Chapter 14
An Investigation of Visual and Manual Behaviors Involved in Interactions Between Users and Physics Simulation Interfaces

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Introduction

Improving students' in-depth understanding of physics conceptual frameworks is a central goal of physics learning. Traditional instructional approaches, however, have been repeatedly reported as having little effect on achieving this goal (e.g., Hake, 1998; Kim & Pak, 2002; Trowbridge & McDermott, 1981), and many educators have strived to advocate alternative approaches that could reach this desirable goal. Among the suggested approaches, inquiry learning has become prevalent since the early 2000s. Duschl (2008) claimed that conducting inquiry activities has the potential for developing students' understanding of the content, practice, and epistemology of science, and Abd-El-Khalick et al. (2004) proposed that inquiry should be treated as the process, as well as the outcome, of science learning. With the rapid development of digital technology, inquiry learning can now be easily implemented in computer environments, such as computer simulations (e.g., de Jong, 2006, 2011; de Jong et al., 2013; Wieman & Perkins, 2005).

Computer simulations open a productive avenue for learning physics. In general, they have two major components, a computational model and an interface (de Jong, 2011). A computational model is a computer program designed for simulating the corresponding, original natural phenomenon or physics system. An interface, on the

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other hand, allows users to interact with the computational model by altering the values of the involved variables. These two components afford computer simulations with highly interactive virtual environments where multiple representations of corresponding models can be demonstrated and manipulated. These sorts of virtual environments create tremendous opportunities for conducting inquiry activities. For instance, some abstract physics concepts, such as electric current, are difficult for students to learn because of their invisibility. Using a PhET simulation (e.g., Wieman et al., 2010), students can not only observe and visualize the movements of imagined particles, electrons, as an electric current, but can also manipulate relevant variables, such as the amounts of resistance and power, to fully investigate the phenomena of electricity. Also, some experiments, such as testing airbag safety (McElhaney & Linn, 2011), can scarcely be performed by students because of their vast expense and restricted access. By using computer simulation, students have access to experiencing "professional" laboratories where they can identify and change relevant variables, test their predictions, and review and interpret the experimental results. Nevertheless, it is worth noting that models and representations displayed in computer simulations are never authentic or realistic; they are simplified and theoretical versions of complex phenomena or systems, which make them adequate media for physics learning.

Previous studies have confirmed the effect of using computer simulations on enhancing students' learning outcomes. For example, in a review study, Rutten et al. (2012) found that, compared to traditional instruction, computer simulations demonstrated a stronger effect on improving students' conceptual understanding and inquiry skills, such as making predictions. Also, Rutten et al. pointed out that representations with different formats, such as dynamic versus static, and concrete versus idealized, might have different effects on conceptual understanding. Similarly, D'Angelo et al. (2014) conducted a meta-analysis of 59 studies on computer simulations, and concluded that learning with computer simulations showed a beneficial effect on facilitating students' STEM (science, technology, engineering, and mathematics) learning in comparison to learning without them. Given that the reviewed studies were all related to STEM domains, D'Angelo et al. specifically indicated that computer simulations had a significant effect on students' inquiry and reasoning skills. Although most studies favored computer simulations over traditional instructional approaches, de Jong (2011) argued that to better understand the effectiveness of computer simulations, it is important to explore how they are used under what conditions.

As mentioned previously, interactivity is a central affordance of computer simulations that provides ample opportunities for conducting inquiry activities. Exploring how users interact with computer simulations, therefore, is an important key to unveiling the processes and outcomes of learning with simulations. Adams et al. (2008), for example, found that if students could only watch, without any interaction with, the representations displayed by a computer simulation, they tended to passively perceive what they observed as a fact without developing any new ideas or insights. In contrast, if the students were allowed to interact with the simulated representation, they might actively pose questions to the simulated models and start to conduct further investigations of the models by manipulating the relevant variables. In other words, interactivity might be a trigger for students to actively conduct inquiry activities within a computer simulation. Moreover, by conducting inquiry activities, students could retrieve their prior knowledge and integrate it with the information they had observed and received from the simulations (de Jong, 2011). They could, therefore, develop a deeper understanding of the simulated models and achieve better learning outcomes. Nonetheless, there has been little study on investigating the detailed processes of using computer simulations, and it remains unclear how the process of interacting with simulations affects students' learning achievements.

To uncover how students interact with computer simulations, some studies began to explore the detailed processes of using simulations. In particular, because the interaction between users and a simulation interface involves visual attention, specific technologies and techniques could be employed to better investigate the highly interactive processes. For example, Chiou et al. (2019) used eye-tracking techniques to study how students used computer simulations. They found that the spatial distributions and temporal sequences of visual attention could be used to account for the learning processes and outcomes of using simulations. More specifically, students who paid more attention to the target simulated phenomena were more likely to accomplish the inquiry task than those who paid scare attention to the target phenomena. In addition, regarding the sequences of visual transition, students who first fixated on the instructional information and then on the target simulated phenomena were more likely to provide a correct answer to the inquiry question. The rationales behind the usage of eye-tracking techniques are *immediacy* and *eye-mind* assumptions (Just & Carpenter, 1980). While the former assumes the direct temporal sequence between perceiving and processing external visual stimuli, the latter proposes a correspondence between what is visually perceived and what is mentally processed. These two assumptions together adequately connect the visual behaviors and mental operations while using computer simulations, and serve as a solid foundation for utilizing eye-tracking techniques for studying the interaction between users and simulation interfaces.

