An Ambient and Pervasive Personalized Learning Ecosystem: "Smart Learning" in the Age of the Internet of Things

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Abstract. Despite recent advances in technology, personalized learning to address diverse needs of students remains difficult to achieve at scale. With the availability and affordability of smart devices in the era of the Internet of Things, learners, parents, and educators are more "connected" than ever before. Education stakeholders and technology developers can leverage these advances to collect data about, inform, deliver, and improve education for all learners. In this paper, we review the core components of a Smart Learning framework and describe a personalized mastery-based learning system that leverages the framework to deliver personalized learning at scale. In the context of Smart Learning in the Internet of Things, we propose an Ambient and Pervasive Personalized Learning Ecosystem (APPLE), a learner-centered approach that uses Bloom's Four Agents of Change in the Internet of Things ecosystem to provide learners a comprehensive and personalized learning experience. This ecosystem uses people, processes, data, things, and networked connections to create new capabilities, richer learning experiences, and unprecedented educational opportunities for learners, educators, and families. We further discuss the challenges surrounding the implementation of such an ecosystem, specifically calling for applications of learning engineering approaches, the need of interoperability across systems and components, and the importance of ethical considerations.

Keywords: Smart learning · Internet of Things · Personalized learning · Adaptive instructional systems

1 Introduction

The K-12 student population in the United States is one of the most diverse in the world, and growing more so (de Brey et al. 2019; Geiger 2018; NCES 2019). Students arrive in the classroom from different cultural, socio-economic, and linguistic backgrounds, with varying degrees of prior knowledge, skills, aptitudes, and levels of parental or caregiver support. In recent years, learner diversity has experienced significant increases in levels of students living in poverty, students with learning

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disabilities and/or learner differences, second language learners, students identified as gifted and talented, as well as students recovering from trauma (NCES 2019; Pape 2018).

Where learning takes place also varies. Many students no longer do most of their learning in formal learning environments (i.e., the classroom). Students have moved away from what has previously been estimated as a 90–10% split of formal to informal learning, and now are estimated to learn equally in formal and informal contexts (Kinshuk et al. 2016). Today's students are surrounded by technology and media they can learn from. The availability of information at the tap of a button, or a search on Google has widened already vast differences in student prior knowledge. It is impossible for teachers to know the depth or breadth of knowledge which students have gained outside of traditional school contexts, making it ever harder for teachers to design appropriate instruction that can keep students engaged and progressing efficiently.

These issues, among others, present a number of challenges for teachers and schools who have been tasked with increasing student performance as demonstrated on state, national, and international assessments of academic achievement. A review of the scores of U.S. students reveals the extent of the challenge, with more than 2 of every 3 fourth grade students not proficient in grade level expectations for reading, math, and science – an academic performance that does not improve as students move on to successive grades (de Brey et al. 2019).

Given the lack of achievement in the face of such extensive learner diversity, the current one-size-fits-all factory model of education, where a teacher provides the same content at the same pace to all students, is simply not working (e.g., Rose 2016). Personalized education is one key way to ensure that individuals students' needs are being met. Unfortunately, personalization remains very difficult to achieve at scale, especially in an educational context that has not changed much in the past century.

2 One-Size-Fits-Me: Personalization in the Internet of Things

The growth of personalization in the commercial sphere through the use of technology has increased in recent years, with consumers moving away from one-size-fits-all products and programs to one-size-fits-me-perfectly (Forbes Insights 2019). Media consumption is an illustrative example of this, as more consumers have cut the cord to television and cable services to embrace more selective, customizable streaming platforms that adapt to the individual consumer through recommendation engines and data collection on viewing practices. This kind of personalization is growing throughout the commercial sector. To wit, the number of personal health apps has exploded in recent years as consumers look for ways to use technology (e.g., smart phones, smart watches, activity trackers and other wearables, etc.) to provide more information about their personal health and wellbeing (Bakker et al. 2016; Lin et al. 2018). Apps that track heart rates, daily steps, nutrient consumption, workout regimens, blood sugar, and more, all collect personal user data, "talk" to one another to create personal profiles, and make relevant recommendations to the user (Rodrigues et al. 2018). Individually these apps are useful; combined they are far more than the sum of their parts. Working together, these apps empower more informed users who are then equipped with personal, meaningful knowledge about how to live healthier, active lives. Beyond providing relevant, personalized knowledge to the user, many apps and devices go even further, using principles of behavioral psychology to encourage and motivate users to change behavior, abandoning self-sabotaging habits for healthy ones (Bakker et al. 2016; Lin et al. 2018).

