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Relationships among Watching Behavior, Learning Flow, and Learning Achievement in a Video-based Learning Environment*

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ABSTRACT

This study aimed to identify watching behaviors matched with instructional events in a general video-based learning environment and investigate the relationships among the watching behaviors, learning flow, and the learning achievement. The watching behaviors were fixation, saccade, and pupil dilation, among others, and those of 61 participants were recorded throughout their course of learning. The level of their learning achievement and learning flow were also collected. The experiment stimulus was an about 10 minutes of a video clip, and it was about the normal distribution in the statistics course. Under the purpose of research, the most frequent watching behaviors relying upon the instructor's behavior were identified, and the correlation and regression analyses were performed repeatedly using the watching behaviors, learning flow, and the learning achievement as the variables. In this study, the regression models for predicting the learning achievement, along with the watching behaviors and learning flow, were not clearly developed; however, the process of this research suggested certain meaningful implications for interpreting the learners' state in the progress of learning and suggesting directions for the future statistical analyses. Further discussion is included.

1. Introduction

Today, we are living in what may be called a "hyper-connected," "network" society, where everything is interconnected. The spaces in which learning takes place are not limited to the traditional classrooms where teachers and students meet face to face. By using personal devices as learning environments, online learning has expanded, and learning can take place beyond time and space (Garrison, 2011).

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Online learning is implemented based on instructional design models that are not so different from those of the off-line learning, which incorporate analysis, design, and developmental process. However, while teachers make countless real-time decisions and facilitate interactions between students and themselves, it is not easy to continuously observe their students' progress in the online learning environments, and hence, the learners' reactions tend to be presumed exclusively from course achievements or satisfaction scores.

Recently, as the technology that reflects the context of real-time learning situations has continuously developed, and as interest in big data has expanded across society, in the field of education, there are increasing efforts to understand the learners' participation, progress, and performance during the actual learning process and further optimize learning based on a proper understanding of the real learning contexts. These efforts are centered on "learning analytics," defined as an interdisciplinary study supportive of decision-making practices concerned with teaching and learning based on evidence from data measurement, collection, analysis, and prediction (Jo, 2015). In the initial stage, learning analytics focused on data analysis; however, recent research has expanded into diagnosis to link the results of learning analytics to effective interventions in the actual learning situation.

One promising example of data representing real learning contexts is the watching behavior data. Eye is a sensory organ that collects visual information and delivers it to the brain, and researchers have long been interested in the relationship between the eye and psychology in various academic contexts. In the field of education, eye is regarded as a sensory receptor that enables selective perception and attention in accordance with information processing theories. Early studies were conducted mainly in relation to reading and information processing (Rayner, 1998), but a recent focus has been designing effective multimedia (Mayer, 2010).

In terms of emotional and psychological states during learning, flow has been studied under various definitions depending on the researchers' areas of interest. Flow is reported to affect learning outcomes by facilitating voluntary learning activities (Palloff & Pratt, 1999); it is a subjective psychological condition and is not easy to measure (Seok & Kang, 2007). Until now, most researchers have measured flow with questionnaires, but recently, psychophysiological responses have been used for more objective measurement. However, although the relationship between flow and focused attention has been researched based on psychophysiological responses (e.g. Jung et al., 2012), previous researches have lacked any efforts to understand the learners' flow in the real learning contexts. Therefore, this study aimed to identify the characteristics of the watching behaviors for learning, and confirm the relationships among the watching behaviors, learning flow, and learning achievement. Below are the research questions for these objectives.

1. What are the characteristics of the watching behaviors that appear in a video-based learning environment?
2. In the video-based learning environment, do watching behaviors and learning flow during the whole learning period predict a learner's academic achievements?
3. In the video-based learning environment, do watching behaviors and learning flow during specific sections predict a learner's academic achievements?

