Using Real-Time Online Preprocessed Mouse Tracking for Lower Storage and Transmission Costs

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Abstract
Pageview is the most popular webpage analytic metric in all sectors including blogs, business, e-commerce, education, entertainment, research, social media, and technology. To perform deeper analysis, additional methods are required such as mouse tracking, which can help researchers understand online user behavior on a single webpage. However, the geometrical data generated by mouse tracking are extremely large, and qualify as big data. A single swipe on a webpage from left to right can generate a megabyte (MB) of data. Fortunately, the geometrical data of each x and y point of the mouse trail are not always needed. Sometimes, analysts only need the heat map of a certain area or perhaps just a summary of the number of activities that occurred on a webpage. Therefore, recording all geometrical data is sometimes unnecessary. This work introduces preprocessing during real-time and online mouse tracking sessions. The preprocessing that is introduced converts the geometrical data from each x and y point to a region-of-interest concentration, in other words only heat map areas that the analyzer is interested in. Ultimately, the approach used here is able to greatly reduce the storage and transmission cost of real-time online mouse tracking.

Keywords: mouse tracking; online; real-time; preprocess; storage cost; transmission cost; geometrical data; region of interest; webpage; big data

Introduction
We are living in the age of information where information and communication technologies are becoming mainstream [1]. Computers and the Internet have become inseparable from our daily lives. It is now possible to do many things without the need to travel and wait; examples include, long-distance communication through online text, voice and video calls, social interaction via social media, online learning, ecommerce or online shopping, and many forms of entertainments such as online music, online videos, and online games. Most importantly, the Internet has become the primary source of information around the world.

Online analytics has become a major area of interest because it enables the study of users’ online behaviors. These include, users’ attentions and, students’ performance in online learning. Businesses also use online analytics to capture consumers’ interests in ecommerce, web design and evaluation, etc. Most websites today, use traditional web analytics such as page views, hits, and top exit pages [2]. However, for interactional analysis, further metrics are required. For example, traditional web metrics cannot tell where a user is directing his or her attention or how much interaction has occurred on a web page. In other words, pageview can determine what,
when, who, and (to a limited extent) where a user is viewing, but it cannot determine which part of the webpage (the more detailed "where") and how a user is viewing it [3].

The best method available today for measuring user attention is eye tracking [4]. This method tracks eye ball movements to determine where the user is gazing. The most fundamental aspects of eye movements are fixation and saccade, where fixation is the process of fixing the gaze to a certain point of interest (POI), and saccade is the process of moving the gaze to another POI [5]. This method has been implemented in many fields, mainly in computer science, engineering, education, medicine, and psychology. However today, eye tracking requires expensive and specialized hardware that is not suitable for wide implementation [6].

Although eye tracking remains a tool for the laboratory, an alternative method has been invented, mouse tracking [7]. Instead of eye movements, mouse tracking tracks mouse movements and other helpful events. The fundamental strategy of mouse tracking is the recording of mouse clicks, mouse movements, and scrolls. Eye and mouse tracking have been implemented in the fields of education [8] [9], reading patterns [10], search engines [11], visual navigation [12], web evaluation and usability [13] [14]. Mouse tracking can be treated either independently [15] or as a correlation to eye tracking [16] in other words, as replacement.

The biggest problem with default mouse tracking (as well as eye tracking) is the huge volume of data generated, which can be categorized as big data [17] [18]. This high volume is due to the use of geometrical data where each event that occurs on each point of the webpage is recorded. If the distance between left and right is 1000 pixels, then a swipe from left to right will generate 1000 rows of tables. However, analyst may not need all of the mouse tracking data that is generated. Therefore, this paper proposes preprocessing the data based on the analyst’s needs. The preprocessing in this case determines the region of interest in other words; which area the tracking should capture rather than capturing each point of interest. Furthermore, the preprocessing is conducted not only online, but also in real-time mouse tracking session.

Related Work
Implementations of Eye and Mouse Tracking
The use of eye [19] and mouse [20] tracking began in the early 20th century, and since then, there have already been many laboratory experiments conducted using these technologies. Today, there are many attempted implementations of eye and mouse tracking, but it is unclear how widespread and long-running they are. For eye tracking, there is no chance of implementation outside laboratory unless one of two requirements is met: (1) affordable and mainstream hardware [6] or (2) optimal usage of web cameras [21] [22] on laptops and/or cameras on smartphones. By contrast, widespread implementation of mouse tracking is already possible because the required hardware is available by default in all computers and smartphones, but the problem is the generation of big data (the same is true of eye tracking as well).

