Video Features, Engagement, and Patterns of Collective Attention Allocation: An Open Flow Network Perspective

Jingjing Zhang [1], Yicheng Huang[2], Ming Gao[3]

Abstract

Network analytics has the potential to examine new behaviour patterns that are often hidden by the complexity of online interactions. One of the varied network analytics approaches and methods, the model of collective attention, takes an ecological system perspective to exploring the dynamic process of participation patterns in online and flexible learning environments. This study selected "Fundamentals of C++ programming (Spring 2019)" on XuetangX as an example through which to observe the allocation patterns of attention within MOOC videos, as well as how video features and engagement correlate with the accumulation, circulation, and dissipation pattern of collective attention. The results showed that the types of instructions in videos predicted attention allocation patterns, but they did not predict the engagement of video watching. Instead, the length and whether the full screen was used in the videos had a strong impact on engagement. Learners were more likely to reach a high level of engagement in video watching when their attention had been circulated around the videos. The results imply that understanding the patterns and dynamics of attention flow and how learners engage with videos will allow us to design cost-effective learning resources to prevent learners from becoming overloaded.

Notes for Practice

- A six-minute timeframe is not the gold standard, but the "shorter the better" approach applies to video design.

- The use of screen recordings or full screen has a strong impact on engagement with video.

- The types of instructions in videos relate to the allocation patterns of learners' collective attention.

- Learners are more likely to engage with videos when they are already paying attention rather than at the start or end of their online learning session.

Keywords
Network analysis, collective attention, video, interactions, extensibility

---

Corresponding author [1]Email: jingjing.zhang@bnu.edu.cn Address: School of Educational Technology, Beijing Normal University, Haidian District, 100875, Beijing, China. ORCID ID: https://orcid.org/0000-0002-0584-534X
[2]Email: hych_0819@163.com Address: School of Educational Technology, Beijing Normal University, Haidian District, 100875, Beijing, China.
[3]Email: mgao519@126.com Address: School of Educational Technology, Beijing Normal University, Haidian District, 100875, Beijing, China. ORCID ID: https://orcid.org/0000-0003-0129-703X

1. Introduction

Massive open online courses (MOOCs) are a well-researched but still controversial phenomenon, offering important opportunities for learning and teaching on a global scale (Ang et al., 2020; Jordan, 2014; Reich & Ruipérez-Valiente, 2019). At ClassCentral, for example, by 2020, more than 1,800,000 learners followed approximately 16,300 MOOCs (Shah, 2020). In these MOOCs, many learning resources in the form of video lectures, quizzes, etc., were provided to learners to gain or exercise knowledge (Breslow et al., 2013). While more MOOCs are continually being offered online, "A wealth of information creates a poverty of attention" (Simon, 1971, p. 40). The lack of learner support becomes even more problematic for self-regulated MOOC learning. When facing an excessive, ever-increasing volume of online learning resources, MOOC learners need to be able to navigate themselves to select what and how to learn in online spaces (Agonacs et al., 2020). Nevertheless, learners are not the best judges of the integrity of a body of subject knowledge since they do not possess the depth and breadth of understanding to make decisions about what to learn. MOOC learners face a great challenge: how to notice, select, navigate,

and learn from ever-growing video resources effectively in MOOCs. After all, failing to do so may affect commitment and engagement, ultimately resulting in incomplete courses (Shapiro et al., 2017; Terras & Ramsay, 2015; Watted & Barak, 2018). In this respect, MOOCs are costly to learners, as massive amounts of video resources constantly consume their attention (Zhang, Lou et al., 2019). This view contrasts with the mindset that MOOC learning is low cost from an economic perspective and urges us to further understand how MOOC learner groups allocate their attention to provide better learner support to avert cognitive overload.

Educational psychologists have long studied attention. In the past, they focused on understanding its role in the acquisition or use of experimentation to test hypotheses (Pashler & Sutherland, 1998). The theoretical views adapted from cognitive psychology, however, have been weakly constructed (Posner & Rothbart, 2007), as experimentation is unlikely to provide a real or authentic learning context to validate these hypotheses derived from differing theories. MOOCs certainly provide an authentic online learning context and dataset for studying attention and learning at scale. As a massive body of MOOC learners enters the MOOC space, it seems more important to know how different cohorts of learners allocate attention at the collective level to allow us to design cost-effective learning resources to prevent learners from becoming overloaded.

The term "collective attention" was first proposed by Wu and Huberman (2007) in their work "Novelty and Collective Attention." They used this concept to create a framework for using data-mining techniques to interpret online behaviours, associating it with the popularity and innovation of knowledge or information. The model of collective attention provides an ecological system view to understand heterogeneous behaviours in MOOC learning. Thus, this study adopted the open-flow network of collective attention to model clickstream data from "Fundamentals of C++ programming" (Spring 2019) offered by XuetangX to investigate a correlational relationship between the features of the MOOC video lectures, student engagement with them, and patterns of attention allocation (i.e., the accumulation, circulation, and dissipation of collective attention). Two sub-research questions were answered: 1) To what extent do participants engage with videos?; and 2) In what ways is collective attention accumulated, circulated, and dissipated while interacting with videos?

2. Using Learning Analytics to Understand Video-Based Learning

As an emerging field, learning analytics (LA) refers to "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long et al., 2011, p. 1). In LA, new methods and tools were adopted to induce a better understanding of learning behaviours and experiences (Long & Siemens, 2011) and inform a better design of learning environments (Colpaert, 2016). Recent studies have demonstrated that the LA approach provides new research opportunities to understand the online behaviours of MOOC learners in real and authentic learning contexts, in contrast to traditional experimentation. LA has the potential to generate new insights, often hidden in complexity, from digital footprints in online environments (Holmes et al., 2019).

The major MOOC platforms — Coursera, edX, and XuetangX — have shown that MOOC videos seem to provide authentic learning contexts for knowledge acquisition or transfer (Giannakos, 2013; Giannakos et al., 2014; Guo et al., 2014). This is especially pertinent to online learning where instructions are primarily in video format (Duhring, 2013). Many empirical studies have shown that learners spend most of their time on videos (e.g., Breslow et al., 2013; Kizilcec et al., 2013; Seaton et al., 2014). Guo and colleagues (2014) conducted the first analytic study to correlate video presentation styles with engagement using 6.9 million video viewing sessions of four courses in edX. In their study, they sorted videos manually into two major types: lectures and tutorials. They adopted a standard metric used by YouTube and Wistia, the length of time that students spend on videos as engagement time, and identified that production and presentation styles, such as slides, code, Khan-style, classroom, studio, and office desk, to some extent, affect engagement time with videos (Guo et al., 2014). Their studies made an important contribution to instructional design to define key design principles for video production in the context of video learning at scale. In the past few years, as video use has continued to provide a main method for instruction, there have been wide explorations (Giannakos, 2013) of video length (Guo et al., 2014; Luo et al., 2018), speaking speeds of lecturers (Lemay & Doleck, 2020), segmentation of video lectures (Kay, 2012), variations in instructor audio streams (Kim et al., 2014), and video lecture types, such as voiceover presentations, lecture captures, picture-in-picture style, and Khan style (Chen & Wu, 2015; Hansch et al., 2015; Ilioudi et al., 2013; Kokoç et al., 2020; Sadik, 2016). Other studies have compared hand-drawn versus narration-over-PowerPoint (Chen & Thomas, 2020) or looked at screencast video lectures (Chen et al., 2020; Swarts, 2012).

More advanced learning analytics approaches have been used to understand how video lecture design relates to learning behaviour, such as re-watching, and learning performance (Guo et al., 2014; Sinha et al., 2014). Many scholars have used clickstream data to examine the impact of instructional design elements (course content, teaching methods, etc.) on learning experiences (Jung et al., 2018). Others have explored how video interactions affect learning effectiveness, dropouts, etc. (Sinha et al., 2014). Contradictory results were also found in different studies. For example, Homer, Plass, and Blake (2008) found that teacher presence in a video may increase a learner's cognitive load, perhaps because of the split-attention effect created

by the teacher and the PowerPoint slides. In contrast, Guo and colleagues (2014) found that teacher presence has a positive effect on the number of videos students watch, perhaps because it helps learners form a sense of interacting with "real" teachers face-to-face (Tu, 2002).

Given that learning content, objectives, presentation styles, and length can be extremely diverse, one of the greatest challenges is to generate theories, principles, and guidelines to inform the development of videos for learning at scale (Giannakos, 2013). Multimedia learning theories, cognitive load, and attention have been used widely to interpret learning analytics studies in video-based learning. According to the cognitive theory of multimedia learning (CTML; Mayer, 2001), multimedia instructional design schemes (Sweller et al., 1998), and cognitive load theory (CLT; Sweller et al., 2011), learning is a positive and active process of selecting, organizing, and integrating information, which takes place in the cognitive structure with limited capacity (Mayer, 2014a). Earlier scholars (e.g., Basil, 1994; Lang et al., 1996; Lang, 2000) have also used the "limited capacity information processing approach" to illustrate that learners can only apply a limited number of cognitive resources to different tasks. In relation to these theories, Giannakos and colleagues (2014) found that video-based course design is closely related to redundancy, modality, and split-attention effects, which affect sustained attention, emotion, cognitive load, and learning performance. In recent years, signalling (Panev et al., 2020), embodiment and temporal contiguity (Chen et al., 2020), and modality (Wang et al., 2017) have also been increasingly studied in video-based learning. For example, a study by Fee and Budde-Sung (2014) supported Mayer's principles of multimedia design in signalling, segmenting, and personalization. Although some contradictions to Mayer's principles, e.g., the principles of redundancy and coherence, were also found in some studies, Mayer's (2014b) principles are widely accepted and used in designing video lectures.

In studies using Mayer's (2014a) principles to inform the design of videos, the relation between video lecture types and attention has attracted increasing consideration by scholars. Chen and Wu (2015) investigated the impact of different types of video lectures on sustained attention levels, affective status, cognitive load, and learning performance. They found that learning performance was better when picture-in-picture videos were used rather than voiceover videos, as the latter distracted learners; thus, their cognitive load increased excessively. Kizilcec et al. (2015) indicated that instructor-present videos positively affect the visual attention that learners pay to lectures. Pi et al. (2017) found that instructor pointing gestures affect learner visual attention, thus improving learning performance. Wang et al. (2017) reported that learners are likely to attend to instructor presence, which they found to be a positive predictor of participant satisfaction levels.

These previous studies investigating the possible impact of video lecture types on visual attention and learning attempted to generate theories and principles for personalized learning models in the context of video lectures. These studies provided important evidence about which types of video lectures are most effective for learners and what attention levels. Nevertheless, MOOC learners present a massive heterogeneous body of different learner profiles, including attention level. Although personalization is important in designing videos, it is rather challenging to design personalized video-based learning to accommodate massive crowds of learners. Learners with different levels of sustained attention ask for different types of videos to cater to their different cognitive styles, which leads to different learning performances. Thus, some new metrics to measure attention at the collective level might be an alternative approach to inform instructional design for video learning at scale. Different approaches and methods of examining attention at the collective level might provide more options for learners as a group to identify what and how to learn.