Visual behaviors alone, however, could not fully account for the interaction between users and computer simulations. This is because users need to manually "touch" the interface to manipulate the variables involved in the simulated models. These manual manipulations are usually done by hand and finger movements, such as clicking, dragging, and dropping the buttons of a mouse. Moreover, it is worth noting that manual manipulations could not be effectively performed without visual attention. To carefully investigate the user-interface interactions in computer simulations, it would be better to examine the concurrence between visual behaviors and manual manipulations. Nevertheless, to date, little research has been conducted to concurrently investigate both visual attention and manual manipulation as the detailed interactive process of using simulations. This present study, therefore, attempted to bridge this gap for an in-depth understanding of the process of using computer simulations for learning physics.

Research Questions

Based on the aforementioned description, this study was conducted to answer the following questions:

1. How did students interact with a simulation interface while conducting a physics inquiry activity in a computer simulation?
2. What patterns of visual and manual behaviors might lead to the successful completion of a physics inquiry activity?

Methodology

Participants

The participants in this study were 40 seventh graders (22 females and 18 males; range from 12 to 13 years old) recruited from a junior high school in southern Taiwan. They had never learned physics concepts related to refraction in a formal setting before participating in the study. These participants were divided into two groups according to their answers to the inquiry question given in the physics simulation (which will be introduced later). While those who provided a correct answer were assigned to the correct group, those who offered a wrong answer were assigned to the wrong group. As a result, there were 21 participants in the correct group (10 females and 11 males) and 10 participants in the wrong group (12 females and 7 males). The result of a t test showed that there was a significant difference in the pretest scores (this will be described later) among these two groups ($t = 2.16$, $p = .04$), suggesting that the two groups had different levels of prior knowledge about basic optics.

Simulation

This study adopted a computer simulation, refraction of light, developed by Chiou et al. (2019) as an inquiry environment to be investigated. The simulation was specifically developed for students to learn a physics conception, refraction. By using this simulation, students could change the media within which a light ray propagates, and could observe how the ray bends when coming into another medium. Figure 14.1 shows the interface of the simulation, including six major areas: Question, Up panel, Down panel, Light, Reflection, and Refraction. The Question displays an inquiry question that provides guidance for students to conduct an investigation within the simulation. The Up and Down panels are two control bars where students can adjust the indices of refraction of the upper and lower media, respectively. The Light area contains a flashlight by which students can change the angle of the light source, that is, the incident angle. The Reflection and Refraction areas display the reflected ray

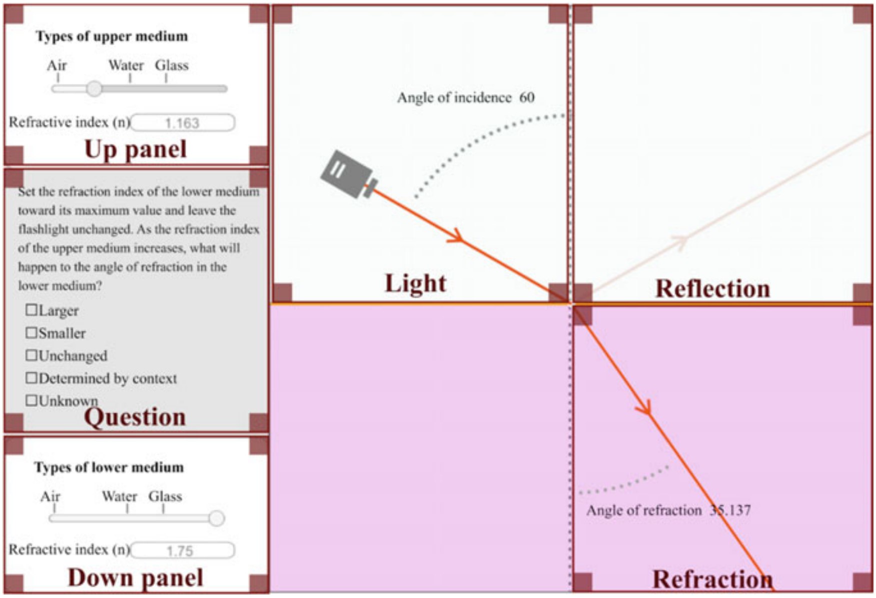


Fig. 14.1 The interface and AOIs of the simulation

and refracted ray, respectively. In brief, users can change the position of the flashlight and the materials of both the upper and lower media to observe the relationship between the incident angle and the refracted angle. Moreover, when the incident angle is greater than the critical angle, total reflection occurs and the reflected ray will be presented in the Reflection area.

