Chapter 14: Provision of Data-Driven Student Feedback in LA & EDM

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ABSTRACT

The areas of learning analytics (LA) and educational data mining (EDM) explore the use of data to increase insight about learning environments and improve the overall quality of experience for students. The focus of both disciplines covers a wide spectrum related to instructional design, tutoring, student engagement, student success, emotional well-being, and so on. This chapter focuses on the potential of combining the knowledge from these disciplines with the existing body of research about the provision of feedback to students. Feedback has been identified as one of the factors that can provide substantial improvement in a learning scenario. Although there is a solid body of work characterizing feedback, the combination with the ubiquitous presence of data about learners offers fertile ground to explore new data-driven student support actions.

Keywords: Actionable knowledge, feedback, interventions, student support actions

Over the past two decades, education practice has significantly changed on numerous fronts. This includes shifts in educational policy, the emergence of technology-rich learning spaces, advances in learning theory, and the implementation of quality assurance and assessment, to name but a few. These changes have all influenced how contemporary teaching practice is now enacted and embodied. Despite numerous paradigm shifts in the education space, the key role of feedback in promoting student learning has remained essential to what is viewed as effective teaching. Moreover, with the massification of education, the need for providing real-time feedback and actionable insights to both teachers and learners is becoming increasingly acute. As education embraces digital technologies, there is a widespread assumption that the incorporation of such technologies will further aid and promote student learning and address sociocultural and economic inequities. This positivist ideal reflects the notion that technologies can be adopted to enhance accessibility to education while creating more personalized and adaptive learning pathways.

In this vein, the fields of learning analytics (LA) and educational data mining (EDM) have direct relevance for education. LA and EDM aim to better understand learning processes in order to develop more effective teaching practices (Baker & Siemens, 2014). The analysis of data evolving from student interactions with various technologies to provide feedback on the learner's progression has been central to LA and EDM work. In this chapter, we argue that feedback is one of the most powerful drivers influencing student learning. As such, the overall quality of the learning experience is deeply entwined with the relevance and salience of the feedback a student receives. Moreover, the provision of feedback is closely related to other aspects of a learning experience, such as assessment approaches (Boud, 2000), the learning design (Lockyer, Heathcote, & Dawson, 2013), or strategies to promote student self-regulation (Winne, 2014; Winne & Baker, 2013). Although the majority of the discussion in this chapter can be applied across all educational domains, the review focuses predominantly on post-secondary education and professional development.

THE ROLE OF DATA-DRIVEN FEEDBACK IN LEARNING

Discussions about feedback frequently take place within a framing of assessment and student achievement (Black & Wiliam, 1998; Boud, 2000). In this context, the primary role of feedback is to help the student address any perceived deficits as identified through the completion of an assessment item. Ironically, assessment scores and student achievement data have also become tools for driving political priorities and agendas, and are also used as indicators in quality assurance requirements. Assessment in essence is a two-edged sword used to foster learning as well as a tool for measuring quality assurance and establishing competitive rankings (Wiliam, Lee, Harrison, & Black, 2004). While acknowledging the importance of assessment for quality assurance, we focus specifically on the value of feedback often associated with formative assessment or simply as a component of student completion of set learning tasks. Thus, this chapter explores how student trace data can be exploited to facilitate the transformation of the essence of assessment practices by focusing on feedback mechanisms. With such a purpose, we highlight and discuss current approaches to the creation and delivery of data-enhanced feedback as exemplified through the vast body of research in learning analytics and educational data mining (LA/EDM).

