Chapter 27
Visualization and Dashboards: Challenges and Future Directions

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1 Introduction

Instructional technologies provide researchers with significant opportunities in order to facilitate learners' learning and design more effective learning environments. Nowadays, it is seen that especially digital learning environments are used intensively as instructional technology. Large amount of data about the learning experiences of learners are recorded in digital learning environments. Log data contains important information for learners, instructors, institutions, and decision-makers (Yoo et al., 2015). Thus, learning experience of learners in digital learning environments is being improved (Sin & Muthu, 2015). There are some major challenges in digital learning environments such as lack of quality log data, and analyzing, and understanding data (Kuosa et al., 2016). At this point educational data mining and learning analytics give researchers various opportunities. Educational data mining is a method used to discover meaningful structures and latent patterns in e-learning environments (Baker & Siemens, 2014). Educational data mining enables to discover meaningful patterns based on the system usage of learners, instructors, and administrators in order to increase the quality of online learning environments (Romero & Ventura, 2010). Learning analytics use dynamic data in

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digital learning environments and enable (a) real-time modeling about learners and learning, (b) estimation and optimization of learning processes, and (c) assessment, revealing, and analysis of data for learning environments and educational decision-making (Ifenthaler, 2015). Analyzing of log data can present some opportunities as supporting self-regulation, more effective learning experience with personalized learning, and increasing awareness of the learning process (Drachsler et al., 2014). The aim of learning analytics is to present highly adaptable and personalized learning environments (Ifenthaler & Widanapathirana, 2014).

One of the important issues in digital learning environments is visualization of the patterns in a way that learners or instructors can understand it (Duval, 2011). Patterns which are related to the learning experiences of learners in digital learning environments are presented via dashboards. A dashboard is a learning analytics application that used to support learning processes of learners by providing information about learning experiences (Yoo et al., 2015). Most of the studies about dashboards aim to (i) support awareness and reflection, (ii) self-regulation, and (iii) monitoring (Jivet et al., 2017). Expectations of learners from dashboard system which are based on learning analytics include (a) support planning and organization, (b) adaptive recommendation, (c) individual analysis of learning process, and (d) providing self-assessment opportunity (Schumacher & Ifenthaler, 2018).

On the other hand, many studies have been mentioned that there are deficiencies in the field of visualization and dashboard (Bodily et al., 2018; Sarikaya et al., 2018; Sedrakyan et al., 2019). Within the scope of this chapter, (a) detailed information about visualization and dashboard is given, (b) researches in the field of literature in the context of visualization and dashboards are examined, (c) design principles are introduced, and (d) visualization and dashboard existing challenge and its future directions are discussed.

2 Background

2.1 Visualization

Looking into the history of visualization, it is possible to see that it is expressed as "information visualization." "Information visualization is the use of computer-supported interactive visual representations of abstract data to amplify cognition" (Card, Mackinley, & Shneiderman). The aim of information visualization helps to discover relations among data via visuals (Herman et al., 2000). In other words, information visualization aims to present unstructured information in databases/data warehouses with various visual techniques in a way that individuals can understand. Nowadays ICT can facilitate visualization but the activity that happens in the mind (Mazza, 2010). The important factors of visualization effectiveness are data, task, internal representation, and cognitive ability (working memory capacity, domain knowledge, etc.) (Zhu, 2007). As can be seen, visualization is related to many fields. Many principles should be taken into consideration when selecting and presenting visualization techniques. Visualization should be familiar and interesting

to the learner in order to help learners to understand and interpret data (Kuosa et al., 2016). Within the scope of this research, visualization is discussed in the context of digital learning environments. Having a visual overview about the learner's learning experience can be useful for instructor and learners (Duval, 2011). Visualization helps to promote not only problem-solving but also reflection (Rieber, 1995). In addition, learners' awareness of the learning process increases through visualization (Khan & Pardo, 2016). It is easy to use visualizations in digital learning environments for students who have knowledge of visualization techniques (Sedrakyan et al., 2017). The use of these visualization techniques in digital learning environments has become widespread especially with learning analytics. Learning analytics use algorithmic analysis or information visualization in order to increase self-awareness and reflection based on tracking learning activities (Duval et al., 2012). Information of learners' learning experiences and learning performances in digital learning environments are presented to stakeholders via dashboards.

