla bir şekilde ilişkili olsa da videoların içeriğinin öğrencilerin videolarla etkileşimleri üzerinde bazı etkileri olması muhtemeldir. Örneğin, sık sık duraklatmak ve oynatmak, video içeriğinde bazı zorluklara işaret edebilir (Li ve diğerleri, 2015). Bu nedenle video özellikleri hakkında bilgi mevcut olsaydı, öğrencilerin video katılım davranışlarını açıklamak için ek bilgiler elde edilebilirdi. Gelecekteki araştırmalar, KAÇD öğrencilerinin video katılımının davranış kalıplarını açıklarken video özelliklerinin analizini dikkate almalıdır.

Introduction

Massive Open Online Courses (MOOCs) have revolutionized the traditional methods of teaching, ushering in a new era of learning experiences for both educators and learners (Milligan et al., 2013). Among the various components of MOOCs, videos serve as a pivotal medium for delivering and teaching fundamental concepts (Guo et al., 2014). With the video-based learning approach, MOOCs attempt to mimic traditional teacher-student interaction while aiming to maximize student engagement in online learning (Guo et al., 2014; Walji et al., 2016). Accordingly, research shows that MOOC learners immerse themselves mostly in videos compared to other course components (Kizilcec et al., 2013).

Learners engage with videos in diverse ways (Akcapinar & Bayazit, 2018; Guo et al., 2014), which may include specific actions such as playing, pausing, rewinding, fast-forwarding, and so on, depending on the affordances of the video player utilized (Glance et al., 2013). These interactions generate valuable fine-grained data that can provide insights into the unique learning habits and behaviors of individuals regarding their engagement with videos.

As a result, such data holds significant potential for enhancing our understanding of MOOC participants' learning processes and for determining proper pedagogical interventions (Hu et al., 2020; Seaton et al., 2014). In the pursuit of this potential, several studies have been conducted to reveal the complex nature of student interactions within videos. In particular, researchers have employed various statistical techniques to uncover patterns and meaningful connections within the rich dataset of video interactions (Boroujeni & Dillenbourg, 2019; Su & Wu, 2021). These studies have contributed to our broader comprehension of how learners engage with video content and can pave the way for the development of more personalized and effective learning experiences within MOOCs.

However, the research on clustering students based on their video interactions is still in its early stages and holds immense potential for further exploration. Several research studies have employed clustering techniques using interaction variables distinct to their own contexts, thus leading to inconsistent learner profiles across different investigations (Li et al., 2015; Zhang et al., 2022). Many of the interaction metrics investigated (such as filtering, bookmarking, proportion of skipped video content) are advanced and specific to certain players utilized (Yoon et al., 2021; Brinton et al., 2016), which can pose challenges when attempting to replicate research findings in different contexts. In other words, these metrics are not always readily available in typical video players, making the transfer of research findings to common educational settings difficult. Moreover, most studies have traditionally categorized learners into specific profiles based on their overall video engagement activities (Kizilcec et al., 2013; Li et al., 2015). However, it is important to acknowledge that students may exhibit varying engagement behaviors across different sessions, which might be influenced by factors such as their session-specific goals and the complexity of the concepts being covered (Matcha et al., 2020). That is, labeling students with a single profile may provide a narrower perspective on their video engagement behavior. Session-based analysis would allow us to analyze the behavior in a specific session more accurately than the student's overall behavior.

Furthermore, there is limited understanding of how successful and failed students interact with videos. While some dropout prediction research, such as the work conducted by Hasan et al. (2020), has employed video engagement metrics as indicators of academic success or failure, these studies fall short in explaining how video engagement behavior unfolds differently between successful and failed students. Other researchers commonly identified the link between passive video viewing behavior with low performance (Yoon et al., 2021) but they did not delve deeper into the intricacies of the relationship. Further research is needed to gain a comprehensive understanding of how students of varying achievement levels tend to interact with videos. Knowing the video engagement behaviors associated with higher (or lower) achievement can help in designing interventions that promote the desired behaviors, ultimately fostering learning in MOOCS and other video-based learning contexts.

