Chapter 9
Moving Forward

9.1 Self-Learning and Learning Analytics

One of the key goals of education is to help students improve their own abilities to learn effectively. However, this is not an easy mission. Students have to acquire various skills to set targets, monitor their progress towards these objectives, correct performance if necessary, and analyze outcomes when concluding the next performance. You will need to find ways to move forward if you are confused or otherwise stalemate in the learning process. Understanding how to help students improve these skills was a central challenge for many researchers in education and learning psychology. These attempts were mainly found in self-regulated learning (SRL) (Panadero, 2017), which we term Self-Learning or Independent Learning.

9.1.1 Self-Regulated Learning Across Educational Environments

Self-regulated learning has a long history, and over the last two decades, it has become a major focus in education-psychology (Panadero, 2017). Self-regulated learning is characterized as "self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals," according to Zimmerman (Lodge, Panadero, Broadbent, & Barba, 2019). SRL models consistently demonstrated their significance and effect on student success and learning (Lodge et al., 2019). SRL has become more common in computer-based learning environments in recent years.

This development is also related to a wider discussion of how technology affects the learning process. There are many main explanations. Educational institutions at

S. K G, M. Kurni, *A Beginner's Guide to Learning Analytics*, Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-030-70258-8_9

all levels are under rising pressure to offer high-quality education to a growing number of students with greater effectiveness. The rapid speed of change in the world makes it difficult for students to prepare for their careers and live in a dynamic social and economic milieu. Students who complete formal education may expect retraining and/or change over their working lives, likely more than once. This continuous need for education led to introducing concepts such as the twenty-first-century skills that are transferable skills that underly lifelong education (Aspin, Chapman, Hatton, & Sawano, 2012).

Lodge et al. (2019) and others say that SRL is key to allowing students to manage this new reality. It is also clear that SRL has a role to play in seeking to understand complex issues. It is easy to be fooled without having sufficient ability to decide how much you do or do not do about a subject. Some claim that skill is a form of critical thinking or digital literacy (Miller & Bartlett, 2012). Whatever the mark, it is a matter that students increasingly need the capacity to learn, upgrade, and judge complex and structural concepts.

As we discussed, this is a challenge given the kind of digital environments in which students study. Importantly, all stages of education are becoming omnipresent interactive learning environments. Where once the word 'blended learning' has been used to describe a formal education system in which innovations are combined, almost all formal and informal learning can now be included in the phrase. This technological explosion causes some important side effects that have significant repercussions while considering SRL. These include increased criteria for self-directed students (Hoffman & Ritchie, 1997). Increasingly adaptive and personalized interactive learning environments enable students to participate in successful SRL (Greene, Moos, & Azevedo, 2011) and face obstacles as they learn, such as avoiding multifaceted or accessing social media temptations.

Another result of this is that teachers find it more difficult to track student development. When students engage more and more with interactive worlds, the contact between students and teachers decreases proportionately. Therefore, teachers who work in such environments have trouble deciding when intervention is appropriate (Arguel, Lockyer, Lipp, Lodge, & Kennedy, 2017). On the other hand, certain of these settings can evaluate students and recognize those who require intervention. Ever-expanding class sizes amplify this added complexity for teachers. Providing individual students with personalized intervention, as required, is an extremely challenging challenge for teachers in physical and virtual classrooms in the twenty-first century. A particular promise of learning analytics is the opportunity to encourage students to improve their SRL skills, free teachers to intervene more focused and complex.

When trying to understand the consequences of students spending time in different learning environments for SRL, it is helpful to consider student growth levels of granularity. It is reasonably straightforward to obtain a significant student accomplishment at the macro level by analyzing how they advance academically. In the sense of higher education, this reflects the successful completion of the subject/unit/module. Therefore, early use of Learning analytics focused on this macro-level analysis (e.g., Macfadyen & Dawson, 2010). While it is relatively easy to see signs that students will struggle at this level to self-regulate learning, it is difficult to decide why. Many factors may lead to students' success that cannot include their self-regulating ability in their studies.

On the other hand, it has been effective to evaluate how students participate in self-regulated small-scale lab-based observation studies at the microlevel. For example, Antonietti, Colombo, and Di Nuzzo (2015) researched self-regulation processes when performing a digital learning challenge involving various multimedia content mixtures. The laboratory-based environment in which this study took place permitted the collection of rich physio-logical, behavioral, and self-reporting data. Multiple SRL indicators are much easier to obtain in managed environments of this kind, a privilege that "in the wild" does not afford digital environments. Extensive work is also done by nStudy et gStudy (e.g., Perry & Winne, 2006) and by Azevedo, Johnson, Chauncey, and Graesser (2015) by Phil Winne. However, it is complex to translate data from laboratories like these into the real world to use education technology (Lodge & Horvath, 2017). A highly managed environment will help better understand how SRL students participate in digital and online learning, but it is unlikely that the SRL student can have clear answers.

Consequently, the interest and need to help SRL in digital environments is growing alongside an interest in understanding what these environments mean for SRL. Helping students navigate digital knowledge channels that are constantly ambiguous and contradictory is crucial to their long-term learning. More and more critically, students must develop cognitive task abilities that cannot be automated soon. Dealing with difficult, systemic information is not currently or possibly feasible for computers soon. However, dealing with such concepts requires an advanced SRL power. Together, educational researchers and educators must concentrate on improving SRL in digital settings, including how learning analytics can be used to support this imperative.

9.1.2 Learning Analytics for SRL

Learning analytics to support SRL usually has two elements: a calculation and a recommendation (Winne, 2017). The calculation, for example, a notation about presence, count, proportion, length, probability, is based on traces of acts performed during one or more episodes of analysis (Roll & Winne, 2015). A numerical report with or as visualization may be submitted. Examples may be a stacked bar chart showing relative proportions of highlights, tags, and notice produced during the analysis of each of several Web pages, timeframes marked with dots to indicate when specific traces were formed, and a node-link graph showing links among words in a glossary with heat map decorations showing how often each term was operated on while studying.

This aspect represents knowledge identifying COPES in the history of a student relationship directly or by the transformation. Table 9.1 displays illustrative trace data that could be mirrored.

A "simple" history of trace data mirrored back to a learner can be affected or contextualized by other information: features of materials such as length or a readability index, demographic data describing the learner (e.g., prior achievement,

Table 9.1 Analytics describing COPES facets in SRL (Winne, 2017)

S. No	COPES facet	Description
1.	Conditions	Presence/absence of a condition within a learning episode Onset/Offset along the timeline in a study or across a series of episodes
2.	Operations	Frequency of SMART operations (see Table 9.2) Sequence, pattern, conditional probability one SMART operation relative to others
3.	Product	Presence Completeness (for example, number of fields with the text entered in a note's schema) Quality
4.	Standard	Presence Precision Appropriateness
5.	Evaluation	Presence Validity

hours of extracurricular work, postal code), or other characterizations of leaners such as disposition to procrastinate, a degree in a social network (the number of people with whom this learner has exchanged information) or context for study (MOOC vs. face-to-face course delivery, opportunity to submit drafts for review by peers before handing in a final copy to be marked) (Table 9.2).

