Identifying Gaps in Use of and Research on Adaptive Learning Systems

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Abstract: Adaptive learning systems have become increasingly common across age groups and content areas. Many adaptive learning systems personalize the learning experience based on students' prior knowledge, preferences, learner profile, system usage, learning style, and/or learning perceptions. In addition, various learning algorithms have been developed over the years, such as item response theories, Markov modelling, recurrent neural networks, and Bayesian knowledge tracing (BKT). Although western countries have generated numerous efficacy studies, Chinese adaptive education is in its earliest stage, with few efficacy studies conducted in this context, which is a gap in this field. This position paper describes one Chinese adaptive learning system, Squirrel AI Learning, and invites further research on adaptive learning systems in China and other Asian countries.

1 INTRODUCTION

Adaptive learning systems have become increasingly more popular across age groups and content areas. As adaptive learning system use has grown, so too has research on their efficacy for learning. This paper details gaps in the research and in the use of adaptive learning systems. After discussing adaptive learning systems in general, we address a case study on Squirrel AI Learning in greater depth.

Adaptive learning systems use comprehensive data analytics and machine-learning algorithms to provide individualized, computer-based learning experiences. Many adaptive learning systems personalize the learning experience based on students' prior knowledge, preferences, learner profile, system usage, learning style, and/or learning perceptions (Nakic et al., 2015; Xie et al., 2019). As students spend more time in the system, the system may develop a more detailed understanding of students' needs and preferences, resulting in greater personalization (Hauger & Köck, 2007; Van Seters et al., 2012). Aspects of the system that may be personalized vary, but often include the learning sequence, item difficulty, and learning supports provided.

For many years, computer scientists and cognitive scientists have developed adaptive learning systems that use artificial intelligence to mimic the interactions of one-on-one human tutoring (Merrill, Reiser, Ranney, & Trafton, 1992). Developers have created systems that present content, pose questions, assign tasks, provide hints, answer questions, and suggest improvements to learners based on their prior behaviors (Ma, Adesope, Nesbit, & Liu, 2014). Adaptive learning systems follow a similar "closed loop" architecture that gathers data from the learner and then uses that data to estimate the learner's progress, recommend activities, gives hints, or provides tailored feedback. The adaptive system's algorithms typically make such decisions by referring

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to a domain model of the knowledge to be learned, a student model of learners' background characteristics (knowledge level, affect, and motivation), and a task model that specifies features of the learning activities (e.g., questions, tasks, quizzes, dynamic hints, feedback, prompts, and recommendations) (Lee & Park, 2008).

Adaptive learning systems utilize various algorithms, such as item response theories, Markov modelling, recurrent neural networks, Bayesian knowledge tracing (BKT), natural language processing, and other machine learning models to personalize the learning sequence for each student.

This personalization is based on system-generated student profiles, informed by a students' performance on an initial knowledge diagnostic and continuously updated with student usage data and learning behaviors. As students spend more time in the system, their learning profiles become more accurate and allow for greater personalization (Hauger & Köck, 2007; Van Seters et al., 2012).

Historically, adaptive learning systems utilize different models for estimating a learner's level of domain knowledge. Some focus on how well learners implement core steps in tasks (Koedinger, Anderson, Hadley, & Mark, 1997); some examine learners' problem-solving behaviors and compare them to models of both correct and incorrect behaviors (Aleven, McLaren, Sewall, & Koedinger, 2009); others present specific problem-solving situations and check for common errors (Mitrovic, 2012; Ohlsson, 1992). Some use natural language processing to measure how well learners articulate common learning goals or misconceptions (Graesser, VanLehn, Rose, Jordan, Harter, 2001), while still others model a learners' understanding at each point of interaction (Piech et al, 2015; Yudelson, Koedinger & Gordon, 2013).

Often, the content area being assessed is linked to the requirements for the algorithm that is used. For example, in content areas where knowledge components can be clearly distinguished, as in algebra, a model like Bayesian knowledge tracing may work well for modelling student behaviour and providing guidance for learning. However, in a content area, like English, where writing a coherent argument is important, natural language processing is an important algorithm to include. Use of knowledge components is also a common metric used to trace student understanding in adaptive learning systems. A knowledge component is a description of a mental structure a student uses to accomplish steps in a problem or task (Koedinger, Corbett, & Perfetti, 2012). A knowledge component relates features of a question or task to a response given by a student.