Theoretical Models of Feedback

Although there is no unified definition of feedback in educational contexts, several comprehensive analyses of its effects on learning have been undertaken (e.g., Evans, 2013; Hattie & Timperley, 2007; Kluger & DeNisi, 1996). In sum, strong empirical evidence indicates that feedback is one of the most powerful factors influencing student learning (Hattie, 2008). The majority of studies have concluded that the provision of feedback has positive impact on academic performance. However, the overall effect size varies and, in certain cases, a negative impact has been noted. For instance, a meta-analysis by Kluger and DeNisi (1996) demonstrated that poorly applied feedback, characterized by an inadequate level of detail or the lack of relevance of the provided information, could have a negative effect on student performance. In this case, the authors distinguished between three levels of the locus of learner's attention in feedback: the task, the motivation, and the meta-task level. All three are equally important and can vary gradually in focus. Additionally, Shute (2008) classified feedback in relation to its complexity, and analyzed factors affecting the provision of feedback such as its potential for negative impact, the connection with goal orientation, motivation, the presence in scaffolding mechanisms, timing, or different learner achievement levels. Shute noted that to maximize impact, any feedback provided in response to a learner's action should be non-evaluative, supportive, timely, and specific.

Early models relating feedback to learning largely aimed to identify the types of information provided to the student. Essentially, these studies sought to characterize the effect that different types of information can play on student learning (Kulhavy & Stock, 1989). Initial conceptualizations of feedback were driven by the differences in learning science theorizations of how the gap between the actual and desired state of the learner can be bridged (cf. historical review Kluger & DeNisi, 1996; Mory, 2004). According to Mory (2004), contemporary models build upon pre-existing paradigms by viewing feedback in the context of self-regulated learning (SRL), i.e., *a style of engaging with tasks in which students exercise a suite of powerful skills* (Butler & Winne, 1995). These skills, setting goals, thinking about strategies, selecting the right strategies, and monitoring the effects of these strategies on the progress towards the goals are all associated with student achievement (Butler & Winne, 1995; Pintrich, 1999; Zimmerman, 1990). As part of their theoretical synthesis between feedback and self-regulated learning, Butler and Winne (1995, p. 248) embedded two feedback loops into their model. The first loop is contained within the so-called *cognitive system* and refers to the capacity of individuals to monitor their internal knowledge and beliefs, goals, tactics, and strategies and change them as required by the learning scenario. The second loop occurs when the product resulting from a student engaging with a task is measured, prompting the creation of *external feedback* relayed back to the student; for example, an assessment score, or an instructor commenting upon the completion of a task.

Hattie and Timperley (2007) have provided one of the most influential studies on feedback and its impact on achievement. The authors' conceptual analysis was underpinned by a definition of feedback as *the information provided by an agent regarding the performance or understanding of a student*. The authors proposed a model of feedback articulated around the concept that any feedback should aim to reduce the discrepancy between a student's current understanding and their desired learning goal. As such, feedback can be framed around three questions: *where am I going, how am I going, and where to next*? Hattie and Timperley (2007) proposed that each of these questions should be applied to four different levels: learning task, learning process, self-regulation, and *self*. The learning task level refers to the elements of a simple task; for example, notifying the student if an answer is correct or incorrect. The learning process refers to general learning objectives, including various tasks at different times. The self-regulation level refers to the capacity of reflecting on the learning goals, choosing the right strategy, and monitoring the progress towards those goals. Finally, the *self* level refers to abstract personality traits that may not be related to the learning experience. The process and regulation levels are argued to be the most effective in terms of promoting deep learning and mastery of tasks. Feedback at the task-level is effective only as a supplement to the previous two levels; feedback at the self-level has been shown to be the least effective. These three questions and four levels of feedback provide the right setting to connect feedback with other aspects such as timing, positive vs. negative messages (also referred to as polarity), and the consequences of including feedback as part of an assessment instrument. These aspects have been shown to have a interdependent effect that can be positive or negative (Nicol & Macfarlane-Dick, 2006).

In reviewing established feedback models, Boud and Molloy (2013) argued that they are at times based on unrealistic assumptions about the students and the educational setting. Commonly, due to resource constraints, the proposed feedback models or at least the mechanism for generating non-evaluative, supportive, timely, and specific feedback for each student is impractical or at least not sustainable in contemporary educational scenarios. At this juncture, LA/EDM work can play a significant role in moving feedback from an irregular and unidirectional state to an active dialogue between agents.