The second element of Learning analytics about SRL is a recommendation – what improvements can be made to learn and improve it. Three aspects of COPES can be managed directly by learners: operations, standards, and certain circumstances. Products are only indirectly controllable since their features rely on (1) circumstances under which learners, under particular information chosen for operations, may choose to vary; (2) what operations they choose to enforce in manipulating information. Evaluations are calculated by the match between product attributes and the basic criteria for certain items accepted by the learner. Recommendations on changing conditions, operations, or standards can be focused on results from mining data that are not influenced by theory, study findings in learning, and combination.

If a recommendation is given or not, changes in the student's conduct trace a student's assessment that (1) prior learning methods were not adequately productive or acceptable, and (2) the student expects that the recommendation or its adaptation would benefit from a shift. Learning analytics in this sense update external conditions previously and deliver new internal conditions. Together, there is a potential for intervention, but this is only for two reasons. Firstly, students should not know how to make a recommendation or how to do so. Second, they monitor their learning because students are agents.

Therefore, learning review provides students with the ability to practice SRL, but they choose what to do. This logic has a significant corollary. If a learning analytic is provided without a recommendation for intervention, there is an incentive for a learner to study alternatives beforehand and now choose to practice by themselves.

Table 9.2 SMART cognitive operations (Winne, 2017)

S. No.	SMART cognitive operation	Description	Sample traces
1.	Search	Directing attention to particular information	Opening successive bookmarks using a search tool
2.	Monitor	Comparing information presentations in terms of standards	Highlighting text (the information highlighted meets a standard, e.g., important)
3.	Assemble	Relating items of information	Tagging Assigning two bookmarks to a titled folder
4.	Rehearse	Maintaining or re-instating information in working memory	Reviewing a note Copying, then pasting
5.	Translate	Transforming the representation of information	Paraphrasing Describing a graph, equation, or diagram in words

In other words, encouragement and current learning tactics may be examined by omitting recommendations and guidance for action.

9.2 Life-Long Learning and Learning Analytics

Lifelong learning is a term that incorporates a wide range of learning formats and is generally considered as education throughout the lifetime (Kalz, 2015). Lifelong learning may occur outside an education institution (non-formal) or accidentally and not intended (informal) in the formal sense organized by an educational institution. Every purposeful learning activity carried out permanently to develop knowledge, talents, and abilities can be considered lifelong learning. Due to global demographics, environmental imperatives, the prevalent access to knowledge through digital technologies, and the pace of innovation in science and technology, lifelong learning is critical in the twenty-first century. As a result of these factors, there is a growing need to equip people with knowledge in educational institutions and train them to upgrade their knowledge, skills, and competencies and accept responsibility for learning throughout their lives.

The (Kalz, 2015) describes the elimination of obstacles to lifelong learning as a significant point of action to be addressed by R&D and society in general.

- Poor family learning culture
- Lack of funding for lifelong learning
- Learning providers not adapted to students' needs
- Inadequate information systems to draw learners to learning
- Distance from the provision of education

- Lack of facilities at home
- Belief that the benefits system discourages learning

Although educational institutions emphasizing supporting short episodes of learning have generally offered the learning technology, little attention was paid to supporting the diverse spectrum of environments, lives, and individual characteristics of learners. Koper and Tattersall (2004) argue that time frames and the episodic and multi-institutional character of lifelong learning have not historically been expressed in conventional technical learning.

In the area of technology-enhanced learning (TEL), in recent years, a range of research recommendations have been established that help solve today's challenges by lifelong learners. This segment explains the use of learning analytics for lifelong learning.

The modeling and understanding of learner behaviors and contexts are one of the challenges in the field of TEL. Since lifelong learners may constantly change their learning context, location, goals, learning environment, and learning technology, it is not easy and promising to consider the learner's current situation to personalize and adapt to the learning environment. A lifelong learner can start his or her day on a trip by reading a working textbook on his or her tablet computer, continue working on a particular problem in a professional social network and participate in an online master class on a subject he or she wants to develop expertise in the evening. These brief episodes of 1-day learning reflect a symbolic image of lifelong learning as a whole. Learners are interested in various learning environments, different learning formats, and various learning technologies. The study, design, and identification of the learner context have historically been approached from the perspective of adaptive hypermedia (AH) under the learner paradigm (Brusilovsky & Henze, 2007). Using an analysis of the student behaviors and contexts, algorithms have been developed to predict the learner's behavior, provide instructions for the learning process, or personalize the learning presentation. However, in this work, there is a major limitation. The processing and rationalization of data work well in closed environments, including a particular electronic learning environment (for example, a learning management system). However, the incorporation of data from various learning contexts, as presented above, poses limitations. This is the 'open corpus problem' (Brusilovsky & Henze, 2007). Open corpus AH operates not on a closed collection of resources identified at the time of design but on the premise that learning resources and the meaning of learning context continuously change and expand.

Several initiatives for lifelong learner modeling have been launched to resolve this problem and to enable customization. A learner model is a total of all the information that a software system has about a learner. This model is continuously updated during learning and should represent the current state of learners' knowledge. While conventional learner models were closed and used only by technological infrastructure, newly open learner models for learner use were suggested and evaluated. The user is presented with the current state of such a learner model and various ideas about the advantages and the administration of such an open learner model. Bull and Kay (2010) define autonomous open learner models as totally controlled by learners rather than system-controlled or cooperatively controlled learner models. This approach solves the customization barrier of technical lifelong learning and gives learners control over their digital representation in a learner model.

Kay (2008) goes one step further in this approach and aims to connect and integrate learner models from different contexts into long-term learning models that incorporate lifelong learners' multiple contexts. In addition to collecting and storing such data, she also proposes incorporating lifelong learner model representations into lifelong learners' work contexts. This direction is also discussed in a relatively young research topic in the field of TEL known as 'Learning Analytics' (Griffin, McGaw, & Care, 2012). Learning analytics take advantage of available broad datasets (in terms of learners, classes, actions, etc.) to provide input for various stakeholders (learner, instructor, organization) in the form of practical visualizations. Although many projects in the field remain within the conventional limits of educational segments or organizations, many authors advocate a more open approach to learning analytics that is potentially useful in the context of lifelong learning (Shum & Ferguson, 2012). Approaches that track and collect students' behaviors in various TEL environments have particular potential to allow students to link different learning contexts (Romero-Zaldivar, Pardo, Burgos, & Delgado Kloos, 2012). Therefore, open student models and learning analytics reflect new technical solutions that can help learners link their knowledge from their learning experiences in various learning environments and contexts and dismantle personalization obstacles to lifelong learning.

