EMERGING TECHNOLOGIES

SCALING UP AND ZOOMING IN: BIG DATA AND PERSONALIZATION IN LANGUAGE LEARNING

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APA Citation: Godwin-Jones, R. (2017). Scaling up and zooming in: Big data and personalization in language learning. *Language Learning & Technology*, *21*(1), 4–15. Retrieved from http://llt.msu.edu/issues/february2017/emerging.pdf

INTRODUCTION

From its earliest days, practitioners of computer-assisted language learning (CALL) have collected data from computer-mediated learning environments. Indeed, that has been a central aspect of the field from the beginning. Usage logs provided valuable insights into how systems were used and how effective they were for language learning. That information could be analyzed to improve instructional design and delivery. Maintaining learning histories and personal profiles of individual learners enabled a program to adapt the delivery of learning materials to the record of student performance. Given a limited number of users working within a single system, the data generated could be collected and analyzed easily, using simple methods and tools such as spreadsheets and basic data models. The situation today is quite different from that scenario. Learners are likely to be using multiple online tools and services, all of which may be recording data. That includes general use software and services such as Facebook and Google, as well as mobile devices. If they are university students, they are likely to be generating data points through a learning management system (LMS) as well as from other university-level systems. The vast amount of information collected today from our use of online tools and services provides a huge storehouse of information that can be mined to provide both general usage trends and individualized reports. This *big data* offers valuable teaching and learning insights. In this column, we will be looking at what this may mean in language learning. That will include discussion of the emerging field of learning analytics, the use of learner models, and the opportunities afforded by data tracking for personalized learning.

LEARNING ANALYTICS

As Cope and Kalantzis (2016) point out, capturing and analyzing data in computer-mediated learning environments is nothing new. What has changed in the last decade is the immense volume of data generated and collected—some purposely, others incidentally. Some of that data is structured and intended for data analysis, for example, if it comes from an LMS or from an intelligent language tutor. Other data is unstructured, for example, if it comes from texts in blog posts or input from sensors on mobile devices. All of that data is coming in a continuous stream, as digital devices have become ubiquitous human companions. The flood of data offers new opportunities in a variety of areas, from tracking consumer preferences and trends in business and commerce (*business intelligence*) to providing early alerts about at-risk students (*educational data mining*). The volume and variety of data necessitates the use of data management and analysis tools well beyond Excel. The R programming language is used in many fields, including linguistics, for statistical analysis and modeling. It is open source and offers add-on packages and plug-ins for functions such as text mining and work in natural language processing and sociolinguistics. For especially large data sets, the Hadoop software library (from Apache) is widely used, as it allows for distributed processing across clusters of computers. Given the importance of large-scale data analysis in many areas, there is a current boom in demand for *data talent* (Trifari, 2016).

In education, analytics is used to identify patterns among students using institutional software or digital services in order to gain insight into learning and administrative practices. That information can be used to both identify and seek to rectify problem areas in instructional design and delivery. On a system level, it may reveal curricular bottlenecks and make predictions in areas such as student retention or graduation rates. Generally in learning analytics, the emphasis has been on quantitative outcomes (such as quiz scores or course grades), not on the learning process. For example, alerts to at-risk students are typically administrative notifications, rather than tailored messages useful for improving academic performance; at most, they may offer recommendations for obvious behavioral changes in areas such as attendance or assignment completion.

In most universities in developed countries, much of the student learning data comes from an LMS. The LMS database tracks and records student use of the system. How fine-grained that data is depends on the particular platform but also on choices made by instructors on whether to initiate view tracking of particular elements of the course. Some of that data may be available to the student, but it is mostly designed for and used by instructors and administrators. Most LMSs have their own built-in data tracking and data visualization tools. In other cases, a third-party tool may be used. At Purdue University, for example, Course Signals (originally developed at Purdue) is used to collect data from the LMS (Blackboard) and the administrative computing systems. All students are placed in a *risk group* determined by a predictive academic success algorithm. Course Signals uses a stoplight system, with groups categorized as red, yellow, or green corresponding to the level of risk. Students and instructors are able to see a graphical representation of the current and historical state of a learner or a course through a dashboard visualization.

