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Analytics 2.0 for Precision Education: An Integrative Theoretical Framework of the Human and Machine Symbiotic Learning

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ABSTRACT: This methodological-theoretical synergy provides an integrative framework of learning analytics through the development of the human-and-machine symbiotic reinforcement learning. The framework intends to address the challenges of the current learning analytics model, including a lack of internal validity, generalizability, immediacy, transferability, and interpretability for precision education. The proposed framework consists of a master component (the brain) and its four subsuming components: social networking, the smart classroom, the intelligent agent, and the dashboard. The brain component takes in and analyzes multimodal streams of student data from the other components with the model-based reinforcement learning, which forms policies of adequate actions that maximize the long-term rewards for both the human and machine in the seamless learning environment. An example case plan in advanced statistics was demonstrated to illustrate the course description, data collected in each component, and how the components meet different features of the smart learning environment to deliver precision education. An empirical demonstration was provided using some selected mulitmodal data to inform the effectiveness of the proposed framework. The human-and-machine symbiotic reinforcement learning has theoretical and practical implications for the next-generation learning analytics models and research.

Keywords: Reinforcement learning, Learning analytics, Symbiotic learning, Smart learning environment, Precision education

1. Introduction

The advent of Information and Communication Technologies (ICT) has yielded explosive and drastic changes in human thinking and decision making (Jordan & Mitchell, 2015). Among the technologies, Machine Learning (ML) is the core of artificial intelligence and data science; via supervised, unsupervised, or reinforcement learning, machines imitate human behavior and thinking and excel in an automatic recursive process (Jordan & Mitchell, 2015). ML's affordance offers us insights into the advancement and development of the next generation of Learning Analytics (LA) to implement precision education (Wu et al., 2020). Mainly, precision education is "an approach to research and practice that is concerned with tailoring preventive and intervention practices to individuals based on the best available evidence" (p. 4, Cook et al., 2018). Whereas, LA is defined as using data from educational institutes to construct prediction models for improving the student learning process (Wu, 2020). More specifically, LA measures, gathers, analyzes and returns students data and information content in order for stakeholders of education to better investigate and understand the environment within and outside the learning entity where learning takes place for personalized feedback and instruction (Siemens & Baker, 2012). Thus, harnessing the power of LA, precision education may be more promising and ready to benefit students and instructor in their learning and teaching with engaging, flexible, adaptive, and personalized diagnosis and intervention. Nevertheless, new challenges arise as to how artificial intelligence and ML can be well applied in LA to achieve precision education for capturing the heterogeneity among learners and facilitating students' learning performance and instructors' teaching quality (Yang, 2019).

Notably, LA has been one of the most innovative areas to accomplish precision education with its leverage in the construction of prediction model and student learning database as well as the analysis of a vast amount of qualitative and quantitative multimodal data for personalized learning (Blikstein & Worsley, 2016). Despite the advantages, there are deficiencies in the current LA that may limit its application for precision education. These deficiencies include lacking in internal validity, immediacy/automated feedback, and generalizability. Specifically, the above-claimed effects of learning and teaching based on learning analytics are post-hoc in nature. The progress and application of the analytical results are not synchronous. Namely, the models or indicators obtained from the previous students can only be used or applied to the students in the next stage or generation, whereby lacking internal validity and failing to inform instructors of their students' recent status.

Meanwhile, the result of learning analytics cannot be used for immediate and real-time diagnosis and automated feedback at the current stage, whereby lacking immediacy (Sedrakyan et al., 2018). Specifically, the criterion-based validity check, usually using the students' grades, limits the possibility to use all the available indicators and all possible actions exhaustively. As a result, it may hinder external validity and damage the generalizability of the LA model.

Besides the constraints mentioned above, additional challenges for the current LA research include the transferability between the different learning systems and translation of the LA results to the instructor or practitioner's language (Baker, 2019). Moreover, researchers have noted that learners' lack of access to their learning data reduces their opportunities to make sense of their learning process and hinders their metacognition and self-regulation (Kitto et al., 2017; Wu, 2014; Wu & Peng, 2017). The limitations and constraints of the current learning analytics models mentioned above demand the attention of the LA research community for achieving precision education.

This study intends to provide an integrative theoretical framework of learning analytics for precision education through the human-and-machine symbiotic reinforcement learning (RL). We contend that the RL can be the core application of the next-generation LA, namely LA2.0, to address the constraints of internal validity, generalizability, immediacy, transferability, and interpretability for the current state of learning analytics so that LA2.0 can be readily utilized to enhance precision education. Thus, we aim to answer two research questions:

- What are the possible components in the integrative theoretical framework of learning analytics for precision education?
- What is the efficiency of this proposed learning analytics framework in modeling learning performance for precision education?

Below we provide the theoretical underpinning of the framework, including smart learning environment, learning analytics and reinforcement learning, and learning analytics 2.0: the framework for precision education.