2. Related Works

2.1 Learning Analytics

Learning analytics is a discipline that measures, collects, analyzes, and reports data on learners and learning contexts in order to understand and optimize the learning environment and process (Lias & Elias, 2011). According to Siemens and Baker (2012), learning analytics is concerned with overall teaching and learning processes through collecting and measuring data from different learning contexts in order to better understand these processes. In a similar vein, Jo (2015) defines it as a converging discipline that supports evidence-based decision-making on teaching and learning by measuring, collecting, analyzing, and predicting data on learning behaviors in the technology-mediated learning environments. Initial research in learning analytics tended to focus on data itself and data mining techniques, but there is a growing tendency with which recent research emphasizes teaching and learning interventions, as noted in its original definition.

Recent learning analytics research can be characterized by two aspects. First, the ratio of social learning analytics is increasing (Shum & Ferguson, 2012) in the efforts to understand and promote the process of social interaction in which diverse individual knowledge, experiences, and perspectives meet. Especially, the demand for this type of data analysis has increased along with the expansion of using social networking services and online education through the massive open online courses (MOOCs) and with the development of network analysis tools based on the theory of social constructivism (Jo, 2015). The second is that it is evolving toward comprehending emotional states (Jo, 2015), particularly motivation, learning flow, and anxiety using physiological signal sensing technology and wearable devices with such features.

Learning contexts can be better comprehended by combining externalized behavior data for interactions by and between humans and learning contents, or between humans themselves and psychophysiological response such as heart rate, eye movement, skin conductance, and facial expression. This point initiates learning analytics to vigorously interact with academic areas such as psychophysiology and evolve into a convergent form.

With the development of this field, available data expands, research methodology tends to become more diverse, and various data analysis methods are applied to learning analytics. Papamitsiou and Economides (2014) carried out a literature review on analytics methodology by referring 40 studies on learning analytics and education data mining published between 2008 and August 2013. They determined that researchers had employed methodologies such as classification analysis, cluster analysis, text mining, association analysis, social network analysis, linkage analysis, modeling, and visualization. And the authors noted that methods of analysis have evolved from the initial studies focused on classification and clustering. That is, as befits its definition, learning analytics is attempting to expand towards a wide range of data and advanced statistical analyses to achieve better learning performance in the process of learning.

2.2 Watching Behaviors

Human eye is a sensory organ that collects visual information and transmits it to the brain. Since it was expressed as the window of the mind by medical scientist Du Laurens, it has been studied in various areas in connection with mental or brain functions.

Attempts to record eye movements began approximately 100 years ago. As the most primitive method, eye movements were checked by using after images, but recently, researchers developed a gaze tracking method using infrared rays to calculate the position of the eyes and moving distance by capturing what is reflected in the eye lens. Eye movement and pupil response are the representative watching behaviors studied through the gaze tracking. Eye movement entails stably maintaining the image of an object in the center of the fovea (the center of the retina) to capture the external environment minutely and vividly (Kim, 1999), which could be classified into two aspects regarding function (Hoffman & Subramaniam, 1995). One is gaze stabilization, which enables an object to remain in the fovea; fixation is a typical example. The other is a saccade, a gaze-shifting mechanism by which the eyes move towards an object of interest to form its image in the fovea.

The and Mavrikis (2016) conducted research on the gaze fixation patterns of 60 students in online programming classes. The tutorial screens provided to the participants were divided into five areas (informative, learning contents, hints, programming editor, and programming results) and the participants' numbers of fixations, durations of the fixations, and saccade sequences were measured. The study has its significance in providing lecturers and designers with the information on the effectiveness of their designs.

In another study, an eye movement analysis was used to understand learning processes and provide interventions in real time to increase the learners' attention. Sharma, Alavi, Jermann, and Dillenbourg (2016) analyzed the eye movements of 27 MOOC participants and calculated "with-me-ness" by numerically measuring how well the learners' gazes followed what was being explained in a video clip. When with-me-ness was low, the students were compelled to focus on the class by marking on the screen what the lecturer was explaining. The results showed that this prescription affected their learning outcomes.

