Chapter 2
The Current Landscape of Research and Practice on Visualizations and Dashboards for Learning Analytics

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1 Introduction

Research on learning analytics (LA) has increased significantly in recent years (Liu et al., 2019b). The field is moving forwards from just understanding the benefits and challenges of LA to a more mature level to gain a deeper understanding of students' learning experiences through analytics (Viberg et al., 2018). Stakeholders such as university instructors and administrators, K-12 teachers and students, and corporations are interested in LA applications, especially how to make sense of big data and how to utilize the data to make evidence-based decisions. With rapid changes in technology, the use of visualizations and dashboards as learning analytics applications shows potentials to provide visual information based on learner-generated data to help stakeholders better understand the data. While progress has been made in this field, much is still to be understood to achieve the benefits of using LA to optimize learning and to improve learning environments for teachers and students.

The purpose of this chapter is to examine the research and practice of using visualizations as an analytic technique in LA research and explore the practice of dashboard designs as a means to communicate the research findings to stakeholders (Alhadad, 2018). This paper has two goals:

Goal 1: To conduct a synthesis on the current literature, 2016–2020, on how visualizations and dashboards are utilized in learning analytics research, both at research and practice levels

Goal 2: To present a case study of our R&D efforts in creating an immersive problem-based learning program for middle school science where we use

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visualizations to report research outcomes and our efforts in designing a dashboard of this program for teachers as a supporting teaching tool

In the following sections, we will first report our synthesis on the current literature, 2016–2020, on how visualizations and dashboards are utilized in learning analytics research, both at research and practice levels. We will then present a case study of our R&D efforts when we use visualizations to report research outcomes and create a dashboard for teachers to use as a supporting teaching tool.

2 Goal 1: Review of Related Literature

2.1 Method

For Goal 1, we conducted a synthesis of the current literature from 2016 to present regarding how data visualizations and dashboards were utilized in LA research. The selection criteria were based on two previous literature reviews on LA in education (Liu et al., 2017, 2019b), but with a focus on LA data visualization and dashboard use in this study. We adhered to the PRISMA literature review methodology and followed the four steps including identification, screening, eligibility, and included (Moher et al., 2009). In this study, we adopted three criteria in selecting articles for consideration: (a) empirical study articles published in peer-reviewed journals, excluding conference proceedings, book chapters, literature reviews, and theoretical papers, (b) research published between 2016 and September 2020 when we started the review on this study, and (c) articles that we could find with the search query: "learning analytics" AND dashboard OR visuali*. The selection of the included articles went through three-rounds of the examination process.

First, we went over the previously selected peer-reviewed journals that were used from the previous literature review (Liu et al., 2019b) and found four journals (*British Journal of Educational Technology; Computers & Education; Computers in Human Behavior; Technology, Knowledge and Learning*) from the previous list were actively producing articles matching our criteria for this study. After including these four journals to our list of journals to review, we added four more journals on educational technology and learning analytics (*Educational Technology Research and Development; International Review of Research in Open and Distributed Learning; IEEE Transactions on Learning Technologies; Journal of Learning Analytics*). After searching each journal for all possible articles during the timeframe from 2016 to September 2020, we came up with a total of 44 articles by this point in the identification step.

Then in the screening step, we excluded articles investigating the effectiveness of visual learning analytics tools, having less focus on the use of data visualization or dashboard in the learning analytics aspect but emphasizing the use of interactive visualizations in teacher professional development programs. Each article was verified by at least two research team members for deciding its inclusion. Next in the eligibility step, we went through the selected articles pertaining to the purpose of this study and Goal 1 of this chapter. We selected those articles that met our review purpose: how data visualizations and dashboards are utilized in LA research and eliminated the articles only focused on the practice-level data visualization and the practitioner articles that only focused on the specific subject matter-based data visualization even though they included the keyword "learning analytics" (e.g., medical studies used data visualization techniques to improve specific medical practices for practitioners). This iterative and selective process produced 37 articles in total for further analysis.

As a result of the above iterative selection process, we created a spreadsheet containing the categories of our research focus in this review which included research questions, data visualization techniques or dashboards for LA researchers as a research methodology, and dashboard use for instructors and learners as a communication tool in the included step. Having read each article for inclusion at a broad level, it became clear to us the articles can be categorized into two big categories (Alhadad, 2018): (a) data visualization technique or dashboard as a research methodology and (b) dashboard use for instructors and learners as a communication tool. To examine the research of using data visualization or dashboard use in LA research more closely from the selected articles, we used three subcategories (type; data; benefit) for "data visualization technique or dashboard for LA researchers as a research methodology" (Alhadad, 2018, p. 62) and three subcategories (data; target user; benefit) for "dashboard use for instructors and learners as a communication tool" (Alhadad, 2018, p. 62). We extracted information to fill these categories in the spreadsheet from each of the 37 articles with its key findings. The information added to each category was double-checked by two team members, and changes were made until all team members reached a consensus on those changed items. In the following, we will discuss the findings of our synthesis.

2.2 Findings

Alhadad (2018) elicits the value of visualizing data largely in two domains from cognitive psychology and visualization science standpoints: as a research methodology and as a means of communication tools. To define the terminologies, the research methodology refers to the use of data visualization or dashboard to enlighten researchers' inquiry process as an analytic technique, whereas a means of communication tools indicates the employment of visualizations by learners or instructors to inform about their educational practices (Alhadad, 2018). For LA researchers, either data visualization technique or dashboard—sometimes both—was used as a research methodology, but dashboard, sometimes it was just called as a tool, was mainly used as a means of communication tool for learners and instructors in our literature review. We found most (n = 36 out of 37) of the LA data visualization or dashboard articles used either data visualization techniques or dashboard as a research methodology or a communication tool, including some studies that

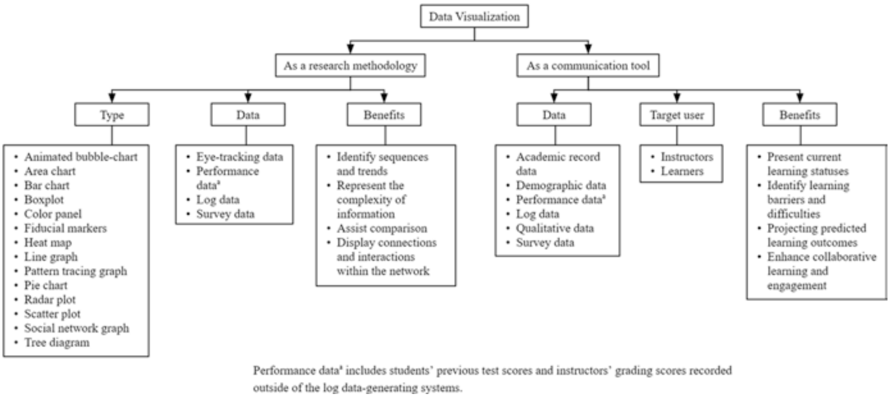


Fig. 2.1 Findings of data visualization uses from the reviewed articles

used both. Figure 2.1 presents the findings from the selected articles and exhibits the structure of the following sections on the findings of this review of literature. In the following, we will discuss the specific findings under each category.