2. Literature review

2.1. Building a smart learning environment for precision education based on the affordance of adaptive technologies

Smart Learning Environment (SLE) is built upon adaptive technologies that satisfy learners of different backgrounds and engage them in context-aware learning activities that suit their goals (Spector, 2014). In higher education, social media is one of the applications of adaptive technologies that enable learners to create their unique Personal Learning Environment (PLE, Dabbagh & Kitsantas, 2012; Wu, 2017). Premised on social media, the PLE encompasses Learning Management Systems (LMS, e.g., Moodle, Canvas, or Blackboard) and thus is more open and flexible than the close systems. Learners can create their PLE using various applications: blogs, wikis, google apps/calendars, dropbox, YouTube/Flickr, etc. to achieve their learning goals considering their interests, preferences, emotions, and attitudes. Learners can also share, communicate, and collaborate by extending their PLE to form a personal learning network or community with experts and more knowledgeable peers. Despite PLE's advantages, people's limited attention resources are significantly challenged by fun and exciting events and activities, such as friends' tweets, photos, fun games, and videos (Wu, Online first; Wu & Xie, 2018). Thus, learning premised on social media may be a double-edged sword due to students' distracted attention and poor self-regulatory strategies (Wu, 2015, 2017; Wu & Cheng, 2019). These external threats in the PLE create an urgency to build an SLE with analytical evidence for students' autonomous and self-directed learning. An SLE should be able to engage students in learning with its technological affordance and meanwhile facilitate students to plan and monitor their learning progress actively.

The extent of an SLE can be categorized by its necessary, strongly desired, and likely features (Spector, 2014). Necessary features imply that the SLE should have evidence to support its effectiveness and efficiency for students' autonomous learning based on diverse and large-scale samples. In terms of the highly desired, engaging, flexible, adaptive, and personalized are the four main features. The SLE may be engaging in arousing and maintaining students' motivation, attention and engagement. Meanwhile, it can be flexible to accommodate changes in the course (e.g., adding new members, changes in learning goals) and being adaptive to students' abilities, interests, or cognitive styles to provide personalized instruction and feedback for those falling behind or progressing ahead. The necessary and highly desired features can benefit from the affordances of Web 2.0 and Web 3.0. Students can actively create their responses and construct knowledge schema with their peers and the instructor synchronously or asynchronously, with the teacher orchestrating and coordinating students' collaboration (Gerstein, 2014). Based on connectivism theorized by Siemens (2005), teaching and learning may represent a combination of numerous activities and networked and interwoven complex relationships. When students share information or post/reply questions and comments by interacting with peers or instructors, they connect their current state of knowledge to form knowledge between ideas, concepts, and domains via specialized nodes and information sources (Wu & Nian, 2021). Thus, built on connectivism (Siemens, 2005), learners of Web 3.0 applications can be creators of content knowledge. They can share their intellectual artifacts with others in networked learning and connect resources, persons, communities, and applications/tools relevant to their learning via the far-reaching web (Berners-Lee et al., 2001). Under this scenario, learning is highly autonomous and self-determined, with teachers taking the role of a coach or cheerleader (Gerstein, 2014).

As for Web 4.0., researchers suggest a symbiotic web where humans and machines have an interdependent and coexisting relationship (Gamberini & Spagnolli, 2016). The concept of human-machine symbiotic relations offers immense possibilities for human learning. In light of Spector's likely features for an SLE: conversational, reflective, innovative, and self-organizing, we envision that the SLE built upon the affordances of Web 4.0 can engage learners in dialogs for problem-solving, create learning progress reports for students' evaluation of their performance, use technologies in innovative ways to support students' learning, and help improve students' performance over time by automatically managing resources and collecting/analyzing data from the learning ecology. To implement these likely features in the SLE requires comprehensive and penetrating learning analytics encompassing all possible aspects of data about students' learning. Below we discuss the now and future of learning analytics regarding its role in the SLE.

2.2. Learning analytics and reinforcement learning

LA's ultimate purpose is to provide precision education for individualized instruction and feedback to enhance students' motivation and achievement with student-related data gathered from multiple sources (Romero & Ventura, 2020; Siemens & Baker, 2012). Nevertheless, the current LA models may constrain their use for such purposes. Specifically, the current LA studies are mostly using off-line training data for prediction based on static models (Nishihara et al., 2017). They cannot provide real-time and immediate feedback or support to facilitate student learning due to programming flexibility and performance limitations. Reinforcement Learning (RL), a broader paradigm of machine learning, may address the constraints mentioned above. RL can fuse and react to multiple sensory data from various input streams, conduct micro-simulations continuously, and figure out the next step (Nishihara et al., 2017). Compared with other machine learning algorithms, RL focuses more on goal-directed learning via interacting with the environment (Sutton & Barto, 2018). The robot has clear goals, perceives the environment, and selects an action to respond to or change the environment. RL differs from supervised or unsupervised learning because it learns the behavior based on the feedback obtained from iteratively interacting with the environment. Thus, RL resembles the conditioning learning of humans or animals (Sutton & Barto, 2018) to master the skill. The RL-based agent/robot applies the concept of "reinforcement" in behaviorism, where humans make decisions based on the state of the current environment and select the corresponding action. Once the environment rewards them, they may maintain and adjust their policy to maximize their long-term reward.