To address the existing gaps in the literature, this research aims to use common and basic video engagement metrics in the identification of video engagement patterns that can be applied to other contexts where a simple video player is used to deliver lectures. It is important to recognize that students may exhibit varying behavioral patterns when watching videos during different study sessions, influenced by factors such as the video content or their confidence levels in the covered concepts (Li et al., 2015). This study follows a session-based clustering analysis approach, which is one of the unique aspects of our research, to draw a more detailed picture of the behaviors exhibited by students during a learning session.

Furthermore, this study seeks to investigate the frequency of these behavioral patterns in relation to the students' achievement status, which is determined by their successful completion of the MOOC. This research study aims to investigate the following research questions:

- What are the distinct video engagement types observed in MOOCs?
- How does the frequency of the behavioral patterns of video engagement vary among students based on their achievement status?

By exploring these research questions, this study contributes to a deeper understanding of video engagement behavior as well as the nuanced relationship between video engagement and academic outcomes in the context of MOOCs. The findings will provide valuable insights for educators and course designers to enhance the learning experience and support students effectively in their video-based learning endeavors.

Background

Video-based learning in MOOCs

Research studies consistently reported that videos have positive influence on learner performance and satisfaction (Armstrong et al., 2011; Shen, 2014). Darmayanti & Nova (2022) focused on evaluating the utilization of interactive videos in English, revealing positive perceptions of students regarding the quality of interactive videos and their impact on learning. Furthermore, Safitri et al. (2021) demonstrated the positive effects of animated videos on students' achievement and motivation in environmental education, indicating the potential of video-based educational tools. Additionally, Vioskha et al. (2021) highlighted the positive attitudes of students towards the application of learning videos in mathematics, indicating the potential of videos in improving learning outcomes. These studies have provided valuable insights into the effectiveness of interactive videos in enhancing students' learning experiences and outcomes across different subjects and educational levels.

Videos, serving as the primary medium of instruction and enabling flexible, accessible learning, have played a pivotal role in the rapid growth of MOOCs. MOOCs, which provide open access to educational courses and materials online, have leveraged the power of videos to deliver engaging and interactive learning experiences to millions in the world (Eisenberg & Fischer, 2014). Videos serve as the cornerstone of MOOCs, enabling instructors to convey complex concepts, demonstrate practical skills, and create immersive educational environments (Stöhr et al., 2019). Consequently, videos have been the most interacted MOOC component by learners (Kizilcec et al., 2013), and have played the most critical role in their learning journey in MOOCs. Researchers have investigated the production style of videos in MOOCs and their effects on students' watching behavior, and reported more favorable results with shorter videos where instructors explain concepts using talking-head and drawing-hand teaching style (Walji et al., 2016). In particular, to achieve effective student learning, it is recommended to segment videos into multiple smaller videos lasting between 5 to 17 minutes (Hew, 2015). This segmented nature of video learning in MOOCs, not only improves learning experience, but also allows capturing engagement at more granular level of concepts.

While MOOCs aim to replicate the learning experience of traditional instructor-led lectures through videos, the success of learners in an online asynchronous environment is greatly determined by their engagement with the video content (Benson & Samarawickrema, 2009). Merely dedicating time to watching videos does not guarantee a profound learning experience. It is crucial for students to cognitively engage while consuming the video content (Yoon et al., 2021). The logs of students' interactions with video players, also known as video trace data or clickstream data, can be utilized to derive meaningful indicators of their engagement in the learning process through videos (Giannakos et al., 2015). Previous research showed that such indicators from activity logs can be effective in producing valid models of students' video engagement behavior (Lan et al., 2017). The subsequent section provides a description of video trace data and elaborates on the video analytics techniques commonly applied in the literature.

Video analytics in MOOCs

This study, focusing on the examination of students' video interaction data, falls within the realm of video analytics research. In the following section, we offer an overview and synthesis of prior studies in the field of video analytics.