Pupil is a vacant circular space in the center of the iris that has the function of controlling the amount of light entering the eye; pupillary response refers to the changes in the size of two muscles of the iris as the pupil contracts and dilates. A series of studies centered on cognitive load were carried out in the late 19th century, and since then, studies have expanded to investigating complicated task performance and intellectual endeavors. Recarte and Nunes (2003) carried out an experiment of giving various cognitive tasks during a driving simulation and confirmed that the pupil expansion was significantly correlated with the psychological workload. Bourisly (2015) conducted a study with adult participants, and the participants' pupil reactions were recorded while the participants were asked to add numbers in ones, tens, and hundreds. As a result of the study, the authors confirmed that the pupil diameter expanded as the number of digits increased and the study was significant in that the pupil response was quantified to the extent of the cognitive load. In a similar vein, Szulewski, Fernando, Baylis and Howes (2014) confirmed that pupil dilation occurred in solving difficult rather than simple multiplication questions.

Pupil reactions have been mainly studied in relation to cognitive load, although there are some cases associated with emotion. The specific study of pupil reaction and emotion began when Lang, Bradley, and Cuthbert (1999) created the International Affective Digital Sounds, 117 emotional vocal sound stimuli. Subsequently, Partala and Surakka (2003) researched emotional stimulation and pupil size changes using the same stimuli, confirming that negative and positive vocal sound stimuli were more significantly correlated with pupil diameter than neutral sound stimuli. Bradley, Miccoli, Escrig, and Lang (2008) conducted a study to explore changes in the pupil size in accordance with emotional stimuli by using the International Affective Picture System (IAPS), which is composed of 1,000 pictures of positive, neutral, or negative stimuli. This study's results also indicated that both positive and negative stimuli were significantly correlated with pupil diameter but that neutral stimuli did not cause any significant changes. There was an experiment with college students in Korea to observe change in the pupil size in connection with visual emotional stimuli using the international affective picture system (Mang, Jung, & Lee, 2013). Through the experiments, the authors confirmed that the pupil was most dilated with negative stimuli, so their results were aligned with other findings from extant research. The findings from the above studies support that pupil reaction is related not only to cognitive load, but also to emotional changes. However, in this study, the stimulus, the learning video clip in statistics, did not contain emotional factors, and thus, we interpreted pupil reaction as the learners' cognitive load.

2.3 Learning Flow

Flow, a concept proposed by Csikszentmihaly, who studied how people can lead more creative, happier live, refers to a holistic emotional state (Csikszentmihalyi, 1975) of exerting full power solely by intrinsic motivation without external rewards and to the optimal experience in which such a state is reached (Csikszentmihalyi, 1990). Flow has been studied in various areas since it was introduced. Researchers in education have engaged in studies using such concepts as cognitive engagement, cognitive absorption, and immersion in line with their own research contexts without largely deviating from the basic assumptions (Agarwal & Karahanna, 2000; Webster & Hackley, 1997; Webster & Ho, 1997). Based on the definitions offered by various scholars, Park and Kim (2006, p. 95) defined learning flow as "the most intensive experience in which all the mental processes and activities are focused on only one thought in order exclusively to solve a task by fully immersing into an academic task or a certain academic activity."

Education researchers studied flow earnestly because it can be used as a psychological mechanism that ignites high concentration and participation (Harju & Eppler, 1997) and because flow, which can give a sense of satisfaction, can enhance a learner's intrinsic motivation (Kim, Tack, & Lee, 2010). To be specific, Kim (2003) designed a comprehensive model that could explain learning immersion among participants in an adult education program and confirmed that intrinsic motivation was an important variable in learning immersion, and that immersion could be enhanced in the programs that entail interacting with learning environments. In the recent years, the scope of the flow research has expanded its boundary to reflect changes in the learning environment, from conventional classrooms to online platforms. Kye and Kim (2008) conducted an experiment to illustrate the relationship between media characteristics, a sense of presence, learning flow, and learning effects in the augmented reality-based learning. The authors selected flow as a factor that could directly or indirectly influence learning outcomes in the augmented reality-based learning and found that flow had significant effects on the learners' satisfaction, knowledge, understanding, and applications as well as on their learning effects.