There are four elements in the RL: policy, reward signal, value function, and model (Sutton & Barto, 2018). The policy perpetuates the RL robot's action with the standard strategy to maximize the value function. The reward signal is the value obtained by the RL robot from the environment to evaluate its action's performance. The value function is the RL robot's expected values/rewards across all the possible actions; the RL robot obtains its value function by continually updating with the latest parameters. Before the RL robot executes its action, models could help predict what reward the environment may give to decide its strategy use. A model-free RL robot can be used for explicit trial-and-error searches (van Otterlo & Wiering, 2012). Alternatively, mode-based RL agents can be applied to reflect the action that gains more weights in reward from the environment (Hester & Stone, 2012). This study proposed the human-machine symbiotic learning analytics framework based on the mode-based RL algorithm as an updated version of the current learning analytics model. The framework may be able to bolster the likely features in the SLE for conversational, reflective, and self-organizing and innovative learning via its low latency and high throughput to support online simulations and the streaming sensory input (Nishihara et al., 2017).

3. Learning analytics 2.0: The framework for precision education

This study aims to address the problems and constraints of the current Learning Analytics to construct a human-machine symbiotic reinforcement learning framework for precision education. A summary of aspects that entail the human-machine symbiotic relationship is exhibited in Table 1. Specifically, humans can provide rules to supplement the building of domain knowledge and just-in-time information to ease the computational complexity with more efficient and effective training results (Sutton & Barto, 2018). Humans can also collaborate with the RL robot by providing adversarial training for valid value evaluations to gain maximum rewards despite extensive simulation training (Pinto et al., 2017). In terms of the distinct style of knowledge building, the result of machine learning training is complex and is rendered powerless unless it can be interpreted by human experts (Vellido et al., 2012). Thus, the learning analytics results with experts' input can be displayed via interactive visualization and dashboards to provide learners and instructors with meaningful interpretation (Aljohani et al., 2019). Moreover, as experts, humans can provide domain knowledge regarding RL's susceptibility to partial information (Abbeel & Ng, 2004).

Table 1. The symbiotic relationship between the machine (the RL algorithm) and human

Aspects that entail the symbiotic relationship	What RL can do	Constraints of RL	How humans can collaborate with RL
The domain of knowledge building	Needs no instruction/knowledge.	Rules needed	Provide rules
Speed of computation	Trial-and-error achieved in seconds.	Not a fast learner without supercomputers due to computational complexity	Provide just-in-time information to help the RL learn faster
The capability of knowledge building	AIs with RL generate their knowledge.	Need valid value evaluation	Provide adversarial training for valid value evaluation
Distinct styles of knowledge building	Has its style of knowledge building.	Difficult to be explained	Interactive visualization and dashboard display based on suggested actions and estimated rewards
Susceptibility to partial information	Could be generalized to other situations.	Not effective with only partial information	Serve as an expert or a community of experts to provide domain knowledge.