DATA-SUPPORTED FEEDBACK

The first initiatives using vast amounts of data to improve aspects of learning can be traced to areas such as *adaptive hypermedia* (Brusilovsky, 1996; Kobsa, 2007), *intelligent tutoring systems* (ITSs) (Corbett, Koedinger, & Anderson, 1997; Graesser, Conley, & Olney, 2012), and academic analytics (Baepler & Murdoch, 2010; Campbell, DeBlois, & Oblinger, 2007; Goldstein & Katz, 2005). Much of this research has taken place within LA/EDM research communities that share a common interest in data-intensive approaches to the research of educational setting, with the purpose of advancing educational practices (Baker & Inventado, 2014). While these communities have many similarities, there are some acknowledged differences between LA and EDM (Baker & Siemens, 2014). For example, EDM has a more reductionist focus on automated methods for discovery, as opposed to LA's human-led explorations situated within holistic systems. Baker and Inventado (2014) noted that the main differences between LA and EDM are not so much in the preferred methodologies, but in the focus, research questions, and eventual use of models.

When considering LA/EDM through the lens of feedback, the research approaches differ in relation to the direction and recipient of feedback. For instance, LA initiatives generally provide feedback aimed towards developing the student in the learning process (e.g., self-regulation, goal setting, motivation, strategies, and tactics). In contrast, EDM initiatives tend to focus on the provision of feedback to address changes in the learning environment (e.g., providing hints that modify a task, recommending heuristics that populate the environment with the relevant resources, et cetera). It is important to note that these generalizations are not a hard categorization between the communities, more so an observed trend in LA/EDM works that reflects their disciplinary backgrounds and interests. The following section further unpacks the work in both the EDM and LA communities related to the provision of feedback to aid student learning.

Approaches to Feedback in Educational Data Mining

Research undertaken in EDM is well connected and related to disciplines such as *artificial intelligence in education* (AIED) and *intelligent tutoring systems* (ITSs) (Pinkwart, 2016). Regarding feedback processes, a considerable number of EDM research initiatives have been concerned with developing and evaluating the effect of adapted and personalized feedback or recommendations to learners (Hegazi & Abugroon, 2016). This work is grounded on student modelling and/or predictive modelling research. Essentially, the focus has been on creating specific systems that can adapt the provision of feedback in order to respond to a student's particular needs, thereby facilitating improvements in learning, reinforcing (favourable) academic performance, or restraining students from performing certain behaviours (Romero & Ventura, 2013).

EDM approaches dealing with the provision of feedback have generally emphasized task-level feedback, with some notable exceptions (e.g., Arroyo, Meheranian, & Woolf, 2010; Kinnebrew & Biswas, 2012; Lewkow, Zimmerman, Riedesel, & Essa, 2015; Madhyastha & Tanimoto, 2009). Early research on EDM (see the EDM conference proceedings of 2008 and 2009) showcased a wide range of approaches aimed at providing feedback to learners through data-driven modelling (e.g., Mavrikis, 2008), learning-by-teaching agents (e.g., Jeong & Biswas, 2008), the provision of on-demand and instant prompts (Lynch, Ashley, Aleven, & Pinkwart, 2008), elaborated feedback as part of assessment tasks (Pechenizkiy, Calders, Vasilyeva, & De Bra, 2008), delayed feedback (Feng, Beck, & Heffernan, 2009), and process modelling (Pechenizkiy, Trcka, Vasilyeva, van der Aalst, & De Bra, 2009). This strand of EDM work includes the forward-oriented efforts for building an understanding of how such models can be enhanced to instrumentalize feedback mechanisms for informing future systems. In other words, algorithms could potentially provide the know-how to influence the design of new systems that provide better feedback. For instance, Barker-Plummer, Cox, and Dale (2009) suggested a need to move beyond the provision of better algorithms and understand how task-level feedback is influenced by the epistemic and pedagogical situation. In other words, the feedback at the level of learning process, or information about self-regulation skills, can help frame feedback at the task level.