2.2.1 The Use of Data Visualization Technique or Dashboard as a Research Methodology

There has been much effort in research communities to represent research data in a more intuitive way to permeate their findings widely while avoiding the common belief that data themselves are neutral and objective (Alhadad, 2018; Gelman & Hennig, 2017; Woodward, 2011). We have found most of the LA researchers ($n = 20$, see Table 2.1 for the details) used various data visualization techniques for straightforward but rich representations of their research findings. Therefore, we examined what kind of data visualization techniques or dashboards researchers used (i.e., type), what kind of data sources they used (i.e., data), and the reasons for them to choose specific techniques or dashboards over others (i.e., benefit) in the following sections as represented by Table 2.1.

Type A number of recent LA studies used graphs or charts ($n = 9$). To represent the quantitative data comparison in a more intuitive way, many researchers used graphs or charts in lieu of showing tables of variables and numbers. For example, Avila et al. (2020) used a bar chart to show the different levels of web accessibility by type of HTML elements such as links or images. A pie chart was also used to show the proportion of accessibility per Web Content Accessibility Guidelines in the study. In another study, Sedrakyan et al. (2020) used multiple pattern tracing graphs to show students' required items for their choice of learning goals. These graphs contained learning resources, time, and performance requirements per chosen goal using bar and layered graphs in one visualization.

Table 2.1 Details of the reviewed articles used data visualization technique or dashboard as a research methodology

Author (year)	Type (data)	Benefit
Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2019)	Scatter plot (Log data)	Compare the multivariate analysis of variance (MANOVA) in a single shot
Avila, C., Baldiris, S., Fabregat, R., & Graf, S. (2020)	Proportional bar chart; pie chart (Survey data)	Show the different accessibility across different tools on the web like links or images; the pie chart shows the proportion of accessibility
Caprotti, O. (2017)	Markov chain diagram (Log data)	Visualize student progress in the information space of a course as a graph
Crick, R. D., Knight, S., & Barr, S. (2017)	Heatmap; line graph (Survey data)	Be more explicit about what is uncertain about the questionnaire result data
De Laet, T., Millecamp, M., Ortiz-Rojas, M., Jimenez, A., Maya, R., & Verbert, K. (2020)	Boxplot; bar panel (Log data)	Examine the average interaction time in minutes; the impact of new modules on the dashboard on perceived support of the advisor, relation between perceived support and average time of the new dashboard, and changes in workload between certain periods of time; visualize the identified themes in the 14 staged advising dialogues
Echeverria, V., Martinez-Maldonado, R., Shum, S. B., Chiluiza, K., Granda, R., & Conati, C. (2018)	Heatmap (Log data)	Represent the intuitive comparison of teachers' gaze behavior between exploratory versus explanatory visualizations
Fiel, J., Lawless, K. A., & Brown, S. W. (2018)	Scatter plot (Log data)	Identify and investigate various patterns of timing behavior that might emerge in an actual course. Also enables an easy division of groupings of "early starters" or "late starters" relative to their peers and not necessarily restricted by course raw time
Guerra, J., Ortiz-Rojas, M., Zúñiga-Prieto, M. A., Scheihing, E., Jiménez, A., Broos, T., … & Verbert, K. (2020)	Proportional bar chart with different color (Survey data)	Show the different proportion per group
Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020)	Box plot; bar plot (Survey data)	Overlay the expert and student responses with different colors for easier comparisons
Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019)	Gradient color panel (log data)	Show the percentage of teachers who actually accessed the system in relation to those who were originally given access to the system

(continued)

Table 2.1 (continued)

Author (year)	Type (data)	Benefit
Liu, M., Lee, J., Kang, J., & Liu, S. (2016)	Area chart; line chart (Log data)	Represent multiple layers of information in a single view which enables researchers to understand how the patterns may vary according to students' learning characteristics
Liu, M., Kang, J., Zou, W., Lee, H., Pan, Z., & Corliss, S. (2017)	Radar plot; area chart and scatter plot (Performance data[a])	Compare high- and low-performance groups' learning patterns in an intuitive way
Martinez-Maldonado, R., Shum, S. B., Schneider, B., Charleer, S., Klerkx, J., & Duval, E. (2017)	Fiducial marker (Eye-tracking data)	Generate reliable footprints of collaboration quality and separate productive from less productive groups of students
Nagy, R. (2016)	Animated bubble chart (Performance data[a])	Select and watch the path of a single student while conducting a one-on-one interview about their efforts
Pardos, Z. A., & Horodyskyj, L. (2019)	Scatter plot (Log data)	Not specified
Pardos, Z. A., Whyte, A., & Kao, K. (2016)	moocRP dashboard (Log data)	Prepare data for developing instructor and researcher-oriented interfaces
Rienties, B., Herodotou, C., Olney, T., Schencks, M., & Boroowa, A. (2018)	Bar chart (Log data)	Help teachers/teaching staff make informed design alterations and interventions based upon learning analytics data
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020)	Pattern tracing graph (Log data)	Present the pattern for all groups and indicate which group has the pattern of expected or unexpected
Tan, J. P. L., Koh, E., Jonathan, C. R., & Yang, S. (2017)	Radar plot; bar graph, social learning network graph; line graph (Log data)	Show each student's 21c skills strength compared to her/his peers; show each student's mindset soundness compared to peers; reflects students' position and influence within the WiREAD learning network; show each student's reading achievement compared to peers
Van Horne, S., Curran, M., Smith, A., VanBuren, J., Zahrieh, D., Larsen, R., & Miller, R. (2018)	Bar graph; boxplot (Log data)	Show the distribution of the dashboard; shows course grade for matched triplets

[a]Performance data include students' previous test scores and instructors' grading scores recorded outside of the log data-generating systems

Other than graphs or charts, plots were the second most popular type ($n = 7$) in data visualization types in LA studies followed by mappings ($n = 3$). To name some examples of plot and mapping uses, Gutiérrez et al. (2020) showed their survey results through box and bar plots. By overlaying expert and student responses with different colors, the researchers facilitated the comparison between the two groups. In addition, Echeverria et al. (2018) visualized four teachers' gaze behaviors through heatmaps and explored the different learning analytics use patterns influenced by whether data storytelling elements were added to the data visualization or not. The example heatmaps of exploratory and explanatory visualizations depicted in this study better showed data storytelling elements had the potential to assist teachers in exploring visualizations easily.