3. Using Network Analytics to Understand Online Learning Behaviours

Learning analytics offer an increasing opportunity to understand learning behaviours on a large scale. One approach is lag sequential analysis (LSA), which highlights significant sequential behaviours in relation to the temporal dimension (Chen et al., 2017; Knight et al., 2017). LSA is commonly used for analyzing the learning trajectories of those participating in learning activities in guided or well-designed explorative and collaborative environments (e.g., Li et al., 2021; Sun et al., 2021; Zhang, Gao et al., 2019; Zheng et al., 2021). The identified patterns of sequential behaviours could help researchers and instructors provide personalized feedback (Hou, 2012; Hwang & Chen, 2017; Yin et al., 2017), promote knowledge construction (Lan et al., 2012; Lin et al., 2013; Yang et al., 2015), etc. However, in a MOOC environment, with much looser governance, varied short, segmented clickstreams might not be meaningful when using LSA to examine significant sequences of non-guided, non-facilitated learning behaviours.

The learning analytics field has gradually realized a pressing educational need to understand behaviours using a network paradigm (see Poquet, Hecking et al., 2020). Using such an approach dates back to Albert, Jeong, and Barabási's (1999) classic work on the Worldwide Web. In learning analytics studies, research has relied heavily on social network models to interpret interactions between people, assuming their behaviours will be influenced by others in their neighbourhoods, such as friends, peers, and classmates (e.g., Joksimović et al., 2016; Oleksandra & Shane, 2016; Gillani & Eynon, 2014). Social network analysis has promised to significantly change the way we examine the nature of online learning behaviours that mainly occur in forums (e.g., Hernández-García et al., 2015; Poquet, Tupikina et al., 2020; Kellogg et al., 2014; Stepanyan et al., 2013;

Zhang, Skryabin et al., 2016; Poquet & Jovanovic, 2020; Chen & Poquet, 2020). The social network model is a powerful, useful tool for examining relationships between actors. Still, it has limitations when examining the dynamics in MOOCs with high rates of attrition and unequal learner participation patterns. In classic social network modelling, when highly active learners drop out, the network is likely to encounter a sudden change in structure, creating challenges in modelling the changed dynamics of interactions. This has been recognized as the important nature of online learning, where learners can enter and leave in a flexible manner.

Unlike social network models or other closed network models, the collective attention model is closely related to those commonly used in network science, such as metabolic and genetic regulatory networks. As mentioned above, the concept of collective attention was first proposed by Wu and Hubermman (2007). They found that "collective attention" effectively explained the growth and decline of the attention of one million people who read news on interactive websites (a nonexperimental scenario). Later, collective attention was modelled using an open, balanced flow system, where attention was usefully modelled as dynamic flows circulating between online resources in a way similar to energy flows between species (Odum, 1983), flow of goods between countries (Leontief, 1986), and money or value flows between industrial sectors (Miller & Blair, 2009; Raa, 2005). Such a metaphor treats online learning as various patterns of rapid and constantly changing behaviours on the network representations of knowledge (Baronchelli et al., 2013). Thus, cognitive aspects (e.g., memory, thought, and attention) can be re-examined using this sort of new model of network dynamics at the collective level. Regarding theories of open system and network dynamics, the dynamics of clickstreams can be seen as equivalent to an embodiment of a continuous attention flow (Kammenhuber et al., 2006). In open, flexible learning environments such as MOOC contexts, this new type of network model accounts for varied, individualized participation patterns of learning. In a loosely organized learning environment, the dynamics of learning behaviours, including learners who perform well (or fail) and those who may drop out, are equally important, since designing online educational resources attempts to resolve educational equality and meet the needs of individual learners (Zhang et al., 2021). This short, heterogeneous, atypical learning behaviour might be well poised to make valuable interpretations of typical MOOC behaviours for creating a sustainable future learning environment, similar to the creation of robust electricity and energy systems using open, balanced network modelling (Helbing, 2013). The more robust and balanced a flow network is, the more likely it is that a corresponding social-ecological learning space can be created to address the problem of lack of instructional and social support (Zhang, Lou et al., 2019). As we can see, the concept of collective attention has not been defined precisely as the capability of individuals in a single state or a condition; rather, in the digital age, it has a broad meaning (see adetailed review of collective attention in the work of Zhang, Lou et al., 2019).

4. Methods

4.1. Context of the Study

After conducting a detailed investigation of all available courses on XuetangX, the "C++ language programming foundation (Spring 2019)" was selected as the case for this study. This course was selected because various types of instructions, including introductions, lectures, examples, summaries, and experiments, were found in course videos. In addition, the videos were presented in diverse formats, such as projection demonstrations or PowerPoints, while switching between human and computer interfaces. By the end of 2020, more than ten thousand students had signed up for the chosen course. Of these, 6,278 actually watched the course videos. Two instructors taught the course in co-operation. The lead instructor was responsible for delivering the videos, while the other presented lab experiments for C++ on a computer.

Similar to many xMOOCs, most interaction with content is via video. The course has six chapters comprising 73 units. In these units, one or more videos is embedded, presenting knowledge in small chunks to aid in information digestion. In total, 114 videos are provided. As clickstream data were stored in association with the unit URL, we took the course unit as the smallest unit of analysis for data processing and modelling collective attention networks. In the format of "html, " other learning resources are text-based content, and some are course requirements and logistics. The course also contains unit quizzes and discussion forums, similar to conventional MOOCs.

4.2. Data Preparation

The correlation analysis used video lecture types (such as length of video, type of video, and presentation type) and engagement(watching and re-watching patterns) as the independent variables (see Table 1, and Sections 4.3, 4.4, and 4.5) to examine any differences in patterns of attention allocation (i.e., accumulation, circulation, and dissipation of collective attention) in relation to features associated with MOOC video lectures and engagement with videos.

Table 1. Variables Used in Correlation Analysis

Variable	Variable	Type	Range
Video lecture feature	V_Length: Video length	Numerical	ranging from 52 to 1549
	F_Instruction: Type of video	Categorical	five possible values: 1) introduction (8.22%); 2) lecture (67.12%); 3) example (4.11%); 4) experiment (13.70%); 5) summary (6.85%)
	F_Knowledge: Knowledge type	Categorical	three possible values: 1) declarative knowledge (36.99%); 2) procedural knowledge (17.81%); 3) both declarative and procedural knowledge (45.21%)
Video presentation type	P_Screen_full: Using PowerPoint slides in full screen	Categorical	yes (with 54 examples) and no (with 19 videos)
	P_Screen_recording: Using Screen recording to show	Categorical	yes (with 21 examples) and no (with 52 videos)
	P_Teacher_Switching: Different postures taken from different angles	Categorical	yes (with 40 examples) and no (with 33 videos)
Engagement with videos	B_Watch: Watching behaviours	Numerical	ranging from 0.5365 to 0.9566
	B_Rewatch: Re-watching behaviours	Numerical	ranging from 0.0577 to 0.3275
Allocation pattern of collective attention	Ai: Accumulation	Numerical	ranging from 0.002 to 0.137 (normalized)
	Cui: Circulation	Numerical	ranging from 0.003 to 0.047 (normalized)
	Di: Dissipation	Numerical	ranging from 0.003 to 0.071 (normalized)

4.3. Video Lecture Features

In this group of variables, the length, type, and knowledge type were analyzed to represent the features associated with video design. Whether the full screen was used, whether screen recording was used, and whether different instructor postures recorded from different angles were used represented the presentation type.

4.3.1. Video length

Within the 73 video units provided in this course, the total length of the 114 videos is approximately 16.82 hours. The longest video lasts 25.82 minutes (i.e., 3-14) while the shortest is 52 seconds (i.e., 2-10), with an average length of about 8.85 minutes. Most videos (71.23%) are longer than 6 minutes, which does not follow the six-minute timeframe proposed by Guo et al. (2014) as the standard for the actual time learners spend on a video.

4.3.2. Type of video

According to the course design, the videos are segmented into five categories to guide learners in understanding: introductions (I_Introduction), lectures that deliver conceptual knowledge (I_Lecture), examples that provide cases for understanding procedural knowledge (I_Example), experiments that demonstrate how to run C++ code through a screen recording (I_Experiment), and summaries (I_Summary). More details and explanations are summarized in Table 2. Each unit includes these five types of instruction, except for Unit 1, which has no summary video. Moreover, this course is a typical xMOOC, which predominately uses lectures assisted by PowerPoint slides to deliver knowledge (i.e., 67.12% of the lectures are of this type). As a programming language course, 13.70% of the videos provide examples that demonstrate how to run C++ code in experiments that use screen recordings. A few examples (4.11% of the videos) for understanding procedural knowledge are provided.

Table 2. Different Types of Video Instruction

Variable	Explanation	Percentage	Format
I_Introduction	Guiding learners to understand the course	8.22%	
I_Lecture	Using PowerPoint slides to deliver knowledge	67.12%	
I_Example	Providing examples for understanding procedural knowledge in PowerPoint	4.11%	
I_Experiment	Running C++ codes in experiments	13.70%	
I_Summary	Summarizing the material	6.85%	

4.3.3. Knowledge type

For each video, the knowledge type was manually categorized into one of three groups. As shown in Figure 1, 45.21% of the videos provide both declarative and procedural knowledge. For example, when teaching the concepts of "function" and "array," the teacher often presents how to write the code and explains some related applications at the same time. In contrast, 36.99% of the videos only provide declarative knowledge, and 17.81% only provide procedural knowledge.
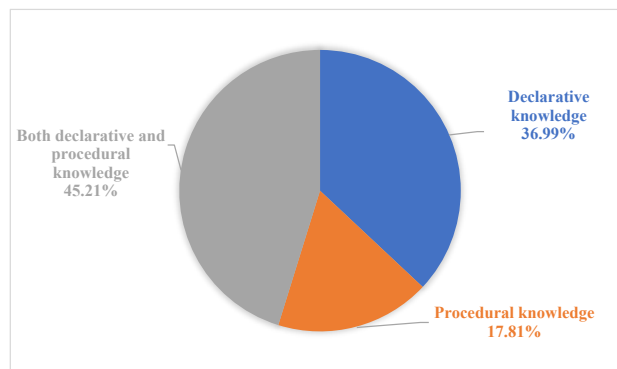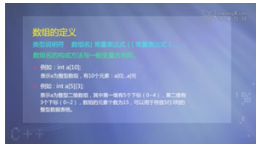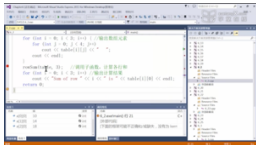

Figure 1. Distribution of declarative and procedural knowledge.

4.3.4. Presentation types of videos

In addition to the varied types of instruction delivered, the different presentation types were extracted, as summarized in Table 3, i.e., whether the PowerPoint slides took up the full screen (Screen_full) or if a screen recording was used (P_Screen_recording), the teacher's presence (P_Teacher_presence), and whether the teacher changes posture via different recording angles (P_Teacher_switching). In the studied MOOC, teachers appear in each of the 73 videos; thus, the variable (P_Teacher_presence) was not included in the data analysis. The majority of videos (73.97%) use PowerPoint slides in full-screen mode to deliver knowledge (P_Screen_full), while 28.78% use screen recordings (P_Screen_recording). Lecturers in 54.80% of the videos switched recording angles for their lectures (sitting on a chair or standing at a podium; or switching between near and far distances; P_Teacher_switching), and 45.20% did not change their position.