IMPROVING THE USEFULNESS OF LEARNING ANALYTICS

Verbert, Duval, Klerkx, Govaerts, and José (2013) provide a meta-analysis of 15 different learning analytics dashboards. They conclude that almost all the implementations are designed primarily for instructors and administrators. The study offers suggestions for improving learning analytics' usefulness to students, including adding more detailed analyses of learning activities and providing additional visualizations targeted specifically to students. The authors point out that there have been few studies analyzing the real impact of learning analytics on improving teaching or learning. Link and Li (2015) give examples of the Performance Dashboard used in Blackboard—in their case, for an English writing course. The authors suggest a research agenda for the use of learning analytics aligned with principles of second language acquisition. They lay out a recommended research agenda on learning analytics, which includes analysis of the use of learning analytics in classroom environments; longitudinal studies; and, crucially, empirical studies on what kinds of collected data are shown to be useful in improving language learning.

Learning analytics dashboards generally provide data on a single learning environment, most commonly an LMS. As such, they give an incomplete picture of student learning, in that students may be using additional online or physical resources which supplement the formal learning environment, whether the course be online or face-to-face. In that sense, learning analytics, as currently used, may provide a distorted view of learning behaviors. Furthermore, as Nic Giolla Mhichíl, van Engen, Ó Ciardúbháin, Ó Cléircín, and Appel (2014) point out, there is the potential for students to forego use of learning resources not reflected in their dashboard, thus inhibiting learner agency. There is the possibility that the learning analytics dashboard will highlight activities that are incidental to actual student learning, such as the frequency of log-ins to an LMS, providing to students a false sense of what matters in learning.

One of the difficulties that learning analysis dashboards have in more fully reflecting the extent of student learning activities is the difficulty in obtaining and aggregating data from other sources, whether that be other online learning services or social media platforms. Some resources may make available methods to send or export data, such as public APIs (Application Program Interfaces), but that shared data may not come in a format readily usable by the learning analytics tool. This problem of sharing and interoperability involves both technical difficulties (what data structure to transmit) and ethical or privacy issues. Consumers are understandably leery of their individual online data being tracked and shared, and learners are likely to have similar concerns (see Drachsler & Greller, 2016).

On the technical side, there are several initiatives underway to provide a standard way to record and send evidence and results of online actions and activities. There are official (ISO, W3C) standards for data exchange, such as SDMX (Statistical Data and Metadata eXchange) encoding and the Data Cube Vocabulary, which is a web standard for linking related data sets and content using RDF (Resource Description Framework). Berners-Lee, the director of W3C, has promoted the framework of Linked Data, the use of standard web technologies such as HTTP and RDF to enable webpages to share information which is machine readable. Linked Open Data refers to freely available data sets, such as those from DBpedia, a dataset containing data extracted from Wikipedia articles, or GeoNames, which provides descriptions of geographical features worldwide. The experienceAPI (also known as TinCan or xAPI), originally developed as a replacement for SCORM (Sharable Content Object Reference Model), provides a way to describe online activities through a deceptively simple schema of *subject-verb-action*, familiar from the concept of triplets in RDF and in other methods for describing data structures. It is being used principally in business and commercial transactions. However, we are starting to see its use in educational environments, including in learning analytics (Kitto et al., 2016). An emerging standard likely to be supported widely in education is the Caliber framework from IMS Global, as it has been developed with extensive participation by universities. It builds on the very successful LTI standard. Caliber can be implemented in a variety of ways, but its basic functionality is launched by linking to the SensorAPI JavaScript implementation in a webpage's HTML and providing parameters for the events to be recorded.