Today's research focuses on open learning models and learning analytics to improve understanding of the learning process itself and its impact on metacognition. On the other hand, the assessment contexts were chosen predominantly concentrate on schools' context, and the transition of outcomes to authentic lifelong learning contexts cannot be accomplished without limitations. A relatively high visual literacy level is a constraint for both methods discussed here to use the data representation supplied. Therefore, some problems in open learning models and learning analytics relate to promoting learners' visualization methods and data on learning activities.

9.2.1 Establishing a Lifelong Learning Environment Using IoT and Learning Analytics

Cheng and Liao (2012) jointly considered IoT (Internet of Things) and learning analytics techniques to evaluate students' learning process for lifelong learning support.

They used IOT and learning analytics techniques to build the environment ELLA (Environment for lifelong learning using learning analytics) that combines devices such as mobile devices, KIOSK, copy machine, RFID locker, Dom-air-conditioner, school bus, VOI, SMS, information service, web terminal, vacancy in the classroom,

classroom entrance, garage, student ID, electronic student ID, library, etc. Teachers may use these devices to teach their students, pick their teaching strategies, and provide different information and teaching contents according to the learning strategies.

The learning analytics system will collect IOTE data and provide the instructor with learning success and outcomes interpretation. The instructor will change the teaching methods and instructional practices and increase learning efficacy through the learning analytics framework's recommendations. Also, students could benefit from the learning analytics framework and improve their learning performance and quality.

As for learners, ELLA has the following features:

- In this environment, learners can access all their physical resources through their student ID or NFC cell phones.
- IOT technique has been used to store and evaluate all records of students' physical resource usage in schools in this environment.
- Learners can use mobile devices to access all kinds of resources and reviews and recommendations given by ELLA on the internet.
- Prior arrangements can be made before classes by pre-visual data generated by teachers.
- They can give teachers feedback and information and build learning activities on the internet at any time through mobile devices.
- They can use the mobile device to record the entire learning process and put them in LMS (including video recording).
- They can use mobile devices and the Internet to chat and video call online at any time with their classmates and teachers.
- They can engage in cooperative learning, debate, and exchange of experiences with their classmates.
- They can exchange information and share their records.
- The learning process will be saved permanently in LMS.
- They can monitor and examine all sorts of learning data in detail, including participation, conversations, practice, purchasing physical books, and even data copying and course material arrangements.

ELLA had the following characteristics for teachers:

- Teachers can access the physical tools they need to learn through their Instructor ID or NFC mobile phones.
- Teachers can upload or share all kinds of learning resources using a Mobile Device.
- They will collect feedback from students using mobile devices and engage in their study activities in ELLA, and give suggestions at any time.
- Teachers can always access students' real-time activities and historical learning records through ELLA.
- They can make online conversations and video calls with students at any time through the Internet.

- They will cooperatively learn, chat, and exchange experiences with students through this environment.
- Teachers can exchange information and documents with students.
- Their instructions will always be saved in LMS.
- All their teaching records, including discussion, guidance, copying of data, and the arrangement of contents, can be documented and examined in detail through this environment.

9.3 Present and Future Trends of Learning Analytics in the World

9.3.1 Trends that Influence Learning Analytics

Data has become an integral component of organizations in recent years. Trainers and L&D practitioners will use the power of Big Data to assess how well online training programs influence learners. The learning analytics market is primed for huge growth, with many developments shaping the future of learning analytics in organizations.

It would be correct to suggest that learning analytics can turn learning experience for students in an organization. The following trends (eThink, 2019; Katambur, 2020) influence learning analytics and add a new dimension to online training.

1. ***Personalized learning:*** The days when a one-size-fits-all training curriculum was administered to the students have gone. The emphasis is now on customized learning, with online education services designed for various students or classes. Learners in an organization should pursue their own course of learning at a comfortable rate. The quality and quantity of knowledge obtained from analytics offer insight into learners' preferences and learning styles. For instance, if learning analytics suggests that a student spends too much on a given portion of the e-learning course, videos, or links to additional material may enhance the student's understanding of the contents.
2. ***Cloud Analytics:*** More organizations can opt for cloud analytics as the data volume grows rapidly. With the growing security and efficiency of cloud computing, the use of data analytics with cloud computing increased. An LMS like Effectus, for example, can be installed on a cloud server, and the data monitored can be used for gaining insight into the status of online training programs. Cloud-based systems offer a flexible framework to store data and provide an efficient solution for data analytics.
3. ***Self-service analytics:*** Learning measurements are important in an organization to operate the L&D unit. Many organizations depend on LMS to determine the business effect of learning. However, according to a Bersin survey, 69% of organizations do not have analytical skills. Does this suggest that organizations must start employing more data scientists to make their data meaningful? Not at

all, since self-service analytics will help here. In order to make efficient use of self-service analytics and to make informed decisions, L&D practitioners and functional managers do not need to have IT or statistical context. Modern LMSs are well configured with dashboards and reports to reliably inform you about your organization's online training programs' status. Reports can be personalized with the support of an LMS vendor if appropriate.

4. ***Machine Learning:*** In learning analytics, there is a vast amount of training data that can be difficult to track and evaluate. For educational leaders to make the most of these data to understand and improve student learning, practitioners of learning analytics now aim to machine learning algorithms and approaches. Machine learning already influences many fields, including personalized learning, prediction of test results, risk determination of students, rise in graduation rates, and more. Learning analytics draws significant numbers now – all areas related to machine learning – from fields such as predictive modeling, statistics, and computer science. Therefore, integrating these two fields makes sense and is potentially the future of smart learning analytics.
5. ***Deep Learning:*** Deep learning is one development that will undoubtedly affect future years on learning analytics. With deep learning, data parameters are set such that the computer recognizes patterns after data runs across several processing layers. Deep learning algorithms are potentially one of the most useful methods for big data analytics. Deep learning is quite useful for the study of how people speak, read, and learn. Human intervention is not required because the machine can predict what learners know and do not know by reacting to tests and engaging with learning material. At present, the only thing not conducive to deep learning is that it is too costly.
6. ***Self-regulated learning:*** There are significant variables in self-regulated learning that could affect student progress. Why did one learner not successful in completing their learning activities while others succeed? To provide individual students with the best resources, the institutions need to consider certain variables, recognize trends, and resolve their educational design weaknesses before it is too late. By incorporating learning analytics, educational decision-makers may now evaluate student data from students enrolled in a course – be it online, in-class, or blended – to provide instructors and designers the knowledge they need to direct strategies for greater student retention and performance. Integration with key IT infrastructure, such as the institution's LMS, is important in providing seamless access to all applicable educational data.
7. ***Predictive analytics:*** Training programs are not limited to classrooms in an organization. The way corporate training is provided shifts from Massive Open Online Courses (MOOCs) to eLearning courses and enhanced reality. L&D managers are also required to answer questions like:

   - Will the online training program give a successful return on investment?
   - What training strategy fits best for each segment of the workforce (e.g., new hires, leadership teams, sales teams, etc.)?