As mentioned above, flow has been researched as a definitive psychological factor that affects learning outcomes and enhances the desire for learning by promoting voluntary and participatory activities (Palloff & Pratt, 1999), in both conventional and online learning environments. However, the measurement of previous studies was dependent on self-evaluation surveys, and thus, there was a limit to fully valuing the results of these self-reported surveys. In this respect, psychophysiological measures are considered to complement the limitations of self-reporting measures, by minimizing the biases in judgment caused by the participants' subjective assessments and without disturbing the process of an experiment (Jung, 2013). The discipline entails the changes in physiological activities triggered by the human psychological states and focuses on the principles of the human cognitive, emotional, and behavioral phenomena. The use of psychophysiological measures also has the limitation in that defining what psychological state a measured response reflects; in other words, a specific physiological response is rarely associated with a single psychological state. Thus, Ravaja (2004) recommended that several physiological indicators be used in conjunction to accurately understand the relationships between physiological responses and psychological phenomena.

Park (2011) and Jung et al. (2012) experimentally verified physiological indicators to explain the flow state. They measured the visual responses of video game users and found that eyebrow wrinkle muscles, large cheekbone muscles, electromyograms, and skin conductivity had significant effects in predicting the flow state and that visual responses were different in accordance with game execution time and game types. Novak et al. (2000) developed a model for connecting psychological states to immersion and found that focused attention had the strongest effect on immersion. Meanwhile, attending, that is focusing on a given assignment or purpose (Gibson & Rader, 1979), requires deliberateness and intent during learning, and it has been researched in a similar vein. Previous studies reported attending and focusing can be measured by physiological measurements, such as brain activity, heart rates, fixation rates, pupil responses, and blink frequency (Graham, 1992; Palmer et al., 1993). Considering the results of the previous studies, it seems possible to measure psychological immersion, related to attending and focusing, in an actual learning context based on the physiological responses. Therefore, we collected the learners' watching behaviors during the video-based learning and aimed to identify the relationships between watching behavior, learning flow, and learning achievement.

3. Methodology

3.1 Experimentation

This study was carried out with 61 students of A University in Seoul for 15 days. Each study participant took the steps of the experiment: pre-test > video learning > post-test > questionnaire. The stimuli used for the experiment was approximately a ten-minute lecture on a subject of normal distribution. It was one of the basic statistics courses provided on the Korean Open Courseware. Specific details are illustrated in <Table 1> and [Figure 1].

Table 1. Construction of video lecture

Lecture Type	Timestamp	Sub-theme
-	00:00~00:04	Intro
Concept explanation	00:05~01:37	Probability and randomness
	01:38~03:00	Shape of normal distribution
	03:01~04:01	68-95-99.8 Rule
	04:02~05:01	Normalization of normal distribution
	05:02~06:14	Using table A
Problem solving	06:15~10:10	Pregnancy period with uneven nutritional status

The eye tracker, Tobii Pro X2-30, was employed to measure the watching behaviors of the participants (refer to [Figure 2]). Concerning learning flow, scales developed by Agarwal and Karahanna (2000) were partly modified to fit the context of the study. Equivalent tests, pre- and post-test, were carried out in order to measure the learners' prior knowledge and their learning achievement. All the processes including an introduction to the experiment, video learning, pre-test, post-test and survey were conducted on the web pages. The entire experimental process took more or less one and a half hour per participant, and given the long-term nature of the experiment, instructional pages guiding each experimental step were inserted to minimize differences depending on each facilitator in the progress of the experiment.