Pretest

This study developed a pretest for assessing the participants' conceptual understanding of optics. This test was reviewed by two physics educators to ensure its face and content validity. In particular, because the participants had never learned the concept of refraction before participating in this study, the pretest focused only on some basic ideas of optics, such as straight propagation of light, shadow, and reflection. The pretest had 12 items in total, and the Cronbach's α is .60, indicating a proper level of internal consistency.

Apparatus

This study utilized a specifically developed eye-tracking system for recording and processing the participants' visual and manual behaviors while using the simulation. The eye-tracker used in this system was the Eye Tribe, which had a sampling rate of 30 Hz and was mounted under a 14" screen of a laptop that was used to run the computer simulation. While using the simulation, the participants rested their chin on a chin holder to prevent rapid head movement, and the distance between the participants and the laptop screen was about 65–70 cm. Our eye-tracking system included a computer program that was developed to identify fixations based on the raw data recorded by the Eye Tribe and to calculate the eye-tracking measures required for this study. The system can also record a participant's manual behaviors (mouse logs) simultaneously. The validity of the eye-movement data generated by our eye-tracking system has been carefully examined and reported with a correction rate of 99.81% (please refer to Hsu et al. [2016] for more details).

Data Collection Procedure

This study carried out the following procedure for data collection. In the beginning, the pretest was administered to each individual participant. Then, each participant went through a five-point eye-tracking calibration. If the calibration was successful, the participant started to use the computer simulation. S/he was allowed to play with the simulation to get familiar with its interface. Subsequently, the participant began to conduct an inquiry task shown on the interface: "*Please first set the refraction index of the lower medium toward its maximum value and leave the flashlight unchanged. Then try to adjust the refraction index of the upper medium and observe the path of the ray of light in the lower medium. As the refraction index of the upper medium increases, what will happen to the angle of refraction in the lower medium*?" The eye-tracking system with an Eye Tribe was employed to record the participant's visual behaviors and log data while s/he was using the simulation. The inquiry task was self-paced and the participant could spend as much time as needed to complete the task. Once the participant finished the inquiry task by submitting an answer, the eye-tracking system was immediately turned off and stopped recording. The participants spent an average of 48.99 s ($SD = 23.78$) to complete the inquiry task.

Data Analysis

This study aimed at examining the differences in the processes of using the simulations of those students who provided correct and wrong answers. Therefore, the participants were first divided into two groups based on the correctness of their answers to the inquiry question. Then, a series of between-group comparisons were made in terms of eye-movement indices, log data, lag sequential analyses, and heat maps. In the following, we will describe these four data analysis approaches.

Eye-Movement Indices

To analyze the spatial distribution of the participants' visual attention, we defined seven areas of interest (AOI) within the interface of the simulation. Six of the seven AOIs directly correspond to the major functional regions of the interface, which are the Question, Up panel, Down panel, Light, Reflection, and Refraction (please refer to the Simulation section for the meanings of these regions). The remaining AOI is Out, which refers to the region outside all of the previous six AOIs.

With respect to the seven AOIs, seven eye-movement indices were adopted for further analysis. First of all, we calculated the total time (TT) that each participant spent on each AOI. Second, the total fixation duration (TFD) of each AOI was calculated to reveal the accumulated time that each individual fixated on the corresponding region of the interface. Third, we calculated the total fixation count (TFC) of each AOI to understand the frequency with which each individual fixated on the area. Fourth, by dividing TFD by TFC, the average fixation duration (AFD) could be obtained. Fifth, to better understand the portion of time that each participant spent on each AOI, we calculated the percentage of time spent in zone (PTS) by dividing the time spent on each AOI into the total time of using the simulation. Sixth, the time to first fixation (TFF) was calculated to reveal how long it took for each participant to first allocate their visual attention to each AOI. Finally, we computed the first passing time (FPT) to represent the duration starting from the participants' first arrival to the departure of each AOI. The definitions and meanings of the seven eye-movement indices are listed in Table 14.1. Based on the values of the seven eye-movement indices, a series of non-parametric, Mann-Whitney U tests were performed to examine the differences in the distributions of the visual attention of the two groups.

Log Data Analysis

To understand how the participants manually manipulated the interface, we carefully examined the log data recorded while they were using the simulation. We first checked every adjustment each participant made with the control panels of the interface, that is, the up panel, the down panel, and the light. Each adjustment was defined as one manipulation, and the numbers of manipulations could be accumulated as total manipulation count (TMC). Moreover, each manipulation was labeled with a starting point (S) and an ending point (E), and the time period between the starting and ending point was defined as a manipulation duration (MD). With respect to each control panel, every single manipulation duration could be added up to total manipulation