To begin with, video analytics in education, particularly in K12 and higher education, is an active area of research. Yürüm et al. (2022) highlighted the use of video clickstream data to predict university students' test performance, emphasizing the comprehensive educational data mining approach. Giannakos et al. (2014) designed an open-access video analytics system for a video-assisted course. They suggested that video analytics might provide insights into student learning performance and inform the improvement of teaching tactics. In their study, Khalil et al. (2023) explored student video engagement in three disparate cases: SPOC, MOOC, and an undergraduate university course. The three cases indicated the important role of the content type, the length, and the aim of the video on students' engagement.

A distinguishing characteristic of MOOCs is that the platforms where they are hosted stores all user interaction data as detailed clickstreams, providing a detailed history of how user engaged throughout their learning journey in a MOOC (Kay et al., 2013; Mubarak et al., 2021). As part of the clickstream data, most video players in MOOC platforms also store students' video interaction records. The types of these records may vary depending on the capabilities of the video player and the tracking capabilities available. While commonly recorded video events include play, pause, rewind, and forward (Li et al., 2015), video players with advance interactive and social features such as annotating, bookmarking, and commenting, can capture richer data for analysis (Chatti et al., 2016; Mirriahi et al., 2016). Video clickstream data is typically recorded as raw data with timestamps, providing a complete history of each users' actions in a video session.

Researchers exploited the video clickstream data for several research purposes in MOOCs. One main focus has been the prediction of dropouts (or success) using indicators of engagement with course videos. For example, Mbouzao and his colleagues (2020) developed three cumulative metrics that describe video engagement at rather coarse level and used them for the early prediction of success in a MOOC. Their findings revealed that these video engagement metrics proved to be robust predictors of success, even when based on interaction data collected during the initial week of the course. Mubarak and his colleagues (2021) conducted a study to predict student performance by using fifteen variables derived from video clickstream data and reported a very high classification accuracy with the Short-Term Memory Network (LSTM) algorithm. However, the researchers did not report the predictive power of specific variables.

In a different study, researchers predicted in-video quiz performance by using engagement indicators derived from students' interactions with each video separately

(Brinton et al., 2016). The authors proposed two frameworks for representing video-watching behavior (event-based and position-based), and they found that the models based on these frameworks can substantially improve prediction quality. However, their approach was rather complex and difficult to replicate in different contexts. With an attempt to examine the predictive power of different video-engagement indicators, Lemay and Doleck (2020) found that frequency of video viewing per week as a better predictor of course performance than individual viewing features. In particular, according to the findings, the number of videos viewed explained more variance in the dependent variable compared to all other count-based predictors combined such as number times a video is played or paused.

Prediction research has provided evidence regarding the importance of video engagement on performance and highlighted critical indicators of engagement associated with higher performance. However, this research fails to explain how students engage with videos. In complement, researchers also focused on clustering students based on their engagement patterns to identify groups of students exhibiting distinct engagement behaviors. An important study in this strand was conducted by (Yoon et al., 2021), where they used a custom video player allowing advance features such as bookmarking, commenting, annotating, and filtering. By examining eleven engagement indicators (such as number of plays, comments posted), the authors identified four behavioral patterns (i.e., browsing, social interaction, information seeking, and environment configuration) and two clusters of students namely active learners and passive learners. While this study effectively utilized a wide range of indicators, it was limited by a small sample size, resulting in the identification of only two common learner profiles (active vs. passive). In a similar study, Li and her colleagues (2015) derived 8 video features mostly based on play, pause, and seek actions. Their analysis using the eight features resulted in nine different clusters, each of which was simply named according to the corresponding dominating feature. The authors, without providing detailed information about the behavioral patterns, reported the associations between clusters and student performance (grouped as weak vs strong students).

Although clustering is widely used in the learning analytics literature, its application to video clickstream data remains limited. Further research is necessary to explore video engagement behavior at session level, rather than just the user level. This is important because learner behavior may vary across sessions where they may be watching distinct videos linked to different concepts. Conducting clustering analysis on video sessions can provide more comprehensive insights into video-watching behavior and yield a better understanding of how various video engagement patterns are associated with success or failure. Accordingly, in our study, we employed a clustering analysis at video session level using basic metrics that can be easily derived from any video clickstream. In addition, we examined how behavioral patterns differ between successful and failed students.