The following are selected attempts at implementation eye tracking:
- Adaptive E-Learning via the Eye Tracking (AdELE) frame-work, adaptive, integrated, and real-time eyetracking during e-learning processes [8] [23].
• Eye tracking based emphatic software agent (ESA), an eye tracking software that captures the state of awareness of the learners and responds accordingly [24].
• Enhanced exploitation of eyes for effective e-learning (e5Learning) [25].
• Eye tracking based adaptive and personalized e-Learning Systems (AeLS) [26].
• Eye tracking based programming tutoring system (Protus) [27].

The following are selected attempts at implementation mouse tracking:
• A mouse tracking web application developed by Zushi et al. [9] for their own specific learning management system (LMS).
• Moodle LMS mouse tracking plugin [28] [29] [30].
• Mouse tracking web browser plugin and client side programming script [31] [32].

Some commercial and open source software programs are as follows:
• Open Gaze and Mouse Analyzer (OGAMA), an open-source software designed to analyze eye and mouse movements in slideshow study designs [33].
• Mousetrap, an integrated, open-source mouse-tracking package on OpenSesame for laboratory experiments [34].
• Known commercial applications: Lucky Orange, Hotjar, Crazy Egg, Fullstory, Pengage, Heatmap.com, Smartlook, ContentSquare, SessionCam, Seevolution, Capturly, Inspectlet, MouseFlow, Clicktale, and Tamboo [35].

Default Eye and Mouse Tracking Generates Big Data

Although eye and mouse tracking are not yet mainstream, rumors spread that due to large amounts of data generated, they could not be widely implemented other than at big corporations such as Google and Microsoft, which have gigantic data centers. University network and server administrators are hesitant to implement tracking technologies because they not only generate massive amounts of data, but also eye and mouse tracking are not replacements for existing systems but rather additions. Huang et al. [11] performed a mouse tracking experiment on Bing’s search engine and immediately reduced the sampling rate because the data were too large.

Leiva and Huang [36] believed that a swipe could generate a megabyte of data and the authors further investigated and proved that rumor to be true. While a half-year of Moodle log data with approximately 40 students is only approximately 300 kilobytes (kB) [37], mouse tracking data and other event data generated by approximately 22 students reaches approximately 100 megabytes (MB) in only 2 hours [31], and that figure will double if eye tracking is included. Imagine how much data would be produced by a university with a large number of students if mouse tracking were running on its website for years.

According to an article by Adekitan et al. [38], Nigerian University Internet traffic can reach terabytes (TB) in a week and is regarded as big data. The authors’ previous mouse tracking session [31] also reaches the same level of Internet traffic if over 100 students are present. Other than volume, mouse tracking met the other 5Vs criteria of big data [17]: velocity, the amount of data generated especially in real-time which is explained in further sections, veracity; meaning that data loss may often occur due to limited connectivity, which can lead to inconsistent data; variety, which is discussed in further sections and previous work [31]; and value, which is discussed in the next paragraph.
It would be wise to start investing in eye and mouse tracking just as big companies today are investing in big data [39], as the data generated by eye and mouse tracking are valuable. By analyzing big data, interesting information can be derived that gives us the knowledge needed to make optimal decisions [40]. Just as companies study customers’ data to find opportunities to increase their revenues [41], traders analyze historical trading data and current sentiments to find optimal positions [42], researchers study optimal prevention, diagnosis, and treatments in Medicare [43], and planners monitor smart cities [44], researchers can use eye and mouse tracking to identify online viewers’ attention, behavior, their evaluation of web contents, etc.

Reducing Eye and Mouse Tracking Data
During high-intensity activities, a user may generate an average of 70 hertz (Hz) or 70 events per second [45], meaning that 70 rows per second will be generated on a table. The traditional way of reducing the size of these tracking data is by reducing the sampling rate [11]. Furthermore, the sampling rate should be adaptive and not static. In other words, snapshots should only be taken when an event occurs such as when the mouse cursor moves or a click occurs, and snapshots should not be taken during idle sessions. Performing transmission in real-time helps distribute the transmission burden across time, avoiding bottlenecks. In other words, the tracking data are immediately transmitted to the server at each event occurrence rather than transmitting the mouse tracking data all at once at the end of the session. Compression methods can also be utilized as demonstrated in Leiva and Huang’s work [36], but their transmission method is still likely not real-time and is suspected to transmit the compressed tracking data all at once in the end of each session.