A large portion of the studies related to adaptive feedback have been developed through intelligent tutoring systems (ITSs; e.g., Abbas & Sawamura, 2009; Eagle & Barnes, 2013; Feng et al., 2009), learning management systems (LMS; e.g., Dominguez, Yacef, & Curran, 2010; Lynch et al., 2008; Pechenizkiy et al., 2008), or equivalent single-user systems that provide a set of learning tasks to students in specific knowledge domains. Most of these systems capture student models in different ways: from traces of student behaviour, knowledge, achievement, cognitive states, or affective states for example. Based on these models, the system commonly offers various types of task-level feedback, such as next-step hints (e.g., Peddycord, Hicks, & Barnes, 2014); correctness hints, also known as flag feedback (Barker-Plummer, Cox, & Dale, 2011); positive or encouraging hints (Stefanescu, Rus, & Graesser, 2014); recommendations on next steps or tasks (Ben-Naim, Bain, & Marcus, 2009); or various combinations of the above. Hence, studies into behaviour modelling have been integral for developing automated feedback processes in EDM research (DeFalco, Baker, & D'Mello, 2014).

In recent years, EDM work in student modelling has been enriched by the emergence of new methods allowing researchers to generate feedback mechanisms for less structured learning tasks. An example includes the provision of formative and summative feedback on student writing (Allen & McNamara, 2015; Crossley, Kyle, McNamara, & Allen, 2014). The emergence of more sophisticated sensing devices and predictive algorithms has allowed the enhancement of student models by including traces of more complex human dimensions such as confidence, attitude, personality, motivation (Ezen-Can & Boyer, 2015), and affect (Fancsali, 2014). These more nuanced data aid the development of better responsive adaptive feedback mechanisms that can be personalized for each student. In parallel with the sophistication of student models, some researchers explored the notion of open learner modelling (OLM; Bull & Kay, 2016). The notion of OLM is similar to that of visual data representations but applied to the model built by a tool. OLMs originated within the AIED community in pursuit of providing less prescriptive forms of feedback compared with recommendations, corrective actions, or next-step hints. OLMs have gained renovated interest, as they allow the user (learner, teacher, peers, et cetera) to view and reflect on (or even scrutinize) the content of the learner model presented in human understandable forms. One of the advantages of these models is to help learners reflect and encourage self-regulating skills.

Recently, scaling up feedback gained traction in scholarly EDM work due to the increasing popularity of massive open online courses (MOOCs; Wen, Yang, & Rosé, 2014). Besides providing personalized feedback for student work in MOOCs (Pardos, Bergner, Seaton, & Pritchard, 2013), there is an interest in generating mechanisms to enable fair access to high-quality feedback in large cohorts. Some feedback solutions are addressing complex, open-ended learning tasks, building upon peer feedback (Piech et al., 2013) or through the provision of video-based feedback (Ostrow & Heffernan, 2014).

Although there has been a major emphasis in EDM to provide task-level, real-time feedback to students, other approaches have also been explored. For example, some efforts have focused on providing delayed feedback to avoid interruptions in students' learning processes (Feng et al., 2009; Johnson & Zaïane, 2012). There has also been interest in EDM to go beyond "corrective" feedback and understand the role that the polarity (positive, negative, or combined feedback) and the timing of feedback can play in students' dialogue (Ezen-Can & Boyer, 2013), in confidence (Lang, Heffernan, Ostrow, & Wang, 2015), or in collaborative scenarios (Olsen, Aleven, & Rummel, 2015). Providing feedback systematically targeting different levels of student activity is yet to receive due attention, though some examples have been offered. For instance, in Arroyo et al. (2010) digital learning companions acted as peers that provided feedback at cognitive (hints), affective (e.g., praise), and metacognitive levels (e.g., showing progress). The cognitive level, or the provision of hints, was offered at the task level. Showing progress addressed the capacity of self-reflection (i.e., monitor progress towards a goal). Other examples of feedback addressing regulation of learning have focused on supporting SRL behaviour and self-assessment (Bouchet, Azevedo, Kinnebrew, & Biswas, 2012); scaffolding high-level students strategies (Eagle & Barnes, 2014); recommending strategies of knowledge construction (Kinnebrew & Biswas, 2012); and understanding how feedback sits in students' learning processes (Howard, Johnson, & Neitzel, 2010).