Personalization is big business, with one recent market research study reporting that the wearables market alone is projected to grow by more than 35 billion dollars by 2023 (Technavio 2019). The development of smart technologies that include hardware and software that collect, analyze, and make personalized recommendations based on the individual user's data, has led to what many in the field call the *Internet of Things* (IoT). IoT, a term first used by Kevin Aston in 1999 (Gabbai 2015), has alternately been called the Internet of Everything, the Internet of Anything, the Internet of People, the Internet of Data, and more (Bakarat 2016). Perhaps one of the best descriptions of the IoT defines it as bringing together "*people, processes, data,* and *things* to make *networked connections* more relevant and valuable than ever before—turning information into actions that create new capabilities, richer experiences, and unprecedented economic opportunities for business, individuals, and countries" (Evans 2012, p. 3).

At its simplest, IoT is the idea that all "smart" things are connected—laptops, smartphones, tablets, and other devices—such that they can communicate with one another, share and interpret information, make decisions about how and what information to present, and what suggestions to make to the user. Recent discussions surrounding the IoT have centered on ways to create Smart Cities, Smart Energy, Smart Transportation, Smart homes, and even Smart Security (Bakarat 2016). It seems there is no shortage of "things" that can be made "smart." Consequently, stakeholders in education have and continue to look for ways that the IoT can benefit students through Smart Learning. When considering the definition of the IoT shared previously, an important question for EdTech developers is: *how can we use people, processes, data, things, and networked connections to create new capabilities, richer learning experiences, and unprecedented educational opportunities for children and their families?*

Education stakeholders and technology developers have a powerful opportunity before them to leverage IoT to collect data about, inform, and improve the education of our children. Families and schools are more "connected" than ever before due to the prevalence of smart devices in the home and many 1:1 device programs in schools. Just as commercial technology has been designed to collect data about users' entertainment, media, or health habits, EdTech systems can be designed to collect meaningful data about learner performance, artificial intelligence (AI) can be used to both analyze that data and offer real time program changes in response to that data, and information systems can be designed to communicate data and responses to students, schools, and parents –connecting them in ways that have previously been unimaginable.

3 The Evolution of Smart Learning Programs

Over the past two decades, governments and school systems in various locales around the world have attempted to implement some version of Smart Learning, including Malaysia's Smart School Implementation in 1997, Singapore's Intelligent Nation

Master Plan in 2006, Australia's smart learning collaboration with IMB in 2012, South Korea's SMART education project, New York's Smart School program, Finland's SysTech program, the United Arab Emirates Mohammed Bin Rashid Smart Learning Program in the convening years (Zhu et al. 2016), and more. Each of these programs were considered by their developers to be "smart," yet the concept of what constitutes smart learning or smart education has varied widely across these and other contexts. What is or can be called "smart" is still too new to be fully understood by stakeholders, nor has it existed long enough for consensus to develop (Hoel and Mason 2018; Zhu et al. 2016). The widespread, and at times casual, use of the term has further complicated efforts to research, design, or implement solutions in the field (Hoel and Mason 2018).

Researchers have attempted to bring more coherence to the study and design of the Smart Learning Environments and systems through the development of common language and frameworks. For example, in the inaugural issue of the journal *Smart Learning Environments*, Specter (2014) argued that smart learning systems must be grounded in the philosophical, psychological, and technological domains. In each of these three areas Spector describes various characteristics of smart learning environments (e.g., such as the degree of adaptivity) as *necessary, highly desirable*, or *likely* (see Fig. 1).

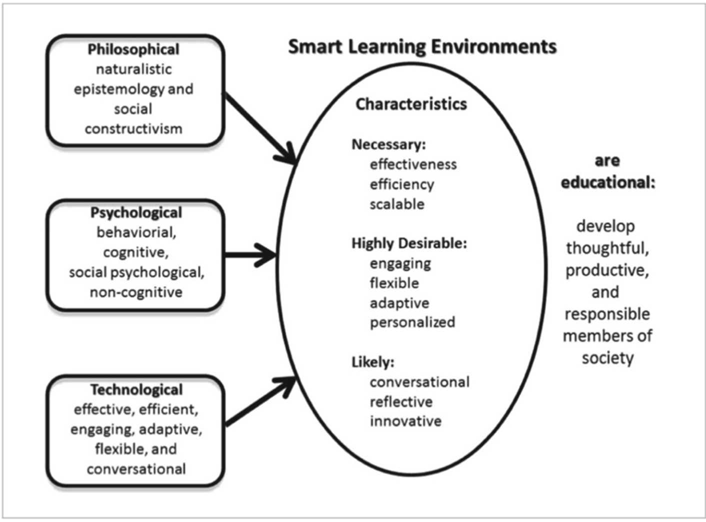

Fig. 1. "A Preliminary framework for smart learning environments" (Spector 2014, p. 8)