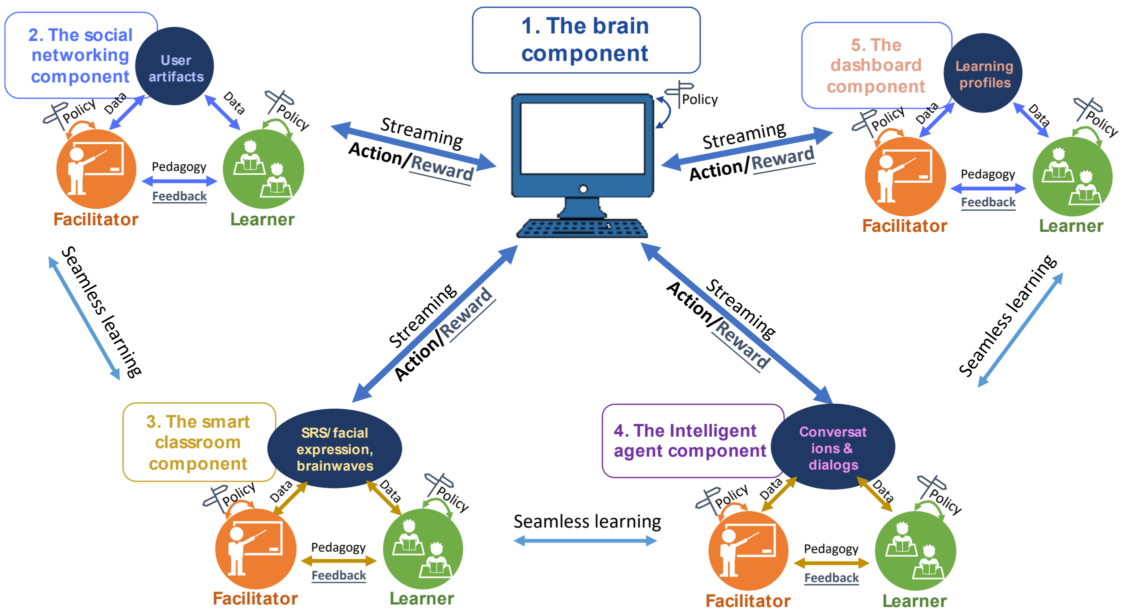


Figure 1. The integrative framework of the human-machine symbiotic learning within the smart learning environment

Harnessing the power of RL, we propose an integrative LA framework for precision education, consisting of five components. We illustrate the association of the five components as shown in Figure 1 and elaborate on the functionality of the components in the following subsections.

3.1. The brain component

The brain is the master component based on connectivism (Siemens, 2005) and RL (Sutton & Barto, 2018). With analytical techniques (e.g., statistics, data mining, supervised/non-supervised machine learning techniques), the brain takes in multimodal streams of students' data in the hybrid seamless instructional settings to build the human-machine symbiotic learning model. The information streams may include automated coding of supervised data and model-free data and metadata (e.g., the number of messages and comments posted on the wall) from the social network component, class attendance, facial expression, physical movement, physiological signals, and instant assessment responses from the smart-classroom instruction component, conversations, and dialogs from the intelligent agent component, and human-computer interactions and information-exchanging visualizations from the dashboard component (e.g., students set goals and regulate their learning based on dashboard feedbacks).

The brain establishes policies to select an action in response to the learning environment with strategies that maximize the value function for the greatest reward; the reward would then inform the brain of the result of the action in a recursive manner for self-organizing. The brain component is designed with 1) low latency and high throughput, 2) dynamic task creation, heterogeneous tasks, and arbitrary dataflow dependencies, and 3) transparent fault tolerance and debuggability and profiling to meet the performance, execution, and practical requirement of emerging real-time machine learning (Nishihara et al., 2017).

3.2. The social networking component

The second component is the social networking component characterized by students' cognitive, affective, and social artifacts created on social media (Lee & Wu, 2013). Specifically, the context of social media use or what and how students are using social media plays a significant role in students' outcomes. Researchers exhibited that students with messages and posts endorsed by two or more robots as statistics-relevant had higher final course grades; moreover, students failing the course had significantly fewer messages endorsed by three robots as statistics-relevant than those who passed (Wu et al., 2020). Therefore, content or the interaction context is the core element that may predict students' performance in social networked learning. Moreover, social presence or the ability to perceive others in the online learning environment is also associated with learners' satisfaction and perceived learning (Dabbagh & Kitsantas, 2012). Thus, learners' posts and comments among peers and instructors and their reactions to others' messages (i.e., emojis, or the buttons of Like, Haha, Love, Wow, Sad or Angry) are essential cognitive and affective artifacts in social networked learning.

By using both supervised text classification and RL enabled student data streaming, the social network component has the potential to classify learners' messages based on the cognitive level or sentiment analysis (Cambria et al., 2017) and send those data along with the metadata (e.g., Facebook reactions) on the social media in real-time to the brain component in order to construct policies in response to the dynamic environment for maximum reward in learning.

3.3. The smart classroom component

The third component is the smart classroom component. It focuses on the observation, monitoring, and interaction among peers and instructors and pedagogical adjustment in the face-to-face classroom using multimodal data for learning analytics. Grounded in connectivism (Siemens, 2005), learning resides in the exchanges of diverse opinions. In the classroom setting, learners can learn from reciprocal inquiry and dialectic learning with their peers and instructors. However, in higher education, the class size causes a barrier in the teacher-student interaction, with negative correlates such as higher dropout rate and retention (Bettinger & Long, 2018). Student response systems (SRS) can improve students' learning, motivation, and engagement and bring more opportunities to improve discussion and interaction between students and teachers and among students for educational purposes (Wu et al., 2019). By implementing formative assessments via SRS adaptively according to the analytical result streamed back from the brain component, the instructors can identify misconceptions in students learning and provide immediate scaffolds or direct explanations on the idea. Besides, students' opinions can be more openly expressed via SRS against conformity or shyness.