Predictive analytics can be used to boost the participation and retention of learners. Predicting whether an employee can pass an online evaluation or whether their participation level can decrease will help trainers develop their training programs. Effective training programs were known to boost retention rates for workers. Predictive analytics are definitely useful to tailor training material to meet business goals.

8. ***Journey Analytics:*** Learning is no longer seen as a siloed process but as an interactive, interlinked experience in a learner's education career with an institution or organization. That is why learning analytics breaks down data silos and weaves together every point with which students interact. By linking learning data normally divided between different systems, leaders can now interpret and use this collective knowledge to improve the learner experience.

   Throughout their full academic lifetime, for example, the Blue Student Journey Analytics (SJA) solutions allow students to access an "always-on" listening platform, automated input collection processes, and decision support – ensuring that institutions have all the knowledge they need to see the whole picture. Many companies still collect a fraction of the potentials of learning analytics, and their capacity is still to be completely exploited. Instead of relying on experience and intuition, companies can use learning analytics to rapidly detect trends that provide insight into the state of organizational online training. In general, learning analytics helps educators and L&D managers have more productive training and training services to benefit modern learners.

9.3.2 Education and Learning Analytics Market (Forecast 2016–2026)

The report (Transparency Market Research, 2020) provides a detailed market assessment. It does this by in-depth qualitative perspectives, historical data, and true market size forecasts. The report estimates have been produced using well-established research methodologies and assumptions. This is used as a repository for analyses and knowledge on any aspect of the market, including but not limited to regional markets, technology, styles, and applications. The following gives an overview of the EDA Market for 2016–2026 (Transparency Market Research, 2020).

The education sector is constantly changing because of rising industry digitalization and mobile devices' adoption by users. The number, variety, and speed of data generation are growing rapidly. These data can be used and analyzed easily to provide powerful insights into user behavior, interests, and future actions. Students who use different educational hubs such as digital channels or university campuses to study leave data footprints during their studies. Universities use this knowledge to consider how students learn and refine their solutions to increase student experience. The educational hubs use education and learning analytics to understand products and their clients better.

Analytical tools enable the education sector to improve its productivity, recognize opportunities and developments, and become more creative. The education sector is rich in data as universities use it and generate vast amounts of data every day. Furthermore, the data produced vary from the socio-demographic information (gender, education level, age, language, etc.) to statistics (frequency and time of use, number of clicks, response time), or performance indicators (for example, test results) to behaviors (machine or individuals' interactions). This knowledge can be used to experiment with various forms of training with students to assess their reaction time, customize and improve their training, and provide them with daily feedback. Education and learning analytics can play an important role in the education field, providing students with better input, retention, improving teaching and learning, and recording attendance information.

Significant factors driving the market in education and learning analytics include the need for data-driven evaluations to enhance education quality and increase mobile learning. The lack of knowledge of analytical solutions among end-users and the need for high-quality professionals to manage and deploy analytical solutions are key obstacles in the market of education and learning analytics.

Based on its part, research, end-use industries, and regions, the global education and learning analytics market can be segmented. The demand for education and learning analytics can be split into software and services in terms of components. The services segment can be further divided into professional and managed services. Professional services include consultancy, integration and implementation services, training, and support services. The global market for education and analysis can be divided into a premise, cloud-based, and hybrid solutions based on software. As far as analytics is concerned, the demand for training and learning analytics can be categorized into the predictive analysis, prescriptive analytics, descriptive analysis, etc. The global education and learning analytics market are divided into K-12, higher education, enterprise, and more based on end-use industries. The enterprise segment can also be divided into large and small, and medium-sized enterprises.

The global education and learning analytics market in North America, Europe, Asia Pacific, Middle East & Africa, and South America can be segmented in terms of region. Business growth in North America is largely due to high technology investment in the region's education field. Developments in IT infrastructure and an increase in propensity to implement BI and analytics in the region are likely to affect the demand in Europe and Asia-Pacific.

IBM Corporation, SAS Institute, Microsoft Corporation, SAP SE, Oracle Corporation, Tableau Software, Blackboard Inc., MicroStrategy Incorporated, TIBCO Software Inc., Alteryx, and Qlik are major players in world education and learning analytics. These businesses invest heavily in research and development to integrate emerging technologies and develop innovative products into their solutions. Also, players enter into strategic alliances with other players to extend their reach and gain market share across the globe.

9.3.3 Learning Analytics in the Future

While Learning Analytics is now in its infancy, learning institutions should be careful: in the end, the way all education is conducted would revolutionize. This section gives you some insights into possible learning research (Alexander, 2018).

1. ***Improved institutional interconnectedness***: The future of Learning Analytics will be how organizations realize the value of creating a coherent, diverse, and integrated learning framework. This daunting concept parallels Brown (2017), who notes that its brick components' interoperability in a cohesive learning ecosystem is the key to the next generation digital learning environment (NGDLE).
2. ***Computers understanding at an equivalent level***: Natural Language Processing (NLP), for instance, breakthroughs have the potential to transform Business Intelligence (BI); Tirosh (2017), for instance, believes that the interaction capacity of machines is as much essential as human interactions (i.e., through chatbots).
3. ***Trying to find out what 'the' humans are 'really' thinking or feeling***: The 'Holy Grail' of Learning Analytics will attempt to understand the person qualitatively; however, around 200,000 anthropocentric years on Earth have transformed person battle experiments into very cunning and very talented people to conceal their true thoughts and intentions. Moreover, while biometric solutions (e.g., iMotions) are rapidly emerging and are believed to have tremendous potential in Learning Analytics, it is not easy to interpret the data.
4. ***Research paradigm assumptions are actually important***: In a world of infinite structured and unstructured data, research approaches in LA analyses need to be carefully considered; for example, the ontology of Nature of Truth is objective and singular (with an inductive methodology of cause and effect) or subjective and multiple (with inductive emerge patterns)

9.4 Measuring Twenty-First Century Skills Using Learning Analytics

The unparalleled possibilities of collecting knowledge on learning and contexts have drawn considerable interest in education. Using data analytics and machine learning approaches, many important questions in education have been answered. Learning analytics can be used to evaluate skills in the twenty-first century, according to Dragan Gašević (2019).

One of these skills, now known as the twenty-first century's skills, is collaborating, solving problems, searching for knowledge, thinking critically and creatively, and efficiently self-regulating learning (Griffin et al., 2012). Their significance in the policy and research frameworks has been stressed, and many employers have strong expectations of these skills required for various jobs. This capacity also enables equal involvement in society and access to numerous public services.

Education organizations at all levels have various services to help improve these skills in response to these demands. Sophisticated approaches to the assessment of twenty-first-century skills were also proposed with increasing focus by policymakers and employers (Wilson & Scalise, 2015).