2 EFFICACY RESEARCH

Efficacy studies from the past 6 years have shown that the use of adaptive learning systems is associated with greater gains in student learning. Across several different types of studies, including a review of 37 adaptive learning efficacy studies, a comparative study of 1,600 adaptive and 4,800 non-adaptive courses, and a large-scale randomized control trial in algebra classrooms, researchers report positive findings when they compare students who use adaptive learning systems in academic contexts to those who do not. In two studies that involved the implementation of adaptive learning systems in mathematics instruction, students' scores on proficiency exams were 8 and 3 percentile points higher, respectively, than the scores of their peers who did not use the learning system (Bomash & Kish, 2015; Pane et al., 2014, 2017).

Despite these promising findings, we know relatively little about for whom and in what contexts adaptive learning systems are most effective. Below we provide an overview of the relevant literature to date and highlight areas for future research and development.

2.1 Learner Characteristics

Adaptive learning systems have potential to promote equity in education by responding to diverse learners' needs in ways that may not be feasible for teachers in traditional classroom instruction. We call for more research on subgroup effects to evaluate whether and how adaptive learning realizes this promise. Do adaptive learning systems work equally well for all learners? Or are they better suited for a particular level of prior knowledge, socioeconomic status, gender, or age range?

Researchers have begun to explore the differential impacts of prior knowledge on students' learning from adaptive learning systems. Many adaptive learning systems personalize the learning experience based on prior knowledge (Nakic et al., 2015), as students with different prior knowledge may benefit from different instructional features (Ayres, 2006; Flores et al., 2012). For example, to avoid cognitive overload in learners with less prior knowledge, adaptive learning systems may tailor worked examples or the degree of learner autonomy (Lee et al., 2008; McNeill et al., 2006; Salden et al., 2009;

Scheiter et al., 2007). Some evidence suggests that such adaptations can be effective: some studies have found that adaptive learning is able to help students with less prior knowledge achieve similar outcomes to students with more prior knowledge (Jones, 2018; Wang et al., 2019). More research is needed to demonstrate which adaptive learning algorithms and features are best suited to addressing the needs of learners with varying prior knowledge.

In addition to adapting to differences in prior knowledge, adaptive learning may also have potential to address equity gaps that affect historically underserved populations, such as students from lower socioeconomic-status (SES) families. These students tend to report lower academic participation and academic achievement on math and reading assessments (Dahl & Lochner, 2012; Willms, 2003). Initial research suggests that such students may benefit from adaptive learning systems in academic settings. A study by Yarnall and colleagues (2016) assessed 2-year and 4-year college students' impressions of adaptive learning systems in higher education and found that 2-year college students, who are more likely to be lower SES, rate adaptive learning systems more favourably. More of these students also reported positive learning gains than their 4-year institution peers. In two cases reported in this study, Pell grant students showed similar positive learning outcomes associated with using adaptive courseware to those reported for the general population. More research is needed to explore adaptive learning systems' promise with lower SES students, and to elucidate the most effective adaptations for this population, such as those that address prior knowledge gaps and learner motivation.

More research is needed on the efficacy of adaptive learning systems for K–12 students. Most adaptive learning efficacy studies are conducted with higher education students. A systematic review of 70 articles on adaptive and personalized learning published from 2007 to 2017 found that the largest share, 46%, included higher education students. Less than half that, 21% of studies, included elementary students, and only 9% included middle and high school students (Xie et al., 2019). While K–12 efficacy studies in adaptive learning are less common, some suggest adaptive learning can be effective for elementary students (Mettler et al., 2011) and middle school students (Feng et al., 2018).

2.2 Content Areas and Features

A systematic review of 70 articles on personalized and adaptive learning found that many studies are conducted in certain content areas, while in others there have been few studies. Xie (et al, 2019) report that the most studies are conducted in engineering and computer science, followed by languages, mathematics, and science. Content areas like health (medical/nursing), social science, art/design, and business management have few or no efficacy studies using adaptive learning systems. While there is a larger proportion of research conducted on adaptive learning systems in more traditional school content areas (e.g., math and science), there is little research done on adaptive learning systems in content areas that are more commonly found in college courses or professional training (e.g., health/medical/nursing). This is consistent with prior studies (e.g. Alexander, Rose, & Woodhead, 1992) that discussed the limited domain knowledge of researchers who developed adaptive learning products.