In addition to students' responses to the formative assessment via SRS, their facial expressions, physical movements, and physiological signals (e.g., skin conductance and brainwaves) may also be recognized to detect their learning emotions. Advances in machine learning have made real-time facial expression recognition of emotions feasible. Using automated recognition of facial recognition, researchers found that students' upper face movements are related to engagement, frustration, and learning, while mouth dimpling positively predicts learning and self-reported performance (Grafsgaard et al., 2013). Real-time facial and head gesture recognition can also successfully identify students sleeping, yawning, and smiling as well as nodding, shaking, and tilting with high accuracy (Deshmukh et al., 2018). Besides, in face biometric systems, the non-contact algorithms have been carried out for virtually physiological signal detection, e.g., pulse rate registration, directly from face images captured from motion videos (Lewandowska et al., 2011). Moreover, students' physiological signals such as skin conductance also exhibited a positive correlation with their self-reported mental efforts in solving ill-structured problems (Larmuseau et al., 2019). These non-verbal signals can provide the instructor with valuable information about students' attentional and cognitive states, engagement, and motivation for the instructor's pedagogical adjustment to facilitate students' learning and help manage student attendance (Kar et al., 2012).

Students' responses via SRS, facial, physical movements, and physiological signals can also be coded, classified, and preprocessed by edge computing mobiles and terminals (Shi et al., 2016). The coded responses can be sent to the brain component via the streaming technology to establish, maintain, or adjust policy for obtaining the maximum reward.

3.4. The intelligent agent component

The fourth component is the intelligent agent component. Though the instructor and peers can interact with the learner and exchange ideas and opinions, the time and space constraints would limit the currency of knowledge creation and co-construction. To address the possible limitation of failing to provide just-in-time feedback and scaffolds, we propose the intelligent agent component that can work as a bridge in the relationship among the content, peer, and the instructor for knowledge transfer and creation. Intelligent agents are applications of artificial intelligence built upon machine learning and natural language processing for personal, conversational, and engaging ways of learning. Intelligent agents can serve as the role of the more knowledgeable other in the zone of proximal development (Vygotsky, 1987) to assist in completing the task, answering conceptual questions, or prompting learners' reflection or metacognition in a conversational way. Nonetheless, most intelligent agents are still based on fixed rules and may not provide feedbacks given students' characteristics and needs (e.g., Pereira, 2016).

RL and task-based design empower the proposed intelligent agent component. It uses streaming student data from the brain component, the social networking component, and the smart classroom component to provide real-time scaffolding on students' misconceptions and guide students' critical thinking to achieve their learning goal. The conversation, dialogs, and interaction between the learners and intelligent agents can also be exported to the brain component to improve the human-machine symbiotic reinforcement learning mechanism.

3.5. The dashboard component

The fifth component is the dashboard component, which is in charge of multiple sensory data gathering, cleaning, storage, and management and visualizing each student's learning profile. Research has documented the advantages of the learning analytic dashboards, such as to identify students' role in online learning or their interaction with others (Ferguson & Shum, 2012), to enhance the adviser-student dialog via visualizing the study progress and comparison with peers for discussion and argumentation (Charleer et al., 2018), and to support students' self-regulated learning with corresponding features of self-monitoring and self-assessment complemented with customized feedbacks (Schumacher & Ifenthaler, 2018). Students can also compare their class participation and performance with the class's average performance or the best-achieving students by available factors (Aljohani et al., 2019). Linking the learning analytics dashboard display with learning science concepts, researchers propose that the dashboard design should help students in the planning, performance, and adaption phases of their learning (Sedrakyan et al., 2018). Nevertheless, there are still challenges for the learning analytics dashboard design, including 1) difficulty in modeling the dynamics of learning, 2) failure to taking into account of learner characteristics, 3) limitation in the modality of student data, and 4) inclusion of student data from a single platform (Sedrakyan et al., 2018).

The current study proposes a human-machine symbiotic reinforcement learning framework using the fine-grained and accumulated learning progress data to investigate and predict students' next-stage action based on their previous moves. Therefore, it may help resolve the problem of lacking internal validity and avoid providing feedback based on the previous sample's data to the students of the ongoing section.

4. Empirical demonstration and discussion

This section provided an example course plan in a graduate-level advanced statistics course to depict the integrative theoretical framework. As a demonstration for the proposed integrative LA framework, we then conducted an empirical analysis with available data from the four subsuming components obtained from an advanced statistics course. Though the analytical model reported here was still post-hoc in nature, we can envision the development of a human-machine symbiotic learning when all the multimodal multiple-source data are incorporated and streamed to the brain component. The brain, which is powered by the RL mechanism and statistical modeling, can then establish real-time policy and decision making for precision education.

4.1. Description of the components in the example case plan

In response to our first research question, we described the course component and data that can be collected in each component to demonstrate how each component meets different features of a smart learning environment for precision education in Table 2. The brain's primary function is to establish policies with strategies that maximize value functions for the greatest reward and meet the performance, execution, and practical requirement of reinforcement learning (Nishihara et al., 2017) so that it can coordinate all the components in the integrative framework. Specifically, the advanced statistics instructor can design the course using a flipped learning approach; therefore, in the social networking component, students can preview the course videos on Youtube or LMS before the class. Students can also review the video lectures afterward based on their study pace. The instructor creates a statistics learning Facebook group to share information and seek help via posts and comments for seamless learning and self-regulation.