Table 3. Video Presentation Type

Variable		No. videos	Screenshot		No. videos	Screenshot
P_Screen_full (using PowerPoint slides in full screen)	Yes	54 (73.97%)		No	19 (26.03%)	
P_Screen_recording (if not, using PowerPoint slides)	Yes	21 (28.77%)		No	52 (71.23%)	
P_Teacher_switching (Different postures taken from different angles)	Yes	40 (54.80%)		No	33 (45.20%)	

4.4. Watching and Re-watching Patterns

In this group of variables, building upon the work of Guo and colleagues (2014), we calculated the average lengths of watched (B_Watch) and re-watched percentage of videos (B_Rewatch) to examine engagement. The B_Watch variable was numerical, ranging from 0.5365 to 0.9566, and the B_Rewatch variable ranged from 0.0577 to 0.3275.

4.5. Accumulation, Circulation, and Dissipation of Collective Attention

Using social networks to model the flexible nature of MOOC learning poses challenges since students learn at their own pace, and most drop out before completion (Zhang et al., 2021). Consequently, such network structures encounter sudden changes that are unlikely to converge in network dynamics. Thus, new network models are needed to address the problem of high attrition rates and highly unequal participation patterns. The proposed new network model can be seen as a transposition of the social network matrix; that is, the matrix is flipped over its diagonal in linear algebra. The new proposed network model use nodes to represent resources, and links to resemble learners as they come and go via resources. Since most MOOC learning resources are predesigned, the learning resources as nodes were relatively unchanged during the course. The flexible manner of online learning, where learners come and go, can be represented by the links added, revised, and removed using such network dynamics. This transposed model is similar to resource networks, so classical network metrics — indegree, outdegree, centrality, betweenness, closeness, and path — are commonly used to understand how these structures affect learning.

Nevertheless, the traditional closed network mode cannot fully support the dynamic nature of learners interacting with context as a constantly changing process (Whitt, 1984). To examine network dynamics, an open network model is more capable of modelling attention as flow (similar to modelling food or money as energy flow) to reach dynamic equilibrium (Nicolis & Prigogine, 1977). In contrast to a closed network of resources, where the link represents the weight of human-context interactions, an open network uses the links to embody input and output flows, representing energy exchanges (e.g., attention, money, electricity, jobs) with the surroundings. Using ecosystem theories to view online learning and courses provides insight into self-organizing behaviours (Schneider & Kay, 1994a), which are commonly found in open and complex systems with a flow of energy. Ecosystems are viewed as dissipative structures in self-organizing processes open to energy flows (Schneider & Kay, 1994a). We argue this is a much-needed theoretical framework for a sustainable educational system.

Therefore, in this study, we consider attention flow as a dissipative process in an open system to better understand the attention allocation patterns for videos. Similar to any energy flow (Annila, 2010), the pattern will meet the minimum energy cost, which is essential for instructional design strategies. Such understanding of patterns of attention flow allows us to design cost-effective learning resources to prevent learners from becoming overloaded (Zhang et al., 2019). For example, our previous study showed that the amount of attention flow decreased exponentially with increased flow distance, at a rate of 26%. Reorganizing learning resources with reference to their associated "tropic level" in "the learning chain" (i.e., the food chain) can therefore help learners effectively access the most importance resources without being overloaded (Zhang et al., 2019). In addition, scaling phenomena were found consistently in the open model of cities (Rees, 2012) or transportation (Cantarella & Cascetta, 1995) as dissipative systems. Based on the scaling law (Kleiber, 1932), we theorize that online learning is a growing

phenomenon that consumes learner attention at the collective level. The increasing accumulation of attention produces an incremental circulation across learning recourses within the system. The proposal of this theorization may allow for the development of measures and metrics useful for the instructional design of online courses. The contribution of these conceptualizations goes beyond other recent work in this area.
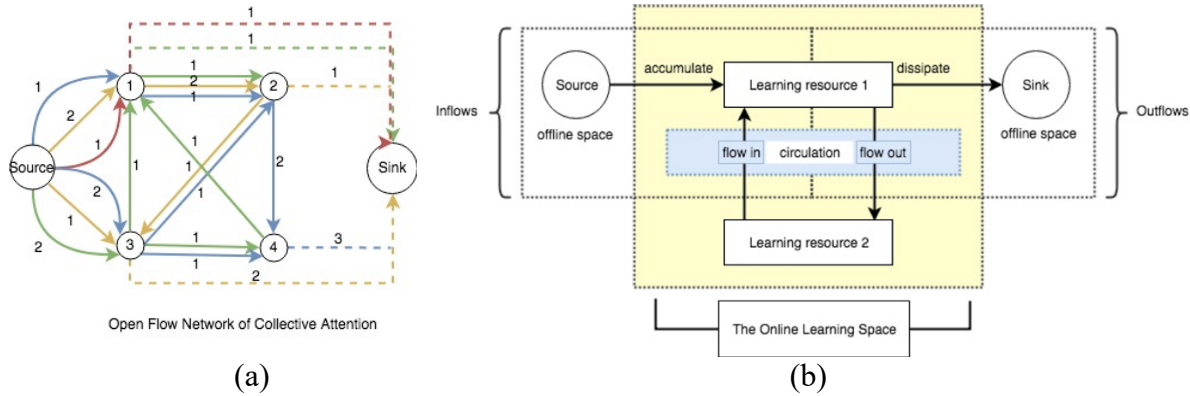

Figure 2. The accumulation, circulation, and dissipation of attention flow in the open flow network of collective attention (from Zhang, Gao et al., 2019, p. 287).

Conventionally, open network models are formulated to follow an equilibrium approach to create consistent and balanced flows in and out of densities. Building upon research on collective attention flow networks (Gao et al., 2019; Guo et al., 2015; Zeng et al., 2020; Zhang, Luo et al., 2016; Zhang, Lou, et al., 2019), an open-flow network of collective attention was created. As shown in Figure 2b, learning resources were represented by nodes, and edges illustrate the extent to which collective attention flowed in and out of these nodes. We can describe this open-flow network using a flux matrix $F = \{f_{ij}\}_{(N+2)(N+2)}$, where f_{ij} is the attention flow from i to j. N+2 represents the total nodes of this model. Node 0 and node N+1 represent "source" and "sink," while nodes 1 to N represent the nth units of videos in MOOCs.

Two artificial nodes (i.e., source and sink) are introduced to the proposed open flow network of collective attention to ensure dynamic equilibrium in an open system, which forces attention to flow in and out of the online space. The rationale to use the open network to model collective attention reconciles the idea that natural laws operate in open systems (Schneider & Kay, 1994a). For example, this design follows the second law of thermodynamics, derived from the statistical physics of open systems, stating that energy flows from energy sources (high energy density) to energy sinks (low energy density; Mäkelä & Annila, 2010). Echoing Raine, Foster, and Potts's (2006) argument that a reformulated second law of thermodynamics employed by Schneider and Kay (1994b) applies to the economic system, and we believe that Schneider and Kay's ideas also apply in educational contexts: "We believe that our thermodynamic paradigm makes it possible for the study of ecosystems/economics systems [educational systems] to be developed from a descriptive science into a predictive science founded on the most basic principles of physics" (Raine et al., 2006, p. 356; Schneider & Kay, 1994b, p. 25). In such conceptualization, the online learning environment is modelled as an open system with complex structures that allow attention flow to circulate among online learning resources, while exchange (i.e., accumulation and dissipation) occurs in the offline environment. This conceptualization, to some extent, connects online learning with face-to-face learning, via the added artificial nodes. In any case, dissipation is the expected system response. As shown in Figure 2a, collective attention flow in and out of different learning resources (e.g., learning resources 1 and 2) was defined as circulation flow. In contrast, attention flow in from the source to learning resource 1 was defined as accumulation flow, and attention flow out of learning resource 1 to the sink was defined as dissipation flow (Zhang, Lou et al., 2019).

The ultimate result of any network mode is a set of matrices and vectors. Still, these vectors were built in a new and informative way so that the accumulation, circulation, and dissipation flows can be calculated with equations. The attention flow from the node "source" to other nodes represents the time point at which participants go online (i.e., the accumulation of attention ($A_i = f_{0,i}$)). When participants go offline, their collective attention flows out to the node "sink" (i.e., the dissipation of attention ($D_i = f_{i,N+1}$)). In addition, attention will flow among various video resources in the online learning space, and we call this the circulation of attention in learning resources (i.e., the circulation of attention ($CU_i = \sum_{j=1}^{N} f_{j,i}$)). The accumulation, circulation, and dissipation of collective attention across videos could be calculated using clickstream data (i.e., the number of learners represents the amount of attention flow in and out of learning resources). Researchers considered online behaviours that occurred over 25.5 minutes apart as separate sessions (Catledge & Pitkow, 1995). This study used a 30-minute threshold

to delineate a sequence as a new session. In each session, sequential visits to the learning resources resembled the flux of attention flowing in and out of the resources, as represented by an edge between nodes.

In this open-flow network model of collective attention, flow distance was used as an innovative metric to measure the similarities and dissimilarities between learning resources. Flow distance, first proposed by Guo et al. (2015), was defined as the average first-arrival distance between nodes, calculated by an N-order Markov transition. Through the infinite order calculation of Markov transfer, it is obtained that the flow distance from node 1 and node 2 is equal to the sum of the probabilities of learners from node 1 accessing node 2 for the first time after k steps, where k ranges from 1 to infinity. Since flow distance measures the average first arrival distance between two nodes of a learning resource, the concept reflects the average number of steps required for attention flow to circulate from one learning resource to another. Viewing the online and open learning environment from the perspective of an ecological system, the flow distance to the source reflects the importance of the video resource at a collective. Zhang and Lou et al. (2019) found a negative correlation found between flow distance and the amount of attention flow; as the flow distance to the source became shorter, learners were more likely to access this learning resource after entering the online space.

5. Results

5.1. How Do Participants Engage with Videos?

5.1.1. Watching pattern

Between 20 February 2019 and 10 June 2019, the 73 video units were watched 895,332 times by 6,278 participants. On average, participants watched these 73 video units 142 times, and some were watched multiple times. In total, only 182 participants (2.90%) watched all 73 video units, while 2,355 participants (37.51%) only watched one video, which reflects typical MOOC learning behaviour.