Method

Dataset

The data used in this study is composed of interaction logs of participants in an anonymous MOOC. The research data was obtained from a public repository . The raw logs contained 285,120 rows and consisted of several columns including username, session_id, action, object, and time. The action column contained information about the learner activity about four course components: course materials (11,040 rows), videos (9,503 rows), assignments (160,519 rows), and discussions (199 rows). The data set used binary labeling to indicate whether students had successfully completed the MOOC or not. Specifically, students who failed to complete the course were labeled as “1” (n=593), while those who successfully completed it were labeled as “0” (n=214). The dataset does not include details pertaining to the video content or other attributes such as duration or difficulty level. The absence of contextual information in public datasets has been criticized (Authors, 2021).

Data preprocessing

Since this study focuses on students’ video interactions, the data was filtered to retain the logs about students’ interactions with videos, including the following actions: pause, play, or seek. These actions were considered essential indicators for measuring video engagement within the scope of this study. The raw dataset contains records of students’ actions for each video interacted under different sessions. We treated each student’s interactions with each single video as a separate sub-session and computed the video engagement indicators for each sub-session. For example, if a student interacted with video Y during a session with the sequence play-pause- play and with video Z with the sequence play-seek-seek-pause-play, two sub-sessions were created. The resulting dataset contained the computed video engagement indicators for each sub-session, as illustrated in Table 1. Please note that in this derived dataset, the order of the video interactions has no importance.

Table 1. Example rows for demonstration

Sub-session	video_id	play_count	pause_count	seek_count
1	Y	2	1	0
2	Z	2	1	2

This process resulted in 6,656 rows of data about how students interacted with different videos in separate sessions. Notably, the clustering analysis was conducted at the session and video level, rather than the individual student level.

Data analysis

The clustering analysis was performed using k-means unsupervised learning algorithm. K-means is a simple yet effective algorithm that partitions data points into clusters based on the distance between a data point and a centroid (Antonenko et al., 2012). The Scikit-Learn (Pedregosa et al., 2012) implementation of K-means was used with Euclidean distance serving as the distance function. K-means algorithm requires the number of clusters to be predetermined, which necessitates prior analysis to determine the ideal number of clusters from the dataset. The Silhouette coefficient and Elbow method were employed in this study to determine the number of clusters. The silhouette coefficient value closer to 1 indicates dense and well-separated clusters with minimal overlap (Rousseeuw, 1987). The elbow method computes the explained variance (i.e., the sum of squared distances) in terms of the number of clusters (K). The point where the elbow bends is chosen as the optimal number of clusters (Aggarwal & Sharma, 2019). Before the whole analysis, the data was standardized to ensure that all variables have a similar range.

Results and findings

Determining the ideal number of clusters

The Silhouette coefficient was computed for a range of 2 to 10 clusters and visualized as a line chart in Figure 1. The maximum coefficient value was found at three clusters. Thus, according to the Silhouette method, three was decided as the number of clusters to achieve high cohesion (similar sessions are clustered together) and separation (distinct clusters are well separated). To cross check the validity of the number of clusters, another common technique called elbow method, was also applied. The outcome of the elbow technique in this dataset is visualized in Figure 2. Similar to the preceding approach, the elbow technique indicates 3 as the number of clusters.

Figure 1. Silhouette coefficient values for different number of clusters

Figure 2. The explained variance values for different number of clusters

Clusters of video engagement behavior

K-means clustering algorithm was used to identify the groups exhibiting distinct patterns of video engagement among 6656 video interaction sessions in the MOOC. The resulting clusters are presented in Table 2, which also displays the mean values of the three indicators used to measure video engagement (play_video, pause_video, and seek_video).