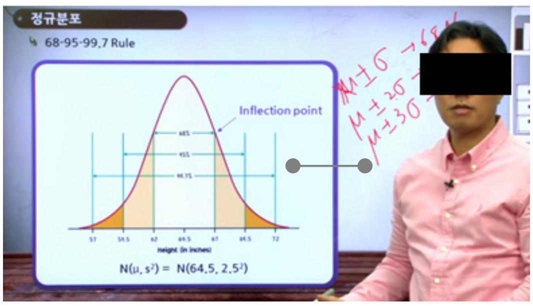

Figure 1. Lecture screen capture

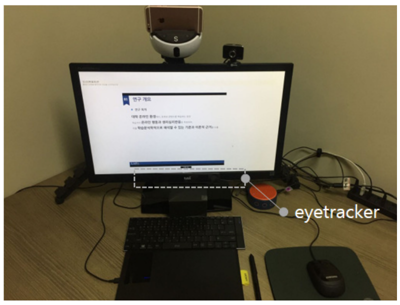

Figure 2. Experimental equipment setting

3.2 Data extraction and pre-processing

Watching behaviors took a series of preprocessing steps (e.g. deleting outliers, missing value estimation, etc.). After that, for each research participant, the preprocessed data was calculated for the five types of watching behavior data. They were average gaze fixation duration time, average saccade duration time, average pupil dilation compared to the baseline, average gazing duration time in the learning section, and distance between the eyes and the screen. Next, these five types of watching behavior data were calculated within three intervals. That is, the data for the whole learning section (Global), lecture type sections (Local 1-2), and subtheme sections (Section 1-6) were developed. For learning flow, average values of 14 questions in the questionnaire were calculated; the learning achievements were calculated as the percentage of the value after dividing differences between the pre-test and the post-test by 12. Concerning the research question #1, the instructor's behaviors, observed in the video, were categorized into 12 realms to understand the characteristics of the watching behaviors depending on the instructor's behaviors in the video-based learning environment.

3.3 Data analysis

First, from the graphs, we compared the average trends of duration of fixation, duration of saccade, and pupil dilation. After checking the overall trend through the graphs, we classified only the values in the top 10% to check the characteristics of the points relating high values per each watching behavior, and the instructor's behaviors and learning materials at those points were matched with the aforementioned classified points. Next, descriptive statistics and correlation analyses were performed to verify the relationships among watching behavior, learning flow and learning achievement. After that, regression analyses were carried out to identify causal relationships between learning achievement and the other variables.

4. Results

4.1 Changes in watching behaviors during learning

To identify the overall variation of the watching behaviors, the average duration of fixation, the average duration of saccade and the average pupil dilation were illustrated as line graphs seen in [Figure 3]. In the case of fixation, generally a longer duration was observed in the concept explanation section than the problem-solving section; it was found that the saccade minutely augmented as time passed. In the case of pupil dilation, high values were observed mostly in the early part of learning; they diminished as learning progressed. The lowest value was recorded at 'Using table A', the last section of concept explanation; after that, it increased slightly in the problem-solving section.