Kinshuk et al. (2016), provided additional context, explaining that Smart Learning moves education processes and pedagogy beyond simple technology-enhanced integration models, *to "enable the fusion of technology and pedagogy to create an ecosystem that involves active participation of teachers, parents and others in the learners' learning process… [and] also provide real-time and ongoing evidence of* *change in knowledge, instilling skills which are seamlessly transferred to learners as they move from one learning context to another" (p. 562).* The use of the word *ecosystem* is purposeful here, in that smart learning environments mirror the complex web of interconnectivity that permeates ecosystems in the natural world. In the natural world, every part of the ecosystem is connected; what impacts one part of the system almost surely will have consequences for other parts of the system (e.g., the butterfly effect, etc.). Beyond expansive interconnectedness, smart learning systems today have evolved to be omnipresent, empowering learners to access and interact with "just-right" learning resources at any time, in any place (Hwang 2014; Kinshuck et al. 2016).

Though various frameworks, terms, and definitions related to Smart Learning might differ, many "smart learning" systems today share three major components. Those components are (1) full context awareness, (2) big data and learning analytics, and (3) autonomous decision making and dynamic adaptive learning (Boulanger et al. 2015; Kinshuk et al. 2016). Across these three domains, Smart Learning environments "*facilitate just-in-time learning as they can provide various levels of adaptation and precision of diversified learning conditions (including curriculum, course content, strategy and support, etc.) for learners*" (Kinshuk et al. 2016, p. 565). We expand upon each of these three components and discuss how each support learning. We also argue for the importance of "small" data for Smart Learning in an IoT world.

3.1 Full Context Awareness

Full context awareness refers to the idea that computer systems have the potential to make sense of context and user behavior in order to provide information and/or services related to the tasks or goals of the user (Kinshuk et al. 2016). As technology has evolved, so has the idea of what it means for technology to be fully context aware. In Smart Learning environments, full context awareness may involve networks of people, processes, and things that combine to gather large amounts of information about the learners and their context in order to provide meaningful learning tasks, scaffolding, and feedback. In traditional learning environments, many learners are under the guidance of one teacher. This can make it difficult for the teacher to be fully aware of each child's performance; what the learner is learning in any given moment, what help or support the learner needs, or how well the learner is mastering the desired content may not be immediately apparent to the teacher. However, with Full Context Awareness, various "*learning management systems, mobile and ubiquitous learning systems, various artificial intelligence based adaptive and intelligent tutoring/learning systems*" (Kinshuk et al. 2016, p. 565) may work together to collect and analyze that data, providing valuable task-relevant information to the learner (through technology user interfaces) and to the teacher who may then take appropriate actions. If suitably advanced, the technology itself may make these adjustments in real time, based on information provided by the learner's behavior in the environment. For example, a Smart Learning system (i.e., synonymous with an adaptive instructional system or AIS) might capture data about the learner while engaged in playing a digital learning game. Based on that data, the system may automatically adjust the difficulty level of that game, while simultaneously providing information to the teacher about any misconceptions that the student might be demonstrating. With that new information, the teacher may conduct an intervention or mini lesson to address those misconceptions.

Full Context Awareness has the potential to empower teachers by helping them to conduct "*direct monitoring of the learning environment, understand learners' conditions and give learners real-time adaptive assistance, while at the same time facilitating independent learning for the learners*" (Kinshuk et al. 2016, p. 565). In sum, a fully contextually aware learning environment is one where processes and "things" are aware of themselves and each other. They are in continuous autonomous communication through active network communication, providing information and services to the entire network, as well as the people (users) who work with the system. As more things become "smart" and connected through networks, the opportunity to achieve Full Context Awareness becomes more possible.

3.2 Big (and Small) Data and Learning Analytics

For a Smart Learning environment to effectively serve the needs of individual students, it is important to collect and analyze data about each student's ongoing performance. Data collection serves a number of purposes, including tracking and drawing conclusions about student performance, making predictions about future learning performance, providing supportive feedback or scaffolding during moments of struggle, identifying student misconceptions that may be interfering with progress or comprehension, detecting and correcting counterproductive learning behaviors, adapting the content in order to personalize learning trajectories over time, and helping to keep students, parents, and teachers informed in real-time about student progress (i.e., Betts 2019; Hoel and Mason 2018; Kinshuk et al. 2016; Owen et al. 2019; Roberts-Mahoney et al. 2016).

Over the past decade, educational data collection has expanded dramatically. Student data bases today hold vast amounts of personal data including, "*student identification numbers, dates of birth, race, socioeconomic status, standardized test scores, attendance records, disciplinary records, health records, learning disabilities, homework completion, as well as student goals and interests*" (Roberts-Mahoney et al. 2016, p. 412). These demographic data can provide even more context about student learning capabilities and performance when combined with data collected during the process of learning. For example, it may be possible to detect that some young learners who have certain commonalities in their data (e.g., 4-year-old students from specific SES, backgrounds, regions or locales, with similar levels of prior knowledge) may perform similarly in a digital game-based Smart Learning system, and would benefit from specific types of support (e.g., receiving extra exposure and exploration on specific early math topics before beginning formal mathematics instruction) to ensure their most efficient pathway toward success (Betts et al. 2020). Powered by that information, student needs can be quickly identified, learning trajectories adapted, and support and scaffolding provided without delay.