Table 2. Emerging clusters of video engagement behavior

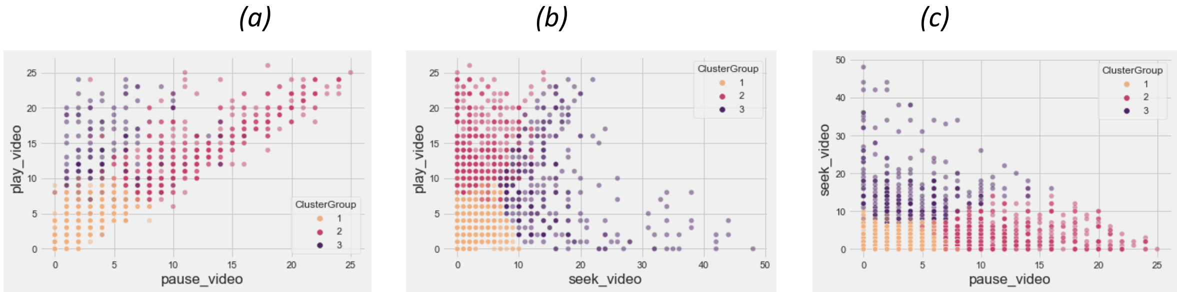
Clusters	Number of sessions	play_video	pause_video	seek_video
1: Static viewing	5369 (80.66%)	2.44	2.01	0.54
2: Engaged viewing	905 (13.60%)	12.31	10.86	3.01
3: Focused viewing	382 (5.74%)	8.68	4.05	13.59

Based on the results presented in Table 2, the majority of sessions (80.66%) were classified under Cluster 1. This cluster is characterized by lower levels of interaction with videos compared to other clusters, and thus labeled as *static viewing*. In this cluster of 5369 sessions, on average students pressed the play button 2.44 times, paused videos 2.01 times, and sought the video 0.54 times. These statistics indicate that for the majority of the sessions, students demonstrated static viewing behavior by merely pausing and playing the videos, thus watching them with minimal interaction.

The sessions under Cluster 2 (13.60%) are distinguished by much higher play and pause interactions compared to other clusters, along with some seeking activities that are higher than cluster 1 but lower than cluster 3. This cluster is labeled as *engaged viewing*, as the sessions involved frequent pausing and replaying videos, indicating student interest and engagement with the video content. That is, the engaged viewing behavior observed in Cluster 2 might indicate a higher level of cognitive engagement, as students may have paused videos to act on the video content (such as checking their understanding, reviewing a formula, or taking notes). However, it is important to note that this cluster contains a relatively smaller number of sessions, suggesting that engaged viewing was not a very common behavior among the MOOC learners.

Cluster 3, which had the lowest number of sessions accounting for only 5.74% of the total, was characterized by a very high number of seeking in videos compared to other clusters, accompanied by frequent pauses and plays that are higher than Cluster 1 but less than Cluster 2. Based on these behaviors, the engagement behavior in this cluster was labeled as *focused viewing*. In this cluster, students appeared to be highly interested in a specific content and searched for the corresponding video segment. Once they found the content, they interacted with it by playing and pausing the video, which is similar to the behavior of the second cluster, but more focused on a specific portion of the video. Focused viewing behavior might be a good indicator of both interest and deeper engagement in learning. However, it was the least frequent behavior observed in this MOOC context.

The relationships between the video engagement indicators were examined to gain a deeper understanding of the video viewing behavior within each cluster. Figure 3 depicts the interactions among the indicators as scatter plots and their corresponding correlations under each plot. In the scatter plots, each point corresponds to a video session, and clusters are indicated by different colors. According to Figure 1 (a), in all clusters, the numbers of plays and pauses were significantly and positively correlated. Although this correlation was particularly strong in clusters 1 and 2, the sessions in cluster 1 (static viewing) exhibited lower levels of play and pause activities than those in cluster 2 (engaged view). In contrast, the correlation between play and pause activities was relatively lower for cluster 3 (focused viewing), as the sessions in this cluster involved mostly seeking the video.