On the other hand, the preprocessing technique presented in this paper is designed to work in real-time. Not only does it reduce the data cost but also distributes the transmission burden across the time domain. The cause of the enormous data generation is the geometrical data or tracking of each location where the events occur, in other words the x and y coordinates. Tracking these coordinates provides rich data but sometimes all of that data is not needed. For example, Rodrigues et al. [28] only analyzed the amount of key up, key down, mouse down, mouse up, mouse wheel, and mouse movement to measure students’ stress, and Li et al. [46] only needed the time spent on each page. In such cases, the geometrical data can be omitted.

At other times, geometrical data are needed; however, it is not each precise x and y point that is needed but rather each area of the page (multiple points) [47]. Preprocessing is common in any data analysis to derive useful data prior to transmission and storage of the collected data. However, the preprocessing presented in this work is performed on the client before transmission and storage to reduce the server’s burden. Unlike typical preprocessing which is performed to filter redundant data, the preprocessing in this work is specifically based on the demands of the administrators or analyzers; in this case, preprocessing omits the geometrical data or groups them to represent certain areas. This study is a complete work of one the author’s previous works [48].
Figure 1 System overview of mouse tracking data transaction [31]. The framework is divided into two sides: one side is the client and the other side is the server. The client and the server are connected via the Internet. The webpage is in the server consisting of HTML, CSS, and JavaScript. The mouse tracking codes, which are event handling and capturing the command to post its data to the server, are inserted in the JavaScript section. When the client accesses the webpage, it will view the contents that consist of HTML and CSS. The mouse tracking codes within JavaScript are run in the background. The mouse tracking data are sent to the server and processed using server programming language, in this case PHP. Finally, the data are sent to the database; in this case, in SQL.

Method and Simulation

System Overview

The overall system is the same as in the authors’ previous work, as shown on Figure 1. Mouse and other event tracking are performed on the client. The tracking codes can be injected internally, for example, as a browser plugin, or externally, for example, where the codes are retrieved alongside the webpage content (hypertext markup language (HTML) and cascading style sheets (CSS)). Then, the client sends the tracking the data to the server to be stored. The code itself for this work is written in jQuery, which is a simpler coding format of JavaScript for document object model (DOM) manipulation. The external code can be written as a plugin if desired; for example, the authors wrote a Moodle plugin. The server side can be in any programming language, but in this work, PHP was used, and the database used MySQL. The codes are available on GitHub [32].

Three techniques of Mouse Tracking

For convenience, the techniques of mouse tracking are divided into three types, as shown in Table 1. They are called default mouse tracking, whole page tracking, and region of interest (ROI) tracking. The default mouse tracking precisely records the geometrical data of the event occurrence such as the horizontal x and vertical y of left clicks, right clicks, middle clicks, mouse movements, scrolls, zooms, and if desired keyboard types. The duration between each event is also measured. Whole page
Table 1  Event monitoring difference between default mouse tracking, whole page tracking, and ROI tracking.

| Events          | Mouse Tracking | Page Tracking | ROI Tracking |
|-----------------|----------------|--------------|--------------|
| Duration        | ✔              | ✔            | ✔            |
| Click Left      | ✔              | ✔            | ✔            |
| Click Right     | ✔              | ✔            | ✔            |
| Click Middle    | ✔              | ✔            | ✔            |
| Mouse X         | ✔              | X            | Partial      |
| Mouse Y         | ✔              | X            | Partial      |
| Touch X         | ✔              | X            | Partial      |
| Touch Y         | ✔              | X            | Partial      |
| Keyboard Type   | ✔              | ✔            | ✔            |
| Scroll X        | ✔              | X            | Partial      |
| Scroll Y        | ✔              | X            | Partial      |
| Other Events    | ✔              | ✔            | ✔            |
| Events Amount   | X              | ✔            | ✔            |

tracking omits the geometrical data and summarizes the number of left clicks, right clicks, middle clicks, mouse movements, scrolls, zooms, and if desired keyboard types that occurred on the webpage. In other words, the amount of activity is measured but not where or when it occurs, and only the total amount of time that the user spends on a webpage is recorded. The most complicated task is ROI tracking, which is a gray area between default mouse tracking and whole page tracking. ROI tracking defines the areas of a webpage to be tracked, for example how many left clicks, right clicks, middle clicks, mouse movements, scrolls, zooms, and keyboard types occurred and how long they occurred on a header, menu, content, footer, etc. This method is ideal because it meets the analyst’s requirements and reduces unnecessary resource costs, but the drawback is the heavy labor required to define the areas of each webpage. An illustration comparing the three types of mouse tracking is shown in Figure 2.