However, there has been considerably less progress in evaluating methods that chart the progress of 21st skills growth "in the wild." For example, the Organization for Economic and Co-operation and Development (OECD) has carried out (complex and collaborative) problem-solving measurements through the Program for International Student Assessment (IPSA). In highly trolled conditions, PISA can be carried out where only predefined messages can be used for communication among human collaborators (Rosen & Foltz, 2014), and the actual collaboration evaluates potential digital-human-collaboration issues (e.g., uncooperative, incompatible) through the joint work between human and computer agents (Rosen, 2014). Moreover, relatively little work has been done in learning environments where pedagogical frameworks can vary from very formal approaches to collective learning through students' concerns needing support from their peers in their classes or a larger social network.

Learning analytics provides promising methods for evaluating 21st skills in authentic contexts (Buckingham Shum & Deakin Crick, 2016). Learning analytics harnesses big data's power to establish measurement techniques - collected as a digital footprint of learners' use of technology – by operating on the intersection between machine learning, measurement sciences, and learning sciences. Recent research has brought promising progress in the validity assessment of learning analytics to provide effective means for the developmental evaluation of skills of the twenty-first century.

9.5 Moving Forward

Present developments in learning analytics research concentrated less on technical advancement and more on the teaching and learning philosophy and concepts. Srećko Joksimović, Kovanović, and Dawson (2019) outlined four promising fields of investigation.

1. **Learning analytics for supporting student learning**: To date, research and development in learning analytics feedback and dashboards have been more focused on teachers instead of customized students. With large data at hand, it became obvious that it was not enough to recognize underlying data trends and forecast future effects. It is also important to recognize custom approaches to learning data presentations that draw on existing academic expertise and practices and do not generate an abundance of information. Also, existing dashboards do not help metacognitive skills development, provide information about successful learning tactics and techniques, and trigger serious problems in their assessment. Thus, there are increasing demands based on dashboards for learning analytics in the literature on learning processes and efficient studying and feedback methods.

2. **Grounding learning analytics in educational theory**: The lack of theoretical support for its study is a common criticism of learning analysis. For instance, the creation of student performance and retention predictive models relies on simple learning proxies. Trace data for students are primarily reported counts in a particular technology. To understand what constitutes a realistic measure of learning, the applicable theory needs to be combined with the analytics involved. Predictive modeling is designed to minimize bias and uncertainty, thus sacrificing theoretical precision for better empirical precision. However, to gain successful insights to advance the learning process, it is explanatory power (theory) that plays this role. In learning analytics, a theory's value is often derived from the principle of truth in educational measurement. The extent to which theory and data endorse the understanding of the measurement is seen as validity.
3. **Learning analytics for feedback provision and instructional interventions**: The emphasis is mainly on the formative assessment of learning (i.e., assessment of the student's learning) and assessment as learning, i.e., assessment as a particular learning activity) and not on the usual summative assessment of learning (i.e.., assessment as a measurement of student's knowledge). This is mainly due to learning analytic methods and techniques that offer students and teachers timely, realistic, and personalized perspectives. There has been a big initiative to move beyond grades to recognize students at risk to evaluate critical thinking, innovation, teamwork, and other high-level processes.
4. **Learning analytics for understanding student emotions**: Emotion is one of the fundamental elements influencing online learning. Every learning activity is typically based on certain emotional responses, either positive (for example, joy, pride, satisfaction) or negative (anger, frustration, anxiety). Several efforts have been made to broaden the most widely adopted method to trace data to recognize learning processes to isolate affective aspects from student experiences with technology. One of the drawbacks of this reexamination is that interaction studies between data and emotions are normally performed in a laboratory where affective states (such as anger, anxiety, or boredom) are reported using different decision protocols or self-reports. The interplay between study and emotion research in learning analytics and multimodal study research has provided exciting new directions. It attempts to detect the effect of body signals that have been made using multiple protocols for classroom observation or coding documented interactions.

9.6 Smart Learning Analytics (Smart LA)

Since its inception, LA has continued to demonstrate its significance in the educational sector. To better understand and improve learning environments (Siemens, 2012), LA requires measuring, collecting, analyzing, and reporting contextual learner data (Siemens, 2012). LA will create better learning environments tailored to its individual needs, talents, and interests (Clow, 2013; Siemens, 2012). When all learning tasks are conducted at a finer degree of granularity – including episodes of study by students, episodes of assessment preparation and completion, and teaching episodes – the personalization of learning experience can be increased in order to generate insight/conception about what learners know and how to facilitate constructional learning (V. S. Kumar et al., 2016).

Recent learning models have been moved from rote learning to inclusive and personalized learning. Therefore, it addressed a fundamental question about how students can make learning practical and meaningful. Tests and/or examinations focused on memorization are becoming increasingly clear that they do not help learn and apply knowledge effectively. Hwang, Tsai, and Yang (2008) and Yahya, Ahmad, and Jalil (2010) argue that students are enthusiastically inspired to learn when they see learning to be important and significant. Lage, Platt, and Treglia (2000) and Sampson, Karagiannidis, Society, and Economy (2002) stress the importance for all students of inclusive learning. Education priorities should also concentrate on how students can be helped by highlighting their unique strengths and weaknesses. Also, learning should be accessible where there is a possibility and should not be limited to a fixed time or place. Such an opportunistic learning mechanism needs the omnipresent presence of learner help, including timely input and technical aid. Contemporary models of learning transition towards more omnipresent and contextualized learning – where personalization means that the students can learn at their own rate and receive individual input addressing individual strengths and shortcomings, leading to the idea that it is more difficult to forget the learnings that take place spontaneously in real life (Sampson et al., 2002).

The idea of "smart learning" has also grown as learning conceptualization has shifted. Since adaptation and personalization have emerged as two main components of smart learning, experts have highlighted the value of using technology to enhance learning (Gros, 2016). A successful technical design goes beyond merely using state-of-the-art training technologies to encourage intelligent behavior, integrating various collective technologies (Höjer & Wangel, 2015). Under the theme of 'smart learning,' concepts like 'seamless learning' and 'ubiquitous learning' have appeared. Sharples et al. (2013) argued that seamless learning allows a person to continuously experience learning in a mixture of places, times, technologies, and social environments. Ubiquitous learning can be seen as a learning experience that is more time and space distributed, such that students can learn in environments where the line between work and play and public and private is established. Essentially, "smart learning" not only emphasizes technology-enhanced learning but provides a way to improve information through the incorporation of different technologies, environments, and components.

Researchers and educators have focused on incorporating a "smart" element into LA. Smart learning is a LA subset that supports such processes and features of smart learning (Giannakos, Sampson, & Kidziński, 2016). Educators may use Smart LA to define and evaluate student comportment, educational merits, and suitability of learning environments and collect information from different sources to distinguish traces that promote educational support (Kinshuk, 2017). Big data creation and emerging modes of information communication and sharing have laid the foundations for more immersive and personalized learning. Data on learner capabilities and competencies and environments where students use particular technologies are useful for evaluating learner behavior, experiences, interests, and skill level changes. As a result, teachers can track each student's learning pattern – i.e., "a network of observed study activities that lead to a measurable chunk of learning" (Kumar et al., 2016), which is a significant data source for the LA. Learning traces allow for personalization so that individual students with different learning styles can follow different approaches, even for the same learning activities.