(a)	(b)	(c)
Cluster 1: 0.81 ($p < 0.05$)	Cluster 1: 0.35 ($p < 0.05$)	Cluster 1: 0.14 ($p < 0.05$)
Cluster 2: 0.83 ($p < 0.05$)	Cluster 2: 0.19 ($p < 0.05$)	Cluster 2: -0.02 ($p > 0.05$)
Cluster 3: 0.43 ($p < 0.05$)	Cluster 3: -0.24 ($p < 0.05$)	Cluster 3: -0.13 ($p < 0.05$)

Figure 3. Interaction between video actions in different clusters

Furthermore, the relationship between playing and seeking video activities was found to be weak and inconsistent across the different clusters, as illustrated in Figure 3 (b). Although clusters 1 and 2 displayed a positive correlation between the two activities, the correlation in cluster 1 (*static viewing*) was relatively higher due to the low level of engagement in both activities. Conversely, in cluster 2 sessions (*engaged viewing*), students were found to be highly in the act of playing videos, while displaying considerably less interest in the seek action. In contrast, clusters 3 (*focused viewing*) revealed a weak negative correlation between the two actions, indicating that focused students spent much effort in seeking some content inside the few played videos.

Last, based on the data presented in Figure 3 (c), it can be observed that the correlation between the seek and pause actions was lower than the correlations between the other video actions. Specifically, significant low correlations were noted in clusters 1 and 3, suggesting no or minimal association between the number of times students seek video and pause video.

Video engagement behavior and MOOC completion status

To answer the second research question, the association between students' course completion statuses (aka., achievement status as success vs failure) and their video engagement behavior was examined in three stages of descriptive analysis. In the first stage, the number of sessions from the three clusters was calculated for successful and failed students to identify the frequency of the session types by the achievement status. Following this analysis, the second stage focused on the percentages of successful and failed students who had at least one session from each cluster. This analysis provided additional insights into the prevalence of distinct engagement behavior in different achievement statuses. Finally, in the last stage, the percentage of students who demonstrated multiple engagement behavior was analyzed for both achievement statuses, thus complementing the earlier analysis involving single engagement behavior.

First, the percentages of sessions belonging to successful or failed students were computed for each cluster, as presented in Table 3. While in cluster 1, the percentages of the sessions were found to be very close between the successful and failed students (54.83% vs 45.17%), the gap between these two student groups increased in cluster 2 (59.00% vs 41.00%) and reached to its maximum in cluster 3 (61.78% vs 38.22%). These results suggest that, regardless of their achievement status, the students demonstrated a high frequency of static viewing behavior. However, the achievement status was more distinguishing in the other two behaviors. Successful students demonstrated engaged viewing and focused viewing behaviors more frequently than failed students.

Table 3. Percentage of sessions pertaining to each achievement group

Status	Cluster 1: Static viewing	Cluster 2: Engaged viewing	Cluster 3: Focused viewing
Success	54.83% (n=2944)	59.00 % (n=534)	61.78% (n=236)
Fail	45.17% (n=2425)	41.00% (n=371)	38.22% (n=146)

The second stage of the analysis focused on the percentages of students who had at least one session from each of the three video viewing behavior clusters. These percentages were computed for successful (n=214) and failed (n=594) students separately, and the results are provided in Table 4. Consistent with the findings discussed earlier, the vast majority of students in both achievement groups engaged in static viewing (cluster 1) at least once. For example, 87.86% of the failed students and 89.25% of the successful students had at least one session of static viewing. However, engaged viewing (cluster 2) and focused viewing (cluster 3) were less frequently observed in both achievement groups, with the percentages being significantly lower for the failed students. In particular, 21.59% of the failed students had a session that involved engaged viewing, and a mere 11.47% had a session that involved focused viewing.

On the other hand, these engagement behaviors were more prevalent among the successful students. Almost half of the successful students (49.07%) demonstrated engaged viewing at least once, and over a one third (36.92%) had a video session involving focused viewing. These results provide some indication of the relationship between achievement status and the presence of engaged viewing and focused viewing behaviors. However, it is worth noting that the overall number of students demonstrating these behaviors was relatively low.

Table 4. Percentage of students per achievement group who have a session in each cluster.