One noteworthy finding was that other than these conventional data visualization techniques mentioned above, some studies introduced a new data visualization technique and dashboard aiming to show their unique findings even more prominently, which also promoted a more convenient way of data analysis sharing. For example, Pardos et al. (2016) developed moocRP model/dashboard utilizing standardized data streaming based on Caliper and xAPI. By streaming data from multiple platforms and standardizing it in advance to feed it to the analysis visualizing sharing tool, known as moocRP in this case, this model not only facilitated learning activity visualization but also eased the data analysis, distribution, and research analytics module reuse. One of the most significant features of this model-based dashboard is integrating data request, authorization, and distribution processes embedded for instructors and researchers in the system. This enables other researchers to apply and adapt the data analysis conducted by third parties to their own datasets without any violation of data ethics such as transparency or privacy. Using this dashboard, researchers simply add or delete the dataset they need from multiple data sources through a few mouse clicks, and they can also utilize visual analytic modules such as Bayesian Knowledge Tracing or course structure visualizer with their selected datasets.

Data In our literature review, we found log data from either learning management systems or educational games were the most dominantly used data source ($n = 14$) for the methodological purposes of visualization. Besides, we found most of the researchers utilized various data visualization techniques to make their findings more accessible to larger audiences because raw log data tend to be too unobtrusive to render any distinct collective patterns or groupings. For example, Aljohani et al. (2019) used a correlational matrix comparing the multivariate analysis of variance (MANOVA) from the log data in a single visualization and showed the distinct positive correlations between multiple variances. In another study, Fiel et al. (2018) used a box plot to identify and investigate various patterns of students' timing behaviors from the log data they collected. This visualization enabled the researchers to detect the different group emergence easily which was divided into four groups by the combination of the students' timing index and their spacing counts.

The second most popularly used data source was using surveys ($n = 4$), and survey results were visualized mainly for the apparent comparison in proportions per different group or individual. To name a few, Guerra et al. (2020) visualized the students' different perceptions regarding the dashboard and their number of special requests by semester in the proportional bar charts with different colors to make the comparison more explicit. Likewise, Gutiérrez et al. (2020) displayed their survey data in the box and bar plots overlaying the survey responses from the pairs (expert versus laymen and expert versus students) for representing the evident differences in those pairs with different colors. Other than log data or survey data, students' performance scores or instructors' grading scores were also included for representation and comparison purposes. For example, Liu et al. (2017) showed students' test scores in radar plots to compare high- and low-performance groups' learning patterns, and Nagy (2016) visualized the teachers' grading scores based on the rubrics per student to assist teachers to track their grading scores of the students.

Infrequently but not rarely, eye-tracking data were collected from separate tools detached from learning management system (LMS) to be compared with the LMS-generated log data or another preexisting dataset to make a better sense of the meaning of teacher or student's behaviors recorded in the log data. For instance, teachers' eye-tracking data were used to match them with the LMS-generated data to find the different teacher behavior patterns upon the exploratory and explanatory visualizations (Echeverria et al., 2018), or students' eye-tracking data were collected to track students' gaze data with them to produce real-time references for teachers to easily decide who or which group needs teacher's support most at the moment (Martinez-Maldonado et al., 2017). In summary, the use of eye-tracking data in our review demonstrated the researchers' intention to enhance their data analysis by adding more contexts to the log data themselves.

Benefit The goal of data visualization is to enable researchers to explain the data in more clear and understandable forms (Chen et al., 2007). Data visualization also delivers a comprehensible picture for researchers to grasp the gist of the outcomes, provides an approach to explore data, and sometimes even generates insightful research results (Chen et al., 2007). In this review, four significant benefits of using data visualization techniques emerged: (a) presenting research results indicating trends; (b) demonstrating multilayered information in a single view; (c) promoting comparisons; and (d) displaying research participants' relationships and interactions within the network identified in a study.

First, data visualizations can present research results in a sequence for researchers to identify trends. For example, Sedrakyan et al. (2020) used a bar chart to show a sequence of trials of completing a chosen learning goal. Specifically, each bar demonstrates an achievement level for each trial, and arrows indicate time spent between the trials, which gives a representative time sequence to show the trend. Also, in the same study, line charts are applied to reveal students' time spent across different trails. In another study, Rienties et al. (2018) selected bar charts to show the changes in assessment submission rate over time, making it easier for researchers to see the trends. A dynamic chart is also used to show the progress as time elapses in the study. In Nagy's (2016) study, he used a three-dimensional motion chart with animated bubbles to track users' achievement paths over time. Since different colors (girls in blue and boys in green) were used to visualize their dissimilar paths, the trends between boys and girls looked more salient. Furthermore, this dynamic and interactive motion chart also allowed researchers to track each individual's behavioral change over time and presented the fluctuation of the academic efforts that students put into, which reveals the diverse individual-level trends within the collective trends categorized by gender. Besides, Fiel et al. (2018) used a scatter plot to present the various timing behavior patterns among the four different groups. The plot showed the unique singularities in the four different groups' trends, especially focusing on each group's timing index and spacing counts about when and how often they completed their coursework.

Second, the data visualization technique allows the representation of multiple layers of information in a single view. For example, Liu et al. (2016) used area graphs with lines to demonstrate the average frequency and duration of tools usage by students across various problem-solving stages from two science knowledge groups. Each tool used by each group was presented in a separate graph but organized consistently in an integrated view: the x-axis is used for showing log time, while the y-axis is used for showing the total duration. Additionally, Liu et al. (2017) used radar plots to represent the multivariate data about the high- and low-achieving groups. By representing five variables in a two-dimensional plot per subject and module, the multiple series of radar plots enriched the contexts of the two groups' distinctive tool-usage patterns.