Table 2. The sample case of an integrative framework of the human-machine symbiotic learning within the smart learning environment

The Master component	The Brain Component			
	• Built upon the smart learning environment (Spector, 2014), connectivism (Siemens, 2005) and the RL algorithm (Sutton & Barto, 2018) • Receive multimodal streams of students' data • Develop the human-machine symbiotic learning model			
Subsuming Components	The social networking component	The smart classroom component	The intelligent agent component	The dashboard component
Course component description	• Before/after the class: The instructor provides course videos for previewing. Students can review the video if necessary. • Before/during/after the class: Students are encouraged to share information and seek help via the Facebook group for seamless learning and self-regulation.	• During the class: The instructor integrates the student response system (e.g., Kahoot!) for quizzes to monitor students' comprehension of the statistics concepts. • Students' facial expressions, physical movement, and physiological signals can be recorded and	The intelligent agent is a students' personalized tutor that can address each student's specific needs or statistics misconceptions based on his/her familiarity with the course materials, e.g., performance on the student response system, posts/comments	The dashboard displays students' statistics learning progress across different platforms (e.g., amount of video viewing, discussion participation, interaction among peer, weekly quiz performance). It takes information from all the previous components plus additional psychological assessments to tailor each student's learning program. Students are allowed to set their learning goals.

		transmitted to the brain component for instant recognition of students' attention and emotional status toward a specific concept of statistics learning.	on the Facebook group, and classroom engagement.	Automated and individualized feedbacks are given considering all available student pre-existing conditions.
Data collected	Course video viewing time on LMS and posts, comments, and reactions (emojis) on the Facebook group	Students' instant responses to the test items, facial expression, physical movement, physiological signals	All available data from the social networking component and the smart classroom component	All available data from the social networking component, the smart classroom component, and the intelligent tutor component plus psychological assessments of students' learning preferences, strategies, and habits, etc.
Features of smart learning environment	Necessary features: scalable, effective, efficient, and autonomous.	Highly desired features: engaging, flexible, adaptive, and personalized	Likely: conversational, reflective, innovative, and self-organizing	Likely: conversational, reflective, innovative, and self-organizing

In the smart classroom component, the instructor can create a quiz bank using the gamified student response system (e.g., Kahoot!) and adaptively use the quiz items based on the brain component's action to monitor students' comprehension of the statistics concepts. Students' facial expression (e.g., yawn, frown), physical movement (e.g., stretch, sleep), physiological signals (e.g., pulse, skin conductance, brainwaves) can be recorded. The signals can then be transmitted to the brain component for instant recognition or automated classification of students' attention and emotion status (e.g., frustrated, confused, happy, bored, or stressful) toward a specific concept of statistics learning. The use of the student response system was shown to increase student engagement in the class. Moreover, instant automated classification of student-related signals can allow the instructor to provide flexible, adaptive, and personalized feedback for each student and ease the instructor's cognitive load given a large class size (Stowell et al., 2010).

The intelligent agent component is designed based on rules and all available information from the social networking component and the smart classroom component. Thus, students' personalized tutor can address each student's specific needs or statistics misconceptions based on his/her unique records. The personal records consist of students' familiarity with the course materials (course video viewing time), performance on the student response system, posts/comments on the Facebook group, and classroom engagement. For example, a student may get a quiz item wrong in the class, or ask for clarification about statistics concept on the Facebook group. Then, the intelligent agent would notice the student's possible weaknesses and provide relevant materials/concepts/questions of different difficulty levels for the student to think or work on and scaffold the learning process. The intelligent agent is an innovative technology that can form a conversational and reflective way of learning and is capable of self-organizing the learning materials and sequences.

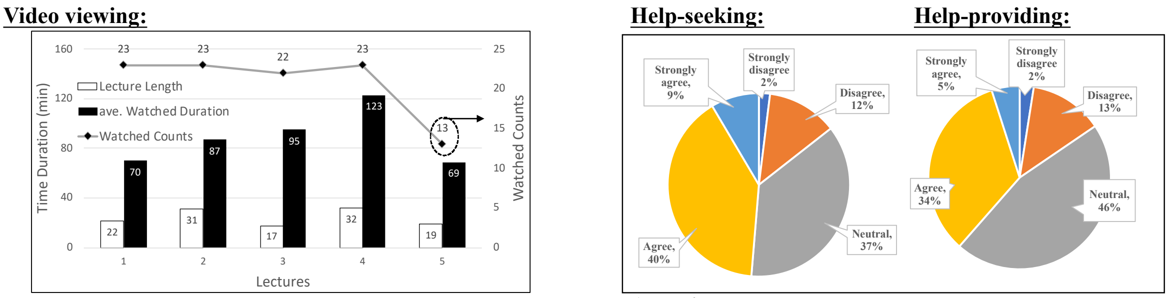
The dashboard component displays students' statistics learning progress across different platforms (e.g., amount of video viewing, discussion participation, interaction among peer, weekly quiz performance). It takes information from all the previous components plus additional psychological assessments (e.g., Internet use habits and epistemic beliefs (Lee, 2018, 2021)) to tailor each student's learning program better. Students are allowed to set their learning goals and regulate their learning using the dashboard components (Sedrakyan et al., 2018). Automated and individualized feedbacks for goal-setting or self-regulation are given considering all available student pre-existing conditions. The feedback distribution algorithm is based on the RL policy that yields the most considerable reward and can avoid students' unrealistic goal-setting or self-evaluation (too high or low) and help them self-regulate their learning. The student learning profiles provided by the dashboard can also be used by the instructor to adjust their course plan and teaching strategies.