The flowchart for each implementation of real-time and online mouse tracking is shown in Figure 3. For default mouse tracking, the information on the event is transmitted to the database each time an event occurs. For example, when a click occurs, the client immediately transmits the information on where and when it occurs. For whole page tracking, the information is summarized as the number of events that occurred, and they are transmitted to the server when the client closes the webpage. The size of the transmitted data is only slightly larger than that of transmitting single click data when using default mouse tracking. Last, for ROI tracking, the information on the webpage area is summarized and transmitted after the mouse cursor leaves the area, and the process repeats on each movement between areas until the webpage is closed.

Simulation
Since the author lacks subjects to perform an implementation, a simulation based on previous mouse tracking data was conducted. The mouse tracking data contain mouse tracking records from two quiz sessions in Moodle. They were conducted on the 3rd of January 2019 between approximately 12:00 and 14:30 Japan standard time. There are 2 sessions, with each session lasting approximately an hour and
Including 22 students (44 total students participating) from the School of Engineering and Applied Sciences, National University of Mongolia accessing the Moodle server at the Human Interface and Cyber Communication Laboratory, Kumamoto.
The data were preprocessed to exclude nonstudents and webpages other than the quiz page data. In other words, the simulation is purely a mouse tracking data transmission, which excludes most of the process, such as accessing the server and navigating the whole Moodle page. This approach shows lower resource consumption than the previous work [31].

The setup can be seen in Figure 4 where a laptop functioning as a client is peer to peer connected to a personal computer functioning as a server. The mouse tracking data are converted into page tracking and ROI tracking data based on Table 1. Three sessions were conducted: the first session was the sending of mouse tracking data to the server, the second session was the sending of page tracking data to the server, and the third session was the sending of ROI tracking data to the server. Since the mouse tracking data contain time interval information between the sending of each event, it is possible to capture the scenario almost exactly.

During these sessions, the data rate is observed, and the central processing unit (CPU) and random access memory (RAM) usages are measured on the server. Figure 4 shows that one laptop serves as a client to send the data to the server which is a personal computer. The client is an MSI Laptop with i7-7820 HK 2.9 gigahertz (GHz) x8 32 gigabyte (GB) RAM while the server is an i7-6850 HK 3.6 GHz x12 32 GB RAM personal computer and the peer to peer connection is a 10 MBps network.

Result
Table 2 Example default mouse tracking data that can be seen in the database table.

| ID | Name       | Date       | Duration | Left Click | Right Click | Middle Click | Mouse X | Mouse Y | Scroll X | Scroll Y |
|----|------------|------------|----------|------------|-------------|--------------|---------|---------|----------|----------|
| 1  | Student 1  | 2019/3/01  | 13.674   | false      | false       | false        | 0       | 0       | 0        | 0        |
| 2  | Student 1  | 2019/3/01  | 0.002    | true       | false       | false        | 1197    | 317     | 0        | 0        |
| 28804 | Student 2 | 2019/3/01  | 0.002    | false      | false       | false        | 1058    | 234     | 0        | 0        |

Table 3 Example page tracking data that can be seen in the database table.

| Name  | Date       | Duration (seconds) | Left Clicks | Right Clicks | Middle Clicks | Mouse Moves | Scrolls |
|-------|------------|--------------------|-------------|--------------|---------------|--------------|---------|
| Student 1  | 14:12:29  | 41                 | 3           | 0            | 0             | 629         | 114     |
| Student 2  | 14:44:09  | 2108               | 157         | 5            | 0             | 20912       | 137     |
| Student 22 | 11:55:14  | 2188               | 157         | 5            | 0             | 20912       | 137     |
| Student 23 | 11:57:37  | 2236               | 323         | 0            | 0             | 17082       | 9039    |

Table 4 Example ROI tracking data that can be seen in the database table.

| ID | Name      | Date       | Duration (seconds) | Area (x1,x2,y1,y2) | Left Clicks | Right Clicks | Middle Clicks | Mouse Moves | Scrolls |
|----|-----------|------------|--------------------|---------------------|-------------|--------------|---------------|--------------|---------|
| 1  | Student 1 | 11:06:39   | 1.179              | header: [0,1920,0,64] | 0           | 0            | 0             | 1            | 0       |
| 2  | Student 1 | 11:06:39   | 1.179              | quiz1: [529,1900,291,570] | 0           | 0            | 0             | 86           | 0       |
| 19062 | Student 23 | 14:44:09  | 0.002              | title: [16,1904,150,270] | 0           | 0            | 0             | 1            | 0       |

Figure 5 CPU usage comparison between default mouse tracking, whole page tracking, and ROI tracking.