Third, data visualization can promote comparisons. Using different colors is a common technique for researchers to show the contrast between groups. For example, Sedrakyan et al. (2020) overlaid both expert and student responses with different colors to compare the difference between the planned performance on a goal-specific task and a student's actual outcomes. Also, radar plots and bar charts are popularly used to show comparisons. For instance, Tan et al. (2017) used a radar plot to show each student's skills strength compared to their peers, and they also used a bar graph for showing each student's mindset soundness compared to their peers. For a small number, heatmaps are also utilized by researchers to make comparisons. In the study conducted by Echeverria et al. (2018), 24 heatmaps correspond to 4 teachers' inspection episodes were created to help researchers perform a rapid visual comparison between 2 types of gaze behaviors (exploratory and explanatory).

Lastly, data visualization can display participants' relationships and interactions within the network. Specifically, Tan et al. (2017) used social network maps to reflect students' positions and their influences on others within the learning network. Each student was represented by a node, and the total nodes were connected by arrows which represented the connections among students as well as the direction of each interaction. The more replies a student received, the larger the node would be. By the visualization represented in this manner, researchers were able to observe the degree of each student's participation and interaction pattern in the course easily. Similarly, Caprotti (2017) used the social network map to display the resources such as quizzes, peer-assessed workshops, and the discussion forum posts that students visited in the course. Each resource that appeared in the log file was displayed as a node, and each node's size corresponded with the students' visit frequency in the visualization. In this way, the researchers were able to explore the students' activity patterns easily, and they discovered that only graded activities that contributed to their final grades were frequently visited by the students.

2.2.2 The Use of Dashboards for Instructors and Learners as a Communication Tool

Dashboard, as a platform for presenting the visualized educational information, has been widely used to empower instructor-learner interaction and support learning practices (Alhadad, 2018). The reviewed articles revealed diverse types of dashboard applications in various educational contexts ranging from online learning environments (e.g., Moreno-Marcos et al., 2019) to face-to-face advising (De Laet et al., 2020). To take a closer look at the dashboard implementation, in the following sections we examined the data sources for the dashboard to convey educational information (i.e., data), the target users that the dashboard was designed for (i.e., target user), and, lastly, the benefits that a dashboard brought to instructors and learners (i.e., benefit) (see Table 2.2).

Data Based on the reviewed articles, log data are the most common data type utilized by the dashboards ($n = 19$) as a communication tool. In fact, instead of simply presenting the raw log data, many dashboards firstly processed the log data using some machine learning models or algorithms and then presented the outcomes. For example, Herodotou et al. (2019) collected students' usage log data such as assignment submission status from a LMS and constructed a prediction model. The outcomes of the prediction were presented on the dashboard to visualize the predictive information on which student was at risk or not of submitting an assignment. In another study, Mavrikis et al. (2019) applied artificial intelligence (AI) techniques to create a series of indicators using students' log data generated in an exploratory learning environment. The indicators were then presented on the dashboard for teaching assistants to monitor students' real-time learning progress. A noteworthy finding was that many dashboards, although the log data provided the bulk of the data source, also integrated with other types of data. For example, Russell et al. (2020) collected and visualized students' performance data such as assignment grades integrated with the log data to present students' learning progress, which provided instructors with a more comprehensive view of the learners' progress in the course.

Other than log data, students' academic records such as course-taking behaviors were also applied to the dashboard design. Guerra et al. (2020) used students' academic record data such as previous course-taking information, the progress of the program, and performance scores to build dashboards to support academic advising in higher education contexts. A similar dashboard design was also applied in the studies of De Laet et al. (2020) and Gutiérrez et al. (2020). After adding more information such as the demographic background to the dashboard, the dashboards in

Table 2.2 Details of the reviewed articles that used dashboard as a communication tool

Author (year)	Data	Target users	Benefit
Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019).	Log data	Instructors	Compare patterns across classes and sections
Aljohani, N. R., Daud, A., Abbasi, R. A., Alowibdi, J. S., Basheri, M., & Aslam, M. A. (2019)	Log data; performance data[a]	Learners	Show the best students' performance averages for each factor to other students
Avila, C., Baldiris, S., Fabregat, R., & Graf, S. (2020)	Qualitative data	Instructors	Help teachers easily identify accessibility failures and quality items that need to be improved before its delivery to students
Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2018)	Log data	Learners	Support the dialogue between adviser and student through an overview of study progress, peer comparison, and by triggering insights based on facts as a starting point for discussion and argumentation
Crick, R. D., Knight, S., & Barr, S. (2017)	Survey data; performance data[a]	Instructors and learners	Help teachers to make decisions to improve outcomes
De Laet, T., Millecamp, M., Ortiz-Rojas, M., Jimenez, A., Maya, R., & Verbert, K. (2020)	Academic record data; performance data[a]	Instructors	Visualize the students' pathway and supports for making study plan
Echeverria, V., Martinez-Maldonado, R., Shum, S. B., Chiluiza, K., Granda, R., & Conati, C. (2018)	Log data	Instructors	See the stories behind the data
Guerra, J., Ortiz-Rojas, M., Zúñiga-Prieto, M. A., Scheihing, E., Jiménez, A., Broos, T., … & Verbert, K. (2020)	Academic record data; performance data[a]	Instructors	Provide the first-year key moments and profiles
Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020)	Academic record data; performance data[a]	Instructors	Provide various visualizations for academic progress
Han, J., Kim, K. H., Rhee, W., & Cho, Y. H. (2020)	Log data; qualitative data	Learners	Monitor students learning status
Hernández-García, Á., Acquila-Natale, E., Chaparro-Peláez, J., & Conde, M. Á. (2018)	Log data	Learners	Detect students' cooperation work achievement using LMS data

(continued)

Table 2.2 (continued)