Status	Cluster 1: Static viewing	Cluster 2: Engaged viewing	Cluster 3: Focused viewing
Success	89.25% (n=521)	49.07% (n=105)	36.92% (n=79)
Fail	87.86% (n=191)	21.59% (n=128)	11.47% (n=68)

The results of the descriptive statics so far demonstrated that students' video watching patterns may vary depending on their achievement status. In the third stage of the analysis, we examined the extent of student engagement by investigating multiple video-watching behaviors. Table 5 presents the percentage of students in each achievement group who exhibited more than one type of video watching behavior. Among the successful students, 24.30% demonstrated all three types of video engagement behaviors, and 46.26% exhibited both static viewing (cluster 1) and engaged viewing (cluster 2). Approximately, 33.64% of the students exhibited both static viewing (cluster 1) and focused viewing (cluster 3), while24.30% demonstrated both engaged viewing (cluster 2) and focused viewing (cluster 3) behaviors. These results suggest that exhibiting multiple engagement behaviors was not uncommon among successful students.

When analyzing the behavioral patterns of the failed and successful students, the discrepancy between the failed and successful students becomes more pronounced. For example, only 5.06% of the failed students demonstrated all three types of behaviors, which is five times less than the corresponding percentage of the successful students. This disparity is consistently large in clusters 1 &3 (9.27% vs. 33.64%) and clusters 2 & 3 (5.05% vs. 24.30%), but relatively smaller in cluster 1 & 2 (19.56% vs. 46.26%). Consequently, when combined with other behaviors, focused viewing (cluster 3) creates a wider gap between the groups. These findings provide additional support for the argument that focused viewing is the most distinguishing behavior that sets successful students apart from their unsuccessful peers.

Table 5. Percentage of students with a session in multiple clusters

	Static & Engaged & Focused	Static & Engaged	Static & Focused	Engaged & Focused
Success	24.30% (n=52)	46.26% (n=99)	33.64% (n=72)	24.30% (n=52)
Fail	5.06% (n=30)	19.56% (n=116)	9.27% (n=55)	5.05% (n=30)

Discussion

This study identified three clusters of distinct behaviors based on students' interactions with different videos in separate sessions. The clustering approach allowed us to distinguish distinct engagement patterns based on the sessions instead of the students, which differs from most research where the clustering was made to group students based on their video interactions and general course engagement (Mirriahi et al., 2016; Su & Wu, 2021).

The most predominant behavior among MOOC learners was static viewing (cluster 1), where students viewed videos with minimal interactions. In this cluster, the play and pause events were infrequent but highly correlated, while the seek events were rare and poorly correlated with play and pause events. Hence, static viewing was possibly utilized by students when they needed to watch an entire video without interruption, with little need for interaction such as playing and pausing. This behavior might be influenced by factors such as video length, concept complexity, and video quality (Colasante, 2022). For instance, when viewing a short or easy-to-understand video, students may need to interact with the video a few times. Furthermore, video sessions with static viewing were almost equally distributed among the high and low achieving students, and nearly 90% of both achievement groups used static viewing at least once. Therefore, although this behavior might be needed most often when watching videos in MOOCs, it should not be considered a distinctive video engagement type between the high achievers and low achievers.

While MOOC learners tended to watch videos rather statistically most of the time, engaged viewing (cluster 2) involving high frequency of play and pause events also occurred occasionally. In engaged viewing, a very strong linear relationship between play and pause events was recorded. The high level of interaction suggests that these students are actively engaged with the video content, possibly pausing to take notes or review complex concepts. This behavior indicates a higher cognitive engagement of students in videos and several factors may motivate students to use it. The type of video content and the complexity of a concept in a video might be the main factors for engaged viewing (Kim et al., 2014). For example, a video may demonstrate the solution of a difficult problem or outline the code written for a complex program, and students may need to pause and replay such video frequently to be able to follow the steps gradually and develop a greater comprehension. Supporting this argument, strong links were noted between engaged viewing behavior and high achievement. As an example, while most of the sessions involving engaged viewing belonged to the successful students, only 20% of the failed students exhibited the engaged viewing behavior. That is, students with this behavior were relatively more successful at the end of the MOOC. This finding offers compelling proof that engaged viewing was an effective strategy for enhancing learning via videos, resulting in improved academic achievement. However, this behavior is less common than static viewing, indicating that most MOOC learners may not be fully leveraging the interactive capabilities of video-based learning.