Figure 6 RAM usage comparison between default mouse tracking, whole page tracking, and ROI tracking.
Table 5  Transmission server resource cost of three mouse tracking technique simulations.

| Statistics       | Default Mouse Tracking Simulation | ROI Tracking Simulation | Whole Page Tracking Simulation |
|------------------|-----------------------------------|-------------------------|-------------------------------|
|                  | CPU (%) | RAM (MB) | Data Rate (kB) | CPU (%) | RAM (MB) | Data Rate (kB) | CPU (%) | RAM (MB) | Data Rate (kB) |
| Minimum          | 0       | 2.88     | 0              | 0       | 1.75     | 0              | 0       | 3.58     | 0              |
| Maximum          | 86      | 3.66     | 228.45         | 12      | 46.8     | 26             | 9       | 2.97     | 0              |
| Median           | 3       | 3.29     | 5.62           | 0       | 1.86     | 0              | 0       | 2.07     | 0              |
| Standard Deviation | 29.09  | 0.25     | 36.8           | 1.24    | 0.06     | 5.05          | 0.05    | 0.04     | 0.08           |

Discussion

Default Mouse Tracking

It is well known that the advantage of default mouse tracking is the detailed and precise data it generates. An example is shown in Table 2. The exact x and y points of the locations of event occurrences, such as left clicks, right clicks, middle clicks, mouse movements, scrolls, zooms, and keyboard types, are recorded, including when and for how long each event occurs. Those geometrical data (x,y) make it possible to reproduce the mouse trajectory shown in Figure 8, and adding the time information enables the trajectory’s replay.

The rumored disadvantage is the huge transmission and storage cost, and this seems to be true judging from Figure 5, Figure 6, and Figure 7. For the 22 students in each session, the transmission resource cost statistics are shown in Table 5. The average data rate was 28 kilobytes per second (kBps) and was able to peak to 228 kBps. For the two sessions totalling 44 students, the data size was approximately 100 megabytes (MB) and Table 2 has 286511 rows. The CPU usage was highly consumptive as well, while the RAM usage was not as consumptive. Even worse, mouse tracking is not a replacement for the existing logging method but rather an addition; in other words, it is expected to add an additional burden to the existing system if mouse tracking is implemented. These data were generated from a 2 1/2 hour mouse tracking session; thus, imagine how much resource mouse tracking would consume if it were run on a university scale with thousands of students for 24 hours daily.
Figure 8 Visualization of mouse tracking data. Default mouse tracking data can visualize exact points of location, the left image is click visualization and the middle image is a heatmap based on the duration the mouse cursor stays on each point, while ROI tracking can only visualize defined areas and show flows between areas shown on the right image.

Webpage Summarized Mouse Tracking

By omitting the geometrical data (x,y) and summarizing the numbers of events that occurred, the data became as small as possible, as shown in Figure 5, Figure 6, and Figure 7 (although they can be further reduced slightly by compression and removal of unnecessary characters and variables). The table was reduced to one row per webpage visit; in this case, Table 2 with 286511 rows was reduced to 26 rows, as shown in Table 3. As shown in Table 5, the data size was reduced from 100 MB to 16 kB. The average data rate was reduced from 28 kBps to 10 Bps. Although there is still RAM usage, CPU usage is slightly visible. Among the three mouse tracking
methods mentioned in this work, this technique is the most advantageous in terms of resource cost.

However, the disadvantage compared to the three mouse tracking techniques is that it provides the poorest information that makes it impossible to create any visualizations, as shown in Figure 8. The information tells only how many events (such as left clicks, right clicks, middle clicks, mouse movements, scrolls, zooms, and keyboard types) occurred and the length of time that the user spends on the webpage. Nevertheless, the information is richer than traditional logs, as shown in Table 3.

Region of Interest Mouse Tracking
This technique is the best of the three, as the desired information is based on the analyst’s preferences, and there are lower resource costs than in the default mouse tracking shown in Figure 5, Figure 6, and Figure 7. Analysts chooses the areas to be analyzed. In this case, the authors defined the following areas for the quiz session: header, title, menu, footer, and each question section. It can be seen in Figure 8 that it is possible to create heatmaps of high activity areas, although it is not possible to create precise mouse trajectories as default mouse tracking, but it is possible to capture amounts of movement between areas. The duration is also based on each area. The data size is 5.4 MB with 19062 rows shown in Table 4. As shown in Table 5, the average data rate is 2.28 kBps and the average CPU and RAM usage are 0.87% and 1.85 MB which are lower than in default mouse tracking. Based on the algorithm of this method, the resource cost should be based on the number of defined areas, where the more areas, the larger the resource cost (note that default mouse tracking cost the largest because the webpage has been divided into the smallest possible areas, which are the x and y points of a webpage).