Author (year)	Data	Target users	Benefit
Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019)	Log data; demographic data	Instructors	Predict on a weekly basis whether (or not) a given student will submit their assignments
Martinez-Maldonado, R., Shum, S. B., Schneider, B., Charleer, S., Klerkx, J., & Duval, E. (2017)	Log data	Instructors and learners	Gain a better understanding of student's learning paths
Mavrikis, M., Geraniou, E., Gutierrez Santos, S., & Poulovassilis, A. (2019)	Log data	Instructors	Provide eight traits of this dashboard that mentioned in the paper
Mejia, C., Florian, B., Vatrapu, R., Bull, S., Gomez, S., & Fabregat, R. (2017)	Survey data; demographic data	Learners	Create awareness among students about their reading difficulties, learning style, and cognitive deficits to facilitate reflection and encourage their self-regulated learning skills
Michos, K., & Hernández-Leo, D. (2018)	Log data	Instructors	Not specified
Molenaar, I., & Knoop-van Campen, C. A. N. (2019)	Log data	Instructors	Display real-time data on learner performance to teachers, and it impacted the pedagogical actions of teachers
Moreno-Marcos, P. M., Alario-Hoyos, C., Munoz-Merino, P. J., Estevez-Ayres, I., & Kloos, C. D. (2019)	Qualitative data	Learners	Support the proposed 3S methodology
Pardos, Z. A., Whyte, A., & Kao, K. (2016)	Log data	Instructors	Provide support for instructional actions
Park, Y., & Jo, I. H. (2019).	Log data	Learners	Detect students' behavior pattern on dashboard
Roberts, L. D., Howell, J. A., & Seaman, K. (2017)	Log data	Learners	Support students' learning experience
Russell, J. E., Smith, A., & Larsen, R. (2020)	Log data; performance data[a]	Learners	Show students' weekly progress and grade
Sadallah, M., Encelle, B., Maredj, A. E., & Prié, Y. (2020)	Log data	Instructors	Detect the reading barriers that learners face with content and to identify how their courses can be improved accordingly

(continued)

Table 2.2 (continued)

Author (year)	Data	Target users	Benefit
Schumacher, C., & Ifenthaler, D. (2018)	Log data	Learners	Understand one's learning habits, track the progress towards goals, optimize one's learning paths, or adapt to recommendations
Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020)	Log data	Not specified	Enhance students' motivation
Tan, J. P. L., Koh, E., Jonathan, C. R., & Yang, S. (2017)	Log data; qualitative data	Learners	Foster greater self-awareness, reflective, and self-regulatory learning dispositions; enhancing learning motivation and engagement; nurturing connective literacy among students

[a]Performance data include students' previous test scores recorded outside of the log data-generating systems

these studies presented detailed information of undergraduate students' academic path in the institute, which provided advisors a holistic view about students' overall progress, thus enabling them to deliver better instructions through more personalized advising.

Last but not least, some dashboards also collected and processed qualitative data such as the posts students composed in the discussion forums. For example, Moreno-Marcos et al. (2019) applied sentiment analysis techniques to categorize students' forum posts and replies in a MOOC. The dashboard could present the proportion of each sentiment category (positive, negative, neutral) of the forum each day and the trend across the time to inform further instruction design. In another study, Tan et al. (2017) collected students' comments generated in an online learning environment—WiREAD—and used the length of comments to create radar charts as indicators to identify the students' different levels of participation. The radar charts presented the learning behavior patterns for an individual student as well as the whole class, which provided insights for the future learning analytics dashboard design.

Target User In the reviewed literature, dashboards were designed for two groups of target users: learners (n = 14) and instructors (n = 14). For learners, some dashboards were developed to promote their self-reflective learning process through visualization in the dashboard. For example, Charleer et al. (2018) used the dashboard to provide key moments of students' performance, such as exam scores. Roberts et al. (2017) also applied a feature to the dashboard to compare each individual to the overall performance of the class, supplemented by the progress bars for showing the number of site visits, engagement level, the number of assessments submitted, and the grade level for each subject. In addition, some dashboards were designed to draw students' attention to their possible at-risk behaviors. In this respect, Herodotou et al. (2019) designed a predictive dashboard to identify students' at-risk behaviors such as not submitting assignments. Gutiérrez et al. (2020)

also designed a similar predictive system using predictive algorithms to display students' academic risk on the dashboard.

Dashboards designed for instructors could help them visualize learners' performance to gain a better understanding of current academic development. For example, Guerra et al. (2020) designed the dashboard for advisors to visualize students' past and current performance and progress, which supported instructors to advise on students' study plans and help students achieve content knowledge mastery. Also, De Laet et al. (2020) used a dashboard to enhance the communication between advisors and students in developing study plans. Sometimes, dashboards were also designed for instructors to monitor learners' learning behavior and academic progress. For example, Sedrakyan et al. (2020) processed students' log data to provide the visualization of their learning trends in radar graphs. In addition, some dashboards were designed to enable instructors to offer academic recommendations. In this regard, Sadallah et al. (2020) applied an assistant mechanism to empower instructors with the data of remediation suggestions once the dashboard identified learners' academic issues.

Benefit The reviewed articles showed the benefits of using data visualization or dashboards as a communication tool in the following four aspects: (a) presenting current learning status; (b) identifying learning barriers and difficulties; (c) projecting predicted learning outcomes; and (d) enhancing collaborative learning and engagement.

A number of studies indicated dashboards were beneficial for presenting learners' current learning status. For instance, Han et al. (2020) provided a student dashboard informing students about how many comments a student had posted, which peers the student had interacted with, and what argumentation elements such as reason(s) or claim(s) were included in their comments. To better support students, the researchers also inserted help buttons for the students to use so that instructors would be notified once the students requested help. This dashboard enabled students to own autonomy in managing their own learning pace and provided them with a comprehensive image of their learning progress. In another study, Aljohani et al. (2019) implemented a student dashboard called "Analyse my Blackboard Activities (AMBA)" to reveal the hidden patterns of learner's behaviors and attitudes. Using the students' log data from their blackboard LMS, this tool provided each student his/her own learning statistics with other comparatives selected by the instructors, such as class average, average of active students, and average of best student performance. Supported by the dashboard, the students were able to see their current learning progress and performance versus the whole class. Moreover, some studies focused on the use of dashboards to demonstrate students' learning progress. For instance, Park and Jo (2019) provided a dashboard using students' online learning log data to present learners' status such as how long and how often they accessed certain learning materials. In this case, students were able to get a better sense of their own learning behavior patterns and be informed about what learning activities were yet to be explored.

In addition, dashboards are beneficial for identifying learning barriers and difficulties. Avila et al. (2020) used an analytic tool, Analytics Tool to trace the Creation and Evaluation of OERs (ATCE), to trace the creation and evaluation of open educational resources embedded in the ATutor LMS. They concluded that ATCE allowed the instructors to identify what they needed to improve for their courses and the visualizations helped instructors identify their failures in preparing quality learning materials in advance of the student's use in a real scenario. While Avila et al. (2020) used ATCE to help teachers identify the barriers for improvement, Mejia et al. (2017) used another dashboard called Panel de Analíticas de Aprendizaje de Dislexia en Adultos (PADA) to help students create awareness about their reading difficulties and cognitive deficits. PADA was designed to facilitate students' reflections on the reading process and encourage them to develop self-regulated learning skills in the study.