OPEN LEARNER MODELS

The Caliber framework is likely to be used primarily institutionally, at least initially, to aggregate data from sources beyond the LMS. Some of that aggregation is happening currently through the widespread adoption of the LTI standard, which allows third-party tools and services to send data reports to an LMS (or to other software). In that way, the LMS is able to build a kind of learner model—that is, a profile of an individual learner which provides information on current and past learning experiences. In the typical LMS, that learner model is likely to be limited to what is contained in the electronic gradebook in tabular form, with grades from scored activities (e.g., quiz data, test scores, third-party tool data) and status updates on assignment completion. Drilling down on the items may provide specifics about the score (e.g., items answered correctly, number of attempts, etc.) as well as statistics on the student score compared to the class as a whole. Some LMSs have more flexibility in extending the learner model to include more categories of information. That is particularly the case for Moodle, with its widely used plugin architecture. Tongchai (2016) provides an example of customizing Moodle to create a more comprehensive learner model.

The concept of a learner model is familiar in CALL, as it relates to intelligent language tutors (ILTs) which incorporate a sophisticated and fine-grained learner model to track student performance. This learner model is quite different from that in an LMS, in that it assesses student activities as compared to knowledge in a specific domain—in an ILT, a language or aspects of a language. An ILT will therefore include a knowledge model that is used to analyze actions of the user, for example, parsing utterances in order to provide feedback. Each action taken by the user is recorded and the learner model is correspondingly updated. The system uses that data to determine the sequencing of learning materials supplied to the user. ILTs such as E-Tutor provide a means for the user to access the learner model so as to see the status of progress within the system (Heift, 2008). How much information is provided, and how, varies with the system.

The learner model in an ILT normally reflects student performance only within that system. Like the learner model in an LMS, the data remains in the system, often in a non-standard, proprietary format. The learner model is open in that it is viewable to the user, but it is not visible outside the system or generally exportable. In contrast, an independent learner model is not tied to any one particular system and is intended to serve as an aggregator and repository of learning data from multiple sources. Such learner models are different from those in an ILT in that they are “framed around the learning resources, not a model of the knowledge or skills of the learner” (Bull & Kay, 2016, p. 308). An independent learner model may be associated with a specific course or particular program, or may be generated by an individual learner. Most likely, the use of an independent learner model will begin in an institutional setting, but with the goal of having the learner continue its use beyond the institution. This is the case with a system used in Europe, the Next-TELL project (Next generation Teaching, Education, and Learning for Life). The principal goal of Next-TELL and similar systems is to provide useful metacognitive information to the learner, to aid in reflection, planning, and self-monitoring (Bull & Kay, 2016). The system can receive, through its own API, data automatically sent, and can also include manually entered information, as appropriate, from a teacher or from the student. Data from social media, such as Facebook posts, can be included as well. The learner model can be displayed to the user in multiple ways, including a tree map, concept map, or a tag cloud. A recent study (Bull & Wasson, 2016) illustrates a variety of such visualizations in the service of language learning. The authors point to the advantage of systems in which students are able to choose the kind of visualization they prefer. That preference might depend on the context. A tree map display, for example, may work best for mobile devices, as it manages display on a small screen well by displaying initially a broad overview, with detailed information available with a click or touch.

Some independent learner models take a step further in empowering learners by making the learner model not only accessible to the student, but negotiable as well. LEA’s Box (Learner Analysis toolbox), which builds on the Next-TELL platform, allows users to make changes to their profiles not only by adding additional data streams, but also by revising some of the evaluative statements. They may, for instance, supply evidence of a higher level of knowledge in a particular area than is indicated in the learner model. The updating capability allows for the potential revision of an individual learner model to reflect learning from informal or alternative sources. For some systems, a machine intelligence is built in and allows negotiations with the user. That may entail a level descriptor being challenged by the student, and in dialogue with the system, having that claim be accepted or denied. In this way, there is evidence of a more objectively established record of achievement than may be the case in self-evaluations. Open and independent learner models offer a further benefit to learners: the ability to share their learning experiences with their peers—something difficult to do within an LMS or in an ILT. This allows for reflection and discussion of learning strategies and resources. In one project reported in Bull (2016), a Facebook group was set up expressly to encourage discussion of learner models. Bull and Kay (2016) provide a framework for evaluating open learner models, as well as a comparative summary of the most widely-used systems. The authors also describe a means for integrating data from online games, envisioning a situation in which game play is paused at suitable points to encourage noticing and reflection on language use.

