EdTech for Learning Outcomes and Impact: A Comprehensive Approach

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***Abstract*— A precise estimation of learners' abilities is the first and foremost step in personalized learning including EdTech solutions. Predictive analytic techniques such as Item Response Theory (IRT), Bayesian Knowledge Tracing (BKT), and Performance Factor Analysis (PFA) are established practices to achieve this purpose. However, the complexity, cost, and time involved in calibration, and the challenges in online implementation, have led to the adoption of simpler alternatives such as Elo, machine learning, and artificial intelligence. Nevertheless, the estimation of abilities is just one facet of personalized learning, and designing effective personalized learning experiences is equally essential to guide learners through their unique learning journeys and drive improvement in learning. The research body provides mixed evidence regarding the impact of EdTech on learning outcomes. Designing impactful learning experiences requires a foundation in scientific principles drawn from learning sciences and learning design and a sharp focus on learning progressions. A one-size-fits-all approach is quite unlikely to yield significant learning gains. The importance of robust implementation models cannot be underestimated, as even the best designs can falter if poorly executed. Learning science and design principles not only assist in developing effective EdTech products but also inform professional development programs to ensure the intended usage of the product and services. The objective of this paper is to understand different EdTech models and propose a coherent design and implementation framework to enhance their effectiveness and impact on learning.**

Keywords—Personalised learning, Measurement model, Learning science and design, Impact, Outcomes

I. INTRODUCTION

Unprecedented growth in technology and innovation in recent years has greatly transformed the landscape of education. There is widespread enthusiasm among governments, schools, and communities around the potential use of technology in various educational processes and substantial investments are being made accordingly. Evolving fields like machine learning, big data, and artificial intelligence have further intensified the integration and uses of technology in the education systems. There appears to be a general agreement among the public regarding the potential benefits of EdTech in enhancing the learning experience and improving outcomes, but what kind of technology and in what context - remains an area of discussion. As investments and available options continue to grow, students, parents, teachers, and decision-makers face a tough and genuine challenge – what to choose. On the other hand, there is mixed evidence regarding improvement in learning outcomes because of the use of technology [1], [2]. Severe concerns have been raised regarding the prevailing learning crisis, which has worsened further post-COVID, as revealed in the Learning Poverty Report [3]. In the Indian context, around one-fourth of grade 8 students were unable to read a paragraph, and half of grade 8 students were unable to do simple division sums even prior to COVID-19 [4], and as per the 2022 reports the downward slope has become steeper [5]. Students lacking basic reading and arithmetic abilities are less likely to achieve grade-level learning outcomes and that is evident from the National Achievement Survey [6]. In this scenario, one may ask – "Is the desire for improved learning driving the growth in technology, or is the technology driving the learning reforms?".

Researchers have identified a mismatch between how students learn and how the curriculum is delivered [7], [8]. Figure 1 shows that students' abilities within each grade level are highly heterogeneous suggesting that employing a one-size-fits-all approach to teaching and learning does not lead to optimal results. Learning systems need to cater to individual learners' readiness and needs. This fact hardly finds any consideration by curriculum designers and classroom teachers.

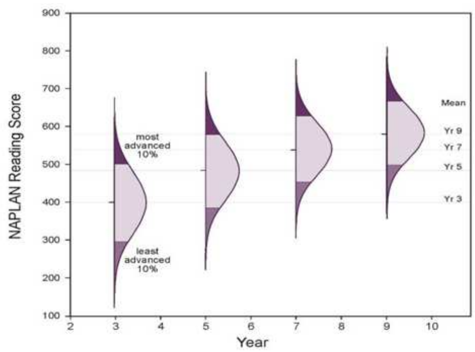

Figure 1: Performance of students in NAPLAN reading

However, designing a learning environment that caters to diverse needs is very challenging, as learners differ not only in their needs but also in their learning characteristics such as preferences, learning styles, objectives, expectations, and specific skill levels. The objective of this paper is to understand common models used in EdTech and propose a coherent design and implementation framework to enhance its effectiveness.

II. MODELING LEARNER AND COGNITION

Personalized learning solutions require a deeper understanding of learner behavior and learning domains.

A. Learner models

Learner models with diverse characteristics and modeling techniques have evolved over a period of time and have been successfully integrated into various personalized and adaptive systems. Initially, the focus was on learner's knowledge and cognitive attributes, but recent developments have expanded learner modeling to consider learning styles, behaviors, and

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emotions to enhance learning efficiency and satisfaction [9], [10]. Learning styles, encompassing visual, auditory, or kinesthetic preferences, are considered to match content formats with individual needs. Behavioral aspects, such as engagement and motivation, are tracked to adapt task-difficulty and provide timely interventions, while emotions, like frustration or engagement, are leveraged to customize the learning experience. Learner modeling has helped education systems move from a one-size-fits-all approach to a personalized, student-centric paradigm, where education caters to each learner's uniqueness.

While these models help to identify learner traits, the next task is to design interventions based on the thoughtful application of theories and insights from various disciplines, enabling learners to move on their own learning paths.