Moreover, dashboards are used for projecting predicted learning outcomes. The learning analytic system in the study of Herodotou et al. (2019) used a traffic light system to predict whether the students at risk were submitting their assignments. Specifically, the red color in the system indicated students at risk of not submitting their next assignment. In this way, students could receive early intervention if they were at risk; as a result, it prevented students from missing assignment dues and falling behind their peers. In another study, Russell et al. (2020) examined the effects of the LA dashboard use with at-risk students and showed the benefits of using such a dashboard. They found this dashboard use was effective not only for students' overall progress but also for enhancing final grades of the at-risk students.

Finally, dashboards can also promote learning engagement and enhance collaborative learning. Tan et al. (2017) demonstrated how a dashboard—WiREAD—was used to support collaborative critical reading and discussion. This dashboard provided an interface for students to peer review and critique each other's writing, which fostered greater self-awareness and collaborative learning disposition and also nurtured connective literacy among the students. In another study, Aljohani et al. (2019) implemented a dashboard, allowing students to see their learning statistics from the blackboard LMS. The comparison feature of the dashboard enabled students to compare their personal learning behavior frequency with the average frequency in the most active group in the class. This comparison raised every student's awareness about the most active students' work and contributed to the increased students' engagement as a whole in the study.

3 Goal 2: A Case Study

In this section, we present a case where we use visualizations to report research outcomes and our efforts in designing a dashboard for teachers as a supporting teaching tool. This case study serves as an example to support the review of literature in the previous section by illustrating how researchers and designers can use visualizations and dashboards both at the research and practical levels.

3.1 Context of the Case Study

This case study is situated in the context of Alien Rescue, a virtual technology-enriched program for 6th grade space science (AR, https://alienrescue.edb.utexas.edu). This program is designed by the researchers and designers at the University of Texas at Austin. The goal of the program is to engage middle school students in solving a complex problem that requires them to use tools, procedures, and knowledge of space science as scientists and to apply processes of scientific inquiry while learning about our solar system. Students who act as young scientists are charged to find new planet homes for six displaced aliens. It uses problem-based learning pedagogy and aims to enhance middle school students' problem-solving skills. It is aligned with national science standards and Texas Essential Knowledge and Skills (https://alienrescue.education.utexas.edu/teacher/) and has been used by schools in at least 30 states in the USA and 4 countries. Delivered entirely online, the program is designed for 12–15 days with 45-min class session each day. But with appropriate adaption, it can be used from grades 5th to 9th according to schools' curriculum needs and time available.

3.2 Using Visualization as a Research Tool to Communicate Research Findings

As researchers and designers, we have published numerous research studies relating to the Alien Rescue program. In publishing our research findings, we have used visualizations as a research tool to communicate the research findings (Alhadad, 2018). For example, in Liu et al. (2015), we used visualizations to show how learners accessed different tools in Alien Rescue. Figure 2.2 presented multiple layered information showing tool use frequency and duration over a time period by four conceptual categories in one single visualization. The study by Liu et al. (2019b) used visualizations to illustrate the differences in using the tools based upon the log data between different groups over a period of time (see Fig. 2.3). More recently, Kang and Liu (2020) used visualizations to present the problem-solving workflow by students at risk vs. students not at risk in 1 day (see Fig. 2.4).

While the visualizations from the above studies drew upon the log data, in a study by Liu et al. (2019a), visualizations were also used to present findings from the qualitative data regarding students' perceptions of their experience in using Alien Rescue. Figure 2.5a showed students' interview responses to compare their experience with Alien Rescue to other science classes, evaluating whether they were able to learn science better, the same, or worse through Alien Rescue. The keywords describing why they learned better with Alien Rescue are displayed in Fig. 2.5b. Together, these examples illustrate visualizations can be effective in communicating research findings not only among researchers but also to a general audience.

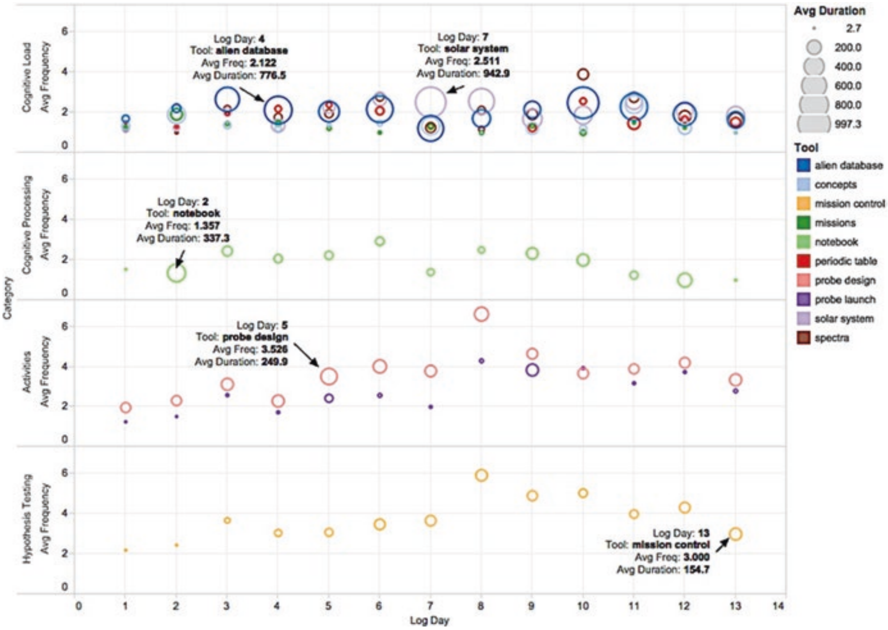


Fig. 2.2 Average frequency and duration of tool use over 14 days by four conceptual categories