LEARNER MODELS AND LANGUAGE LEARNING

Open learner models have been used in language learning for some time. As discussed above, ILTs such as E-Tutor incorporate a student model, accessed in that system via a Report Manager. In addition to E-Tutor’s Heift (Simon-Fraser University), another prominent researcher in the area of intelligent tutors is Bull from the University of Birmingham. Her work goes back to the 1990s and Mr. Collins, an online tutoring system for Portuguese (Bull, Pain, & Brna, 1995). That implementation uses a very restricted domain, namely the placement of clitic pronouns in Portuguese. The learner model there is of interest in that it supplements the record of past student performance by including language learning strategies and students’ knowledge of other foreign languages. A principal goal of Mr. Collins is to raise the language awareness of the student. Students are encouraged to frequently consult the learner model, which provides analogies and indicators of possible transfers from other languages (especially from Spanish) among other features. There is also some limited ability for the learner to negotiate with the system in cases where the learner disagrees with the contents of the model. As in other open learner models, the inspection and negotiation in Mr. Collins occurs through a menu selection, rather than through chatbots or other forms of interaction. The creators of Mr. Collins describe it as a “learning companion system,” in that it seeks to create a collaborative model (Bull et al., 1995, p. 65).

In Mr. Collins, student responses are often accompanied by students being asked to provide their degree of confidence in the correctness of their answers. This information is used to contribute to the student belief model in the system and in providing feedback and offering repair strategies. Mr. Collins is typical of open learner models in that the emphasis is on the learning process and therefore on formative assessment, with the end goal of encouraging learner autonomy. A simple implementation of this approach is the OLMlets project (see this YouTube video) discussed in Bull and Kay (2013), which proved to be effective in student knowledge in the area of metacognition. Another example of an independent learner model designed to prompt metacognition is the NoticeOLM, specifically designed to encourage students to notice language features (Bull & Kay, 2013). The system uses highlighting techniques to draw attention to grammatical elements. The system was found to be effective with adult second-language learners of English. Such systems typically use skill meters to compare their performance and knowledge to the expert model as well as to other peers. A simple model is the OLM LA (Open Language Model for Language Awareness) used for Chinese learners of advanced English (Xu & Bull, 2010).

The encouragement to share findings in learner models, an important feature of the systems discussed above, is also central to the SCROLL project (Sharing Student Learning Logs; Mouri & Ogata, 2015). The project involves students of Japanese as a second language using smartphones for learning vocabulary. Students create log entries, optionally accompanied by photos, upon encountering culturally significant expressions going about their day-to-day lives in Japan. The log entries are automatically tagged as to time and place. The system uses the open source data visualization widgets SIMILE to create *time-maps* and other visualizations which allow users on Google Maps to see the location of the log entries as well as those generated by other students at that location. This collaborative approach signals to users the salience of particular expressions, given the density of log entries. The timestamps provide the ability to connect use of the expression to particular times, such as days of the week or time of the day. The linking of vocabulary learning to a particular time and place likely helps the mnemonic process, providing also an opportunity for recall and reflection individually or in groups.

PERSONALIZED LEARNING THROUGH DATA

Creating personal profiles or learner models can enable filtering of content so as to direct learners to resources likely to be most appropriate for their proficiency levels, learning goals, and content preferences. This can be enabled in different ways, including in formal learning environments, as discussed above. Another possibility is the use of recommendation systems, which draw on individual profiles to offer suggested learning materials, in effect acting as personalized information agents. Given the information overload of the Internet today, such systems are being widely deployed**.** Music, book, and movie sellers such as Apple, Amazon, and Netflix have recommendation systems based on previous consumer choices, the user’s ratings of purchased or viewed items, and ratings from other consumers. Sunil and Saini (2013) provide a meta-analysis of 10 recommendation systems used in education.