B. Learning science and learning design principles

Relying solely on intuition or personal experiences is not sufficient for achieving intended learning outcomes. Learning science research suggests that clarity of learning outcomes is the pivot for enhancing students' learning abilities and the efficacy of learning tools. Principles of learning sciences guide through how design decisions impact learning outcomes by assessing the logic behind these decisions, aligning them with academic and socio-emotional goals, and identifying potential unintended consequences and riskiest assumptions [11]. Design research consists of not only learner profiling but also analyses the behaviors of educators and other stakeholders with the intent to enhance the overall learning experience, promote engagement, and improve learning outcomes through the strategic use of technology [12]. User-centered design is a critical approach in EdTech design research.

Research in learning design explores the incorporation of emerging technologies like artificial intelligence, virtual reality, augmented reality, and gamification in educational contexts. Researchers investigate how these technologies can support personalized learning, offer immersive experiences, and foster collaboration among learners, enhancing engagement and effectiveness [13]. The collaboration, creativity, and problem-solving aspects of EdTech design research, along with the integration of emerging technologies, hold the potential to create innovative and inclusive educational solutions. Applying learning science and design principles to design EdTech empowers both educators and learners with effective tools drawn upon the evidence-based practices, maximizing their impact on learning outcomes.

C. Theories of cognitive learning

Cognitive learning theories are rooted in the concepts of working memory (WM) and long-term memory (LTM), and emphasize the role of information processing in learning [14]. WM, with its limited capacity and short retention period, poses a challenge for instructional designers, who then employ techniques like rehearsal and chunking to enhance learning effectiveness by reducing cognitive overload when instructional materials exceed this capacity [11], [15]. Researchers have suggested multiple ways to reduce cognitive load, and one of them is the cognitive theory of multimedia learning. The overarching principle of multimedia learning is that we learn more effectively from words and pictures than from words alone.

The Zone of Proximal Development (ZPD) of Vygotsky serves as a guiding principle how to adjust content and difficulty based on student performance, ensuring a challenging yet attainable learning experience, allowing them to progress at their optimal pace, fostering critical thinking, and problem-solving skills through scaffolding [16].

III. Learner Models for Skill Estimation

Skill estimation is the most important aspect of adaptivity and learning personalization and a wide range of tools and techniques and learner measurement models are used to achieve this. These models follow Ausubel's proposition – the most important single factor influencing learning is what the learner already knows, ascertain this and teach [them] accordingly [17]. Models based on this proposition include traditional models such as the Item Response Theory (IRT) originally developed for adaptive testing [18], as well as specialized models such as Bayesian Knowledge Tracing (BKT) [19] and Performance Factor Analysis [20].

The use of IRT in personalized learning solutions has revolutionized the way educational content is delivered to students. IRT is a powerful psychometric framework, which enables the assessment of individual student abilities and the same framework has been used to tailor learning experiences that cater to each student's unique needs. Such learning solutions utilize IRT and intelligent tutoring systems (ITS) to dynamically adapt content and difficulty levels according to individual student performance [21]. This approach is versatile, and applicable to various subjects and educational levels. Teachers gain insights from IRT-based data analysis and make informed instructional decisions and targeted interventions while ITS provides real-time feedback and individualized support, enhancing the learning experience, deepening subject understanding, and increasing student engagement. The Rasch model is the simplest and most widely used IRT-based learner models.

BKT attempts to capture students' knowledge state indicating mastery, while IRT and PFA rely on a logistic regression model to estimate latent traits based on students' knowledge state and the difficulty of learning items. These approaches are complex to be integrated into online adaptive systems as they generally require extensive calibration of model parameters.

The Elo rating system commonly employed for rating contests and sports is being explored in educational systems to estimate student skills and item difficulty. It is characterized by its simplicity, speed, resilience, and sensitivity to order, which makes it suitable for integration into adaptive educational platforms, particularly for the purpose of updating students' skill levels. This model operates efficiently with a minimal number of parameters as compared to IRT, which makes it more adaptable to online learning environments. However, research suggests that Elo based learner model is suitable mainly for adaptive practice or low-stakes testing [22].

The Elo system interprets a student's response to an item as a match between the student and the item, calculating the probability of a correct answer through a logistic function based on the difference between the student's skill and the item's difficulty. While it offers practical estimates for guiding adaptive learning, it lacks the statistical assurances of well-calibrated IRT models used in computerized adaptive testing. The Elo rating system closely resembles the one-parameter

Rasch model in IRT, differing primarily in parameter estimation. IRT assumes constant student skill (common in testing scenarios), while Elo can track changing skill levels that can be easily adjusted.