Many researchers have researched areas such as how teachers can use LA to develop student abilities, build smart environments, and apply emerging technologies. However, few researched Smart LA's ability to facilitate engaging and personalized learning, i.e., smart learning. In the current work, Boulanger et al. (2015) have analyzed Smart LA with a Smart LA framework SCALE case study and its efficiency in improving student outcomes. Giannakos et al. (2016) have also discussed the Smart LA principle of video-based learning.

9.6.1 Key Features of Smart LA

A comprehensive analysis of learners and environments is part of Smart LA (Kumar, 2018). Smart LA includes many types of data to identify traces of learning that inform the creation of better learning environments. Researchers and/or teachers face the task of finding and collecting applicable data sources and efficient data processing and interpretation as it is available.

Teachers, students, and parents will observe improved learner learning abilities by observing the subsequent learning traces. A residue of learning is generated when both finely-grained student teaching and research findings are collected and interpreted at various times. These real-time findings will help personalized learning that meets the needs of individual learners. This can be an individual undertaking (i.e., instructor, student, or parent) or a collective effort. With Smart LA, researchers can accurately evaluate and predict the essence of learning, including learner effort and performance, in different environments. Consequently, different organizations should provide sufficient administrative support based on policies aimed at competency-based learning. The main features of Smart LA are as follows (Kumar, 2018).

1. ***Learner awareness:*** Smart LA encourages understanding of acute learning. Learners are best served by their own success in the course of learning. Students who know their learning behavior may monitor their progress and seek appropriate assistance to develop their learning habits. Smart LA makes students more conscious of ways to perform best. One of Smart LA's feedback channels is to imagine the improvement in learning. Such visualization should be carefully planned so that efficient pedagogical approaches become feasible for smooth communication between students, teachers, and the analytical framework.

Diverse data sensors provide learner information such as performance, metacognitive capacities, cognitive ability, learning strategies, successful state, and physiological symptoms. Smart LA will use these data sets to personalize the study experience. Personalization starts in many cases with learner modeling, which derives students' attributes from raw data sets and the importance of learning strategies. Models arise in learner modeling from the study of interactions between learners with their learning environments that expose important learner information such as knowledge levels, weaknesses, and misconceptions. A learner model continuously updates the sensor data, and Smart LA gives students access to such models, which individualize learning experiences and empower students to reflect, prepare, and track their own learning.

2. ***Sensitivity to technology:*** Technology is essential to Smart LA. Sensitivity to technology ensures the most efficient use of software and promotes the personalization of content and learning. Users need to consider the key features of various technologies and equipment incorporated in Smart LA and e-learning applications to best leverage their resources and customize their functionality dynamically. Teachers, for example, should know what device or technology their teaching is best supported. Feature refers to tools integrated into a device or software that allows it to perform its tasks. Features include display capabilities, audio, video capabilities, multi-lingual capabilities, and platform consistency. Another notable problem is the centralism of big data. Smart LA is powerful in its ability to merge various data sources. Technological developments mean that people can access smart LA software from various devices while collecting generalized knowledge remains key. Continuous data analysis often allows pedagogical scientists or the system to acquire new knowledge structures from the analyzed data and create more knowledge structures that support the learner's dynamic adoption.
3. ***Location awareness:*** Location-based technology promotes location-based learning. The former helps to classify learners' locations while using the software and the latter transfers information by identifying wireless interface and sensor networks that constantly adapt to the user location. Existing wireless technologies provide GPS, Wi-Fi, RFID, and Bluetooth positioning systems to track user positions automatically. Location – both the learners' physical place and learning opportunities – is critical to contextual learning. Location-sensitive learning opportunities are growing. For example, recognizing students with identical characteristics and learning interests in neighboring locations enables them to relate to their shared learning benefits.
4. ***Surrounding awareness****:* After developments in location-aware technology and devices, the concept of mobile learning originated. Mobile learning refers to the ease at which learning travels at learners and is not limited to mobile learning. Furthermore, mobile learning is not technology but the nucleus of learning. It deals with "mobile" learners. In essence, technology offers learners the ability to learn in various environments, while mobile learning facilitates the development of specific training programs focused on both the learner-specified goals and certain context-aware information systems in different fields. The word

"context-aware" refers to providing knowledge related to their tasks within unique contexts for users. Mobile learning includes students in their surroundings, encourages authentic, collaborative experiences and informal learning. Embedded in the community, learning lets students learn, however they wish. Real-life physical objects are now becoming important vehicles for location-based adapted learning.

For example, museums are used to connect QR codes to various display boards, both indoor and outdoor. Learners with smartphones or the like will gain additional knowledge and communicate with digital representations of displayed objects by scanning QR codes. Such well-designed mobile learning systems exemplify both ubiquitous and personalized learning. For example, if a user scans the same QR code repeatedly, a well-designed customized system can recognize the user's study progress and adjust subsequent information rather than always providing the same information.

Understandably, knowledge cannot be divorced from the cultivation of intelligent learning environments. Combining the benefits of physical and multiple virtual learning environments – assisted by the holistic internet of things and certain ubiquitous sensing devices – ensures the whole toolkit for knowledge of meaning. Students can learn at their own speed with location awareness, and teachers can track students' progress, adapt feedback, and support to the applicable big data from their respective smart learning environments. The collection and review of student data offers a deeper understanding of learning experiences and encourages personalized instruction, introducing appropriate and effective learning opportunities into the learning environment.

9.7 Case Study. Learning Analytics to Support Self-Regulated Learning in Asynchronous Online Courses: A Case Study at a women's University in South Korea

In this study, Kim, Yoon, Jo, and Branch (2018) used learning analytics to investigate SRL in an asynchronous online course. For this analysis, student log data were used to detect unknown but current SRL patterns. Specifically, student SRL profiles were first observed using their accumulated log traces, and their SRL processes were analysed over time using log variables and cluster membership every week.

This study's background was an introductory course on business statistics for undergraduate students at a private women's university in South Korea. The courses were compulsory for students who majored in business but were available to other students as an optional course. The courses' contents were provided asynchronously online except for four special face-to-face meetings; two were intended to teach students the assessment style and provide specific information on the course, while the other two were intended for mid-term and final exams. In addition to the two tests, students had to apply two different tasks to solve statistical problems relevant to what they had learned from the video lectures. The course used the university LMS, where students watched the teacher's pre-registered video lectures and downloaded the related course materials; new lecture videos and material were uploaded regularly. The teacher made daily announcements on the course schedule, deadlines, technical problems, changes to the course, and main updates. A Q&A board was set up to encourage students to ask questions or comment on the course content.