Approaches to Feedback in Learning Analytics

Within the research in LA, a focus on feedback is generally interpreted as the need to communicate a student's state of learning to various stakeholders, i.e., teachers, students, or administrators. Early LA research (e.g., LAK 2011 and 2012 conference proceedings) did not focus on feedback per se, but emphasized LA as a discipline that needed to close the loop via scalable feedback processes (Clow, 2012; Lonn, Aguilar, & Teasley, 2013) to produce "actionable intelligence" (McKay, Miller, & Tritz, 2012). LA research recognized that feedback is conveyed through a multitude of disciplinary voices to humans with varying understandings of the agency and nature of learning (Suthers & Verbert, 2013). In line with that, Wise (2014) urged the design of data-driven learning interventions with awareness of how they are situated in their respective sociocultural contexts, and with the specific aim of addressing student support. Due to the significance of the context, perception and interpretation of data-supported feedback has been a distinct theme within LA feedback-related research. The LA community has searched for evidence and practices to ensure that the dialogue between the analytics and the stakeholders is taking place as imagined by the researchers. For instance, Corrin and de Barba (2015) inquired into student perceptions of dashboards; Beheshitha, Hatala, Gašević, and Joksimović (2016) examined if students with different achievement goal orientations perceived dashboard feedback in the same way; and a few studies investigated ways of making generated research more meaningful by combining qualitative interviews or the work of human interpreters with the data-driven analyses (Arnold, Lonn, & Pistilli, 2014; Clow, 2014; Mendiburo, Sulcer, & Hasselbring, 2014; Pardo, Ellis, & Calvo, 2015). The exposure of learners to some form of summary or indicators of their activity cannot be connected with a concrete level of feedback in the taxonomy proposed by Hattie and Timperley (2007). However, dashboards usually contain task level information, as inferring information about the learning process or self-regulation skills is much more challenging.

Similar to EDM, the interest of the LA community is in the provision of automated, scaled and real-time feedback to learners for self-monitoring and self-regulation processes, the third level in the taxonomy proposed by Hattie and Timperley (2007). Such direction has been well-captured through a steady growth of LA applications as tools for visualization, reflection, and awareness (e.g.,Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Verbert et al., 2014). Although specific task-level feedback is of less prominence than in EDM/ITS approaches, LA emphasizes more of the human-agency involved in interpreting and acting upon feedback. LA tends to promote process-level feedback by visualizing traces of learning activities. For instance, learning dashboards capture data sources, such as time spent, resources used, or social interaction, to enable learners to define goals and track progress towards these goals (for further review see Verbert et al., 2014). Recent applications of learning dashboards are shifting from the count of time or use of learning-related objects to visualizing progress related to a conceptualized process, e.g., table-top visualizations for inquiry-based learning (Charleer, Klerkx, & Duval, 2015), or visualizations of learning paths within competence graphs (Kickmeier-Rust, Steiner, & Dietrich, 2015). Visualizations informed by social network analysis (Dawson, 2010; Dawson, Bakharia, & Heathcote, 2010), as a part of social learning analytics (e.g., Ferguson & Buckingham Shum, 2012), remain a popular type of feedback on the social interaction process. These have been recently extended to help learners reflect on who they talk to, or where they are positioned in learner networks "in the wild," i.e., in distributed social media, such as Twitter or Facebook, and beyond the LMS (e.g., Bakharia, Kitto, Pardo, Gašević, & Dawson, 2016). Such network visualizations have also been offered to groups as representations of collective knowledge construction.