On average, 6,278 participants watched 86.78% of the total time of all the videos. There were 258 participants (4.11%) who only watched 1% of these videos. The video about "constexpr function" in Unit 3 (3-9, 2.43 minutes long) was watched extensively, as participants watched 95.66% of its content. The lecturer talked about a new function in the C++ 11 standard in this video, which may have kept learner attention. In contrast, the first introduction video in Unit 1 (1-1) is 8.87 minutes long and includes the syllabus, teaching methods, and learning suggestions, but 53.65% of participants only watched it halfway through. To some extent, this implies that learners in this chosen course seemed to know what they aimed to study and went directly to it.
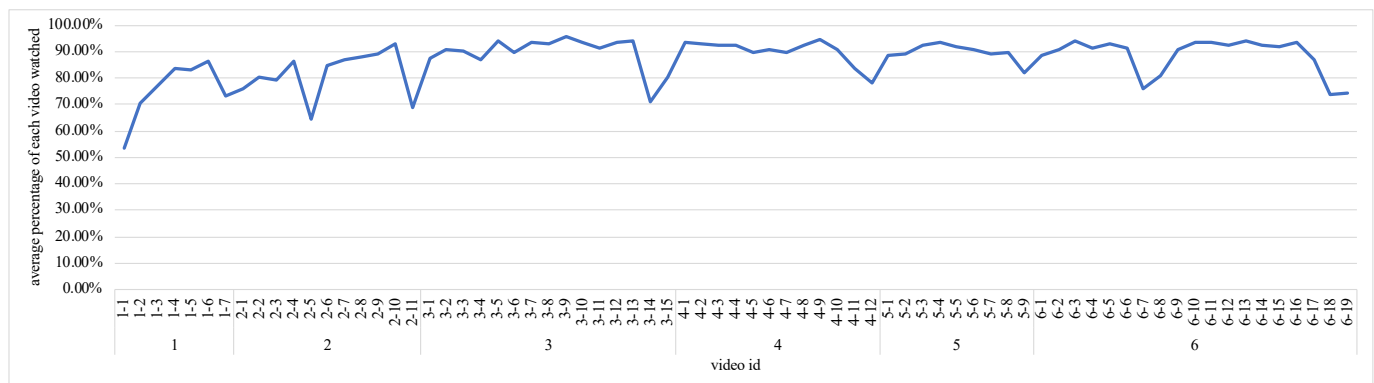

Figure 3. Average percentage of video watched.

5.1.2. Re-watching pattern

Re-watch behaviours were identified when a participant reassessed a video and stayed for more than 5% of its length. A total of 22.84% of participants re-watched videos, while 77.16% did not re-watch any. The two highest ratings for a re-watched video were 4-4 and 6-15, which were re-watched more than 60 times.
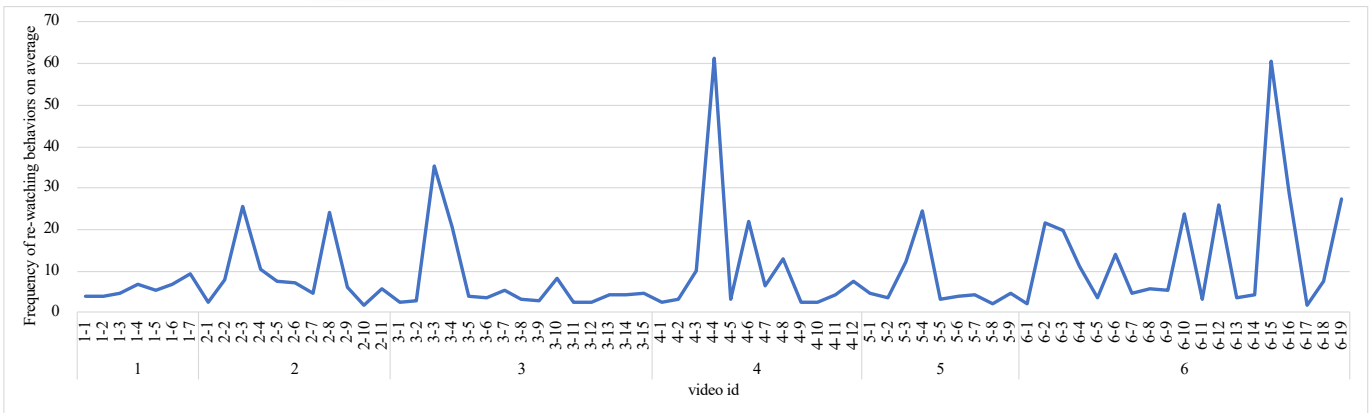
Figure 4. Average frequency of re-watching.

Compared to their first-time watching behaviours, participants were less likely to re-watch videos from start to finish. On average, only 19.56% of full-length videos were re-watched, which was far less than the percentage of the first viewing (an average of 67.23% of video length). The first video (1-1) in Unit 1 was still least likely to be finished when the participants re-watched it. One video (4-4) in Unit 4 was re-watched for longer than any other, on average for 32.75% of its length. This video, 7.98 minutes long, delivers knowledge through an ordinary lecture format, with screen recording and full-screen PowerPoints both being used. Additionally, the instructors varied their postures in the video, which were filmed from different angles.
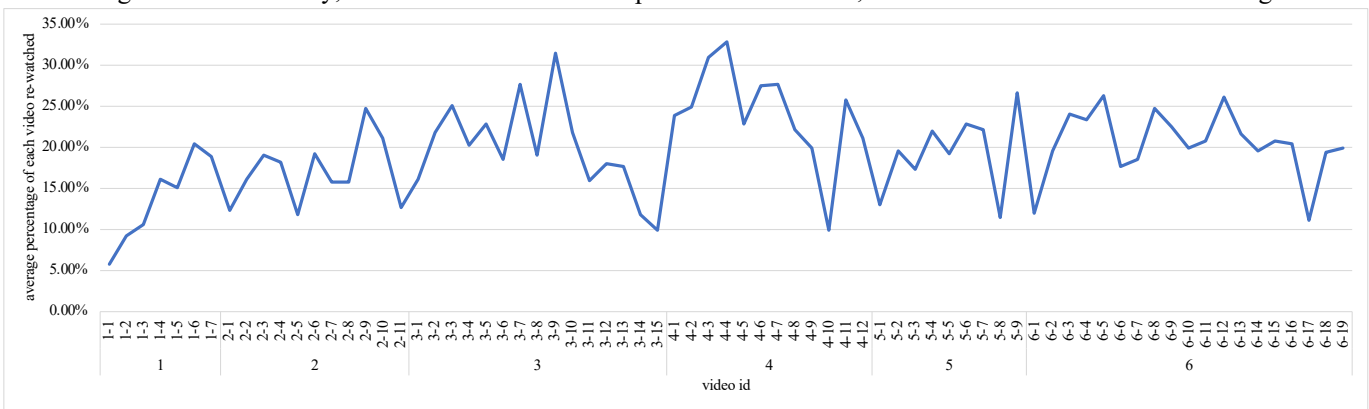

Figure 5. Average percentage of re-watched video length.

5.2. How Collective Attention is Accumulated, Circulated, and Dissipated

The accumulation, circulation, and dissipation of collective learner attention were identified using the collective attention model. Figure 6 presents Gephi's visualization of the collective attention network in which the nodes represent the 73 video units. The colour of the node illustrates the chapter to which it belongs, and the scale of the node represents the total amount of attention flow. The direction of the link between nodes indicates that collective attention flows from node x into node y, and the thickness of the link indicates the flow distance between them. As shown in Figure 6, the "source" node and the "sink" node, which represents the offline space, were connected to varied video nodes. In total, 75 nodes were connected via inflow and outflow of collective attention, resulting in 2, 559 links. The average degree of nodes is 34.12, the diameter is 3, and the average path length is 1.541. No particular predefined tree structure of the MOOC design was illustrated in this network. The total flow amount of the first 3–4 units of each chapter is usually larger, and the flow amount of the following units is less. As shown in Figure 6, the distance between learning resources in Chapters 4 and 5 are likely to be grouped, which implies that collective attention circulates more often across these chapters, when learners were studying the topics of "class and object" and "data sharing and protection."

The larger the value of flow distance (i.e., the thickness of the link) between two learning resources, the greater the probability that collective attention circulates across these two resources. The flow distance between v1-3 to v3-1, v3-13, v6-19, and the other 17 nodes is the shortest, which implies that the collective attention flow is unlikely to circulate across these learning resources. Taking the ecological view to understanding collective attention, the development of a greater diversity of learning resources to generate a more complex structure leads to more attention flow circulating across the learning resources

at more hierarchical levels, contributing to the growing scale of online learning as a living system. The more circulations across the learning resources in such a living system, the more sustainable this online course is likely to be.
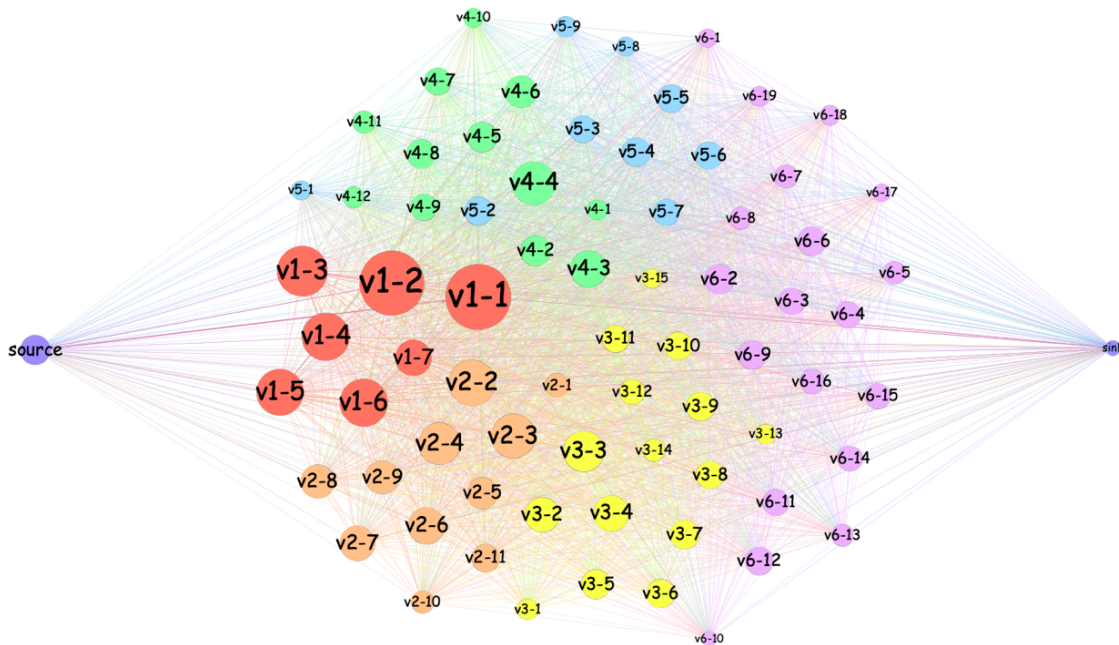

Figure 6. An open-flow network of collective attention.