At first, 382 students were registered for two semesters, 188 in the first semester and 194 in the second semester. However, in the first semester, only 106 students and 178 students in the second, along with their consent form, returned the completed survey, allowing 284 student data in additional analyses. All 284 participants were graduates; of these, 45 (15.8%) were fresheners, 76 were sophomores (26.8%), 73 (25.7%) were juniors, and 90 (31.7%) were seniors. They came from 45 different majors, and only 11 (3.9%) of them were business major students. Also verified that nobody took the course in both the semesters. The students are well aware that the log data are only used for testing purposes and that they are not seen or used for grading by the teacher.

The data used for this analysis included student logs and survey responses consisting of an SRL questionnaire and demographic questions. They analysed the data and identified three distinct profiles of online self-regulation with distinct interaction patterns. Students with self-regulation actively pursued assistance, but students with weaker self-regulation abilities did not actively seek assistance in online discussions.

This study's results gave an extensive account of pupils' various learning habits with various SRL profiles. This study will help us understand how students with different SRL profiles behave differently over the entire course. The research and practice contributions of this study can be summarised as follows.

1. Firstly, this study helps develop successful online learning environments to consider potentially different SRL profiles for students. The proposed log variables can guide future research and practice and promote more debate about how students with different SRL profiles can deliver customized interventions. This research will inform the design of successful SRL support by linking student SRL profiles, actual behaviours, and learning outcomes.
2. Second, proof-based learning analytics was conducted to structure log variables that mirrored theoretical and empirical evidence from the previous research. Therefore, this study's results contribute to the knowledge base so that students can better understand how they learn and how education can be structured to help SRL in asynchronous online courses. Also, it offered opportunities for future studies to analyse SRL in similar online environments in terms of selecting indicators and linking them with the current theoretical framework.
3. Third, this research applied an innovative analytical approach to student SRL trends over time. Clustering and classification methods were combined to assess student behaviour predictors' contributions at various times. Nonparametric methods have made it possible to evaluate the highly correlated unstructured

dataset for which conventional parametric methods cannot work adequately due to the high probability of infringing modelling assumptions. Using the one non-parametric classification model that included all of the predictors, the probability of Type 1 errors occurring during each week of the course was decreased. Finally, this study showed the ability of learning analytics to discover emerging SRL trends.

9.8 Conclusion

There has been a growing interest in learning analytics in technology-enhanced learning (TEL). LA methods share a shift from data to analysis to action to learning. The environment of TEL is evolving, and this should be reflected in future LA approaches to better learning experiences. In this chapter, we presented a summary of the range of possibilities opens up by LA. We explored some promising avenues for future LA research. That includes self-learning, lifelong learning, and smart learning. We also presented a summary of the present and future developments of Learning analytics in the world. This chapter added a lot to LA research because it offers a more substantial and forward-looking view of LA and its related developments and provides a promising path for the twenty-first century in this emerging field.

9.9 Review Questions

Reflect on the concepts of this chapter guided by the following questions.

1. What is Self-Regulated Learning (SRL)? Describe its importance.
2. How will Learning Analytics be used for SRL? Explain.
3. What do you mean by Lifelong Learning? What are the various barriers to it?
4. How do you establish a Lifelong Learning environment? Explain the role of Learning Analytics in doing so.
5. Write a note on the present and future trends of Learning Analytics in the World.
6. What are the past and future trends in Learning Analytics Market? Provide a brief report.
7. How will Learning Analytics be used in measuring twenty-first Century skills? Explain.
8. What is Smart Learning Analytics (Smart LA)? List and explain the key features of Smart LA.

References

Alexander, C. (2018). *Trends in learning analytics: Educational institutions take heed - eLearning industry*. 2018. https://elearningindustry.com/trends-in-learning-analytics-educational-institutions-take-heed

Antonietti, A., Colombo, B., & Di Nuzzo, C. (2015). Metacognition in self-regulated multimedia learning: Integrating behavioural, psychophysiological and introspective measures. *Learning, Media and Technology, 40*(2), 187–209. https://doi.org/10.1080/17439884.2014.933112

Arguel, A., Lockyer, L., Lipp, O. V., Lodge, J. M., & Kennedy, G. (2017). Inside out: Detecting learners' confusion to improve interactive digital learning environments. *Journal of Educational Computing Research, 55*(4). https://doi.org/10.1177/0735633116674732

Aspin, D. N., Chapman, J. D., Hatton, M., & Sawano, Y. (2012). *Second international handbook of lifelong learning*. Springer: Springer Dordrecht Heidelberg London New York

Azevedo, R., Johnson, A., Chauncey, A., & Graesser, A. (2015). Use of hypermedia to assess and convey self-regulated learning. In *Handbook of self-regulation of learning and performance* (p. 13109) https://doi.org/10.4324/9780203839010.ch7

Boulanger, D., Seanosky, J., Pinnell, C., Bell, J., Kumar, V., & Kinshuk. (2015). SCALE: A competence analytics framework. In *State-of-the-art and future directions of smart learning*. (Issue October, pp. 19–30). https://doi.org/10.1007/978-981-287-868-7

Brown, M. (2017). The NGDLE: We are the architects. *Educause Review, 52*(4). https://er.educause.edu/articles/2017/7/the-ngdle-we-are-the-architects%0Ahttp://files/4246/the-ngdle-we-are-the-architects.html%0Ahttps://er.educause.edu/articles/2017/7/the-ngdle-we-are-the-architects

Brusilovsky, P., & Henze, N. (2007). Open corpus adaptive educational hypermedia. *The Adaptive Web*, *4321*(January 2007), 325–341. https://doi.org/10.1007/978-3-540-72079-9

Buckingham Shum, S., & Deakin Crick, R. (2016). Learning analytics for 21st century competencies. *Journal of Learning Analytics, 3*(2), 6–21. https://doi.org/10.18608/jla.2016.32.2

Bull, S., & Kay, J. (2010). Open Learner Models. *Advances in Intelligent Tutoring Systems, 308*(September), 301–322. https://doi.org/10.1007/978-3-642-14363-2

Cheng, H. C., & Liao, W. W. (2012). Establishing an lifelong learning environment using IOT and learning analytics. *International Conference on Advanced Communication Technology, ICACT*, 1178–1183.

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education, 18*(6), 683–695. https://doi.org/10.1080/13562517.2013.827653

eThink. (2019). *3 new learning analytics trends driving education*. https://ethinkeducation.com/blog/learning-analytics-trends-driving-education/

Gašević, D. (2019). Using learning analytics to measure 21st-century skills. *Research Conference, 2019*, 46–50.

Giannakos, M. N., Sampson, D. G., & Kidziński, Ł. (2016). Introduction to smart learning analytics: Foundations and developments in video-based learning. *Smart Learning Environments, 3*(1). https://doi.org/10.1186/s40561-016-0034-2

Greene, J. A., Moos, D. C., & Azevedo, R. (2011). Self-regulation of learning with computer-based learning environments. *New Directions for Teaching and Learning, 119*, 1–7. https://doi.org/10.1002/tl.449

Griffin, P., McGaw, B., & Care, E. (2012). *Assessment and teaching of 21st century skills*. Cham, Switzerland: Springer.