As data is collected from thousands, tens, or even hundreds of thousands of individuals, trends and patterns emerge that combine with individual student performance data to create more powerful and precise predictive learning models that are personalized for each student. De Mauro et al. (2016) define Big Data as "*the information asset characterized by such a High Volume, Velocity and Variety to require specific technology and Analytical Methods for its transformation into Value*" (p. 131). Rich student interaction data from Smart Learning systems can support a broad range of analyses critical to understanding learning in the context of education. These large digital event streams enable the application of methods tailored to high-volume educational data, such as learning analytics and educational data mining (LA/EDM; Baker and Siemens 2014). These approaches empower the use of large educational data streams to mine organic learner patterns related to elements like student performance, affect, and behavior (Baker and Yacef 2009). In a wide range of other game-based research (e.g., Owen and Baker 2019), LA/EDM analyses have been used to uncover emergent learner patterns related to elements like strategy (e.g., Asbell-Clarke et al. 2013), student attrition (Hicks et al. 2016), player profiles (e.g., Slater et al. 2017), and learner affect (Kai et al. 2015; Rodrigo and Baker 2011). Rich event-stream data in game environments enables such investigations, which can inform potent data-driven design and personalized formative feedback (e.g., Ke et al. 2019).

It is also important to note that this embrace of "big data" does not mean that we ignore the importance of "small data" for Smart Learning in the IoT. On this topic, Lindstrom (2016) has aptly titled his book "Small Data: The Tiny Clues That Uncover Huge Trends". Not all questions, particularly those regarding causation, are answerable with big data. In education, small clues about the learning process and how to improve it can often come from data on a smaller scale: classes of students rather than whole grade levels, schools, or districts. Such data can be collected using formative assessments, human observations, face-to-face conversations, reflections and surveys, etc., revealing important information such as a student's confidence level when answering a question, their beliefs about the topics being taught, aspects of student-teacher personal interaction that may reveal important information like physical or mental health issues, problems at home, etc. that may more accurately support individual students' needs. These small clues are often hidden in the complex fabric of values, behaviors, and cultures that determine how teachers, learners, and parents interact. Understanding this complexity requires that we also be sensitive to small data.

3.3 Autonomous Decision Making and Dynamic Adaptive Learning

Another important key feature of Smart Learning systems is their ability to automatically collect data about each learner in the system. These data are likely to go beyond learning performance to include their socio-emotional behaviors as well. The data collected can be organized using AI algorithms to create a personalized profile of the learner. Based on the analysis of those data, a Smart Learning system makes inferences, draws conclusions, and makes decisions about what actions to take. Actions taken by the system may include a variety of things such as, adjusting the difficulty level, providing scaffolding or "just in time" feedback to help the learner get through a particularly challenging task, move the learner forward or backward within the system, notify the teacher of the need for remediation, or more.

This type of autonomous decision-making and dynamic adaptive learning is not limited to digital-only environments. For example, Kinshuk et al. (2016) point out that

Smart Learning environments that combine both digital and physical may benefit as well. Using collected data, some Smart learning systems can make recommendations to teachers about the types of interactions learners would benefit from most (e.g., reading specific books in the classroom library), or the best location for suggested activities (e.g., specific learners may improve their comprehension by engaging in a collaborative group reading), or even the types or problems that would most benefit the learner's progress at any given moment (e.g., learner "x" would benefit from more practice with multi-step word problems, etc.). This decision-making is autonomous, and the suggestions for how the learning environment might be adapted for student personalization are dynamic. Providing this type of guidance to teachers empowers them to extend the Smart Learning environment beyond the digital realm into the physical lives of children in and outside of the classroom.

4 The Learner at the Center of Smart Learning

Many existing Smart Learning systems (i.e., AISs) are mastery-based. The goal of mastery-based systems is to help learners master specific learning outcomes, usually through personalized learning trajectories that adapt based on the learner's existing levels of prior knowledge, learning pace, and need for remediation, support, or acceleration (Betts 2019). Mastery-based systems originally evolved from the work of Bloom (1984), who spent years studying the best practices of effective teaching and learning, and whose major contribution directly promotes personalization and learner variability. Bloom developed a framework for learning that goes beyond the immediate interactions of students and teachers, to include the other significant forces for learning in the learner's life. As Bloom (1984) described in his seminal work on mastery learning, there are Four Agents of Change: the *materials*, the *student*, the *teacher,* and the learner's *environment* (both inside and outside school), of which parents are a critical component – especially for young children. In order to significantly improve student learning, all four agents of change must be addressed.