5.2.1. The accumulation of collective attention

As mentioned above, the accumulation of collective attention of each node (i.e., video unit) shows how much collective attention was allocated first to this node when learners entered the online space. Figure 7 shows that the average accumulation of collective attention varied among different videos (blue line). Different videos accumulated various amounts of collective attention; that is, the accumulation flow fluctuated greatly. For example, video 1-1 ($A_{1-1} = 0.137$), video 2-2 ($A_{2-2} = 0.035$), and video 4-4 ($A_{4-4} = 0.031$) accumulated the greatest amount of collective attention when participants began their online learning (the amount is min-max normalized in the figure). Throughout the course, the accumulated amount decreased, which implies that participants might have started with earlier videos every time they went online before they followed their learning plans in different units. Within each unit, this pattern was significant. The earlier videos (e.g., the first lectures) were more likely to accumulate more attention than other videos in the same unit, which implies that participants were likely to start with the first lecture videos (rather than the introduction videos) every time they went online (except the very first video 1-1 in unit 1).

5.2.2. The circulation of collective attention

Circulation represents the process of collective attention circulated between different videos units in the online space. Figure 7 shows that the average amount of collective attention circulated across different videos presents a similar mountain-like pattern (orange line). After accumulating attention in the first lecture videos in the units, more collective attention was spread around later lectures and example videos, usually provided after the first lecture video (e.g., 2-6 to 2-9, 3.5 to 3.12, 4-6 to 4-10, 5-2 to 5-8, 6-2 to 6-17). The actual amount of collective attention circulated between different videos was significantly higher than the amount accumulated for all videos, which shows that participants might have left the online space more flexibly, but they also watched different videos, and their attention circulated between different videos more frequently than the accumulated attention.

5.2.3. The dissipation of collective attention

The attention dissipation of one resource represents how much collective attention has left the online environment from this particular resource. Figure 7 shows the average collective attention dissipated from different videos to the offline space (grey line). The patterns are rather similar to the accumulation and circulation patterns, which implies that more accumulated or circulated attention led to more attention being dissipated to the offline space, except for videos 2-5, 5-2, 6-2, and 6-8. More attention flows circulated through videos 5-2 and 6-2, but fewer were dissipated from them, which implies that participants were less likely to leave the online space after they had watched them. In contrast, less attention flows circulated through

videos 2-5 and 6-8, but more attention dissipated from them, which indicates that participants were more likely to leave rather than keep watching other videos.
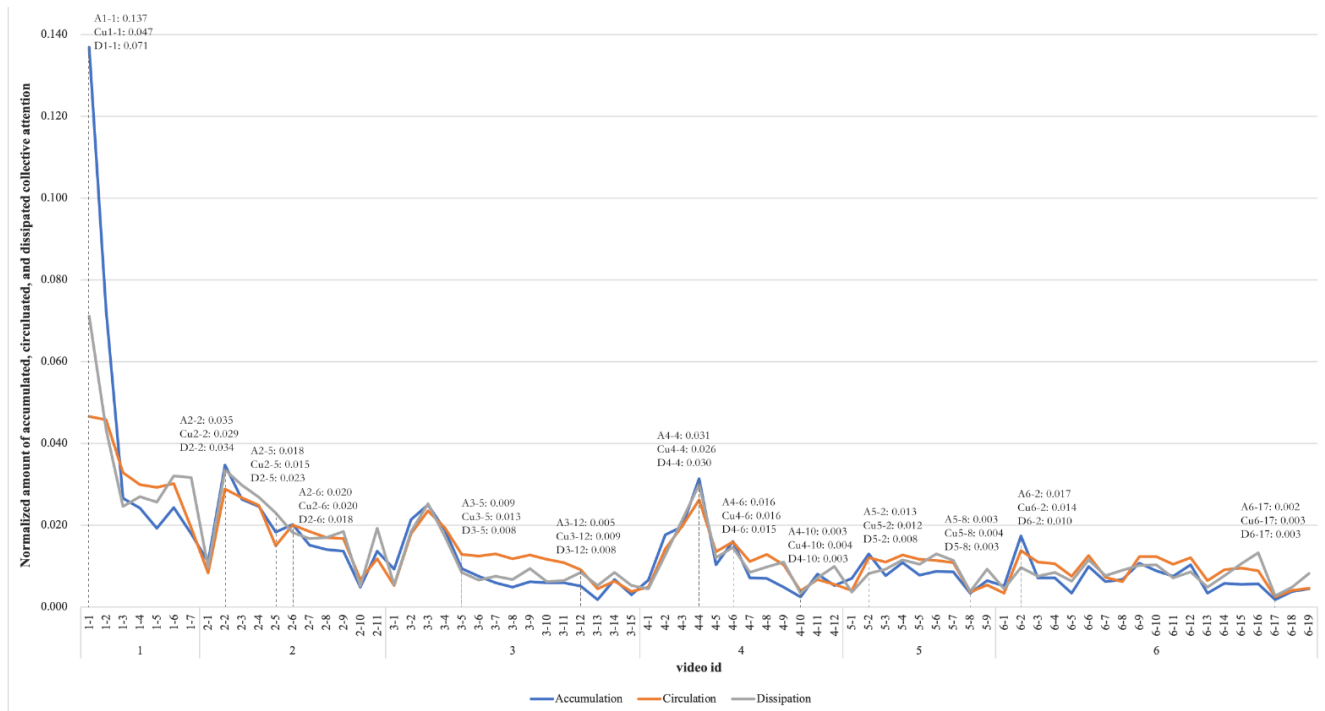

Figure 7. Accumulated, circulated, and dissipated amounts of collective attention in different videos.

5.3. Predicting Attention Allocation Patterns

Kendall tau was used to identify the relationships between the video lecture features (categorical variable) and the patterns of collective attention allocation (continuous variable); or in other words, the features of MOOC videos and student engagement with them. As shown in Table 4, the type of instruction (F_Instruction) in the videos significantly correlates with the amount of collective attention accumulated or circulated through ($p < .01$). No significant relationships were found between the allocation patterns of collective attention and the knowledge presented or how the videos were presented.

As shown in Table 4, participant engagement (B_Watch) is a negative predictor for the accumulation and dissipation of collective attention ($p < .001$), but the engagementin terms of re-watching videos did not correlate with the collective attention flow. Screen recording was used in videos, and video length significantly correlated with participant engagement (watching variable; $p < .001$). PowerPoint slides used in full screen also affected the participant engagement (watching variable; $p < .001$). For the learner re-watching variable, video length also negatively correlated ($p < .01$). Screen_full also significantly correlates with the re-watching variable ($p < .01$). Interestingly, there was a statistically significant relationship between learners watching and re-watching at the 0.001 level.

Table 4. Correlation Between Video Lecture Features, Participant Interaction, and Allocation of Collective Attention

			Video lecture feature			Video presentation type			Engagement with videos	
			V length	F Instruction	F Knowledge	P Screen full	P Screen recording	P Teacher switching	B Watch	B Rewatch
Allocation Pattern of Collective Attention	**Ai**	Spearman's rho	0.239						-0.35**	-0.02
		p value	0.041						0.002	0.867
		Kendall's Tau B		-0.274**	0.158	0.061	0.06	-0.005		
		p value		0.004	0.094	0.537	0.545	0.96		
	Di	Spearman's rho	0.286						-0.339**	0.012
		p value	0.014						0.003	0.918
		Kendall's Tau B		-0.135	0.19	0.104	0.136	0.002		
		p value		0.178	0.044	0.293	0.169	0.982		
	CUi	Spearman's rho	0.019						-0.13	0.057
		p value	0.876						0.272	0.631
		Kendall's Tau B		-0.246**	0.236	0.244	-0.027	-0.019		
		p value		0.006	0.012	0.014	0.788	0.85		
Engagement with Videos	**B_Watch**	Spearman's rho	-0.653***						—	
		p value	<.001						—	
		Kendall's Tau B		-0.193	0.112	0.406***	-0.375***	-0.062	—	
		p value		0.035	0.224	<.001	<.001	0.52	—	
	B_Rewatch	Spearman's rho	-0.328**						0.506***	—
		p value	0.005						<.001	—
		Kendall's Tau B		-0.047	0.197	0.289**	0.024	0.139		—
		p value		0.606	0.033	0.003	0.807	0.151		—

Note. ** $p < .01$, *** $p < .001$

6. Discussion

In summary, the following conclusions can be drawn. Although a six-minute timeframe is not the gold standard that instructors must follow, it is important to bear in mind that "the shorter the better" principle can help learners engage more with videos (in terms watching and re-watching). Apart from keeping videos short, using screen recordings or PowerPoint slides in full screen had a strong impact on engagement with the videos in the MOOC context of learning C++ programming. The types of videos (i.e., introduction, lecture, examples, experiments, summary) predict the collective attention accumulated or circulated. This segmentation has strong implications for selective learning. As high levels of engagement with videos occur in the process of attention circulation, a key aspect for future research is how to circulate learner attention around different videos, which can help them reach a higher level of engagement.

Designing videos for MOOCs is not the simple task it appears to be since it involves a complex process of transforming theoretical principles and empirical evidence into practice (Giannakos et al., 2014). Understanding how different types of video lectures predict engagement with videos and allocation patterns of collective attention will contribute significantly to efforts to assess simple but effective principles for designing MOOC video lectures. This study contributes to the field by providing new ways of understanding how participants attend to videos, move around them, and leave the online space. These new metrics can make valuable contributions to video design. As Poquet, Lim, and Mirriahi (2018) pointed out, despite an increase in empirical research on the use of videos in education, we still lack an overview of the specific impacts of videos on different learning outcomes.

6.1. Shorter is Better

Although previous studies (e.g., Guo et al., 2014) have argued that participants are unlikely to watch videos longer than six minutes, only one-third of the videos in the selected MOOC follow this principle. Perhaps instructors are not aware of this research finding, but it is more likely that they must consider instructional design, artistic vision, pedagogical strategies, subject knowledge, etc., when designing course videos. In contrast to most MOOCs available online, the studied course has adopted different presentation types of videos, similar to what Guo et al. (2014) and Chen and Wu (2015) have suggested. Considering all these design issues, video length seems to have been a minor issue for instructors, with the consequence that the longest video (i.e., 3-14) lasts 25.82 minutes, the shortest (i.e., 2-10) lasts only 52 seconds, and the average length is approximately 8.85 minutes. Nevertheless, video length was found to correlate negatively with the extent to which participants engage with videos (in terms of the percentage of videos they watch); thus, perhaps "the shorter the better" applies to future instruction design in video-based learning.

6.2. Screen Recording or Full Screen?

In the studied course, three presentation types of videos were used: screening recording, full-screen mode with PowerPoint slides, and instructors varying their position between sitting and standing. In some videos, lectures were recorded from different angles to present close and far images of the instructors. These presentation types did not affect the allocation of collective attention, perhaps because collective attention was directed mainly by type of video (i.e., introduction, lecture, examples, experiments, and summary). However, the use of screen recordings or PowerPoint slides in full screen had a significant effect on the extent to which the participants engaged with videos (i.e., how long participants were likely to watch). Additionally, full-screen use of PowerPoint slides significantly predicted how long they spent watching videos. Of course, their watching pattern correlated significantly with the re-watching pattern. These findings suggest that using a full screen to highlight important knowledge seems to be more likely to engage participants. This result is consistent with previous studies (e.g., de Koning et al., 2009; Mautone & Mayer, 2001; Pi et al., 2017). This implies that certain cues (e.g., colouring and underlining) added to learning materials can help direct participant attention (de Koning et al., 2009; Mautone & Mayer, 2001), and can help explain why detailed texts or illustrations of conceptual or procedural knowledge in PowerPoint slides or C++ codes in the running time (full screen) help direct participant attention to the learning content. Several other studies (van Gog et al., 2014; Kizilcec et al., 2015; Wang et al., 2017; Wang et al., 2020) found that the inclusion of the instructor, eye contact, or body language in the videos created a sense of social presence (Gunawardena, 1995), thus helping to increase learning performance (Beege et al., 2017; Leong et al., 2017). Instructors appear at some point in each of the 73 video units in the studied MOOC, which supports the inclusion of instructors to create social presence. Although this study did not explore whether the presence of the instructor creates a split-attention effect (Mayer & Moreno, 1998; Mousavi et al., 1995), the results showed that switching to full-screen to present PowerPoint slides or the use of screen recording in videos had a strong impact on engagement with video.