The only disadvantage of this technique is the manual labor required. Unfortunately, the analysts must define the areas of each webpage manually. This requires considerable time and labor.

Conclusion and Future Work
Preprocessing mouse tracking data during real-time and online sessions helps reduce the storage and transmission costs. The techniques presented in this work are whole page tracking and region of interest (ROI) tracking. Although the amount of reduced data is very dependent, there are fixed theories. The fixed theories are as follows: whole page tracking reduces the mouse tracking data into one row of tables per webpage visit, and ROI tracking reduces the data into one row of tables per area visit. Selecting the right technique can help reduce the storage and transmission costs while still obtaining the necessary data.

Although this concept works perfectly, but there are still problems with execution. Whole page tracking transmits the data only when the user leaves the page, and if the problems lie with the browser, there is currently no way to tell the user to wait before the transmission process finishes. There will definitely be cases where data are not fully transmitted. The problem for ROI tracking is that it is still manual, and the labor required to manually define the areas of each webpage is considerable. It would be desirable to build an automatic method of area definition in the future.
Declarations

Availability of data and materials
The datasets generated and/or analyzed during the current study are available in the Mendeley repository in 'Pre-processed Mouse Tracking Data' directory [49]:

- Table 2, Table 3, and Table 4 data are available in file mouse_tracking_mongolia_anonymous.ods [50].
- Figure 5, Figure 7, and Table 5 are based on files: cpurammousetracking.txt [51], cpurampagetracking.txt [52], cpuramroitracking.txt [53], mousetrackingsimulationpcapng [54], pagetrackingsimulationpcapng [55], roitrackingsimulationpcapng [56].

Competing interests
The authors declare that they have no competing interests.