Bloom's Four Agents of Change are particularly useful when viewed through the lens of Smart Learning, as Smart Learning systems have the power to integrate all four agents in ways that seamlessly work together to help the learner achieve learning outcomes. Additionally, Smart Learning systems that address Bloom's Four Agents of Change have the ability to do this at scale, for thousands of children simultaneously, which has been unobtainable through Bloom's mastery learning model alone (Betts 2019).

In a speculative article that echoes Bloom's framework, Ginsburg (2014) imagines a Smart Learning environment that would teach early childhood mathematics to the youngest learners. Beginning at age 3, the child would receive a personal tablet (which Ginsburg calls "Tubby") designed to function as a playmate of sorts for the child. Through Tubby, the child is presented with "microworlds" designed to sequence early childhood mathematics content in accessible and developmental ways. Through interactions with the child, Tubby collects data on what the child already knows, what the child needs to know, and what the child is most likely ready to learn next. It uses the algorithms of AI to test these "hypotheses," collect more data, and adapt to the child's individual need for support.

Ginsburg's vision goes beyond addressing only the learner and materials, and includes the important roles of teachers, and the environment beyond the school, reinforcing once again the need to consider Bloom's Four Agents of Change (Bloom 1984; Ginsburg 2014). Ginsburg describes a learning environment where people, processes, and things are fully connected, and where Tubby's operating system is engaged in ongoing, stealth assessment for the purposes of collecting data, feeding it to the teachers and parents, suggesting videos, books, and additional activities all at the child's just-right developmental level as part of a self-reinforcing cycle of progress through the desired content. At the time Ginsburg imagined this version of Smart Learning, it was perhaps still a fantasy (he even called it such in the title of his piece). However, advances in technology have made all that he imagined possible, and more.

5 A Personalized Mastery Learning System

Today, education technology developers seem closer to Ginsburg's dream than ever before, as they attempt to *use people, processes, data, and networked connections to create new capabilities, richer experiences, and unprecedented educational opportunities for children and their families.*

A contemporary example of how one EdTech developer is working to realize this vision is Age of Learning, Inc.'s Personalized Mastery Learning System (PMLS; Dohring et al. 2017) that uses the IoT (people, processes, data, things, & networks) as well as Bloom's Agents of Change to drive a multi-pronged approach to teaching early mathematics and reading skills to children 4–8 years old. The result is two independent personalized game-based learning systems, ABCmouse Mastering Math™ and ABCmouse Mastering Reading™, designed to help young learners build a strong foundation of mathematics and reading, respectively.

Within PMLS, an evidence-centered design (ECD) approach (Mislevy et al. 2003) is used to structure embedded assessment in a game context, with an emphasis on aligning target knowledge, skills, and abilities with desired evidence and in-game assessment tasks designed to elicit such data. Such an approach provides context-rich interaction data streams that enable a broad range of analyses, including investigation of emergent learner patterns (Baker and Yacef 2009). Research has shown that ECD-based educational games can capture emergent, EDM-based insights with implications for iterative design (e.g., DiCerbo et al. 2015, Hao et al. 2016; Slater et al. 2017; Stephenson et al. 2014). When game-based assessment is a part of the development from conception, game design is founded in the consideration of learning evidence, which enable assessment to be embedded into the core mechanics of game play (Grace 2014). This integrated game-based assessment (iGBA; Owen and Hughes 2019) approach is core to the design and production of PMLS. The result is context-rich and detailed iGBA-based data that allow for iterative, data-driven design for improved learning and engagement via a range of methods, including evaluation of designed assessment, as well as broader explorations with LA/EDM to enhance intelligent system response in real time. These data also have implications outside the system, as event-stream insights can be surfaced to teachers to allow classroom-based intervention and student support, and to parents who receive (through a mobile application on their smart phone) both performance updates and recommendations regarding how best to support their learner with just-right activities at home.

While Mastering Reading has only just newly been released (early 2020), evidence suggests that Mastering Math (released in 2017) integrates well into formal learning environments, as recent classroom-based research suggests, providing promising learning results with PMLS and informing future development of the systems (Betts et al. 2020; Thai et al. 2019). Mastering Math currently features approximately 130 games, covering number sense and operations concepts and skills for pre-kindergarten through second grade. Consistent with good assessment practices, every game is designed with a clear learning objective, learning task, and evidence in mind; and each learning objective is supported by an interactive instruction level, as well as several layers of scaffolding and feedback. To support personalized instruction, the adaptive system decides what games to recommend and at which difficulty level using a pre-determined knowledge map of learning objectives and their prerequisite relationships (i.e., a node map). Adaptivity functions within individual games to provide scaffolding with each level of skill difficulty, between games to adjust to students' difficulty needs, and across the system to personalize learning trajectories for each learner based on performance (Betts 2019; Betts et al. 2020). Assessment is embedded throughout the play experience, including game-based pretests and final assessment tasks at a granular skill level.