4.2. The empirical demonstration of an LA based on an actual course

In response to our second research question, we simulated a prediction model in the brain component on students’ learning performance to test the efficiency of the LA model. Specifically, we modelled the prediction effectiveness of an LA based on some selected multimodal and multiple-source data from an actual course. Participants were 23 graduate students taking an advanced statistics course. In the social networking component, the duration of each individual’s time spent on each part of a video lecture was recorded, including the time paused and replayed. Students also provided ratings of their perceived help-seeking desire and help-providing capability, as well as a brief reflection of what they have learned and they wanted to share after viewing the lecture videos. Moreover, students’ posts and comments on the Facebook group were classified into statistics relevant or irrelevant using supervised machine learning (Wu et al., 2020). In the future, we hope to replace the classification process by the RL with expert’s rule to establish real-time policies and provide immediate personalized feedback. Further, in the smart learning classroom, students’ responses to the in-class quizzes was recorded using the gamified instant response system (i.e., Kahoot!). We created a proxy variable for the intelligent agent component by dividing the number of responses a student received from the instructional team by the total messages the students posted. The proxy variable may function similarly as the adaptive tutoring when a student signals the need for help. The proxy variable was created in place of the personalized feedback in the intelligent agent component for demonstration purposes; however, it only considered feedback received from the instructor and teaching assistants. Thus, more research is needed to advance the development of intelligent agents based on rules and multimodal and multiple-source inputs.

As a visualization to help students’ self-regulation, we built a dashboard based on students’ video viewing and perception/reflection data. As illustrated in Figure 2, the dashboard presented the duration of each lecture, the average students’ time spent viewing each lecture, and the number of students who watched the video on the upper left-hand side. On the upper right-hand side, the pie charts presented the percentages of students in terms of the degree of their perceived help-seeking desire and help-providing capability. The bottom left-hand side and bottom-right hand sides exhibited all students’ qualitative accounts of their brief learning reflection and perception about the lectures, respectively. The visualizations can be provided to students on a weekly basis; thus, the dashboards may enhance students’ understanding of their learning in comparison to the whole class for goal-setting and self-regulation. Instructors can also use the learning analytics dashboards to monitor each student’ learning progress over time and identify students who are in need of help at the earliest stage to prevent them from falling behind or failing the course.

The Learning Record of a Unit: Multiple Regression



I have learned:

- There’s even a space before “Orc”. If TA hadn’t mentioned that, I would have to waste a lot of time for debugging my code.
- The ultimate purpose of regression is the effective prediction that does not need to wait for the results to be read out.
- Multiple Regression is different from simple linear regression. More independent variables are added in while the dependent variable remains to be only one.
- Regression + residual = real data. We should focus on the standardized regression coefficient. Under the consideration of theory, it’s better to put more than only one meaningful independent variables into the regression model. To some extent, it represents a more realistic model.
- The larger the tolerance, the better the model. On the other hand, the smaller the VIF, the better the model.
- $SS_{total} = SS_{regression} + Ss_{error}$. We should refer the standardized coefficients.

Anything want to share:

- It’s interesting~~
- (Blank)
- I’m still confused about the post-hoc after the linear regression analysis as shown on page.12 in the handout.
- It’s so great that I can adjust the video to a faster speed. When it comes to the film quality, however, it only provides 480p, which is a bit obscure.
- (Blank)
- Not yet, I’m still digesting the knowledge.
- I’m in favor of this topic. I believe it’s very useful.
- I have to rush to the next video. Bye~
- I still can’t understand the concept about the collinearity. Hope there will be more explanation in the future.
- Good job. Very clearly.

Figure 2. The illustration of a learning analytics dashboard

To simulate the analytical functioning of the brain component, we constructed a regression model using the multimodal and multiple-source data described above in predicting students’ final course grades, controlling for students’ gender and prior knowledge in statistics. The regression result was shown in Table 3. Students’ prior knowledge, in-class quizzes (Kahoot!), the number of messages classified by the ML as relevant, and their perceived help-seeking desire were associated with higher final course grades with statistical significance. The model explained 80.83% of the variance (adjusted R2) in the scores of the final course grades.