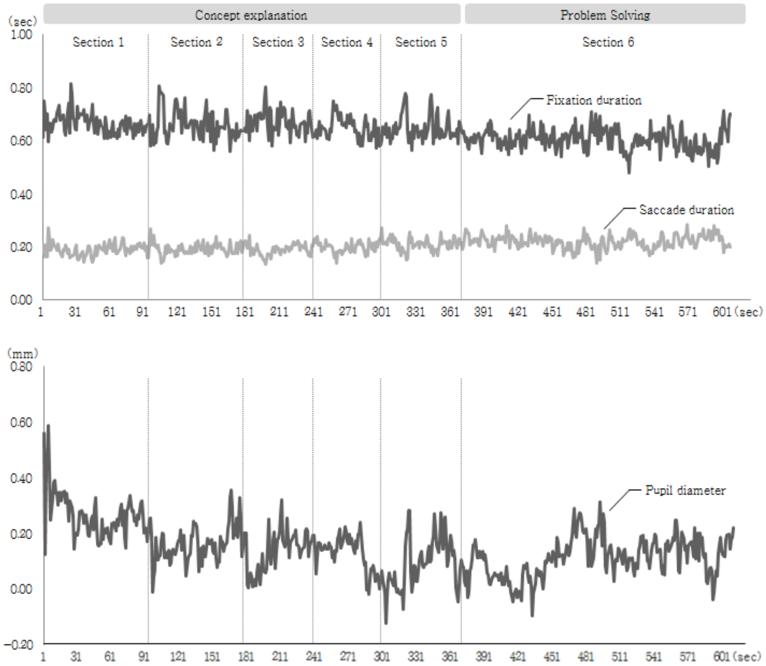

Figure 3. Variation in watching behaviors

After checking the overall changes by graphs, top 10% of each watching behavior was matched to the instructor's behaviors at the time the behavior occurred, to analyze the characteristics of the watching behaviors (refer to <Table 2>). The fixation frequently occurred when the instructor wrote something on the board (13 seconds), pointed a certain part of the learning material with his hand (8 seconds) and when the instructor's gaze moved (4 seconds). Additionally, the saccade occurred when a certain part of the learning material was pointed to by hand (13 seconds), images of the learning material were switching on the screen (5 seconds), and he wrote something on the board (4 seconds). Lastly, the pupil dilation occurred when the instructor took a gesture to offer some explanations (8 seconds), moved his gaze (7 seconds) and pointed to a certain part of the learning material with his hand (6 seconds).

Table 2. Top 10% of each watching behavior matched to instructor's behaviors

Instructor's behavior	Matched time with top 10% watching behavior (sec)		
	Fixation	Saccade	Pupil
Explaining essential part for problem solving	-	-	3
Unnecessary gesture	-	-	2
Gesture for explanation	2	1	8
Moving the direction of gaze	4	2	7
Moving position	-	-	-
Writing on the board	13	4	3

Instructor’s behavior	Matched time with top 10% watching behavior (sec)		
	Fixation	Saccade	Pupil
Obscuring notes on the board	-	-	1
Reading learning materials	1	1	-
Highlighting learning materials	3	-	-
Pointing to learning materials by hand	8	13	6
Explaining to learners	-	-	-
Shifting learning material	3	5	3

4.2 Predicting learning achievement with segmentation

The process of processing, verifying, and elaborating the collected data in several variables has been repeated to explore the learning outcome prediction model through watching behaviors and learning flow. What was found was written in accordance with the analytical steps to illustrate the results of the study. The average of learning flow for the total of 14 questions was 3.24, and concentration was recorded the highest among the sub-items. Learning achievement was calculated as the gap between before and after learning, and the average improvement rate of academic achievements was 29.78%. The average pre-test score was 3.70, while the average post-test score was 7.28.

Correlation analysis was performed to check correlations among the watching behaviors, learning flow and the learning achievement during the whole learning process. The results demonstrated that no watching behavior variable correlated to the learning achievement; the pupil diameter and fixation had significant correlations; the fixation and saccade had negative correlation. A negative correlation between fixation and saccade was an expected result given that the gaze type data of the eye tracker was measured either by fixation or saccade.

Since watching behaviors representing the whole learning section did not show any significant correlation with learning flow or learning achievement, watching behavior variables, segmented by each lecture type (concept explanation section and problem-solving section), were analyzed subsequently. According to the results, watching behaviors representing each lecture type did not show significant correlations with learning flow or learning achievement, except for the variable ‘zone in L1’. Thus, a multiple regression analysis was not implemented with these lecture type variables.

Further analyses were carried out after segmenting watching behaviors into smaller units (sub-theme sections), and some of the watching behavior variables showed significant correlations with learning achievement. That is, fixation S1, zone in S2, zone in S4 and zone in S5 had negative correlations with learning achievement. To investigate the influence of these variables on learning achievement with controlling the pre-test scores, a hierarchical regression analysis was implemented. The results are provided in <Table 3>.

Table 3. Hierarchical regression analysis for learning achievement

(*n*=61)

Variable		Model 1		Model 2	
		β	t	β	t
Control	(Constant)	39.42	8.068*	104.91	4.640*
	Pretest	-2.60	-2.809*	-2.29	-2.487*
Predictor	Fixation S1			-.11	-1.76
	Zone in S2			-.36	-.90
	Zone in S4			-.74	-1.25
	Zone in S5			-.06	-.12
	$R^2(\Delta R^2)$	.12		.24(.13)	
	F	7.891*		3.527*	

*p < .05

In Model 1, the pre-test scores were assigned as the factor affecting learning achievement and Model 2, fixation S1, zone in S2, zone in S4, and zone in S5 were assigned additionally. As demonstrated in the analytical results, the F-statistic of Model 1 was 7.891 while that of Model 2 was 3.527, and both of them were statistically significant. However, in both Models, the pre-test, which was the control variable, was found as the significant one explaining learning achievement, and the watching behaviors could not predict learning achievement significantly.