To develop *Mastering Math*, Age of Learning implements a learning engineering approach (Thai and Rothschild, under review; ICICLE 2019) with a cross-disciplinary team of curriculum specialists, learning and data scientists, and professional game developers. This team collaborated to create a game-based learning solution built upon rigorous academic curriculum, developed with a high degree of polish and engagement value, and grounded in principles of evidence-centered design, game-based assessment, and educational data mining.

The PMLS, in real time, collects and interprets rigorous data in order to inform and modify content for students, as well as to inform teachers and parents. This system goes beyond mere information reporting, as it uses best practices in motivational digital content development to suggest, encourage, and motivate students, parents, and teachers to take action based on the information presented about each learner. This PMLS leverages smart tools (e.g., phones, tablets, laptops, etc.) to connect, in real time, the content to be learned (***materials***), the ***student***, the ***teacher***, and their parents (***environment***); in other words, the PMLS networks people, processes, and things to provide a context aware, personally adaptive learning experience that is driven by big data and small data, learning analytics and educational data mining (Owen and Hughes 2019; Betts 2019; Betts et al. 2020; Owen et al. 2019). Current ongoing research based on this system shows promising results and provides a basis for what Smart Learning might look like, or at least what it can look like right now, incorporating the tools and technology available to developers at this point in time.

Age of Learning is not alone in their efforts to move the field of Smart Learning forward. Similar efforts can be found with other research-based personalized learning frameworks such as the Generalized Intelligent Framework for Tutoring (GIFT;

Sottilare et al. 2012) and the Knowledge-Learning Instruction Framework (KLI; Koedinger et al. 2012) and LearnSphere (formerly PSLC DataShop; Koedinger et al. 2010).

6 What the Future Holds: Ambient and Pervasive Personalized Learning Ecosystem (APPLE)

The mastery-based Smart Learning systems taking advantage of the IoT available today are just the tip of the iceberg, though it is possible to imagine what such systems in the future might include. With that in mind, we propose a new vision for an Ambient, Pervasive, Personalized Learning Ecosystem (APPLE) that organizes Smart Learning and the IoT through the lens of Bloom's Four Agents of Change, in order to achieve a truly learner-centered framework founded on research-based best practices in teaching and learning (see Fig. 2). In this framework, people, processes, data, and things are networked in context from the learner outward. The learner, at the center of the framework, interacts with formalized learning materials presented through a variety of technology types (e.g., smartphones, tablets, computers, laptops, eReaders, etc.). These devices, along with the educational materials they supply, collect user data and provide information to the learner's educators. This information consists of meaningfully interpreted data, along with recommendations and suggestions for avenues of support, which may include additional scaffolding and/or remediation, or it may include extension, enrichment, or acceleration.