A recommendation system for selecting appropriate reading materials for ESL students uses learner-created profiles, surveys of student interest, and results from proficiency testing to analyze content preferences, assess vocabulary knowledge, and determine reading ability (Hsu, Hwang, & Chang, 2013). Students are able to add their own annotations to reading materials and can see the annotations made by other students to that reading. The trial group using the student-adaptive activities scored higher in reading comprehension exams. It is likely that student motivation was enhanced though the personalization process. Nikiforovs and Bledaite (2012) developed a recommendation system for vocabulary development that relies on users supplying a list of texts read (from a selective list) and on an assessment of users' reading proficiency level. The system hosts a large number of texts which were analyzed in terms of syntactical complexity and reading difficulty. Users are given sequential recommendations which are designed to combine likely known vocabulary with a subset of new expressions. For those working on their own, there are online tools and services available which analyze texts to provide guidance as to the appropriateness for their needs and preferences. Text Analyzer is a service which measures lexical density in several languages. Readability Scores uses several different readability algorithms to assess reading difficulty. Such tools help users select from the vast array of texts on the web today. On-the-fly translation and annotation tools and services such as Globefish Instant Translator help make texts accessible to language learners.

An option for learners to track appropriate learning materials is to create a repository of linked resources. This can be managed as simply as adding links to a social bookmarking service such as Diigo, in which resources can be categorized and annotated as desired. Alternatively, resources can be aggregated in a note-taking service such as Evernote, a folder-based system such as LiveBinders, a board pinning system such as Pinterest, or a web curation tool such as ScoopIt. A more individualized approach is the creation of a customizable web page. A page which aggregates online resources an individual finds useful for learning is often referred to as a personal learning environment (PLE). PLEs became popular as widgets proliferated, about a decade ago, (see Godwin-Jones, 2009). Widgets have largely been replaced by mobile apps, however a PLE used as a means to maintain, organize, and share valued resources remains. Case (2015) examines the concept of PLEs in the context of a total language learning environment, both online and physical, while Pegrum (2014) and García-Peñalvo and Conde (2015) highlight the use of PLEs in mobile learning environments. Laakkonen (2011) describes a PLE project in which the creation of the PLE begins in the classroom setting under a teacher's guidance, before becoming an independent resource designed for lifelong learning. It may be useful to have learners begin creating a PLE with the help of a teacher, as there is some evidence that students find creation and use of PLEs initially confusing (Case, 2015). It may also be, as Yu asserts (2015), that students accustomed to teacher-centered learning environments need more help and encouragement in creating and working with a resource that is based on the concept of independent learning.

Resources incorporated into a PLE can be added manually or automatically through subscription, syndication, or other mechanisms which identify semantically tagged resources corresponding to the user's preferences. While the concept of the semantic web (semantically tagged materials based on commonly accepted taxonomies) has not fulfilled its lofty goals (self-organized online data), aspects of that vision have been implemented. Examples include the use of RDF to semantically tagged content, the implementation of controlled vocabularies in projects such as Merlot and Ariadne, and the widespread consumer acceptance of folksonomies used in social media such as Flickr (Devedzic, 2016). The idea of a Personal API is in some ways a successor to the idea of the semantic web, namely using publicly available APIs such as those from Google or Facebook to automatically populate a personal webpage (Flanagan, 2015). The APIs provide access to the rich data collected through the Knowledge Graph, for Google, and through the Open Graph Protocol, for Facebook. The ProgrammableWeb tracks APIs in categories that include translation and language learning. Halimi, Seridi-Bouchelaghema, and Faron-Zucker (2014) describe an *enhanced PLE* that mines the social web for appropriate resources. The SoLearn system discussed in the article uses the concept of a semantically tagged recommendation system (based on the user's tagging history) and the analysis of social media posts. It also includes peer learner information, such as most active learners (in terms of posting frequency) and peers ranked as most reliable (according to ratings). Given the major role social networks play in learning today, it makes little sense to build a PLE that does not incorporate social media in some way.