4.3 Predicting learning achievement using point-in-time data

For each student, the watching behaviors per second were calculated, and every second showing more than + 1SD value of each watching behavior were filtered again. After that, we classified only the moments among the top 10% as the analytical times for predicting academic achievement. The moments among the top 10% were 76 seconds of fixation, 96 seconds of saccade and 67 seconds of pupil diameter. Finally, the frequency of + 1SD and the mean value were calculated as the variables for each student. For convenience, we named those variables fixation Pk, saccade Pk, pupil diameter Pk, fixation frequency Pk, saccade frequency Pk and pupil diameter frequency Pk. According to the results of correlation analysis among the newly generated 6 Pk variables, learning flow and learning achievement, fixation Pk and pupil frequency Pk yielded only significant correlation with learning achievement, and thus, a hierarchical regression analysis was performed by controlling the pre-test scores. The results are provided in <Table 4>. The results of Model 2 demonstrated that fixation Pk and pupil frequency Pk did not predict learning achievement significantly.

Table 4. Hierarchical regression analysis using point-in-time data

(*n*=61)

Variable		Model 1		Model 2	
		β	t	*β*	t
Control	(Constant)	39.419	8.068**	72.682	3.839
	Pretest	-2.601	-2.809**	-2.348	-2.585*
Predictor	Fixation Pk			-37.887	-1.349
	Pupil frequency Pk			-.417	-1.243
	$R^2(\Delta R^2)$	.12		.19(.07)	
	F	7.891**		4.535**	

*p < .05 **p < .01

Additional analyses were performed after dividing the students into the high and low achievement groups, based on the median values of the learning achievement, to check whether the predictive power can be different in line with the level of their learning achievement. The correlation analysis among the variables showed that there is no significant correlation in the low achievement group. In the case of the high achievement group, it was found that fixation Pk and fixation frequency Pk had a negative correlation with learning achievement, while saccade Pk had a positive correlation with learning achievement. The following hierarchical regression analysis (refer <Table 5>) established that Model 1 and Model 2 were statistically significant at a significance level of .05. The R^2 of Model 1 was. 32 and that of Model 2 was .20. In this analysis, Model 2, including the watching behavioral variables, reported that the higher values of saccade lead to the higher levels of learning achievement.

Table 5. Hierarchical regression analysis for learning achievement in the high achievement group

(*n*=37)

Variable		Model 1		Model 2	
		β	t	*β*	t
Control	(Constant)	63.974	14.975**	54.635	2.443**
	Pretest	-4.384	-3.687**	-2.655	-2.246**
Predictor	Fixation Pk			18.149	0.613
	Saccade Pk			92.018	2.21*
	Fixation frequency Pk			-1.191	-2.025
	$R^2(\Delta R^2)$	.32		.52(.20)	
	F	13.59**		6.993**	

*p < .05 **p < .01

5. Discussion and Conclusion

The results of the study are summarized as follows. First, empirical connections between teaching behaviors and watching behaviors were confirmed. By extracting top 10% of each watching behavior moment (fixation, saccade and pupil dilation) and matching instructor's behaviors with those seconds, we could confirm that the fixation mostly occurred when paying attention to a certain area was required, such as writing on the board or instructing a specific part of a learning material. Meanwhile, the saccade mostly took place when switching the focus was necessary. Thus, saccade, which as a reaction to specific behaviors, can be used as a barometer of attention shifting in the video learning environments. In case of the pupil diameter, many cases were overlapped with the instructor's behaviors during the top moments of fixation or saccade; however, there were some behaviors which characteristically occurred only in the top moments of the pupil diameter. It occurred when unnecessary gestures were presented, and notes on the board were obscured by the instructor. Although the seconds were short, they could be confirmed with the pupil diameter alone, and the significance lies in that all of them were the factors disturbing learning, extraneous cognitive load factors. These interpretations can be illustrated as follows ([Figure 4]).