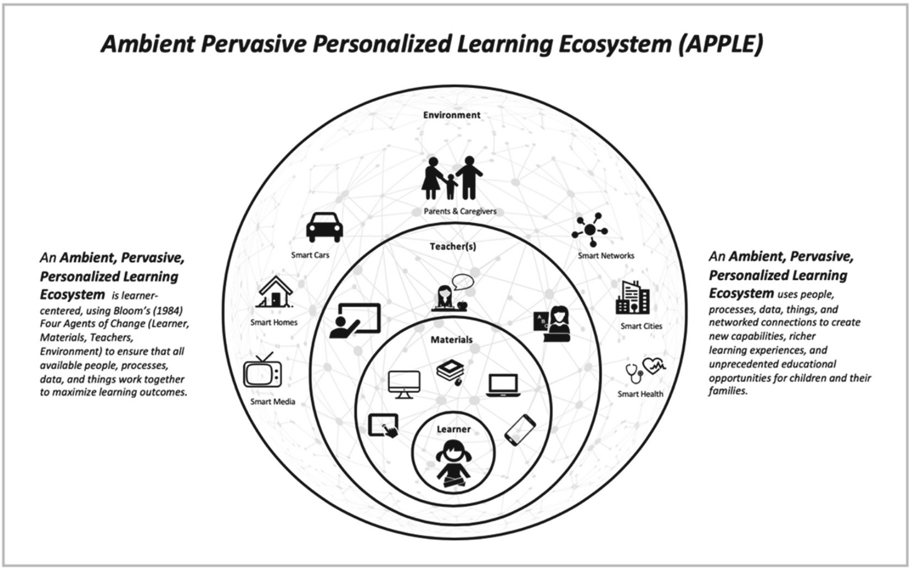

Fig. 2. APPLE: The Ambient Pervasive Personalized Learning Ecosystem

Beyond the formal learning sphere, the APPLE framework seeks to examine all the ways that the IoT present in the learner's environment can contribute to a more comprehensive and personalized learning plan. Data collected from the environment provides information about informal learning opportunities that can contribute to and further the learner's progress. For example, networked connections across the entire ecosystem allow for recommendations at the level where the child's learning can be maximized (i.e. the child's zone of proximal development; Vygotsky 1978). Video programs on media streaming services (e.g., Netflix, Amazon, YouTube, etc.) are recommended at an appropriate developmental level and on topics with which the learner has demonstrated high engagement; on Audible, books are recommended at the just-right listening comprehension level on topics known to be of high interest to the learner.

Behind the scenes, LA/EDM leverages AI algorithms to analyze and interpret data, to develop personalized predictive learning models, and direct the learning systems and materials to adapt in real-time with the learner's needs. Data collected from across a variety of formal and informal learning experiences as well as from a learner's passive consumption would be tracked and its impact on the child's learning trajectory evaluated, driving ongoing customization and adaptivity. In addition, such a comprehensive system could be used to identify, provide remediation and support for, and evaluate other learning needs, such as socio-emotional, metacognition, and executive function, etc. As an example of this, the Personalized Mastery Learning System discussed earlier is already beginning to do some of this work, through the use of data and AI algorithms that may be able to identify the need for additional executive function and fine motor coordination support in young children (Betts et al. 2020).

An APPLE approach would further allow for customization of collaborative learning. Children with similar needs could be grouped and encourage to engage in peer learning sessions. Specific content related to these groupings, or children grouped by interest or passion could be pushed through various smart devices or services (e.g., YouTube channels, etc.). The infrastructure to support these types of customized collaborative learning experiences does not yet exist, but the technology to build them does exist.

7 Challenges to Implementing APPLE

7.1 Evidence-Based Implementation

Enthusiasm remains high related to the ways in which technology might potentially transform education, and how the data created by all technology can bring about a new era of amazing personalized instruction. However, the history of technology in education suggests we need to be skeptical. The radio in the 1930's, film in the 1950's, television in the 1960's and 1970's, desktop computing in the 1980's and 1990's, mobile devices and smartboards in the 2000's, laptops and iPads in 2010's—each innovation had promised much, but never produced improved learning outcomes. For example, a 2007 congressionally mandated study by the National Center for Education Evaluation examined educational technology in 33 school districts and found no evidence that tech-enabled classrooms have helped boost student achievement (US Department of Education 2008).

In 2010's, the country of Peru, as part of the One Laptop per Child Initiative, spent $200 million to distribute laptops to 800,000 students, and found no evidence of improved learning (Horn 2012). Los Angeles Unified School District in California, one of the largest school districts in the US, spent more than one billion dollars to buy 650,000 iPads – one for every student in the district (Newcombe 2015). Program planners failed to consider critical infrastructure changes that might need to be implemented (e.g., not all schools had reliable internet connectivity making it difficult to access online curricula through the iPads), or how teachers might be sufficiently trained to effectively use these technologies (Newcombe 2015). The failure of the program resulted in ongoing lawsuits filed by the district against tablet curriculum providers and ultimately the resignation of the superintendent.

And here we are in 2020, embracing AI and IoT for Ambient, Pervasive, Personalized Learning Ecosystems (APPLE). What makes this time different? A key difference, if we choose to put it to work, is the availability of evidence-based principles from the learning sciences, and an increasingly robust learning engineering approach to apply those evidence-based principles and ideas, together with learner-center research methodologies and appropriate uses of data to drive iterative improvements in real-world settings (Saxberg 2017; ICICLE 2019). Doing this at scale is not at all trivial – requiring hundreds if not thousands of people to alter their thinking and practices around learning, making this a major change project on top of the new engineering challenges that evidence-based work creates. We must also consider carefully the interactions between (1) technology and teachers (how teachers are prepared, supported, and evaluated), (2) blending school and home (how the time a child learns in comfortable, personalized settings can be expanded), and (3) data and competency (how we collect and actually leverage data to systematically track mastery, give feedback, and inform the learning process) (Hess and Saxberg 2014). The good news is, there is a body of evidence available to tap. *Systematically* and *thoughtfully* taking advantage of that knowledge seems to be the key to making it work (e.g., Koedinger et al. 1997; Sottilare et al. 2013; Heffernan and Heffernan 2014; Saxberg 2017; The Learning Agency 2019; Hess and Saxberg 2014).