Feedback aimed towards developing student self-regulated learning proficiency is in its infancy. A promising approach to formative feedback embraces the *self* and various aspects of the learning process to support the development of resilient learner agency (Deakin Crick, Huang, Ahmed Shafi, & Goldspink, 2015). Another recent development includes the provision of feedback to students about their affective states. Grawemeyer et al. (2016) noted that students receiving affect-aware feedback were less bored and more consistently on-task than a comparative peer group receiving feedback only related to their performance. In essence, the authors demonstrate that the automated provision of feedback relating to a student's affective state can aid engagement and on-task behaviour. Ruiz et al. (2016) developed a visual dashboard providing visual feedback about student emotions and their evolution throughout the course. In this instance, the authors used the provision of self-reported emotional states as a source of self-reflection to improve performance and course designs. However, these studies also demonstrate that any noted success appears to be largely dependent on the learners' competence to self-regulate using the feedback from such learning analytics applications. Less reliance on the assumed level of students' competence is found when learning design or technology affordances prompt learner reflection. That is, learner thinking is externalized through writing text or annotations (also in-video), and formative feedback to this written text may then be offered.

The provision of feedback on written text, beyond essay grading, has been tackled by various initiatives in the area of discourse-centred analytics (De Liddo, Buckingham Shum, & Quinto, 2011). Also referred to as writing analytics, this area has a strong presence across the LA/EDM communities, with a significant overlap between methods for automatic text analysis, discourse analysis, and computational linguistics used to identify written text indicative of learning or knowledge construction (e.g., Simsek, Shum, De Liddo, Ferguson, & Sándor, 2014). In short, discourse-centred analytics offers feedback regarding the quality of cognitive engagement, or specifically assisting with aspects of writing as a domain skill, e.g., the quality of insight, genre, and so on (e.g., Crossley, Allen, Snow, & McNamara, 2015; Snow, Allen, Jacovina, Perret, & McNamara, 2015; Whitelock, Twiner, Richardson, Field, & Pulman, 2015). A noteworthy emergent trend within LA research emphasizes analysis of reflective writing (Buckingham Shum et al., 2016; Gibson & Kitto, 2015) offering formative feedback on learner's competency to reflect, potentially deepening individual engagement with both the content and process of learning.

CONCLUSION

This chapter has positioned one of the most influential aspects in the quality of the student learning experience, feedback, within the current research space of the EDM and LA communities. Despite the direct link between feedback and personalized learning, there are still significant gaps to be addressed. A dearth of research explores how students interact with and are transformed by algorithm-produced feedback. Furthermore, the relationship between the type of interventions that can be derived from data analysis and adequate forms of feedback remains inadequately explored. There is substantial literature analyzing the effect of feedback in learning experiences, but the area needs to be revisited with comprehensive data sets derived from technology mediation in learning experiences. In conventional face-to-face and blended learning scenarios, the increase in workload and limited instructor time are affecting the quality of feedback received by students. New emerging scenarios such as MOOCs pose significant challenges in providing high quality feedback to large student cohorts. LA and EDM are exploring how to address these limitations and propose new paradigms in which feedback is both scalable and effective. Although the initiatives in both communities have a strong connection with feedback, they differ in the areas of focal interest within which each discipline is devising its solutions. These foci are complementary, and often build upon each other. Consequently, both disciplines can benefit from a more comprehensive view of the role that feedback plays in a generic learning scenario, the elements involved, and the ultimate goal of prompting changes in the students' knowledge, beliefs, and attitudes. Practitioners from both research communities could well benefit from adopting a more comprehensive framework for feedback that supports a more effective integration across disciplines as well as the combination of humans and technology.

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