6.3. Type of Instruction Predicts Collective Attention

In the studied MOOC, instead of using video length as the criterion to segment the videos, the units were divided into smaller segments — introduction, lecture, examples, experiments, and summary — in terms of instructions adopted in the selected course. This way of categorizing one large video into pieces of videos was process-oriented. Each type of video reflected upon sequential instructional elements commonly used in face-to-face lectures. Participants accustomed to such segmentation are more likely to attend to the videos they want. Thus, it is not surprising that the most-used instruction was still a lecture given by an instructor using PowerPoint slides. The type of instruction in videos did not seem to correlate with the extent of participant engagement (i.e., how long the learners watch or re-watch them), but they significantly correlated with the number of collective videos accumulated or circulated. When videos were categorized in terms of different types of instruction, the categories they belonged to determine whether they were likely to accumulate or circulate collective attention. Some introductory or summary videos were less likely to be viewed or to recapture attention during participant learning trajectories, probably because learners are more likely to be motivated by the knowledge base of the course (Deshpande & Chukhlomin, 2017). Once participants had attended a particular video, there was no significant difference in how long they kept watching or re-watching it. As argued above, then, video length and presentation style predict the extent to which participants engage with it (i.e., how long the learners watch or re-watch it).

6.4. Engagement and Attention Circulation

Building on the work of Guo and colleagues (2014), engagement was measured by the percentage of videos participants watched or re-watched (i.e., watching and re-watching behaviour). In the selected course, the participants watched videos frequently, but only one-third of them watched at least one video from beginning to end, and only 2.9% watched all the videos completely. They re-watched even smaller percentages. Interestingly, participant engagement (watching pattern) negatively affected the accumulation and dissipation of collective attention. This implies that participants who watched videos the longest

seemed to have watched others beforehand and were also more likely to continue viewing more before leaving the online space. Participants who watched a video the longest neither attended to it immediately when they went online nor went offline after watching.

This further reveals that a high level of engagement with videos occurs during the circulation of collective attention among different videos rather than at the beginning or end of the online learning session. Thus, it is important to provide clues to direct participants to watch different videos in such an online environment, spurring their engagement to a higher level. That is, when circulating their attention around different videos, participants were more likely to concentrate on watching or re-watching.

6.5. Network Paradigm

The results of this empirical study suggest that the proposed open flow network model and metrics can be applied productively to better understand learning behaviours at the collective level. Such an open flow network of collective attention presents a new network topology, which differs from the sequential analysis interested in the temporal dimension of learning behaviours and social networks that emphasize interactions between peers and instructors. Although the visualized network of collective attention looks rather similar to the patterns of lag sequential analysis (LSA), both of which use learning resources as nodes, the rationale for doing so in the flow network of collective attention is to avoid the rapid change of network structures, commonly found in social networks using actors as nodes. In addition, a flow network of collective attention uses an open system to model online learning as a growing, living system. The model of collective attention can be seen to be transposed from the social network to better model the dynamic changes of interactions in online learning. Additionally, unlike LSA, which focuses on the significant sequential changes across learning resources, the epistemology behind the proposal of the collective attention network treats attention as a scarce property that learning resources compete for, since a "wealth of information creates a poverty of attention" (Simon, 1971, p. 40). Such conceptualization is poised to create an open, balanced model resembling online, open, flexible learning environments. Thus, methods, tools, and metrics commonly used in the natural sciences (e.g., physics) can be adopted to understand the online learning environment as a social-ecological system (Schneider & Kay, 1994a). In current studies, the amount of attention flow is measured roughly by the number of individuals who migrate from one resource to another, but this is with the understanding that more precise measurement could be used for this network model in future studies. In this respect, the attention measured here is not a psychological metric but is regarded as a human flux used to model a social-ecological learning space in which learning is achieved at the cost of learner attention. Regarding rapid-growing learning analytics studies, using a data-driven approach is important. Still, the conceptualization of the clickstream is even more important for researchers to interpret the patterns identified in varied network models (Chen et al., 2020). After all, network models utilized in learning analytics are not meant to virtualize real interactions but rather to be a lens to discover patterns we would not be able to identify without such a systematic perspective.

7. Limitations and Future Work

Certain limitations are noted in this study. First, this analytic study was conducted in the context of MOOC videos, and the results might not apply to other contexts, since the learning content, objectives, styles, presentation styles, and length can be extremely diverse in different video-based learning (Giannakos, 2013). Second, although this selected MOOC presents different types of videos, a typically high dropout rate was found; thus, the learning performance data were insufficient to inform which types of videos are effective for learning performance. Third, we did not manually categorize teacher gestures (Colliot & Jamet, 2018) or positions (Kim et al., 2014). When considering the presentation types of videos, with more MOOC courses available in future, perhaps such data could be coded meaningfully to gain a better understanding of varied design principles for video lectures. Fourth, due to the lack of complete "play," "pause," and "skip forward/back" data, the allocation of collective attention could be analyzed only at the video unit level. XuetangX has restructured its data source, and future studies could focus more on engagement with videos at this fine-grained level and its relationship with the features of video lectures. Fifth, we measured the amount of attention flow roughly by the number of individuals who navigated from one resource to another. More precise measurement (considering time, frequency, eye-tracking in deep learning modelling) could be used to refine the measure of attention flow in future studies.

Although several limitations have been noted, the results of this study have, to some extent, added new insights into how video features predict the extent to which participants engage with videos (watching or re-watching behaviours), as well as the likelihood of their collective attention accumulating, circulating, and dissipating in the online space. Building upon previous research, this study contributes to the field by focusing on how collective attention flows in and out through videos, which seems to serve as the main learning context for online learning. The reported results suggest that attention allocation patterns and their associated metrics may be useful as indirect implications for online learning.

Declaration of Conflicting Interest

Funding

Acknowledgments

References

Agonacs, N., Matos, J. F., Bartalesi-Graf, D., & O'Steen, D. N. (2020). Are you ready? Self-determined learning readiness of language MOOC learners. *Education and Information Technologies, 25*(2), 1161–1179. https://doi.org/10.1007/s10639-019-10017-1

Albert, R., Jeong, H., & Barabási, A. L. (1999). Internet: Diameter of the world-wide web. *Nature, 401*, 130–131. https://doi.org/10.1038/43601

Ang, K. L. M., Ge, F. L., & Seng, K. P. (2020). Big educational data analytics: Survey, architecture and challenges. *IEEE Access, 8*, 116392–116414. https://ieeexplore.ieee.org/document/9093868

Annila, A. (2010). All in action. *Entropy, 12*(11), 2333–2358. https://doi.org/10.1287/trsc.29.4.305

Baronchelli, A., Ferrer-i-Cancho, R., Pastor-Satorras, R., Chater, N., & Christiansen, M. H. (2013). Networks in cognitive science. *Trends in Cognitive Sciences, 17*(7), 348–360. https://doi.org/10.1016/j.tics.2013.04.010

Basil, M. D. (1994). Multiple resource theory I: Application to television viewing. *Communication Research, 21*(2), 177–207. https://doi.org/10.1177/009365094021002003

Beege, M., Schneider, S., Nebel, S., & Rey, G. D. (2017). Look into my eyes! Exploring the effect of addressing in educational videos. *Learning and Instruction, 49*, 113–120. https://doi.org/10.1016/j.learninstruc.2017.01.004

Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's first MOOC. *Research & Practice in Assessment, 8*, 13–25. https://files.eric.ed.gov/fulltext/EJ1062850.pdf

Cantarella, G. E., & Cascetta, E. (1995). Dynamic processes and equilibrium in transportation networks: Towards a unifying theory. *Transportation Science, 29*(4), 305–329. https://doi.org/10.1287/trsc.29.4.305

Catledge, L. D., & Pitkow, J. E. (1995). Characterizing browsing strategies in the World-Wide Web. *Computer Networks and ISDN Systems, 27*(6), 1065–1073. https://doi.org/10.1016/0169-7552(95)00043-7

Chen, B., Fan, Y., Zhang, G., Liu, M., & Wang, Q. (2020). Teachers' networked professional learning with MOOCs. *PLOS ONE, 15*(7), e0235170. https://doi.org/10.1371/journal.pone.0235170

Chen, B., & Poquet, O. (2020). Socio-temporal dynamics in peer interaction events. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 203–208). ACM. https://doi.org/10.1145/3375462.3375535

Chen, B., Resendes, M., Chai, C. S., & Hong, H. Y. (2017). Two tales of time: Uncovering the significance of sequential patterns among contribution types in knowledge-building discourse. *Interactive Learning Environments, 25*(2), 162–175. https://doi.org/10.1080/10494820.2016.1276081

Chen, C. M., & Wu, C. H. (2015). Effects of different video lecture types on sustained attention, emotion, cognitive load, and learning performance. *Computers & Education, 80*(2015), 108–121. https://doi.org/10.1016/j.compedu.2014.08.015

Chen, H. T. M., & Thomas, M. (2020). Effects of lecture video styles on engagement and learning. *Educational Technology Research and Development, 68*(5), 2147–2164. https://doi.org/10.1007/s11423-020-09757-6

Colliot, T., & Jamet, É. (2018). Understanding the effects of a teacher video on learning from a multimedia document: An eye-tracking study. *Educational Technology Research and Development, 66*(6). 1415-1433. https://doi.org/10.1007/s11423-018-9594-x

Colpaert, J. (2016). Big content in an educational engineering approach. *Journal of Technology and Chinese Language Teaching, 7*(1), 1–14. http://www.tclt.us/journal/2016v7n1/colpaert.pdf

de Koning, B. B., Tabbers, H. K., Rikers, R. M. J. P., & Paas, F. (2009). Towards a framework for attention cueing in instructional animations: Guidelines for research and design. *Educational Psychology Review, 21*(2), 113–140. https://doi.org/10.1007/s10648-009-9098-7

Deshpande, A., & Chukhlomin, V. (2017). What makes a good MOOC: A field study of factors impacting student motivation to learn. *American Journal of Distance Education, 31*(4), 275–293. https://doi.org/10.1080/08923647.2017.1377513

Duhring, J. (2013). MOOC production values: Costs, approaches and examples. http://moocnewsandreviews.com/mooc-production-values-costs-approaches-and-examples/