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Author contributions
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References
1. Information Age. https://en.wikipedia.org/wiki/Information_Age
2. Bluehost: Web Analytics for Beginners - Presented by Bluehost. https://youtu.be/PnVZ7Qa7Qo
3. Purnama, F., Fungai, A., Do, T.M., Siagian, A.H.A.M., Annas, A., Susanto, H., Hendarmawan, Usagawa, T., Nakano, H.: Introductory work on section based page view of web contents: Towards the idea of how a page is viewed. In: 11th International Student Conference on Advanced Science and Technology (ICAST), pp. 9–11 (2016), Kumamoto University
4. Pennic, K.: F-shaped pattern of reading on the web: Misunderstood, but still relevant (even on mobile). Nielsen Norman Group (2017)
5. Holmqvist, K., Wartenberg, C.: The role of local design factors for newspaper reading behaviour-an eye-tracking perspective. Lund University Cognitive Studies 127, 1–21 (2005)
6. Lai, M.-L., Tsai, M.-J., Yang, F.-Y., Hsu, C.-Y., Liu, T.-C., Lee, S.W.-Y., Lee, M.-H., Chioo, G.-L., Liang, J.-C., Tsai, C.-C.: A review of using eye-tracking technology in exploring learning from 2000 to 2012. Educational research review 10, 90–115 (2013)
7. Cooke, L.: Is the mouse a "poor man’s eye tracker"? In: Annual Conference-Society for Technical Communication, vol. 53, p. 252 (2006)
8. Barrios, V.M.G., Gütt, C., Preis, A.M., Andrews, K., Pivec, M., Mödritscher, F., Trummer, C.: Adele: A framework for adaptive e-learning through eye tracking. Proceedings of IKNOW, 609–616 (2004)
9. Zushi, M., Miyazaki, Y., Norizuki, K.: Web application for recording learners’ mouse trajectories and retrieving their study logs for data analysis. Knowledge Management & E-Learning 10, 90–115 (2013)
10. Manson, S.M., Kne, L., Dyke, K.R., Shannon, J., Era, S.: Using eye-tracking and mouse metrics to test usability of web mapping navigation. Cartography and Geographic Information Science 39(1), 48–60 (2012). doi:10.1559/1523040639148
11. Huang, J., White, R.W., Dumas, S.: No clicks, no problem: using cursor movements to understand and improve search. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 1225–1234 (2011). ACM
12. Arroyo, E., Selker, T., Wei, W.: Usability tool for analysis of web designs using mouse tracks. In: CHI'06 Extended Abstracts on Human Factors in Computing Systems, pp. 484–489 (2006). doi:10.1145/1125451.1125557. ACM
13. Navalpakam, V., Churchill, E.: Mouse tracking: measuring and predicting users’ experience of web-based content. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 2963–2972 (2012). doi:10.1145/2207676.2208705. ACM
16. Rodden, K., Fu, X., Aula, A., Spiro, I.: Eye-mouse coordination patterns on web search results pages. In: CHI’08 Extended Abstracts on Human Factors in Computing Systems, pp. 2997–3002 (2008). ACM
17. Hariri, R.H., Fredericks, E.M., Bowers, K.M.: Uncertainty in big data analytics: survey, opportunities, and challenges. Journal of Big Data 6(1), 44 (2019). doi:10.1186/s40537-019-0206-3
18. Barrachina, A.D., O’Driscoll, A.: A big data methodology for categorising technical support requests using hadoop and mahout. Journal of Big Data 1(1), 1 (2014). doi:10.1186/2196-1115-1-1
19. Rayner, K.: Eye movements in reading and information processing: 20 years of research. Psychological bulletin 124(3), 372 (1998)
20. Mueller, F., Lockerd, A.: Cheese: tracking mouse movement activity on websites, a tool for user modeling. In: CHI’01 Extended Abstracts on Human Factors in Computing Systems, pp. 279–280 (2001). doi:10.1145/540676.543233. ACM
21. Sungkur, R.K., Antoaroo, M.A., Beehury, A.: Eye tracking system for enhanced learning experiences. Education and Information Technologies 21(6), 1785–1806 (2016). doi:10.1007/s10639-015-9418-0
22. Zheng, C., Usagawa, T.: A rapid webcam-based eye tracking method for human computer interaction. In: 2018 International Conference on Control, Automation and Information Sciences (ICICAIS), pp. 133–136 (2018). doi:10.1109/ICICAIS.2018.8570532. IEEE
23. Pivec, M., Trummer, C., Pripfl, J.: Eye-tracking adaptable e-learning and content authoring support. Informatica 30(1) (2006)
24. Wang, H., Chignell, M., Ishizuka, M.: Empathic tutoring software agents using real-time eye tracking. In: Proceedings of the 2006 Symposium on Eye Tracking Research & Applications, pp. 73–78 (2006). doi:10.1145/1117309.1117346. ACM
25. Calvi, C., Porta, M., Sacchi, D.: e5learning, an e-learning environment based on eye tracking. In: Advanced Learning Technologies, 2008. ICALT’08. Eighth IEEE International Conference On, pp. 376–380 (2008). doi:10.1109/ICALT.2008.35. IEEE
26. Wei, H., Moldovan, A.-N., Muntean, C.: Sensing learner interest through eye tracking. Technology 23, 22 (2009)
27. Ivanović, M., Klasić-Milićević, A., Ivković, J., Porta, M.: Integration of eye tracking technologies and methods in an e-learning system. In: Proceedings of the 8th Balkan Congress in Informatics, p. 29 (2017). doi:10.1145/3136273.3136278. ACM
28. Rodrigues, M., Gonçalves, S., Carneiro, D., Novais, P., Fdez-Riverola, F.: Keystrokes and clicks: Measuring stress on e-learning students. In: Management Intelligent Technologies, pp. 119–126. Springer, ???. (2013). doi:10.1007/978-3-319-00569-0_15
29. Salmeron-Majadas, S., Santos, O.C., Boticario, J.G.: An evaluation of mouse and keyboard interaction indicators towards non-intrusive and low cost affective modeling in an educational context. Procedia Computer Science 35, 691–700 (2014). doi:10.1016/j.procs.2014.08.151
30. Harrati, N., Bouchrika, I., Tari, A., Ladjaila, A.: Exploring user satisfaction for e-learning systems via usage-based metrics and system usability scale analysis. Computers in Human Behavior 69, 463–471 (2016). doi:10.1016/j.chb.2016.03.051
31. Implementation of real-time online mouse tracking on overseas quiz session from server administrator point of view. Submitted for publication. (2019)
32. Purnama, F.: 0fajarpunrama/Real-Time-Online-Mouse-Tracking-Animation. doi:10.5281/zenodo.2589338. https://github.com/0fajarpunrama/Real-Time-Online-Mouse-Tracking-Animation
33. Volkühler, A., Nardmeier, V., Kuchinke, L., Jacobs, A.M.: Ogama (open gaze and mouse analyzer): open-source software designed to analyze eye and mouse movements in slideshow study designs. Behavior research methods 40(4), 1150–1162 (2008). doi:10.3758/BRM.40.4.1150
34. Kieslich, P.J., Henninger, F.: Mousetrap: An integrated, open-source mouse-tracking package. Behavior research methods 49(5), 1652–1667 (2017). doi:10.3758/s13428-017-0900-z
35. Haije, E.G.: Top 15 Heatmapping Tools You Might Want to Try. https://mopinion.com/heatmapping-tools-you-might-want-to-try/
36. Leiva, L.A., Huang, J.: Building a better mousetrap: Compressing mouse cursor activity for web analytics. Information Processing & Management 51(2), 114–129 (2015)
37. Usagawa, T., et al.: Effectiveness of e-learning experience through online quizzes: A case study of myanmar students. International Journal of Emerging Technologies in Learning (iJET) 13(12), 157–176 (2018). doi:10.3991/ijet.v13i12.9114
38. Adecktan, A.I., Abolade, J., Shabayu, O.: Data mining approach for predicting the daily internet data traffic of a smart university. Journal of Big Data 6(1), 11 (2019). doi:10.1186/s40537-019-0176-5
39. Bughin, J.: Big data, big bang? Journal of Big Data 3(1), 2 (2016). doi:10.1186/s40537-015-0014-3
40. Husain, S.S., Kalinín, A., Truong, A., Dinov, I.D.: Socr data dashboard: an integrated big data archive mashing medicare, labor, census and econometric information. Journal of big data 2(1), 13 (2015). doi:10.1186/s40537-015-0018-z
41. Ahmad, A.K., Jafar, A., Aljoumaa, K.: Customer churn prediction in telecom using machine learning in big data platform. Journal of Big Data 6(1), 28 (2019). doi:10.1186/s40537-019-0191-6
42. Sohanger, S., Wang, D., Pomeranets, A., Khoshgoftar, T.M.: Big data: Deep learning for financial sentiment analysis. Journal of Big Data 5(1), 3 (2018). doi:10.1186/s40537-017-0111-6
43. Dash, S., Shakyaawar, S.K., Sharma, M., Kaushik, S.: Big data in healthcare: management, analysis and future prospects. Journal of Big Data 6(1), 54 (2019). doi:10.1186/s40537-019-0217-0
44. Bibirì, S.E.: On the sustainability of smart and smarter cities in the era of big data: an interdiscipliary and transdisciplinary literature review. Journal of Big Data 6(1), 25 (2019). doi:10.1186/s40537-019-0182-7
45. Rheem, H., Verma, V., Becker, D.V.: Use of mouse-tracking method to measure cognitive load. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 62, pp. 1982–1986 (1988). doi:10.1177/1541931218621449. SAGE Publications Sage CA: Los Angeles, CA
46. Li, L.-Y., Tsai, C.-C.: Accessing online learning material: Quantitative behavior patterns and their effects on...
motivation and learning performance. Computers & Education 114, 286–297 (2017)