Focused viewing (cluster 3), where students sought specific video segments, was the least common behavior among MOOC learners, indicating its rarity. It is characterized by active seeking within videos, suggesting that these students are selectively viewing specific portions of the videos. This behavior was likely employed when students aimed to find crucial information in videos, reflecting their extra effort to fill knowledge gaps and deepen their understanding. This behavior may indicate a deeper level of engagement, as these students are likely focusing on particular topics or concepts that are of interest or challenging to them. Notably, successful students primarily used focused viewing, with over 60% of sessions involving this behavior, while only 11% of failed students exhibited it at least once. Unlike engaged viewing, the difference in focused viewing between successful and failed students was more noticeable, hinting at a link between focused viewing and high achievement, although it was infrequently employed, even by successful students.

In all clusters, the numbers of plays and pauses are positively correlated, indicating that students who frequently play videos also tend to pause them often. However, the relationship between playing and seeking activities varies across clusters, suggesting different patterns of engagement. For instance, in Cluster 3 (focused viewing), there is a weak negative correlation between playing and seeking, indicating that these students spend more effort seeking specific content rather than playing the entire video.

Among successful students, a significant proportion exhibited more than one type of video engagement behavior. This suggests that successful students are not only more likely to engage actively with the video content, but they also tend to use a variety of engagement strategies. These findings underscore the significance of using various video engagement strategies for success in MOOCs. Employing multiple strategies, especially engaged viewing and focused viewing in combination with others, strongly correlated with student success. This reinforces the importance of students' ability to regulate their video-watching behavior effectively, aligning with prior research emphasizing self-regulated learning in online courses (Lee & Lee, 2008; Littlejohn et al., 2016). However, it’s important to note that these are general trends and individual student behaviors can vary. Further research is needed to fully understand the relationship between video viewing behaviors and academic success.

Conclusion

The findings of this research have important implications for the design of MOOCs and other online learning platforms that support video-based learning. MOOC learners may exhibit varying video engagement behaviors and the design of the online learning platforms should consider these behaviors to promote effective and meaningful interaction with video content to create an optimal learning experience. Interventions that support the proper use of engaged viewing may increase students’ learning gains from videos. Drawing from the study’s findings, it’s evident that engaged viewing behavior is characterized by frequent pauses and plays, likely reflecting students’ efforts to take notes during video playback. Accordingly, an example intervention might be a video feature that enables notetaking when a video is paused or a feature that enables highlighting important parts of the video script, which may facilitate the engaged viewing behavior. Similarly, Desai & Kulkarni (2022) highlighted the superiority of interactive videos over linear, demonstrative videos in enhancing students' conceptual understanding and learning outcomes through active engagement. Moreover, interventions that encourage active seeking in videos can be effective in promoting focused viewing and deeper engagement with the instructional content. For example, it could be helpful to implement a bookmarking feature that enables students to mark specific video segments for future reference. This intervention can promote faster access to key information and improve overall learning outcomes. As this study showed that proper engagement with videos in a MOOC might be an important predictor of success, such interventions can support MOOC participants' learning experiences and lead to higher achievement.

The main limitation of this study is the lack of information about the context. In this research, a public dataset consisting of learners' interaction logs in a MOOC was used. Since the data was anonymized, the overall course structure (e.g., the number of modules), the pedagogical approach (e.g., self-paced vs instructor-lead), and characteristics of the videos (length, format, quality, etc.) were unknown. These factors can play a critical role in shaping student engagement and achievement (Er et al., 2019; Lockyer et al., 2013). Although achievement status can somehow relate to students' video-viewing behaviors, the content of the videos could possibly have some effects on students' interactions with videos. For example, frequent pausing and playing may indicate some difficulty with video content (Li et al., 2015). Therefore, if the video characteristics were known, additional insights could be drawn to explain students' video engagement behaviors. Future research should consider an analysis of video characteristics when explaining the behavioral patterns of MOOC learners' video engagement.

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