Fee, A., & Budde-Sung, A. E. K. (2014). Using video effectively in diverse classes: What students want. *Journal of Management Education, 38*, 843–874. https://doi.org/10.1177/1052562913519082

Gao, M., Zhang, J., Sun, D., & Zhang, J. (2019). Using clickstream to understand learning paths and the network structure of learning resources: Using MOOCs as an example. In M. Chang, H.-J. So, L.-H. Wong, F.-Y. Yu, & J.-L. Shih, (Eds.), *Proceedings of the 27th International Conference on Computers in Education* (ICCE 2019), 2–6 December 2019, Kenting, Taiwan (Vol. 1, pp. 324–329). Asia-Pacific Society for Computers in Education. https://www.researchgate.net/publication/338464058

Giannakos, M. (2013). Exploring the video-based learning research: A review of the literature. *British Journal of Educational Technology, 44*(6), 191–195. https://doi.org/10.1111/bjet.12070

Giannakos, M., Chorianopoulos, K., Ronchetti, M., Szegedi, P., & Teasley, S. (2014). Video-based learning and open online courses. *International Journal of Emerging Technologies in Learning, 9*(1), 4–7. https://doi.org/10.3991/ijet.v9i1.3354

Gillani, N., & Eynon, R. (2014). Communication patterns in massively open online courses. *The Internet and Higher Education, 23*, 18–26. https://doi.org/10.1016/j.iheduc.2014.05.004

Gunawardena, C. N. (1995). Social presence theory and implications for interaction and collaborative learning in computer conferences. *International Journal of Educational Telecommunications, 1*(2/3), 147e166. https://www.learntechlib.org/p/15156/article_15156.pdf

Guo, P. J., Kim, J., & Rubin, R. (2014). How video production affects student engagement: An empirical study of MOOCs videos. *Proceedings of the 1st ACM Conference on Learning @ Scale* (L@S 2014), 4–5 March 2014, Atlanta, GA, USA (pp. 41–50). ACM. https://doi.org/10.1145/2556325.2566239

Guo, L., Shi, P., Zhang. J., Wang, J., & Huang, X. (2015). Flow distances on open flow networks. *Physica A: Statistical Mechanics and its Applications.* https://doi.org/10.1016/j.physa.2015.05.070

Hansch, A., Hillers, L., Mcconachie, K., Newman, C., Schildhauer, T., & Schmidt, J. P. (2015) .Video and online learning: Critical reflections and findings from the field. *Social Science Electronic Publishing.* https://doi.org/10.2139/ssrn.2577882

Helbing, D. (2013). Globally networked risks and how to respond. *Nature, 497*(7447), 51–59. https://doi.org/10.1038/nature12047

Hernández-García, Á., González-González, I., Jiménez-Zarco, A. I., & Chaparro-Peláez, J. (2015). Applying social learning analytics to message boards in online distance learning: A case study. *Computers in Human Behaviour, 47,* 68–80. https://doi.org/10.1016/j.chb.2014.10.038

Holmes, W., Nguyen, Q., Zhang, J., Mavrikis, M., & Rienties, B. (2019). Learning analytics for learning design in online distance learning. *Distance Education, 40*(3), 309–329. https://doi.org/10.1080/01587919.2019.1637716

Homer, B. D., Plass, J. L., & Blake, L. (2008). The effects of video on cognitive load and social presence in multimedia-learning. *Computers in Human Behaviour, 24*(3), 786–797. https://doi.org/10.1016/j.chb.2007.02.009

Hou, H. T. (2012). Exploring the behavioural patterns of learners in an educational massively multiple online role-playing game (MMORPG). *Computers & Education, 58*(4), 1225–1233. https://doi.org/10.1016/j.compedu.2011.11.015

Hwang, G. J., & Chen, C. H. (2017). Influences of an inquiry-based ubiquitous gaming design on students' learning achievements, motivation, behavioural patterns, and tendency towards critical thinking and problem solving. *British Journal of Educational Technology, 48*(4), 950–971. https://doi.org/10.1111/bjet.12464

Ilioudi, C., Giannakos, M. N., & Chorianopoulos, K. (2013). Investigating differences among the commonly used video lecture styles. *Proceedings of the Workshop on Analytics on Video-Based Learning* (WAVe 2013), 8 April 2013, Leuven, Belgium (pp. 21–26). https://doi.org/10.13140/2.1.3524.9284

Joksimović, S., Manataki, A., Gašević, D., Dawson, S., Kovanović, V., & De Kereki, I. F. (2016). Translating network position into performance: Importance of centrality in different network configurations. *Proceedings of the 6th International Conference on Learning Analytics and Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 314–323). ACM. https://doi.org/10.1145/2883851.2883928

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *International Review of Research in Open and Distance Learning, 15*(1), 133–160. https://doi.org/10.19173/irrodl.v15i1.1651

Jung, E., Kim, D., Yoon, M., Park, S. H., & Oakley, B. (2018). The influence of instructional design on learner control, sense of achievement, and perceived effectiveness in a supersize MOOC course. *Computers & Education, 128*(2019), 377–388. https://doi.org/10.1016/j.compedu.2018.10.001

Kammenhuber, N., Luxenburger, J., Feldmann, A., & Weikum, G. (2006). Web search clickstreams. *Proceedings of the 6th ACM SIGCOMM Conference on Internet Measurement* (IMC '06), 25–27 October 2006, Rio de Janeriro, Brazil (pp. 245–250). ACM. https://doi.org/10.1145/1177080.1177110

Kay, R. H. (2012). Exploring the use of video podcasts in education: A comprehensive review of the literature. *Computers in Human Behaviour, 28*(3), 820–831. https://doi.org/10.1016/j.chb.2012.01.011

Kellogg, S., Booth, S., & Oliver, K. (2014). A social network perspective on peer supported learning in MOOCs for educators. *The International Review of Research in Open and Distributed Learning, 15*, 263–289. https://doi.org/10.19173/irrodl.v15i5.1852

Kim, J., Guo, P. J., Seaton, D. T., Mitros, P., Gajos, K. Z., & Miller, R. C. (2014). Understanding in-video dropouts and interaction peaks in online lecture videos. *Proceedings of the 1st ACM Conference on Learning @ Scale* (L@S 2014), 4–5 March 2014, Atlanta, GA, USA (pp. 41–50). ACM. https://doi.org/10.1145/2556325.2566239

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analysing learner subpopulations in massive open online courses. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge* (LAK '13), 8–12 April 2013, Leuven, Belgium (pp. 170–179). ACM. https://doi.org/10.1145/2460296.2460330

Kizilcec, R. F., Bailenson, J. N., & Gomez, C. J. (2015). The instructor's face in video instruction: Evidence from two large-scale field studies. *Journal of Educational Psychology, 107*(3), 724–739. https://doi.org/10.1037/edu0000013

Knight, S., Wise, A. F., & Chen, B. (2017). Time for change: Why learning analytics needs temporal analysis. *Journal of Learning Analytics, 4*(3), 7–17. https://doi.org/10.18608/jla.2017.43.2

Kleiber, M. (1932). Body size and metabolism. *Hilgardia, 6*(11), 315–353. https://doi.org/10.3733/hilg.v06n11

Kokoç, M., IIgaz, H. & Altun, A. (2020). Effects of sustained attention and video lecture types on learning performances. *Educational Technology Research and Development, 68*, 3015–3039. https://doi.org/10.1007/s11423-020-09829-7

Lan, Y. F., Tsai, P. W., Yang, S. H., & Hung, C. L. (2012). Comparing the social knowledge construction behavioural patterns of problem-based online asynchronous discussion in e/m-learning environments. *Computers & Education, 59*(4), 1122–1135. https://doi.org/10.1016/j.compedu.2012.05.004

Lang, A., Newhagen, J., & Reeves, B. (1996). Negative video as structure: Emotion, attention, capacity, and memory. *Journal of Broadcasting & Electronic Media, 40*(4), 460–477. https://doi.org/ 10.1080/08838159609364369

Lang, A. (2000). The limited capacity model of mediated message processing. *Journal of Communication, 50*(1), 46–70. https://doi.org/10.1002/9781118783764.wbieme0077

Lemay, D. J., & Doleck, T. (2020). Grade prediction of weekly assignments in MOOCS: Mining video-viewing behaviour. *Education and Information Technologies, 25*(2), 1333–1342. https://doi.org/10.1007/s10639-019-10022-4

Leong, V., Byrne, E., Clackson, K., Georgieva, S., Lam, S., & Wass, S. (2017, December 12). Speaker gaze increases information coupling between infant and adult brains. *PNAS: Proceedings of the National Academy of Sciences of the United States of America, 114*(50), 13290–13295. https://doi.org/10.1073/pnas.1702493114

Leontief, W. (Ed.). (1986). *Input-output economics*. Oxford University Press.

Li, F. Y., Hwang, G. J., Chen, P. Y., & Lin, Y. J. (2021). Effects of a concept mapping-based two-tier test strategy on students' digital game-based learning performances and behavioural patterns. *Computers & Education, 173*, 104293. https://doi.org/10.1016/j.compedu.2021.104293

Lin, T. J., Duh, H. B. L., Li, N., Wang, H. Y., & Tsai, C. C. (2013). An investigation of learners' collaborative knowledge construction performances and behaviour patterns in an augmented reality simulation system. *Computers & Education, 68*, 314–321. https://doi.org/10.1016/j.compedu.2013.05.011

Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review, 46*(5), 31–40. https://doi.org/10.17471/2499-4324/195

Long, P., Siemens, G., Conole, G., & Gašević, D. (Eds.). (2011). Proceedings of the 1st International Conference on Learning Analytics and Knowledge: Connecting the Technical, Pedagogical, and Social Dimensions of Learning Analytics (LAK '11), 27 February–1 March 2011, Banff, AB, Canada. ACM. https://dl.acm.org/doi/proceedings/10.1145/2090116

Luo, Y., Zhou, G., Li, J., & Xiao, X. (2018). A MOOC video viewing behaviour analysis algorithm. *Mathematical Problems in Engineering, 2018*, 1–7. https://doi.org/10.1155/2018/7560805

Mäkelä, T., & Annila, A. (2010). Natural patterns of energy dispersal. *Physics of Life Reviews, 7*(4), 477–498. https://doi.org/10.1016/j.plrev.2010.10.001

Mautone, P. D. & Mayer, R. E. (2001). Signaling as a cognitive guide in multimedia learning how to promote understanding of a scientific explanation. *Journal of Educational Psychology, 93*(2), 377–389. https://doi.org/10.1037//O022-O663.93.2.377

Mayer, R. E. (2001). *Multimedia learning*. Cambridge, UK: Cambridge University Press.

Mayer, R. E., & Moreno, R. (1998). A split-attention effect in multimedia learning: Evidence for dual processing systems in working memory. *Journal of Educational Psychology, 90*(2), 312. https://doi.org/10.1037/0022-0663.90.2.312

Mayer, R. E. (2014a). Incorporating motivation into multimedia learning. *Learning & Instruction, 29*, 171–173. https://doi.org/10.1016/j.learninstruc.2013.04.003

Mayer, R. E. (2014b). Principles of multimedia learning based on social cues: Personalization, voice, image, and embodiment principles. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning*, 345–368. Cambridge, UK: Cambridge University Press.