Table 14.1 Eye-tracking indices for each AOI used in this study

Indices	Description
Total fixation duration (TFD)	The total time spent on fixations; this index might indicate the total visual attention devoted to an AOI in a temporal dimension
Total fixation count (TFC)	The total number of fixations within an AOI; this index might indicate the total visual attention devoted to the AOI in a frequency dimension
Average fixation duration (AFD)	The mean of every fixation duration, i.e., TFD divided by TFC; this index might indicate the depth of information processing, and is often associated with individuals' mental workload
Percentage of time spent in zone (PTS)	The time spent in an AOI compared to the total amount of time spent completing a task; this index might indicate the proportion of cognitive resources used for interacting with the information contained in the AOI
Time to first fixation (TFF)	The duration of time before the first fixation allocated in an AOI; this index might represent the salience of the information contained in the AOI
First passing time in zone (FPT)	The duration of the first time passing through an AOI, i.e., the duration from the first fixation's arrival in an AOI until the first fixation leaving the AOI; this index might indicate the length of time necessary to process specific information, and is often associated with initial information processing such as decoding

Source Cited from "Exploring how students interact with guidance in a physics simulation: evidence from eye-movement and log data analyses," by G.-L. Chiou et al. (2019), Interactive Learning Environments, p. 6

duration (TMD), which represents the total amount of time each participant spent on each control panel. By dividing the TMD into TMC, we obtained the average manipulation duration (AMD) of each control panel. In this study, we used the MC, TMD, and AMD as three major indices to examine the differences in manipulating the interface of the correct and wrong group by conducting a series of Mann-Whitney U tests.

Lag Sequential Analysis

Lag sequential analysis (LSA) is a statistical technique for examining the significance of the concurrence of any two consecutive events (please refer to Bakeman and Gottman [1997] for a detailed introduction of this technique). In this study, the LSA was applied to check whether transitions between any two visual fixations, between any two manual movements, or between visual fixation and manual movement occurred by chance or not. To achieve this aim, we first combined the eye-tracking and log data by jointly ordering each visual fixation and each manual movement with respect to its AOI in temporal sequence. Then, an eye-tracking data analysis tool, Web-based Eye-tracking Data Analyzer (WEDA; Tsai et al., 2018), was utilized to compute the frequency of transitions between any visual fixation and/or manual movement, the transitional probability of each pair of transitions, and its corresponding adjusted residuals (z scores). By checking the amount and distribution of significant transitions obtained by LSA, we could examine the difference in the patterns of interactivity between the two groups (this comparison will be described in more depth in the Results section).

Heat Map Analysis

To further examine the differences in the spatial distributions of the visual attention of the two groups, the WEDA (Tsai et al., 2018), was utilized to generate two heat maps. Based on the locations and durations of the eye fixation data of each group, WEDA calculated the normalized fixation duration allocated on each pixel of the screen. With respect to each pixel, the length of normalized fixation duration was represented by a color spectrum with one end red and the other blue; the longer the normalized fixation duration, the redder; the shorter, the bluer. By examining the insensitivity and locations of the colors shown on the heat maps, we could compare the distributions of visual attention of the two groups while they were using the simulation.

Results

RQ1: How Did Students with Different Learning Performance Distribute Their Visual Attention While Manipulating the Simulation?

Mann-Whitney U tests were conducted to examine the difference in the eye-tracking indices between the correct and wrong groups, and the results that indicate significant differences were shown in Table 14.2. According to the results, some significant differences between the two groups could be identified. For example, with respect to the TFF, the wrong group took longer than the correct group to first fixate on both the Up panel ($U = 115$, $p < .05$) and the Down panel ($U = 107.5$, $p < .05$). In addition, the wrong group appeared to spend significantly more time on the Down panel AOI than the correct group. For instance, they not only had a longer first passing time (FPT, $U = 123.5$, $p < .05$) but also spent more total time (TTS, $U = 120$, $p < .05$) and a higher percentage of time (PTS, $U = 118.5$, $p < .05$) on the Down panel AOI.

The correct group, in contrast, spent a higher percentage of time on the Light AOI (PTS, $U = 276.5$, $p < .05$).

Log Data Analysis

We conducted a series of Mann-Whitney U tests to examine the differences in the mouse control log data of the two groups. Table 14.3 shows the results that reveal statistically significant differences. As revealed in Table 14.2, the wrong group performed significantly higher frequency of manipulating both the Up panel (MC, $U = 129.00$, $p < .05$) and the Down Panel (MC, $U = 103.50$, $p < .05$). While the wrong group also appeared to spend longer manipulating both the Up panel and the Down

Table 14.2 Results of Mann-Whitney U tests on eye-tracking indices

Eye-tracking indices	Wrong group (N = 19)		Correct group (N = 21)		MWU	z
	Mean	SD	Mean	SD		
Up panel_TFF	102.44	61.46	60.25	50.43	115	−2.30*
Down panel_TFF	105.47	69.36	53.00	53.74	107.5	−2.53*
Down panel_TTS	3.48	2.18	2.31	2.76	120	−2.16*
Down panel_PTS	0.07	0.04	0.05	0.05	118.5	−2.20*
Down panel_FPT	1.17	0.90	0.62	0.60	123.5	−2.06*
Light_PTS	0.06	0.03	0.11	0.08	276.5	2.09*