2.2   Dashboard

Dashboard is a rich computer interface with reports, visual indicators, and warning mechanisms that gather information dynamically in the field of business (Malik, 2005). Technologically, dashboards are multilayered applications built on business intelligence and data integration infrastructure (Lempinen, 2012). In this section, it is handled as the learning analytics application for the learning experiences of learners in digital learning environments. Dashboards that used in digital learning environments are structured based on three research areas as information visualization, learning analytics, and educational data mining (Schwendimann et al., 2016). Latent learning patterns of learners in e-learning environments can be discovered with educational data mining algorithms, and these patterns are presented to learners using visualization techniques and dashboards through learning analytics. In this way, e-learning environments can be improved and made more effective. Dashboard presents visual representation of the learner's or course's current and historical status for flexible decision-making in learning environments (Few, 2006). Thus, dashboard research aims to identify which data is meaningful to different stakeholders in education and how the data can be presented to support meaningful processes (Schwendimann et al., 2016).

In addition, through information on the dashboard, students' performance patterns can be explored, problems can be estimated and focused on this problems, and motivational structures can be identified (Podgorelec & Kuhar, 2011). Dashboards provide learners with real-time feedback, suggestions, and/or visualizations in order to support student reflection and knowledge awareness (Bodily et al., 2018). In the literature, dashboards were presented to the learners for comparison with peers, monitoring achievement of learning outcomes, and self-monitoring (Jivet et al., 2017). The benefits of dashboards in digital learning environments are summarized below (Yoo et al., 2015):

- Allow teachers to know students' learning situations in a real-time and scalable way.
- Improve student's self-knowledge levels.
- Make more intelligent decisions with the help of data mining algorithms.
- Help students improve their motivation and self-directed learning ability and achieve their learning goals.

Initial examples of research studies are *Course Signals* (Arnold & Pistilli, 2012) and *GLASS (Gradient's Learning Analytics System)* (Leony et al., 2012). *Course Signals* is a system that can give appropriate feedback to students and provide information about students' performance via signal lights. The other example is *GLASS* and it was developed so that learners can compare themselves with the peers with visualization of the learners' performance. In addition to these studies, SAM (Student Activity Meter) (Govaerts et al., 2012) visualization tool for awareness and self-reflection, LOCO-Analyst (Ali et al., 2012), and eLAT (Dyckhoff et al., 2012) can be given as examples of initial studies of dashboards. It is possible to see that many studies on dashboard have been conducted after these years. The purposes of the dashboard studies in the literature are presented below (Sedrakyan et al., 2019):

- Increase awareness about the learning process.
- Support cognitive process.
- Identify the student at risk.
- Provide immediate feedback.
- Monitor achievement status.
- Provide procedural information.
- Support decision-making.
- Inform.
- Display learner relations.
- Compare.
- Reflect.

Frequent visualization techniques utilized in dashboard studies are bar charts, line graphs, tables, pie charts, indicators, alert mechanisms, and network graphs (Podgorelec & Kuhar, 2011; Schwendimann et al., 2016). Frequent studies focus on learners (Arnold & Pistilli, 2012; Jin, 2017; Khan & Pardo, 2016; Papanikolaou, 2014; Park & Jo, 2015; Şahin & Yurdugül, 2019), instructors (Ali et al., 2012; Dyckhoff et al., 2012; Mottus et al., 2015; Van Leeuwen et al., 2015; Zhang et al., 2018), both learners and instructors (Sedrakyan et al., 2018; Kuosa et al., 2016; Govaerts et al., 2012; Leony et al., 2012), and other stakeholders, such as administrators (Rienties et al., 2016). In addition to these studies, it is seen that there is also research conducted in mobile dashboard design (Fulantelli et al., 2019; Kuhnel et al., 2018; Seiler et al., 2019).

For determining how and to what extent dashboard information will contribute to stakeholders, a benefits matrix may help as suggested in Table 27.1. The individual cells may be completed from individual perspective and provide a first decision point for implementing dashboard features (Ifenthaler, 2020).

Table 27.1 Dashboard benefit matrix

Dashboard goal/stakeholders	Learner	Instructor	Administrative	Researchers
Increase self-awareness				
Support cognitive process				
Determine dropout learner				
Instant feedback				
Display achievement status				
Present procedural knowledge				
Support decision-making				
Reflection				
Comparison				
Participant relations				
Increase participation				

3   Challenges and Future Directions

Learning analytics were presented as an emerging topic for adoption within 4–5 years in the 2011 Horizon Report prepared by the New Media Consortium (Johnson et al., 2011). Learning analytics are still part in the 2020 Horizon Report as "Analytics for Student Success" (Brown et al., 2020). Dashboards are used in order to support decision-making and increase awareness, motivation, and learning (Sarikaya et al., 2018). Graphics, tables, and visuals on the dashboards can be configured through visualization techniques. However, inappropriate designs and digital learning environments can negatively affect the learning processes of the learners. There are also findings that visualization techniques can produce undesirable effects or strengthen negative beliefs about learning and teaching (Gašević et al., 2015). In order to prevent undesirable effects, appropriate visualization techniques and dashboard designs should be developed. In this context, there are some difficulties in visualization and dashboard design. The difficulties encountered about visualization and dashboard design in the literature are presented in Table 27.2.