Miller, R. E., & Blair, P. D. (2009). *Input-output analysis: Foundations and extensions*. Cambridge, UK: Cambridge University Press.

Mousavi, S. Y., Low, R., & Sweller, J. (1995). Reducing cognitive load by mixing auditory and visual presentation modes. *Journal of Educational Psychology, 87*(2), 319–334. https://doi.org/10.1037/0022-0663.87.2.319

Nicolis, G., & Prigogine, I. (1977). Self-organization in nonequilibrium systems: From dissipative structures to order through fluctuations. Toronto: J. Wiley & Sons.

Odum, H. T. (1983). Systems ecology: An introduction. New York: J. Wiley & Sons.

Oleksandra, P., & Shane, D. (2016). Untangling MOOC learner networks. *Proceedings of the 6th International Conference on Learning Analytics and Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 208–212). ACM. https://doi.org/10.1145/2883851.2883919

Panev, I., Preradovi, N. M., & Lauc, T. (2020). Investigating interactivity in instructional video tutorials for an undergraduate informatics course. *Issues in Educational Research, 30*(1), 203–223. https://www.iier.org.au/iier30/mikelic-preradovic.pdf

Pashler, H. E., & Sutherland, S. (1998). *The psychology of attention* (Vol. 15). MIT Press. https://doi.org/10.1016/S0166-2236(98)01235-1

Pi, Z., Hong, J., & Yang, J. (2017). Effects of the instructor's pointing gestures on learning performance in video lectures. *British Journal of Educational Technology, 48*(4), 1020–1029. https://doi.org/10.1111/bjet.12471

Poquet, O., Hecking, T., & Chen, B. (2020). The modelling of digital learning networks. Companion Proceedings of the 10th International Conference on Learning Analytics and Knowledge: Celebrating 10 years of LAK: Shaping the future of the field (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 348–351). Society for Learning Analytics Research (SoLAR). https://www.solaresearch.org/wp-content/uploads/2020/06/LAK20_Companion_Proceedings.pdf

Poquet, O., & Jovanovic, J. (2020). Intergroup and interpersonal forum positioning in shared-thread and post-reply networks. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 187–196). ACM. https://doi.org/10.1145/3375462.3375533

Poquet, O., Lim, L., & Mirriahi, N. (2018). Video and learning: A systematic review (2007–2017). *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (LAK '18), 5–9 March 2018, Sydney, NSW, Australia (pp. 151–160). ACM. https://doi.org/10.1145/3170358.3170376

Poquet, O., Tupikina, L., & Santolini, M. (2020). Are forum networks social networks? A methodological perspective. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 366–375). ACM. https://doi.org/10.35542/osf.io/654ds

Posner, M. I., & Rothbart, M. K. (2007). Research on attention networks as a model for the integration of psychological science. *Annual Review of Psychology, 58*(1), 1–23. https://doi.org/10.1146/annurev.psych.58.110405.085516

Raine, A., Foster, J., & Potts, J. (2006). The new entropy law and the economic process. *Ecological Complexity, 3*(4), 354–360. https://doi.org/10.1016/j.ecocom.2007.02.009

Raa, T. T. (2005). *The economics of input-output analysis*. Cambridge, UK: Cambridge University Press.

Rees, W. E. (2012). Global change and the vulnerability of urban civilization. *Sustainability Science*, 247–273. https://doi.org/10.1007/978-1-4614-3188-6_12

Reich, J., & Ruipérez-Valiente, J. A. (2019). The MOOC pivot. *Science, 363*(6423), 130–131. https://doi.org/10.1126/science.aav7958

Sadik, A. (2016). Students' preferences for types of video lectures: Lecture capture vs. screencasting recordings. *International Journal of Higher Education, 4*(4). https://doi.org/10.5430/ijhe.v4n4p94

Seaton, D. T., Bergner, Y., Chuang, I., Mitros, P., & Pritchard, D. E. (2014). Who does what in a massive open online course? *Communications of the ACM, 57*(4), 58–65. https://doi.org/10.1145/2500876

Schneider, E. D., & Kay, J. J. (1994a). Complexity and thermodynamics: Towards a new ecology. *Futures, 26*(6), 626–647. https://doi.org/10.1016/0016-3287(94)90034-5

Schneider, E. D., & Kay, J. J. (1994b). Life as a manifestation of the second law of thermodynamics. *Mathematical and Computer Modelling 19*, 25–48. https://doi.org/10.1016/0895-7177(94)90188-0

Shah, D. (2020). By the numbers: MOOCs in 2020. https://www.classcentral.com/report/mooc-stats-2020/

Shapiro, H. B., Lee, C. H., Wyman Roth, N. E., Li, K., Çetinkaya-Rundel, M., & Canelas, D. A. (2017). Understanding the massive open online course (MOOC) student experience: An examination of attitudes, motivations, and barriers. *Computers & Education, 110*, 35–50. https://doi.org/10.1016/j.compedu.2017.03.003

Simon, H. (1971). Designing organizations for an information-rich world. Computers, communications, and the public interest, 72, 37. http://digitalcollections.library.cmu.edu/awweb/awarchive?type=file&item=33748

Sinha, T., Jermann, P., Li, N., & Dillenbourg, P. (2014). Your click decides your fate: Inferring information processing and attrition behaviour from MOOC video clickstream interactions. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing* (EMNLP 2014), 25–29 October 2014, Doha, Qatar (pp. 3–14). Association for Computational Linguistics. https://doi.org/10.3115/v1/W14-4102

Stepanyan, K., Mather, R., & Dalrymple, R. (2013). Culture, role and group work: A social network analysis perspective on an online collaborative course. *British Journal of Educational Technology, 45*, 676–693. https://doi.org/10.1111/bjet.12076

Sun, Z., Lin, C. H., Lv, K., & Song, J. (2021). Knowledge-construction behaviours in a mobile learning environment: A lag-sequential analysis of group differences. *Educational Technology Research and Development, 69*(2), 533–551. https://doi.org/10.1007/s11423-021-09938-x

Swarts, J. (2012). New modes of help: Best practices for instructional video. *Technical Communication, 59*(3), 195–206. http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=FE813FC55B0A0A244EA173CFA724EFF2?doi=10.1.1.458.2861&rep=rep1&type=pdf

Sweller, J., Ayres, P., & Kalyuga, S. (2011). Cognitive load theory in perspective. *Cognitive load theory*, 237–242. Springer.

Sweller, J., van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review, 10*(3), 251–296. https://doi.org/10.1023/a:1022193728205

Terras, M. M., & Ramsay, J. (2015). Massive open online courses (MOOCs): Insights and challenges from a psychological perspective. *British Journal of Educational Technology, 46*(3), 472–487. https://doi.org/10.1111/bjet.12274

Tu, C. H. (2002). The measurement of social presence in an online learning environment. *International Journal on E-Learning, 1*(2), 34–45. https://doi.org/10.17471/2499-4324/421

van Gog, T., Verveer, I., & Verveer, L. (2014). Learning from video modelling examples: Effects of seeing the human model's face. *Computers & Education, 72*, 323–327. https://doi.org/10.1016/j.compedu.2013.12.004

Wang, J., Antonenko, P., & Dawson, K. (2020). Does visual attention to the instructor in online video affect learning and learner perceptions? An eye-tracking analysis. *Computers & Education, 146*, 103779. https://doi.org/10.1016/j.compedu.2019.103779.

Wang, J., & Antonenko, P. D. (2017). Instructor presence in instructional video: Effects on visual attention, recall, and perceived learning. *Computers in Human Behaviour, 71*, 79–89. https://doi.org/10.1016/j.chb.2017.01.049

Watted, A., & Barak, M. (2018). Motivating factors of MOOC completers: Comparing between university-affiliated students and general participants. *Internet and Higher Education, 37*, 11–20. https://doi.org/10.1016/j.iheduc.2017.12.001

Whitt, W. (1984). Open and closed models for networks of queues. *AT&T Bell Laboratories Technical Journal, 63*(9), 1911–1979. https://doi.org/10.1002/j.1538-7305.1984.tb00084.x

Wu, F., & Huberman, B. A. (2007). Novelty and collective attention. *SSRN Electronic Journal, 104*(45), 17599–17601. https://doi.org/10.2139/ssrn.989672

Yang, X., Li, J., Guo, X., & Li, X. (2015). Group interactive network and behavioural patterns in online English-to-Chinese cooperative translation activity. *The Internet and Higher Education, 25*, 28–36. https://doi.org/10.1016/j.iheduc.2014.12.003

Yin, C. J., Uosaki, N., Chu, H. C., Hwang, G. J., Hwang, J. J., Hatono, I., & Tabata, Y. (2017). Learning behavioural pattern analysis based on students' logs in reading digital books. In W. Chen et al. (Eds.), *Proceedings of the 25th International Conference on Computers in Education* (ICCE 2017), 4–8 December 2017, Christchurch, New Zealand (pp. 549–557). Asia-Pacific Society for Computers in Education. https://www.researchgate.net/publication/321824916_Learning_Behavioural_Pattern_Analysis_based_on_Students'_Logs_in_Reading_Digital_Books

Zeng, S., Zhang, J., Gao, M., Xu, K. M., & Zhang, J. (2020). Using learning analytics to understand collective attention in language MOOCs. *Computer Assisted Language Learning*, 1–26. https://doi.org/10.1080/09588221.2020.1825094

Zhang, J., Gao, M., Holmes, W., Mavrikis, M., & Ma, N. (2019). Interaction patterns in exploratory learning environments for mathematics: A sequential analysis of feedback and external representations in Chinese schools. *Interactive Learning Environments*, 1–18. https://doi.org/10.1080/10494820.2019.1620290

Zhang, J., Gao, M., & Zhang, J. (2021). The learning behaviours of dropouts in MOOCs: A collective attention network perspective. *Computers & Education, 167*, 104189. https://doi.org/10.1016/j.compedu.2021.104189

Zhang, J., Lou, X., & Guo, L. (2016). Universal patterns and constructal law in open flow networks. *International Journal of Heat and Technology, 34(Special Issue 1)*, S75–S82. https://doi.org/10.18280/ijht.34S109

Zhang, J., Lou, X., Zhang, H., & Zhang, J. (2019). Modelling collective attention in online and flexible learning environments. *Distance Education, 40*(3), 303–308. https://doi.org/10.1080/01587919.2019.1600368

Zhang, J., Skryabin, M., & Song, X. (2016). Understanding the dynamics of MOOC discussion forums with simulation investigation for empirical network analysis (SIENA). *Distance Education, 37*(3), 270–286. https://doi.org/10.1145/3027385.3027391

Zheng, L., Zhong, L., & Niu, J. (2021). Effects of personalised feedback approach on knowledge building, emotions, co-regulated behavioural patterns and cognitive load in online collaborative learning. *Assessment & Evaluation in Higher Education*, 1–17. https://doi.org/10.1080/02602938.2021.1883549