*$p < .05$

Table 14.3 Results of Mann-Whitney U tests on log data indices

Log data indices	Wrong group (N = 19)		Correct group (N = 21)		MWU	z
	Mean	SD	Mean	SD		
Up panel_MC	1.95	1.61	1.05	1.36	129.00	−1.97*
Down panel_MC	2.26	1.37	1.14	0.91	103.50	−2.71*
Light_MC	0.21	0.54	0.67	1.02	247.00	1.64
Up panel_TMD	5.55	6.25	4.09	6.67	142.50	−1.55
Down panel_TMD	4.92	5.65	5.37	6.39	190.00	−0.26
Light_TMD	0.50	1.24	3.40	5.84	253.00	1.84
Up panel_AMD	2.88	4.08	3.10	6.29	168.50	−0.84
Down panel_AMD	2.10	1.86	3.47	3.81	221.00	0.59
Light_AMD	0.38	0.91	2.58	4.13	253.00	1.84

Note MC refers to manipulation count; TMD means total manipulation duration; AMD refers to average manipulation duration

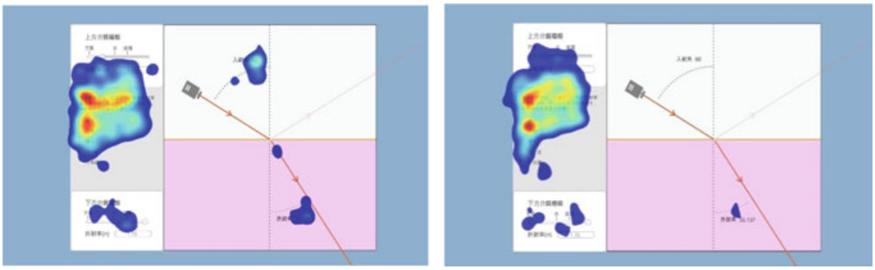


Fig. 14.2 Heat maps of fixation duration: correct group (left) and wrong group (right). Visual attentions were paid to the Lighter, Refraction, and Incident Angle areas for the correct group (left), but not for the wrong group (right)

panel than the correct group, the differences do not have statistical significance. The correct group seemed to demonstrate more manipulation of the Light panel than the wrong group, although the differences do not gain statistical significance either.

Heat Map Comparison

The heat maps that represent the distributions of visual attention of the two groups are displayed in Fig. 14.2. By comparing the two heat maps, it is apparent that the correct group paid more visual attention not only to the text of the inquiry question, but also to the degree of the incident angle, the interface where the ray starts to bend into the lower medium, and the degree of the refracted angle. It is worth noting that the incident angle, the interface, and the refracted angle are the three critical areas that provided the relevant information for correctly answering the inquiry question. The wrong group, however, only paid a little visual attention to the refracted angle, although they allocated similar amounts of visual attention to the Up panel and Down Panel AOIs. It is also worth mentioning that, while the eye-movement indices showed that the wrong group spent significantly longer (TTS) on the Down panel AOI, the intensity of their total fixation duration (TFD) on this AOI does not appear to be different from that of the correct group, as suggested by the results of the Mann-Whitney U tests.

RQ2: Did Students with Different Learning Performance Have Different Visual and Manual Behavioral Patterns?

We conducted the LSA to examine the statistical significance of the visual and manual interactive behavioral transitions demonstrated by the two groups while they were using the simulation. The results of the z scores obtained from the LSA for the two groups were shown in Table 14.4 (in each cell, the upper data is for the correct group, and the lower data is for the wrong group). Each cell indicates a behavioral transition from the corresponding behavior of its *y*-axis to the corresponding behavior of its *x*-axis. All significant transitions ($z > 1.96$) have been marked bold.

The bold z scores (higher than 1.96) were used to create the visual transition diagram of each group, as shown in Fig. 14.3. In Fig. 14.3, while the boxes with a plain background represent AOI on which visual attention was allocated, the boxes with a grey background represent a mouse manipulation. In addition, the arrows in Fig. 14.3 denote significant transitions between any visual or manual events. For example, "Up panel_S → Up panel" in Fig. 14.3a represents a significant transition from a starting click on the Up panel to the Up panel AOI, which means that the participants began to adjust the parameter on the Up panel and then changed to visually fixate on the Up panel AOI. Moreover, the number ".30" close to the arrow represents the probability of transition, which means that once the participants manually clicked the Up panel, they had a 30% probability of switching to visually fixate on the Up panel AOI. Similarly, the "Light → Light_E" illustrates a significant transition from a visual fixation on the Down panel AOI to terminate the manipulation of the Down panel, with a 64% probability.