Adding data from social media is possible in a variety of ways. The Tapor project hosts an annotated list of social media analysis tools**.** A widget from Twitter creates an embedded timeline of tweets to a webpage while a RSS and JavaScript app such as FeedtoJS incorporates blog posts. The Semantically Interlinked Online Community initiative (SIOC) aims to enable integration of social media by providing an ontology for representing rich data from social media in RDF. The standard has been submitted to the W3C. An interesting developing W3C standard is WebRTC. This is an API that enables web browsers to embed applications for communication such as voice calling, video chat, and file sharing. This could make a PLE into a communication hub, moving beyond static content and a set of links. If a learner's aim is to create an online record of achievement, rather than a one-stop learning center, a more appropriate vehicle then a PLE is an online portfolio. A recent report on the use of the electronic version of the European Language Portfolio points to potential benefits (Mira-Giménez, 2017). Some of the same tools discussed above in the context of PLEs could be used here as well. In addition to chronicling social media activity, evidence of learning achievements could be included, such as a badges or MOOC certificates. The popular video-based learning platform, Khan Academy, awards badges for mastery. We are also beginning to see interest in the concept of digital badges in language learning.

CONCLUSION AND OUTLOOK

Big data and learning analytics hold immense potential for enhancing language learning in multiple ways. Vast text collections in multiple languages processed through artificial intelligence and machine learning have tremendously enhanced the effectiveness of machine translators such as Google Translate (Lewis-Kraus, 2016). The same is possible for the usefulness of smart language tutors through the growth of learner corpora and improvements in natural language processing. The more data that become available on user behavior and learning effectiveness, the better predictive models can be built into ILTs and other online learning environments and the more helpful the hints and feedback can be (Heift, 2008). Cope and Kalantzis (2016) assert that "big data can simultaneously support N = 1 and N = all" (p. 9). The idea that the same data can give us both the big picture and detailed information is familiar from the use of Google Maps. The data that helps researchers and instructors gain insights into group performance also enables continuous re-calibration of learning materials to individual learners.

It used to be that the functionality of an intelligent language tutor was hampered by limited storage capacity and slow processing. Today, cloud storage is increasingly inexpensive, while services from Amazon, Microsoft, and others make distributed processing increasingly powerful and practical. Massive data collection and analysis can help improve educational practices in a variety of areas. Mining data collected from different LMS sites can provide evidence for the most effective site designs for different disciplines (Fritz, 2016). This holds true for MOOCs (Massive Online Open Courses) as well, the phenomenon which was largely responsible for the recent burst of interest in learning analytics. Recent research in this area has included development of third-party methods and tools for assessing learning performance in MOOCs, which aggregate data beyond what is normally available within the system and enable different kinds of queries into that data (Cook, Kay, & Kummerfeld, 2015; Pardos & Kao, 2015).

Learning analytics holds the potential not only to improve instructional tools and approaches, but also to benefit research methods and outcomes, informing both second language acquisition theory and CALL practice. The Promacolt project demonstrates how learning analytics can be used to go beyond setting initial parameters in language learning training, through adjusting delivery continuously in response to user performance, as indicated by learning analytics (García, 2011). Cornillie, Van Den Noortgate, Van den Branden and Desmet (this issue) show how revelatory it is to track learner data across environments, incorporating both formal and informal settings, especially mobile-use settings. New tools for analyzing text, such as those developed at UC-Irvine, provide new insights into areas such as collaborative writing (Yim & Warschauer, this issue).