Gros, B. (2016). The design of smart educational environments. *Smart Learning Environments, 3*(1). https://doi.org/10.1186/s40561-016-0039-x

Hoffman, B., & Ritchie, D. (1997). Using multimedia to overcome the problems with problem based learning. *Instructional Science, 25*(2), 97–115. https://doi.org/10.1023/A:1002967414942

Höjer, M., & Wangel, J. (2015). Smart sustainable cities: Definition and challenges. In *Advance intelligent systemes and computing* (Vol. 310, August). https://doi.org/10.1007/978-3-319-09228-7

Hwang, G. J., Tsai, C. C., & Yang, S. J. H. (2008). Criteria, strategies and research issues of context-aware ubiquitous learning. *Educational Technology and Society, 11*(2), 81–91.

Joksimović, S., Kovanović, V., & Dawson, S. (2019). The journey of learning analytics. *Mind, Culture, and Activity, 2*, 37–63. https://doi.org/10.1080/10749039.2019.1686028

Kalz, M. (2015). Lifelong learning and its support with new technologies. In *International encyclopedia of the social & behavioral sciences: Second edition* (Vol. 13, 2nd ed.). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.92006-3

Katambur, B. D. (2020). *5 Trends that Influence Learning Analytics*. https://blog.commlabindia.com/elearning-development/5-trends-that-influence-learning-analytics

Kay, J. (2008). Lifelong learner modeling for lifelong personalized pervasive learning. *IEEE Transactions on Learning Technologies, 1*(4), 215–228. https://doi.org/10.1109/TLT.2009.9

Kim, D., Yoon, M., Jo, I. H., & Branch, R. M. (2018). Learning analytics to support self-regulated learning in asynchronous online courses: A case study at a women's university in South Korea. *Computers and Education, 127*, 233–251. https://doi.org/10.1016/j.compedu.2018.08.023

Kinshuk. (2017). *Improving learning through smart learning analytics (Power Point Slides)*. http://www.ouhk.edu.hk/URC/Sym_OIE_2017/files/Keynote_Kinshuk.pdf

Koper, R., & Tattersall, C. (2004). New directions for lifelong learning using network technologies. *British Journal of Educational Technology, 35*(6), 689–700. https://doi.org/10.1111/j.1467-8535.2004.00427.x

Kumar, K. (2018). Advancing learning through smart learning analytics: A review of case studies. *Asian Association of Open Universities Journal, 13*(1), 1–12. https://doi.org/10.1108/aaouj-12-2017-0039

Kumar, V. S., Kinshuk, Pinnell, C., & Paulmani, G. (2016). Analytics in authentic learning. *Lecture Notes in Educational Technology, 0*(9789811059292), 75–89. https://doi.org/10.1007/978-981-10-5930-8_6

Lage, M. J., Platt, G. J., & Treglia, M. (2000). Inverting the classroom: A gateway to creating an inclusive learning environment. *Journal of Economic Education, 31*(1), 30–43. https://doi.org/10.1080/00220480009596759

Lodge, J. M., & Horvath, J. C. (2017). Science of learning and digital learning environments. In *From the laboratory to the classroom: Translating learning sciences for teachers* (pp. 122–135), Routledge – Taylor & Francis: England, UK.

Lodge, J. M., Panadero, E., Broadbent, J., & de Barba, P. G. (2019). Supporting self-regulated learning with learning analytics. In *Learning analytics in the classroom* (October, pp. 45–55). https://doi.org/10.4324/9781351113038-4

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers and Education, 54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Miller, C., & Bartlett, J. (2012). "Digital fluency": Towards young people's critical use of the internet. *Journal of Information Literacy, 6*(2). https://doi.org/10.11645/6.2.1714

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*(APR), 1–28. https://doi.org/10.3389/fpsyg.2017.00422

Perry, N. E., & Winne, P. H. (2006). Learning from learning kits: gStudy traces of students' self-regulated engagements with computerized content. *Educational Psychology Review, 18*(3), 211–228. https://doi.org/10.1007/s10648-006-9014-3

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *A Time for the Humanities, 2*(1), 7–12. https://doi.org/10.2307/j.ctt13x0cd3.6

Romero-Zaldivar, V. A., Pardo, A., Burgos, D., & Delgado Kloos, C. (2012). Monitoring student progress using virtual appliances: A case study. *Computers and Education, 58*(4), 1058–1067. https://doi.org/10.1016/j.compedu.2011.12.003

Rosen, Y. (2014). Comparability of conflict opportunities in human-to-human and human-to-agent online collaborative problem solving. *Technology, Knowledge and Learning, 18*(3), 147–164. https://doi.org/10.1007/s10758-014-9229-1

Rosen, Y., & Foltz, P. (2014). Assessing collaborative problem solving through computer agent technologies. *Research and Practice in Technology Enhanced Learning, 9*(3), 389–410. https://doi.org/10.4018/978-1-4666-5888-2.ch010

Sampson, D., Karagiannidis, C., & Kinshuk. (2002). Personalised learning: Educational, technological and standardisation perspective. *Interactive Educational Multimedia: IEM, 39*, 24–39.

Sharples, M., Mcandrew, P., Weller, M., Ferguson, R., Fitzgerald, E., & Hirst, T. (2013). *Innovating pedagogy 2014* (issue November). The Open University: United Kingdom.

Shum, S. B., & Ferguson, R. (2012). *Social Learning Analytics., 15*(3), 3–26. https://doi.org/10.1145/2330601.2330616

Siemens, G. (2012). Learning analytics: Envisioning a research discipline and a domain of practice. In *2nd international conference on learning analytics and knowledge* (pp. 1–8). https://doi.org/10.1007/s11434-007-0406-7

Tirosh, G. (2017). *Why natural language processing is the future of business intelligence | sisense*. DZone.Com. https://www.sisense.com/blog/heres-natural-language-processing-future-bi/

Transparency Market Research. (2020). *Education and learning analytics market - global industry analysis, size, share, growth, trends, and forecast 2018–2026* (pp. 1–8), Transparency Market Research: Albany NY – 12207, United States.

Wilson, M., & Scalise, K. (2015). Assessment of learning in digital networks. In *Assessment and teaching of 21st century skills* (pp. 57–81). https://doi.org/10.1007/978-94-017-9395-7_3

Winne, P. H. (2017). Learning analytics for self-regulated learning. In *Handbook of learning analytics* (pp. 241–249). https://doi.org/10.18608/hla17.021

Yahya, S., Ahmad, E. A., & Jalil, K. A. (2010). The definition and characteristics of ubiquiteous learning: A discussion. *International Journal of Education and Development Using Information and Communication Technology, 6*(1), 117–127.