As can be seen in Table 27.2, some difficulties were expressed by different researchers. These difficulties and some solution proposals are as follows.

3.1   Linking Learning Theories

In the literature there is a gap between dashboard design and learning sciences (Sedrakyan et al., 2016; Sedrakyan et al., 2019). Several research related to dashboards consider a final design evaluation of the dashboard, while the design and development process is ignored (Bodily et al., 2018). In order to make dashboard designs more effective and to improve digital learning environments, dashboard

Table 27.2 Challenges of visualization and dashboards

Challenges	Research
Linking learning theories	Bodily et al. (2018), Sedrakyan et al. (2016), Yoo et al. (2015)
Determining effective metrics and effective visualization techniques	Ahn et al. (2019), Sarikaya et al. (2018), Sedrakyan et al. (2018), Yoo et al. (2015)
Data security and privacy	Sarikaya et al. (2018), Dabbebi et al. (2017)
Adaptive dashboard design	Schumacher and Ifenthaler (2018)
Amplifies cognition	Ahn et al. (2019), Yoo et al. (2015), Card et al. (1999)
Acceptance structures	Sedrakyan et al. (2018)

designs should be associated with learning theories, instructional design, and learning design (Ifenthaler et al., 2018). Learning theories are important in order to explain learning phenomenon and also help to design principles for learning environments, content, and tasks (Ertmer & Newby, 1993). In addition, more appropriate instruction and learning design can be structured through linking between learning analytics and learning theories (Ifenthaler et al., 2018; Wong et al., 2019).

3.2 Determining Effective Metrics and Effective Visualization Techniques

Another challenge in dashboard design is which visualization techniques to be used and which learner metrics to show. It is important to identify which metric from students' data is valuable to show (Yoo et al., 2015). A large amount of data about learners are stored unstructured in digital learning environments. However, it is necessary to determine which of these metrics are effective on the learner performance and present them to the learners. In order to determine these metrics, feature selection algorithms used in the pre-process stage of educational data mining can be utilized. Feature selection contributes to reducing the number of metrics/variables (Şahin et al., 2017). It is important to identify the metrics that are important for learners' learning experiences or learning performances, as well as presenting them with appropriate visualization techniques and visuals. In this context, the most important question is which visualization techniques are more appropriate and can be utilized. For this purpose, it is necessary to conduct research on which of the visualization techniques are more appropriate for students and to examine this situation (Sedrakyan et al., 2018). In order to make an effective dashboard design, a theoretical link should be established with human cognition and perception, situation awareness, and visualization technologies, and it should be structured based on this theoretical framework (Yoo et al., 2015). In addition, contextually appropriate presentations, visual language, and social framing issues should be taken into consideration in dashboard design (Sarikaya et al., 2018).

3.3   Data Security and Privacy

The other issues that should be discussed in the design of the dashboard are data design, sharing, security, reliability, and confidentiality (Sarikaya et al., 2018). This issue appears to be discussed not only in dashboard designs but also in learning analytics (Mah et al., 2019) and in related fields (Bertino & Ferrari, 2018; Chen & Zhao, 2012; Song et al., 2012). Which information will be used for learners, who will be enabled to access, and obtaining the permissions of the users can be given as examples which should be discussed under this topic (Ifenthaler & Schumacher, 2019).

3.4   Adaptive Dashboard Design

Dashboards shall be configured to allow a high level of customization (Schumacher & Ifenthaler, 2018). In other words, dashboards that are appropriate for the needs and characteristics of learners should be presented to the learners. For example, comparison with the group to the learners who have high external motivation and the learners who have high internal motivation can be presented with their daily individual performance. However, in order to develop adaptive designs, learning patterns, profiles, or preferences should be discovered based on the individual characteristics of the learners. Personality types, motivation sources, learning strategies, etc. could be indicators for individual characteristics of learners. In addition, adaptive dashboard designs can be structured specific to individual or to groups.