In all fields, the availability of large data sets can lead to evidence-based questioning of accepted theories and practices:

> This is a world where massive amounts of data and applied mathematics replace every other tool that might be brought to bear. Out with every theory of human behavior, from linguistics to sociology. Forget taxonomy, ontology, and psychology. Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity. With enough data, the numbers speak for themselves. (Anderson, 2008, para. 7)

A particularly compelling potential research benefit is the sharing of data used in case studies and other forms of data-based scholarship. This enables research replication, longitudinal analyses, and re-analysis upon the emergence of new tools and approaches. A model in this regard is the DataShop from the Pittsburgh Science of Learning Center, which makes data collected publicly available from online courses and intelligent tutoring systems, including from online programs in ESL, Chinese, and French. The data are available in a standard XML format that can be processed using DataShop's analysis tools or researcher-preferred tools. The Center offers a myriad set of possible research topics using the data, from predicting student performance to testing models of metacognition. An easy way to share research data is demonstrated in White (2015), where data for the study of German in online communities are shared through Dropbox, a popular file hosting and sharing service.

Making analyzed learner data available to students allows individual progress tracking as well as comparisons of individual performance to class norms. Providing continuous feedback on student activities is likely to make students more aware of the learning process, possibly leading to more effective learning strategies. This can blur the line between instruction and assessment, while emphasizing the important role of formative assessment. For individual learners, snapshots from analytics dashboards can be saved and collected in online portfolios—potentially useful in future educational endeavors or professional pursuits. Given its growing importance for both students and learners, everyone in education is likely to need to become more knowledgeable about data analysis:

> To teach and learn in such environments requires new professional and pedagogical sensibilities. Everyone becomes to some extent a data analyst—learners using analytics to become increasingly self-aware of their own learning and teachers as they acquire a level of data literacy required to interpret a student's progress and calibrate their instruction (Cope & Kalantzis, 2016, p. 8).

It is likely that not everyone will be comfortable with the growing role of big data in education. Clearly, there are legitimate concerns over privacy and a lack of transparency in the collection and use of learner data. In spite of anonymization in reported research data, there may be parameters included that can lead to possible identification of individuals.

There is also the danger of overreliance on statistics, reducing the complex process of learning to a numbers game, thereby inviting positivistic and behavioristic responses. Language learning, in particular, is not a linear process—a view learning analytics may encourage. In a study of French Online from Carnegie-Mellon University (using DataShop), Youngs, Moss-Horwitz, and Snyder (2015) point out that some aspects of an online course such as vocabulary learning "might not necessarily show a statistically relevant improvement because each new lesson presents new vocabulary" (p. 349). The study demonstrates how data mining can provide useful information on student behaviors in online courses which affect learning. At the same time, the authors caution that observation of students should factor into the analysis as well, supplying potentially important contextual information. In language learning, relying exclusively on recorded data may distort the learning activities through a lack of consideration of the environment. This points to the continued usefulness of techniques such as eye tracking, keystroke recording, and other sensors (Link & Li, 2015). One of the recent improvements in open learner models is the ability to incorporate multimodal data. A project described by Bull and Kay (2016) used Kinect cameras and directional microphones to add voice recordings and videos of body language or gestures to recorded data in order to provide a fuller and more accurate account of interactions. In this case, students were working in small groups with touch-controlled surface computers. Similar projects are conceivable with tablets or smartphones. The dynamics of peer collaboration, happening face-to-face or virtually, may be a challenge in terms of data recording but could provide a representation of an important aspect of learning today in all fields.

An interesting initiative that uses all available sensors (including on wearable devices) to provide as full a picture as possible of an individual's activities online is the Quantified Self. A study by Rivera-Pelayo, Zacharias, Müller, and Braun (2012) outlines how Quantified Self approaches can support reflective learning. Tools and services adapted for use in that community, as well as those associated with the similar concept of personal informatics, could be usefully investigated for applications in language learning. At the same time, it is important to keep in mind that not all individual learning actions are trackable—face-to-face encounters, peer consultations, or reading, for example. Such actions come to light, not through data collection but through activities such as learner journals or interviews. A more complete picture of student learning may necessitate quantitative data being supplemented by qualitative methods, an important consideration to keep in mind when using big data sets in the service of teaching and learning.

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