47. Koh, K.H., Fouh, E., Farghally, M.F., Shahin, H., Shaffer, C.A.: Experience: Learner analytics data quality for an etextbook system. Journal of Data and Information Quality (JDIQ) 9(2), 10 (2018). doi:10.1145/3148240

48. Purnama, F., Fungai, A., Usagawa, T.: Demonstration on extending the pageview feature to page section based: Towards identifying reading patterns of users. In: 7th International Conference on Science and Engineering, pp. 304–307 (2016). Yangon Technological University

49. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data]. Mendeley Data, v.1. doi:10.17632/vznyfcx9xk.2

50. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/mouse_tracking_mongolia_anonymous.ods]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2

51. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/cpuramrouitracking.txt]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2

52. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/cpurampagetracking.txt]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2

53. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/cpurampagetracking.txt]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2

54. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/mousetrackingsimulation.pcapng]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2

55. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/pagetrackingsimulation.pcapng]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2

56. Purnama, F., Sukhbaatar, O., Choimaa, L., Usagawa, T.: Data for: Implementation of Real-Time Online Mouse Tracking Case Study in a Small Online Quiz [Preprocessed Mouse Tracking Data/roitrackingsimulation.pcapng]. Mendeley Data, v.2. doi:10.17632/vznyfcx9xk.2