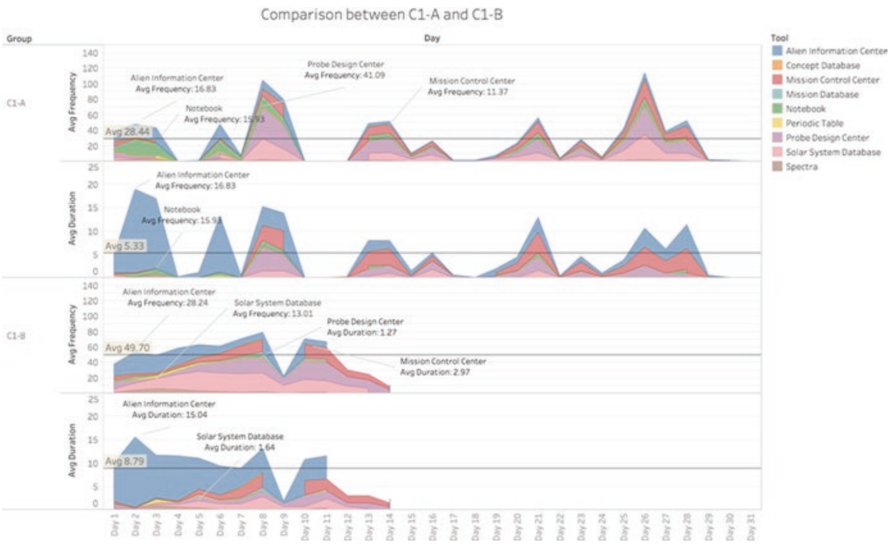
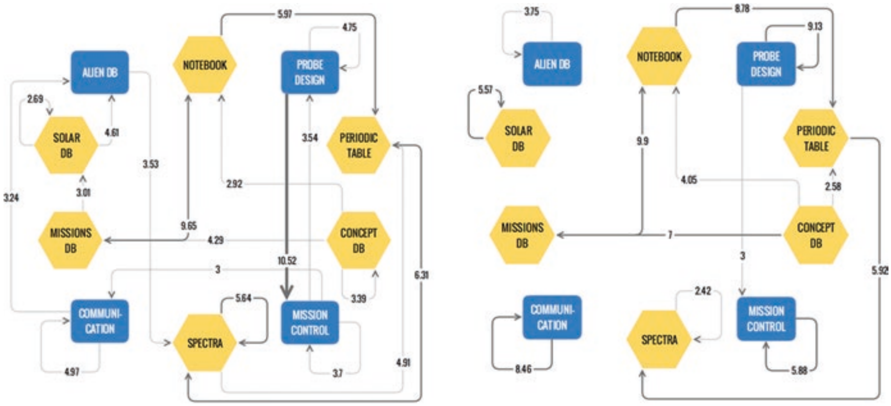


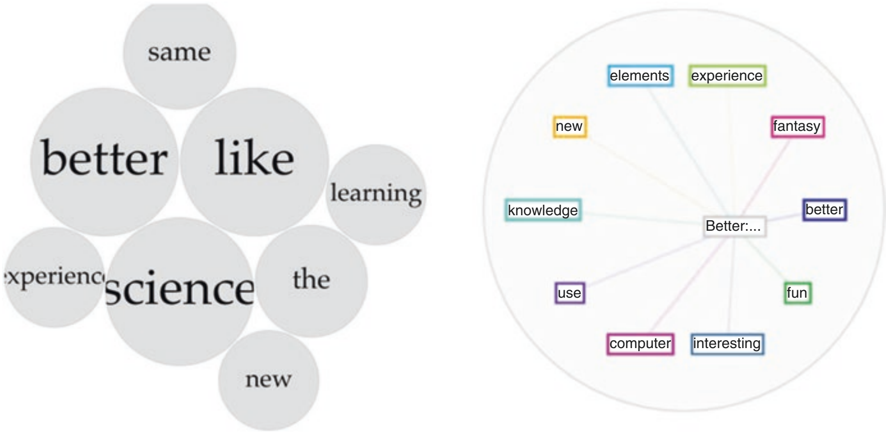
Fig. 2.3 Comparison of tool usage by Group A and Group B over individual days



(a) Day 4: Non-at-risk Students ($n = 104$)

(b) Day 4: At-risk Students

Fig. 2.4 How non-at-risk students (**a**) vs. at-risk students (**b**) navigate through Alien Rescue on a specific day



(a) Terms Berry Visualization

(b) Mandala Visualization

Fig. 2.5 Students stated they learned science better in (**a**) and the reasons for learning better with Alien Rescue in (**b**)

3.3 Using Dashboard with Visualizations as a Means to Communicate Research Findings to Teachers So as to Inform Their Educational Practices

We are the designers and developers of the Alien Rescue program. In our R&D efforts, we aim to incorporate the research findings into the design as guided by the design-based research framework (Barab & Squire, 2004; Design-Based Research

Collective, 2003). In doing so, we have created a dashboard as a way to communicate our research findings to teachers so as to inform their use of Alien Rescue more effectively (Alhadad, 2018). Here we describe two examples to illustrate how we use the dashboard together with visualizations to translate our research findings to practitioners. The data source of these two examples is a dataset of 7,006,045 lines of log data from 8537 students who used the program during a 2-year time span.

The dashboard as an accompanying tool for Alien Rescue is designed for teachers, who are a key stakeholder using the program. The main purpose of this dashboard is to help teachers use the information from the dashboard to monitor students' learning progress more effectively. A key aspect of the problem-solving process in Alien Rescue is a simulation allowing students to design probes where students research various scientific equipment used in both past and present NASA probe missions and construct probes by selecting appropriate probe type, communication, power source, and instruments. While appropriately constructed, probes will provide useful information to further problem solving. Incorrectly equipped probes can malfunction and waste valuable money. As students write justifications of why they need to design a probe in a certain way and in what way the destination planet is suitable for the alien species they are finding a home, providing just-in-time scaffolding to the students can significantly increase their chances of solving the problem. Therefore, one main feature of the dashboard is to auto-classify students' justifications from poorly justified arguments to well-justified arguments (Pan et al., 2021a). An example of this auto-classification feature is presented in Fig. 2.6. Since one justification is required each time a student sends a probe, this example figure shows that in this class students sent more probes on Oct. 20th than the other 2 days. There are more justifications categorized as specific inquiry (dark blue) and random (red) on this day. Using this just-in-time visual representation, teachers can quickly see students' justifications and intervene as needed to assist their students' inquiry processes. For example, seeing a relatively large portion of randomly written justifications displayed in Fig. 2.6, teachers can remind students about the importance of writing the justification and ask them to compose the scientific justification carefully.