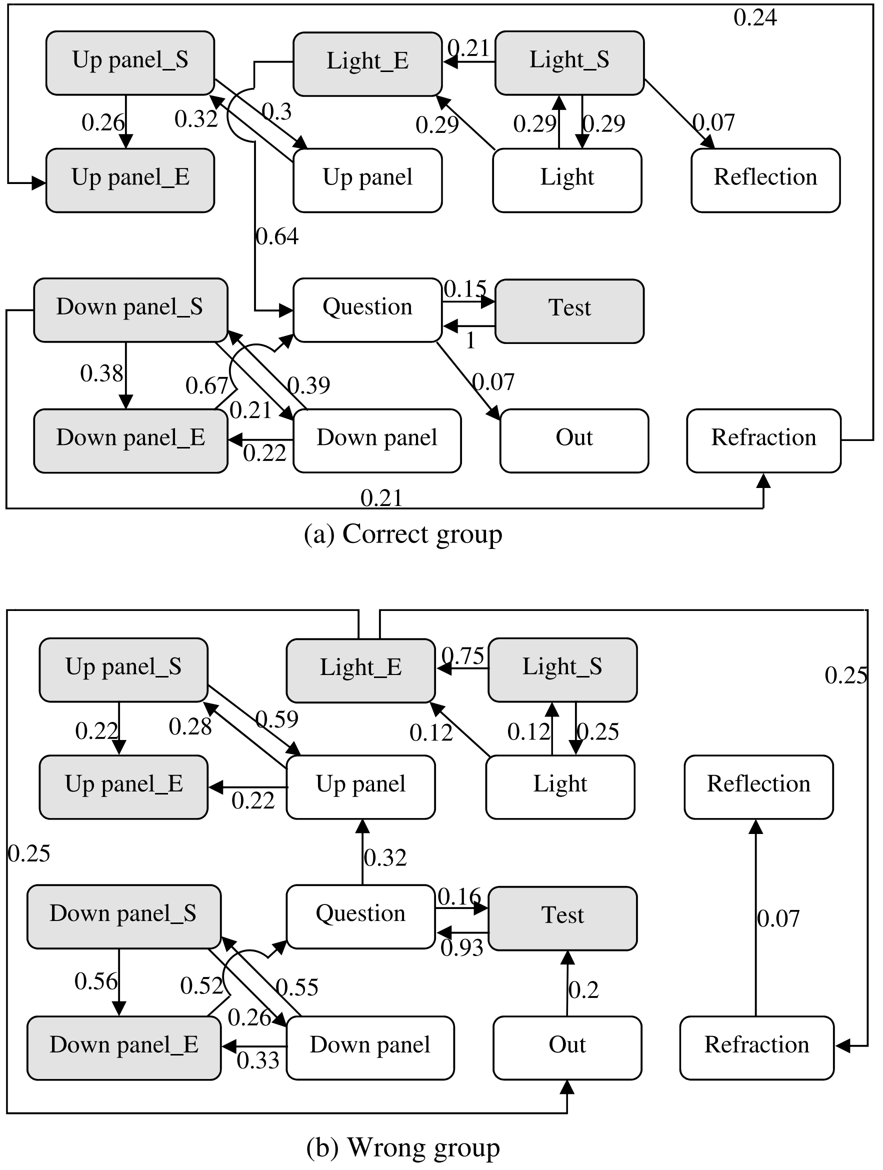
Some common and different patterns of behavioral transitions can be identified in the two diagrams of Fig. 14.3. Regarding the commonality, both diagrams reveal temporal concurrences between visual fixation and manual manipulation. In other words, a manual manipulation either comes from or goes forward to a visual fixation on the same control panel. For example, in Fig. 14.3a, before adjusting the Up panel, the participants might first fixate on the Up panel AOI, represented by "Up panel → Up panel_S." In addition, once starting to adjust the Up panel, the participants might look back to the Up panel, "Up panel_S → Up panel," or just stop manipulating the panel, "Up panel_S → Up panel_E." Similarly, this fixation-manipulation concurrence could also be found on both the Down panel and the Light in both groups.

With respect to the differences between the two groups, the correct group seemed to demonstrate more critical behavioral transitions that are relevant for solving the inquiry question. Take Fig. 14.3a for instance; after clicking the Down panel, the correct group might transfer to visually fixate on the Refraction AOI, "Down panel _S → Refraction," which provided information about the relationship between the refracted index of the lower medium and refracted angle. Also, the transition, "Refraction → Up panel_E," suggested that the correct group would observe the Refraction AOI and then terminate the manipulation of the Up panel. This transition could provide information about the relationship between the refracted index of the upper medium and the refracted angle. In contrast, although the wrong group made some distinct behavioral transitions, these transitions appeared less important for solving the inquiry question. For example, they might end up adjusting the Light and then switch to fixate on the Refraction AOI, "Light_E → Refraction." While this transition might help the wrong group connect the incident angle with the refracted angle, this piece of information was not required for answering the inquiry question. Also, the wrong group made a visual transition from the Refraction AOI to the Reflection AOI,

Table 14.4 *Z* scores of behavioral transitions in the correct and the wrong group