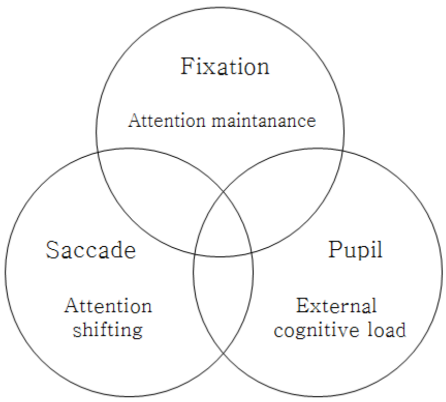

Figure 4. Frame of interpretation of watching behaviors

The framework can be employed in two aspects. First, it can be used when designing a lecture video. A lecturer can make a gesture in a part which needs an extra attention of learners; they can plan to write something on the blackboard in the part when composing a lecture. In addition, the framework can be used for analyzing the watching behaviors of the students in online learning materials and updating the materials to more effective ones. Second, it can be used to evaluate a learner's learning process and to predict the achievement. For example, it is possible to monitor how long a learner fixed his or her gaze on a part requiring attention and to check on what level a teacher's instructive behavior synchronized with gaze leap. Although the statistical analysis of this study failed to find correlations between watching behaviors and teaching behaviors, through further studies engaging sophisticated experiments, the relationship between them could be better identified and interpreted with clarity.

Second, the study aimed to identify causal relationships between learning achievement and the other variables (watching behaviors and learning flow). We converted the learners' watching behaviors into the three categories of variables: the whole period, lecture type, and sub-theme variables. And the eye-tracking data, fixation, saccade, pupil diameter, and zone in, were used for the analysis. We tried repeatedly several correlations and regression analyses but could not find powerful explanatory variables or establish a stable regression model. It was difficult to find the watching behaviors which directly explain learning achievements, and it was not easy to establish a stable regression model. However, we could confirm the direction of future research for identifying the relationships between learning achievement and watching behaviors. To be specific, we confirmed that it is necessary to establish a prediction model that uses the watching behaviors measured in real time as effectively as possible. Moreover, as an analytical unit was departmentalized into more sub-sections, significant correlations and a regression model on learning achievement could be observed with greater frequency. That is, (1) setting temporal section, (2) setting spatial section, and (3) clustering based on learner characteristics had yielded better results.

Third, learning flow, which was second to be tested in the study, did not have a significant correlation to learning achievement, and this could be seen as a contraction to the results of extant studies related to learning flow (e.g. Harju & Eppler, 1997). However, because our experiment was conducted in a general video-based learning environment, the stimulus was about statistics and took a little more than 10 minutes, the learning flow survey questioning the state of extreme immersion like whether a leaner experienced the transformation of time or not could not have been sufficient to explain the immersion state of a learner in this kind of video-based learning environment. Thus, there seems to be a need complementing the measurement that can capture a leaner's immersion state in general video learning environment.

Based on the aforementioned discussion, some suggestions could be made for future research in terms of research design, measurement, and analysis. First, in order to accurately correlate a learner's watching behaviors with specific psychological constructs, such as cognitive load, learning flow or motivation, experimental research conducted based on the stimuli, tailored to the target construct, should be followed. Only when such a sophisticated experimental study lays out the foundation, would it be possible to interpret with accuracy a learner 's watching behavior in general video-based learning environment. Second, it is imperative to expand the realm of analysis by combining with other psychophysiological responses besides the watching behavior data. For example, the study had limitations in discerning what caused the missing data, whether it was caused by drowsiness or mechanical errors. Enhancing the precision of interpretation would be possible if the participants' brainwaves and facial expressions are collected together. Particularly, it is impossible to avoid the data loss of learners in an actual learning situation. Thus, parallel measurement using various devices could be safer to understand the learners' conditions for greater reliability. Lastly, it is necessary to investigate the statistical analysis techniques most suitable for the psychophysiological response data. Psychophysiological data are measured in real time, so a common statistical analysis reporting on a mid-value, like mean, yields a waste of raw data. Therefore, a more advanced analytical method which can handle significant quantities of information containing psychophysiological data should be examined, and this type of approach might contribute to creating an educational intervention ultimately leading to an impact on the actual learning environment.

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