The empirical demonstration provided an initial exploration of the multimodal data from different components of the LA framework in predicting learning achievement. To yield internal validity and immediacy in personalized feedback in the future, the multimodal data can be collected on a weekly basis (or a more fine-grained time period) to form and adjust the RL policies based on students' subsequent formative assessments (e.g., in-class quizzes, midterm, or homework) and expert feedback. The policies can then be used for classification or association of students' learning progress for decision making, such as signaling of wheel-spinning or at-risk of failing.

The empirical demonstration based on an actual course had implications for precision education. First, learners' prior knowledge explained a significant portion of their final course grades. Understanding learners' initial level of the content knowledge can inform the instructor of students who are more likely to need assistance. Next, the Kahoot quizzes and ML classified messages provided additional clues regarding students' learning progress as the semester course went. Learners' with poorer quiz scores and fewer messages endorsed by the ML algorithm may flag at risk of academic failure. Finally, learners' help-seeking tendency may represent their desire to close their knowledge gap. Whereas, those with low help-seeking tendency may signal a reactive learning attitude, and thus, may require more instructor's attention and assistance. Suggestions can then be made to inform instructors of personalized intervention and enhance students' understanding of their learning for self-regulation and goal-setting in an automatic process. The analytical findings are promising and warrant the advancement of LA2.0 for precision education.

Table 3. The multiple regression analysis with multimodal inputs on students' final course grades

	B	*SE*	*β*	*t*	*p*	*VIF*
(Constant)	3.773	12.052		0.313	.758	
Male	2.765	1.904	0.138	1.452	.164	1.171
Prior Knowledge	0.234	0.088	0.310	2.644	.016*	1.784
Kahoot!	0.565	0.127	0.634	4.469	<.001**	2.615
ML_classified Message	0.375	0.135	0.279	2.775	.012*	1.313
Proxy_intelligent agent	-0.025	0.064	-0.038	-0.392	.699	1.204
Help seeking	3.912	1.805	0.255	2.167	.044*	1.792
Help providing	2.828	1.488	0.181	1.901	.073	1.175

Note. $^{*}p < .05$; $^{**}p < .01$.

5. Conclusion

Learning Analytics is one of the emerging learning technologies that apply learner-generated data and all other related information to provide personalized instruction and help learners adapt their learning in the technology-enhanced environment. The proposed human-and-machine symbiotic reinforcement learning has both theoretical and practical implications for the next-generation learning analytics models to implement precision education. From a theoretical perspective, the integrative Learning Analytics framework premised on the RL mechanism with human expert input (i.e., model-based RL) addresses the RL algorithm's limitations by providing rules and just-in-time human expert knowledge exchange. Therefore, RL robots can learn faster without the need for domain knowledge and computation with supercomputers. Valid value evaluations meaningful to humans can also be achieved by providing adversarial training for the RL robot to take appropriate policies of a series of actions to gain the maximum reward (Pinto et al., 2017). As experts, humans can also provide domain knowledge to train the robot to master a new domain learning to avoid local minimum due to its access to only the partial information (Abbeel & Ng, 2004). Moreover, experts can also provide models for the RL robot to learn by itself (Hester & Stone, 2012).

This study addressed the current learning analytics models' challenges and proposed solutions for precision education. Thus, from a practical perspective, the theoretical advances made the proposed LA2.0 possible for precision education by allowing the brain component with the RL algorithm and statistics model to take in multimodal student data streams from its subsuming components for real-time policy establishment and gain the maximum reward based on a series of actions. Subsequently, automated feedback, or scaffolds can be supplemented to the students depending on their individual learning needs, through the RL's dynamic task creation, heterogeneous task deployment, and arbitrary data flow dependencies. After that, the lack of internal validity and immediacy issues can be resolved. The brain component collects learner characteristics data from multiple sources (e.g., psychological assessments, observations, and conversation log) across platforms and creates dynamic and heterogeneous tasks for the RL's self-learning. As a result, the learning analytics model can be generalizable to different samples using various criteria. Besides, the RL mechanism can fuse and respond to multiple sensory data from various input streams. Thus, learner data from one platform can be transferred to another to consider the personalized feedback generation and adaptive course recommendation, targeting each individual for goal-setting and self-regulation.

The learning analytics results are displayed via the dashboard component about learners' learning progress and that of the machine with sensible feedback and suggestions for achieving the learner and the machine's best learning performance. By recognizing and supporting the varied challenges of the current learning analytics model, the proposed integrative LA2.0 framework can fulfill LA's potential to provide personalized and just-in-time high-quality learning for precision education.

This study provided a promising integrative framework of human-and-machine symbiotic learning to inform the next-generation learning analytics models with theoretical and empirical supports. As a caveat, issues such as data format compatibility, data privacy, and information security may cause additional challenges for educational data mining due to significant differences in data privacy and information sharing mechanisms between data producers and data consumers (Wu et al., 2014). Aside from those, the proposed framework can address the challenges of the current learning analytics models to support precision education.

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