		Visual								Manual					
		U	D	Q	L	F	R	O	T	U_S	U_E	D_S	D_E	L_S	L_E
VISUAL	U	0	-0.38	-1.1	0.22	0.68	-0.95	-0.08	-2.28	**7.83**	1.20	0.22	-1.12	-1.33	-1.33
		0	-1.28	0.86	-0.32	-0.63	-1.72	0.13	-2.75	**5.63**	**3.95**	-2.01	-2.80	-0.89	-0.89
	D	-1.67	0	-0.30	-1.23	-0.53	-1.14	0.66	-1.56	-1.20	-1.14	**7.04**	**3.37**	-0.91	-0.91
		-2.30	0	-3.04	-0.79	-0.39	-0.01	-0.93	-1.70	-1.83	-1.8	**8.82**	**4.72**	-0.55	-0.55
	Q	1.18	0.64	0	-1.30	-0.91	-1.70	1.95	**5.48**	-1.13	-2.16	-0.43	-2.16	0.73	-2.06
		1.69	0.61	0	1.19	0.60	-0.81	1.05	**7.53**	-2.31	-2.20	-1.88	-3.87	0.85	-1.34
	L	-1.01	-1.23	-1.79	0	-0.55	1.72	-0.78	-1.59	-1.23	-0.20	-1.26	-1.26	**7.30**	**7.30**
		-0.32	-0.78	-0.14	0	-0.18	-0.49	-0.43	-0.79	0.46	1.82	-0.93	-0.92	**3.71**	**3.71**
	F	-0.74	-0.53	0.18	1.42	0	-0.51	-0.34	-0.69	-0.53	1.59	-0.55	1.42	-0.41	-0.41
		1.28	-0.38	0.74	-0.18	0	-0.24	-0.21	-0.39	-0.42	-0.41	-0.46	-0.45	-0.13	-0.13
	R	-1.59	0.83	-2.29	1.72	1.59	0	-0.72	-0.70	-0.16	**4.05**	-1.16	1.72	-0.87	1.65
		-1.72	0.02	-0.53	-0.49	**4.00**	0	1.23	-1.06	-0.15	1.89	-0.33	1.56	-0.35	-0.35
	O	1.08	0.66	0.24	-0.78	-0.34	0.76	0	1.27	-0.76	-0.72	-0.78	-0.78	-0.58	-0.58
		-0.69	-0.92	0.68	-0.43	-0.21	1.23	0	**2.63**	-1.00	1.28	-1.10	-1.08	-0.30	-0.30
	T	-1.45	-1.04	**5.34**	-1.07	-0.46	-0.99	-0.66	0	-1.04	-0.99	-1.07	-1.07	-0.79	-0.79
		-1.83	-1.11	**5.66**	-0.52	-0.26	-0.70	1.10	0	-1.21	-1.19	-1.32	-1.31	-0.37	-0.37
MANUAL	U_S	**3.31**	-1.20	-1.65	-0.31	-0.53	1.81	0.66	-1.56	0	**4.75**	-1.23	-1.23	-0.91	-0.91
		6.98	-1.80	-3.00	0.46	-0.42	1.83	-1.00	-1.82	0	**3.03**	-2.15	-2.12	-0.59	-0.59
	U_E	-0.84	-0.16	1.00	1.72	-0.51	-0.05	-0.72	0.09	-0.16	0	0.76	-1.16	-0.87	-0.87
		0.74	0.89	0.99	0.49	-0.41	-1.12	0.15	-1.13	1.17	0	-0.39	-2.09	-0.58	-0.58
	D_S	-0.32	**3.37**	-2.68	-1.26	-0.55	**3.64**	-0.78	-1.59	-1.23	-1.16	0	**6.84**	-0.93	-0.93
		-2.86	**4.73**	-3.14	-0.93	-0.46	1.51	-1.10	-2.00	-2.15	-2.12	0	**10.5**	-0.65	-0.65
	D_E	1.07	-0.31	**3.07**	-1.26	1.42	-1.16	-0.78	-0.86	-1.23	-1.16	-0.36	0	-0.93	-0.93
		-1.95	-1.33	**3.50**	-0.92	-0.45	0.63	-1.08	-1.97	0.75	-2.09	1.95	0	1.09	-0.64
	L_S	-1.27	-0.91	-0.66	**3.77**	**2.16**	1.65	-0.58	-1.19	-0.91	-0.87	-0.93	-0.93	0	**3.92**
		-0.89	-0.55	-1.22	**3.71**	-0.13	-0.35	-0.30	-0.55	-0.59	-0.58	-0.65	-0.64	0	**16.66**
	L_E	0.55	-0.91	**2.19**	1.42	-0.41	-0.87	-0.58	-0.23	-0.91	-0.87	-0.93	-0.93	-0.69	0
		-0.89	-0.55	-0.09	-0.26	-0.13	**2.65**	**3.08**	-0.55	-0.59	-0.58	1.06	-0.64	-0.18	0

Note In each cell, the upper and the lower data represent for Correct and Wrong group, respectively. A bold value means a significant transaction occurring from its corresponding behavior of the y-axis to its corresponding behavior of the x-axis. U: fixate on Up panel; D: fixate on Down panel; Q: fixate on Question; L: fixate on Light; F: fixate on Reflection; R: fixate on Refraction; O: fixate on Out; T: mouse click on Test Answer; U_S: Start adjusting the Up panel; U_E: End of adjusting the Up panel; D_S: Start adjusting the Down panel; D_E: End of adjusting the Down panel; L_S: Start adjusting the light; L_E: End of adjusting the light



(a) Correct group

(b) Wrong group

Fig. 14.3 Visual and manual transitional patterns of the two groups

“Refraction → Reflection,” but, again, this transition provided scant information for solving the inquiry question.