Another example is to incorporate a machine learning model as guided by Csikszentmihalyi's flow theory (1975) to provide teachers visual images to show their students' real-time problem-solving status (Pan et al., 2021b). The three problem-solving states classified based upon the flow theory are flow, anxiety, and boredom (see Fig. 2.7). If a student is identified as in the flow state, it means the student is engaged and is using the tools provided in the environment wisely to solve the problem. If a student is identified as in the anxiety state, it means the student is encountering some difficulties and teachers might need to provide some suggestions or guidance. If a student is identified as in the boredom state, it means the student is gaming in the environment such as clicking random places without specific purposes. In this case, teachers can intervene and remind students to stay on task. Using this information, teachers can easily get a sense of how each student is progressing and be more efficient in checking and providing personalized scaffoldings when necessary.

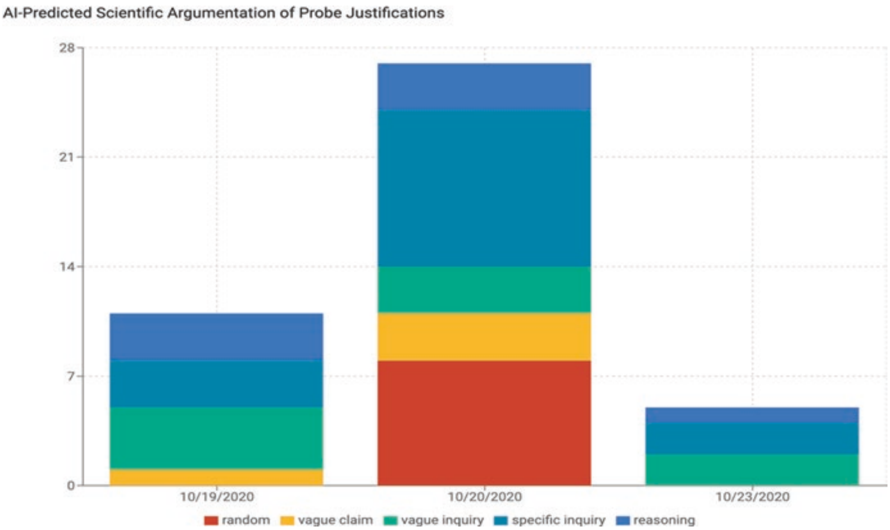


Fig. 2.6 A visual representation of classified students' probe justifications using machine learning techniques (y-axis indicating number of justifications)

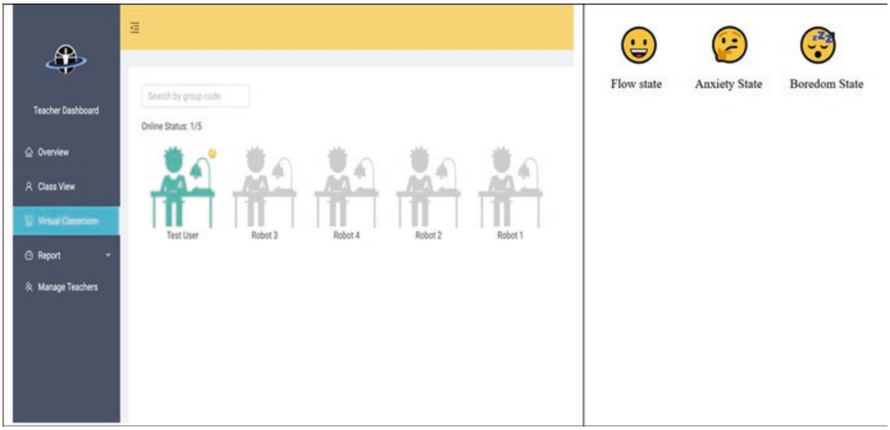


Fig. 2.7 An example showing students' emotional states (**a**) using emojis (**b**) based on Csikszentmihalyi's flow theory

4 Discussion and Summary

In this chapter, we aimed to accomplish two goals. For Goal 1, we conducted a review of literature from 2016 to 2020 on how visualizations and dashboards are utilized in learning analytics research, both at research and practical levels. The findings of our review showed nearly 100% of the included studies used data visualization techniques or dashboards as a research methodology to display findings effectively or as a communication tool to inform learning processes in time. For the use of research methodology, log data from either LMS or educational simulations/games were the dominant data source. For the use of a communication tool, the reviewed articles also revealed diverse data sources with log data being the most common type. Learning analytics dashboards were used to translate a large amount of usage data into interpretable formats to assist users, who were mostly instructors and learners.

For Goal 2, we presented our own R&D efforts in creating an immersive problem-based learning program for middle school science as a case to illustrate how we used visualizations to report research outcomes. The visualizations examples presented here reflected the trends as discussed in Goal 1 in support of the findings of the review of literature. The data source for our research was primarily log data with interview responses as secondary data source. We used visualizations to demonstrate multilayered information in a single view (Fig. 2.2) to illustrate group comparisons (Figs. 2.3 and 2.4) and to display research participants' relationships as they navigated the program (Figs. 2.2 and 2.4). We also discussed how we have designed a dashboard with visualizations to communicate our research findings to practicing teachers so as to support their teaching. The dashboard shows current learning status (Fig. 2.6) and identifies each student's learning barriers and difficulties (Fig. 2.7). Together, this chapter provides a picture of the current landscape of research and practice of visualizations and dashboards for learning analytics.

There are several implications for designing dashboards effectively. First, it is important to provide instructors with information about both individual and group levels. In other words, teachers should receive a more holistic picture of learning progress when they access the information from the dashboard. The information from both individual students and the whole class can help teachers' decision-making related to future lesson planning. Second, instructors play a multitasking role when facilitating problem-solving activities. Instead of delivering large amount of learner-generated behavioral data to instructors, it would be more useful to aggregate and process the data first and then present the information in more easily understandable representations on the dashboard. In our case study, it is not feasible to expect teachers to go through every justification students have composed during each class session. Yet, by presenting the justifications auto-classified into interpretable categories, teachers will be able to take advantage of this processed information in monitoring their students' progress. Third, the dashboard should provide instructors with real-time information which cannot be easily captured via conventional classroom facilitation strategies. That is, if all students are looking at their devices while working on their tasks, it will not be possible for teachers to know which students might need help by simply observing students' physical behaviors or their screens. However, if teachers have access to a dashboard which provides them with real-time information (e.g., students' potential mental status in our case), teachers will be better informed in terms of who and when to provide scaffolding. In conclusion, this chapter shows there are many potentials to use LA-supported dashboards for teaching and learning purposes. We are only at the beginning stage of discovering such potentials.

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