3.5   Amplifies Cognition

Cognitive concepts such as paying attention to cognitive load, human perception, and data literacy, avoiding visual clutter, and dividing data into interpretable sections have direct effects on design (Ahn et al., 2019). Therefore, the visuals and graphics that are presented should amplify the cognition of the learners. (a) Increasing resources, (b) reducing search, (c) enhancing recognition of patterns, (d) perceptual inference, (e) perceptual monitoring, and (f) manipulable environment amplify cognition (Card, Mackinley, & Shneiderman). In this context, it is necessary to develop designs such as presenting information related to each other together, presenting both visual and textual notifications, meaningful information, presenting different visuals and information according to the learners, and presenting graphics that are easy to use by the learners. It is possible to say that the visualization principles of proximity, similarity, enclosure, closure, continuity, and connection introduced by Gestalt in the dashboard designs still remain valid (Few, 2013). Concepts such as ease of use or perceived usefulness are within acceptance structures, and information on this concepts are included under the next topic. The presentation of different visuals or information to the learners is part of the adaptive dashboard.

3.6   Acceptance Structures

The structures in the technology acceptance models should be taken into consideration in the dashboard designs (Sedrakyan et al., 2018). The findings about why stakeholders use the developed e-learning environment or why they do not use it can be revealed through their acceptance structures. By determining these reasons, it will shed light on more appropriate environment designs. The important point is not only to develop a learning environment but also to use the developed environment by its stakeholders in accordance with its purpose. Davis (1989) defined these structures "perceived usefulness" and "perceived ease of use" in the context of *Technology Acceptance Model (TAM)*. Vankatesh et al. (2003) defined "unified theory of acceptance and use of technology (UTAUT)" as "performance expectancy," "effort expectancy," "social influence," and "facilitating conditions." The learning environments should present some features to the learners such as being easy to use, having high-level perceived usefulness, increasing learners' performance, etc. from this perspective. These models can guide researchers as to which visualization techniques can be utilized or what information will be presented to the learners. In addition to these, present sequential pattern via dashboard, intervention design, and dashboard interaction as an interaction type can be shown as future directions of the dashboard. Monitoring learners their own sequential behavior or the behavior of successful students can guide what they should do in the next step. The ultimate purpose of the intervention is to increase student achievement or improve students' learning experience (Pardo & Dawson, 2016). A structured intervention model that developed with learning analytics to support learning and teaching process can improve the learning performance of learners (Wu et al., 2015). At this point, intervention design and integration of this design to the systems are issues to be considered. In the digital learning environments, there are different types of interactions such as learner-learner, learner-instructor, learner-content, and learner-assessment. Besides, recently learner-dashboard interaction has also started to be considered as a type of interaction in the digital learning environments (Khan & Pardo, 2016; Rei et al., 2017). Learners' time spent in the dashboard, interaction behavior after interaction with the dashboard, charts and graphics that were seen by the learners, etc. can provide important information about the learning and teaching process.

4   Design Principles

There is no clear evidence about which features should be included in the design of visualizations (Zhu, 2007). It will be very useful to prepare some guidelines in order to design effective and goal-oriented visualizations (Duval, 2011). Guidelines and design principles can be contributed to the field such as (a) guiding the designers and researchers, (b) determining the issues to be considered in the design, (c) contributing to the evaluation of the developed environments, (d) developing effective

and appropriate designs for the stakeholders, etc. Few (2013) suggest three design principles: (a) the most important information should stand out from others in a dashboard that usually fits limited space on a single screen, (b) the information on the dashboard should support the awareness of the students and aid prompt understanding using various visualization technologies, and (c) the information should be disseminated in a meaningful way, and the information elements should support the students' decision-making goal and ultimate goal. Some design and evaluation principles of the dashboard were defined by Yoo et al. (2015):

- Goal orientation
- Information usefulness
- Visual effectiveness
- Appropriation of visual representation
- User-friendliness
- Understanding
- Reflection
- Learning motivation
- Behavioral change
- Performance improvement
- Competency development

In this context, design principles have been put forth in order to guide researchers and designers as shown in Table 27.3.

Table 27.3 Design principles for visualization and dashboards

Design principle	Design inquiry
Stakeholders	For which stakeholder is the dashboard/visualization intended?
Responsive design	On which device will the dashboard be displayed?
Presenting of essential information	What is the purpose of the presented information?
Presenting data in the context with the interaction types	How does the visualization relate to specific data in a specific context?
Selecting the appropriate visuals for the context	What is an unbiased visualization of the underlying data?
Selection of color	Are color codes included and can they be interpreted?
Dynamic update	What is an appropriate time for updating the visualization?
Presenting of related information together	Which visualizations may benefit from combined representation?
Highlight of important information	Is there information which requires special highlights?
Easy to use	How can stakeholders access the visualization quickly and without barriers?
Inclusive design	Is the design inclusive for any stakeholder?

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