In addition, Xie (et al, 2019) report on the types of learning supports provided by adaptive learning systems. Personalized learning content is the most common feature, followed by personalized learning paths, personalized interfaces, personalized diagnosis and suggestions, personalized recommendations, and personalized prompts or feedback. While many of these personalization features have been studied in some way, a meta-analysis of their impact on student learning has not been conducted. Since adaptive learning systems rarely contain only one way of using personalization, a meta-analysis of these features is particularly necessary as it will provide insight into design features for these systems. However, due to the large range of learner populations, content areas, and system features contained under the adaptive learning systems umbrella, many more studies on efficacy must be conducted.

2.3 Outcomes

As mentioned previously, adaptive learning has been shown to have significant positive impacts on learning outcomes. More research is needed to explore how effects vary by outcome. For instance, consistent with prior studies (Brookhart, 2020; White, 1993), Xie (et al, 2019) have found that positive effects of adaptive learning are more likely to be reported on student affect than on student cognition More research is needed to distinguish which learning metrics are most sensitive to adaptive learning-related change. While some studies measure academic outcomes solely via in-system performance (Bomash & Kish, 2015; Jones, 2018), others have examined adaptive learning's effects on external metrics.

Test scores and assessments are some of the most common external metrics that researchers use to assess the efficacy of adaptive learning systems. Studies that measure student outcomes on assessments have shown mixed, though mostly positive, effects (Fullerton & Hughes, 2016; Yarnall et al., 2016). A review of six studies found that the use of adaptive learning systems in various environments (upper elementary through the workplace) related to positive effects on students' course test achievement (Durlach & Ray, 2011). An important feature of the adaptive learning systems in these studies that may have contributed to the positive results is mastery-based progression, which requires students to demonstrate their knowledge before advancing. Another study review by Yarnall and colleagues (2016) reported that while it positively impacted students' scores on course tests, the use of adaptive courseware did not have significant effects on course grades or completion rates.

3 GLOBAL SPREAD

Adaptive learning systems are increasingly common in western culture, including the United States, United Kingdom, and other regions. Some well-known products already on the market for learners and educators include Knewton (Wilson & Nichols, 2015), ASSISTments (Heffernan & Heffernan, 2014), ALEKS (Canfield, 2001), i-Ready, Achieve3000, Carnegie Learning, Norton, Kidaptive, and DreamBox Learning. Accordingly, many efficacy studies of adaptive learning systems have been only conducted in western countries (e.g., Griff & Matter, 2013; Mettler et al., 2011; Sun et al., 2017).

Meanwhile, in mainland China, adaptive learning systems are only just beginning to gain popularity, even though 19% of all Chinese Internet users have engaged in online education in recent years (China Internet Network Information Center, 2017). While adaptive learning is relatively new in mainland China, it is a Chinese education policy priority (O'Meara, 2019).

3.1 Squirrel AI Learning

Squirrel AI Learning is considered the first commercial adaptive learning system in mainland China. Since its establishment in 2016, Squirrel AI Learning has expanded to serve almost 2 million registered accounts in over 700 cities. These 2 million users are diverse in socioeconomic status, urbanicity, and academic achievement. In addition to this user base, Squirrel AI Learning has opened over 2,000 learning centers in less than 5 years. This rapid expansion is indicative of the gap that adaptive learning fills in the Chinese after-school tutoring market.

In particular, during the coronavirus outbreak in 2020, Squirrel AI Learning is considered an important supplement for student learning while students are required to stay at home and schools are closed in almost all provinces in China. Because of their potential to reach so many students, research is needed to ensure that such learning systems truly support student learning in China and possibly in other countries of Asia.

3.2 Squirrel AI Learning Features

Squirrel AI Learning provides instructions and supports for K–12 students and has the following features:

1. **Nanoscale Knowledge Components.** Squirrel AI Learning breaks down knowledge components into a fine-grained knowledge map with knowledge components organized hierarchically based on the following: relationship to learning progression; adaptive diagnostic pre-assessment; automated differentiated instruction; rich, high-quality learning repository of various types of learning content; immediate feedback and explanations to students and in-class support and intervention by teachers. For example, in junior high school mathematics, 300 knowledge components are dissolved into 30,000 fine-grained knowledge components, and each knowledge component is matched with the learning content. This content may include text items, animation, slides, short instructional videos, etc. A parent knowledge component can be resolved into sub-knowledge components that are more specific and targeted. See figure 1 for an example of the Squirrel AI Learning system, where students receive popup explanations if their attempts are incorrect; students can choose to view video or text explanations.