7.2 Interoperability

With the large amount of learning interaction that can take place in a Smart Learning network, existing industry standards are unable to support the interoperability of the information exchange within and among IoT components and systems, across different informal and formal, physical and virtual settings (Johnson et al. 2017; Thai and Tong 2019). Smart Learning in IoT has the potential to improve learning effectiveness across settings and devices, which involves a move from self-contained software to distributed AI-enabled cloud base systems. For example, the interoperability required to allow for a formal learning program like Mastering Reading to inform and leverage data from more informal learning opportunities such as listening to or reading an appropriately leveled book on Audible or Kindle (and vice versa) requires substantial infrastructure changes to networks, devices, and digital content, data collection, and data sharing protocols - more than exists at the present.

IoT includes all manner of objects and items made "smart," but until virtual infrastructures for data collection, aggregation, sharing, and analysis are built that extend across all of the "smart" things in our world, we will be unable to provide the unprecedented educational opportunities that such data might empower. This kind of holistic transformation of our smart systems requires transparency containing the operation, features, functionality, and use of AI in these systems for the benefit of the users (be it learners, parents, teachers, administrators, etc.). It also requires an exchange of data and semantic interoperability within and across learning and enterprise systems. In other words, machines must not only agree on what data look like, but also what they mean in a larger ecosystem. Such needs are driving recent efforts by the IEEE Learning Technology Standards Committee to provide standardized component definitions of systems and to establish a framework for the development of data interoperability standards (IEEE P2247.2).

7.3 Ethical Considerations

Smart Learning in the IoT raises an indeterminate number of self-evidenced but unanswered ethical questions. The first is about the data. As with mainstream AI, concerns exist about the large amount of data collected to support Smart Leaning, even when data are collected with the best of intentions (i.e., recording of student competencies, emotions, strategies, misconceptions, screen usage, etc. to better help learners learn). Who owns the data? Who can access them? What are the privacy concerns? How should data be analyzed, interpreted, shared? Who should be considered responsible if something goes wrong? As with healthcare, the use of personal data in education requires careful attention.

Another major ethical concern is the potential for bias, conscious or unconscious, that are incorporated into AI algorithms and models in working with large sets of data. Each decision that goes into constructing these algorithms and models might negatively affect the rights of individual students. For example, what happens if a child is unknowingly subjected to a biased set of algorithms (i.e., on the basis of gender, race, age, socio-economic status, income inequality, and so on) that impact negatively and incorrectly on their school progress?

These ethical concerns regarding data and bias are subject of many mainstream discussions, but other issues are possible, including those that are yet to be identified. For example, how does the transient nature of student goals, interests, and emotions impact the ethics of Smart Learning in the IoT? What are ethical obligations of private organizations (i.e., EdTech developers) and public authorities (i.e., schools involved in Smart Learning research?)? How might schools, students, teachers opt out from, or challenge, how they are represented in large datasets? Etc.

Strategies are needed to ameliorate risks of hacking and manipulation. Where Smart Learning interventions target learning, the entire sequence of pedagogical activity also needs to be ethically warranted. It is also important to consider the ethical cost of inaction and failure to innovate against the potential for innovation to result in real benefits for learners, educators, and educational institutions. Ethics of Smart Learning in IoT is complicated, but the potential benefits are paramount. We must all engage in productive dialogue to help ensure that the use of AI and the IoT for Smart Learning reaches its potential and has positive outcomes for all.

8 Conclusion: Summary and New Directions

In light of the stagnation in children's academic achievement as indicated on national and international assessments, combined with increases in learner variability that drive the need for more personalization, it is more critical than ever that we examine and explore the unique opportunities that advancements in technology might make possible in education. The field of Smart Learning and the IoT have advanced to the point where learning environments such as Age of Learning's Personalized Mastery Learning System and those implementing GIFT can *begin* to deliver on the promise of ambient and pervasive personalized learning. However, there is still a great deal of development needed before an ecosystem like APPLE, described in this paper, can come to fruition. Further advances are yet needed in standardizing component and system definitions in this ecosystem, and in the development of interoperability standards and the infrastructures to enable data exchange. In addition, specific challenges unique to the education sector, such as overcoming educator reluctance to implement technology solutions through proper training and implementation plans, as well as strategic plans for how the privacy of children's data will be handled, will need to be addressed.

As our population of diverse learners become ever more connected through personalized "smart" devices, it makes little sense to continue with an educational model based on a century old context. It also makes little sense to ignore the wealth of data that our learners are generating both in formal and informal learning environments, that might be put to use for their educational benefit. As education researchers and stakeholders, we have a role to play in helping to understand, define the scope of, and push the furtherance of the field. The field of Smart Learning, especially as it relates to efficacy and achievement gains is understudied and requires more attention. Our hope is that by establishing the APPLE framework rooted in learning engineering, we have provided a means for others to evaluate and insist on the development of more rigorous Smart Learning systems that utilize the IoT to produce learning outcomes at scale.

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