Discussion and Conclusion

The purpose of this study was to investigate how interactions between users and simulation interface affected students' performance of inquiry activities. In particular, we combined eye-movement and log data to jointly analyze the detailed processes of user-interface interactions. This data collection and analysis approach appeared to be promising and had produced encouraging results.

Regarding the results of the eye-movement analyses, the wrong group paid significantly more visual attention to the Down panel AOI than the correct group in terms of TTS, PTS, and FPT. While adjusting the Down panel was indeed required by the inquiry question, it was never sufficient for successfully answering the question. Paying too much visual attention to the Down panel AOI, therefore, provided little help for completing the task. The results of the heat maps, nonetheless, offered alternative information about how the participants allocated their visual attention while using the simulation. Based on the heat maps, the correct group had longer visual fixations on the Light and Refraction AOIs. More specifically, they paid more visual attention to the incident angle, the point where the incident ray entered into the lower medium, and the refracted angle than the wrong group; observing these three regions was necessary for correctly answering the inquiry question. On the other hand, with respect to the results of the log data analyses, the wrong group tended to manually adjust both the Up and Down panels more often than the correct group. However, the total durations of their manipulation of the two panels were not significantly longer than those of the correct group, indicating that they might have just conducted multiple quick trials instead of carefully observing the effects of their manipulations.

Results of the LSA indicate the benefit of jointly analyzing both eye-movement and log data. In particular, it was the concurrence between the eye-movement and manual manipulation that contributed to the success of the inquiry task. The correct group, for example, made some critical transitions between the Up panel and Refraction and between the Down panel and Refraction. These two temporal transitions provided relevant information about the relationships among the refracted index of both the upper and lower media and the refracted angle, which were both necessary for answering the inquiry question. Moreover, these transitions represent the skills favored by scientific inquiry, that is, making an intervention (cause) and then observing its corresponding result (effect). Chiou et al. (2019) also identified the importance of this sort of visual transition for successful completion of an inquiry task.

The benefit of jointly analyzing both the eye-movement and log data are even more apparent in examining the behaviors of the wrong group. For example, the results of both eye-movement and log data analyses indicate that the wrong group devoted more effort to the Down panel than the correct group did. If these two sources of data were analyzed separately, it would be difficult to explain why the wrong group failed to complete the inquiry task, even though they paid more visual attention and exerted more physical effort to control the Down panel. By jointly analyzing these two sources of data, as demonstrated by the LSA results, we can quickly grasp that the wrong group failed to connect their effort on the Down panel to other relevant AOIs. Without these sorts of meaningful connections, according to de Jong (2011), their visual attention and manual manipulation might result in fragments of information and could not form an integrated understanding of the simulated models, phenomena of refraction, in this study.

Although the joint analyses of eye-movement and log data provide a promising approach to investigate the users' interaction with simulation interfaces, it remains unclear why users behave in this manner to manipulate a computer simulation. In other words, what are the factors that determine how users manipulate computer simulations? As suggested by van Joolingen et al. (2007), the result of this study indicates that the prior knowledge of the users might be an important factor that affects the learning process in a computer simulation. Based on the pretest scores, the wrong group had a significantly lower level of prior knowledge than the correct group. A lack of domain knowledge might keep the wrong group from fully understanding the concepts involved in the inquiry question and the computer simulation. Moreover, they might hold false expectations for the simulation or make incorrect predictions of the simulated phenomena. As a result, they could not form a coherent strategy for making manual intervention and visual observation, and thus failed to complete the inquiry task. Of course, there must be some other factors that affect the interactions between users and simulation interfaces, but, in this study, we could not make any postulations without further evidence.

In summary, this study highlighted the importance of investigating the interaction between users and interfaces to better understand the process of learning with computer simulations. We adopted both eye-movement and log data to jointly analyze the interactive processes of using a computer simulation. The results show that the concurrences between visual attention and manual manipulation were necessary for operating the simulation. Moreover, to successfully complete the inquiry task offered by the simulation, the participants needed to not only connect representations displayed on relevant areas of the simulation in a reasonable sequence, but also to actively integrate them into a meaningful whole. This research approach provides significant benefits over solely analyzing eye-movement or manual manipulation data. Although we identified prior knowledge as a crucial factor that might determine the behaviors of using computer simulations, more factors are needed to fully account for the individual differences in the behaviors. It is therefore suggested that future studies explore more potential factors that affect the interactions between users and simulation interfaces. In addition, more data formats, such as think-aloud verbal reports, could be employed to investigate the cognitive aspect of using computer simulations.

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