2. **Integration of Various Learning Algorithms.** Squirrel AI Learning uses more than 10 learning algorithm technologies, including Clustering algorithm, such as k-means and expectation maximization (EM), logistic regression,

Item Response Theory, graph theory, probabilistic graph model, Bayesian network, knowledge space theory, information theory, source tracing model, knowledge tracking theory, learning analysis technology, and so on. The algorithms help to identify students' weaknesses in current knowledge by tracing the pre-requisite knowledge components of their current learning content. The algorithms determine the recommendation priority of each knowledge component from three aspects: whether the pre-requisite knowledge component is easy to learn, whether its map position is relatively backward, and its central degree. This layered process of identifying student weaknesses creates a solid foundation to effectively promote the learning of current and future knowledge components.

3. **MCM Model (Methodology, Capacity, and Mode of Thinking).** Squirrel AI Learning splits MCM into nanoscale just like the knowledge components, and the ambiguous and incomprehensible capabilities are split into nanoscale capabilities that can be clearly defined. In this way, Squirrel AI Learning can measure the level of a student's capabilities and represent his capabilities quantitatively. At the same time, Squirrel AI Learning ensures that the capabilities can not only be clearly explained by teachers but also understood and digested by students. MCM are curated and summarized; for example, in middle school mathematics, 500 components subdivide into 1,000 application scenarios to make them completely definable, measurable and teachable. Squirrel AI Learning can identify and quantify the capabilities that individuals possess and the capabilities that they need to improve, such as those of a lawyer who is excellent in pattern exploration skills and summarization skills yet lacks the skills needed for analyzing 3D graphics, algorithm construction, and realization. In contrast to the lawyer, a scientist may be excellent at data analysis but poor in linguistic association skills. In Squirrel AI Learning, the users' behavior is taken automatically into account by the algorithm parameters. However, in the initial phase, some of the parameters are set according to experts' experience. For example, the item difficulty is set according to experts' experience if the number of data samples is less than 25. When the number of data samples is more than 25, the item difficulty is computed by machine learning algorithms.

Figure 1: Screenshot of Squirrel AI Learning system.

Note. The question is on the upper left of the white window. The choices are on the right side of the white window. When students answer the question incorrectly, the system gives explanations at the bottom of the white window. The next question is dependent on the correctness and difficulty level of the current question.

3.3 Squirrel AI Learning Efficacy

Multiple efficacy studies have shown that the Squirrel AI Learning platform:

- Improves learning efficiency and students' perceptions of the learning experience, as compared to other learning platforms (Li, Cui, Xu, Zhu, & Feng, 2018)
- Is associated with greater improvements in test scores compared with whole-classroom instruction or small-group tutoring (Feng et al. 2018; Wang, Christensen, Cui, Tong, Yarnall, Shear, & Feng, submitted). This builds upon a review finding that contrary to popular belief, intelligent tutoring is nearly as effective as human tutoring (VanLehn, 2011).
- Is associated with similar gain scores regardless of students' prior knowledge (Wang, Feng, Bienkowski, Christensen, & Cui, 2019).

However, the sample sizes for these studies were not large, the topics covered in these studies were limited, and the interventions of these programs were short-term, e.g. in a couple of days. Future studies examining Chinese adaptive learning efficacies in different contexts are highly needed.

4 CONCLUSIONS

Adaptive learning systems have become more widely used in the last 2 decades and are only becoming more widely used with each passing year. The ubiquity of adaptive learning systems demands wide-reaching studies on their efficacy. Many current efficacy studies apply adaptive learning systems in higher education and in traditional academic subjects (math, science, languages). Further efforts are still needed to determine which outcome metrics are both useful and aligned with the use of adaptive learning systems. Further, more research is needed to address how these adaptive learning systems might address issues of equity or otherwise impact lower- SES students.

One additional gap in the research is in study geography. Many efficacy studies using adaptive learning systems take place in either the United States or the United Kingdom. With the potential to impact many students worldwide, efficacy studies must be undertaken in a wider variety of contexts. We discussed one such case, Squirrel AI Learning, a commercial adaptive learning system in mainland China. However, efficacy studies on Squirrel AI Learning have included limited numbers of participants and a limited range of subject areas. Efficacy studies of different contexts need to be conducted. More importantly, as new technological and pedagogical approaches continue to evolve, more efficacy studies are needed in Asia and worldwide in the future, and we invite more scholars to continue research in the adaptive learning systems field.

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