Both the Elo rating system and the basic IRT models capture symmetric answers, while in many educational applications there may also be an asymmetry between correct and incorrect responses. As an answer to an item is not only evidence of students' knowledge but also an opportunity for learning, such situations demand different updates for correct and incorrect answers. PFA offers solutions in such situations. PFA can be viewed from two different perspectives − as an extension of Elo or IRT, which is a student modeling approach based on the logistic function, and, as a regression model which enables researchers to explore complex datasets and identify underlying latent factors that explain the observed variables. This approach has been extensively used to uncover the underlying structure of personality traits [23], [24]. PFA as a regression model provides researchers with deeper insights into the relationships between variables and enables data-driven decisions.

As stated earlier, ability estimation is one aspect of solutions, which must follow a personalized intervention. The next section proposes a comprehensive approach to designing effective EdTech tools.

IV. A COMPREHENSIVE APPROACH TO DESIGNING EDTECH TOOLS FOR IMPACT

Designing efficacious products needs to be guided by the findings from various disciplines of educational psychology, learning sciences, and instructional design principles supported by data and technology. Given below are key principles for designing effective EdTech tools.

Principle 1: Define the intended outcome

A clear articulation of what purpose a tool intends to serve in terms of learning outcomes is a prerequisite to designing an effective educational experience. It plays a pivotal role in enhancing self-regulation, student engagement, motivation, and overall learning. Research has shown that explicitly defined learning outcomes have a significant impact on student achievement [1]. Well-defined learning outcomes provide learners with direction and purpose. When students understand what is expected of them and what they are expected to achieve, they are more likely to be motivated and engaged in the learning process [25]. This clarity empowers them to set goals, track their progress, and take ownership of their learning journey.

In addition to this, they serve as a common thread among content creators, analysts, and users. While vague goals like "help students learn" lack specificity, outcomes such as "improving foundational reading ability" or "enhancing computational skills" provide a clear goal for all stakeholders including learners. These learning outcomes guide educators in designing instructional materials that align with specific objectives, promoting more effective teaching and learning experiences.

Principle 2: Model cognitive and affective domains

Domain modeling is another key consideration. Often, experience designers emphasize the cognitive domain, overlooking the significance of the affective domains, despite the fact that learning is an interconnected process. Motivation plays a vital role in cognitive processing. There is evidence that learners who are exceptionally motivated and persistent tend to tackle complex challenges and diligently pursue their learning objectives. Instructors and instructional technologies can foster motivation by creating opportunities for success and by framing errors and difficulties as integral components of the learning journey. Motivation and self-management can be fostered through learner autonomy, goal establishment, and constructive feedback that centers on the task, the learner's process, and self-regulation

Principle 3: Model learner and learning

To design effective systems and tools, it is crucial to consider students' needs throughout the process and actively involve them in the development process. Deep probing into how students learn is quite important as how students learn differently. Self-regulation capabilities play a predominant role in achieving learning goals and sustaining learning processes [26]. Fostering accurate metacognition and promoting effective self-regulation are essential aspects of educational technology design to optimize student learning outcomes.

Active learning models, such as project-based learning and problem-based learning, stimulate cognitive engagement, leading to improved complex reasoning skills, critical thinking processes, perceived learning, engagement, attitudes toward subjects, self-directed learning, and autonomy and therefore, deserve attention in the design and implementation of EdTech products.

Principle 4: Apply appropriate learning science and learning design principles

The development of EdTech tools requires a meticulous analysis of how each component influences and enhances the overall learning process, based on the principles of learning sciences drawn from diverse disciplines such as cognitive and educational psychology, neuroscience, behavioral economics, and computer science. Several best practices in EdTech design are discussed in the literature. Spaced practice, which involves spreading out learning activities over time rather than cramming, has been shown to strengthen information retention and counteract the "forgetting curve" [27].

A learning cycle approach supporting inquiry-based learning like the 5E instructional model offers good hope [28]. Additionally, the 5E model offers a structured approach to integrating instructional technology into teacher education programs, guiding educators through various stages of design and implementation [28] and its versatility is evident in its applicability to diverse educational settings, including early childhood education.

Principle 5: Build a robust learning metric and implementation framework

The critical question arises: how many educational technology products truly adhere to these principles? Furthermore, their implementation and product monitoring plans, along with evidence of their impact on intended outcomes, must be clear. Embedding relevant and valid impact measures within EdTech is crucial for real-time utilization, as external measures can be time-consuming and may cause learners to outpace the learning loop. External measures serve better for validation purposes.

However, the success of thoughtfully designed EdTech solutions hinges on the existence of a framework that fosters student and teacher engagement. Implementing comprehensive professional development programs for educators, focusing on the potential benefits and effective integration of technology in the classroom, and tailoring learning experiences can be instrumental levers in this regard.

Educational institutions grapple with technological challenges, including limited access to infrastructure, outdated equipment and software, inadequate technical support, and insufficient funding for modern technology resources. Addressing these challenges requires substantial investments to ensure equitable access for all learners.

V. CONCLUSION

Designing impactful learning experiences hinges on integrating learning content and pedagogy rooted in the robust scientific principles of learning sciences and learning design. Crucially, these experiences should be guided by learning progressions that enable continuous growth in knowledge and skills. EdTech design should be evidence-based, firmly grounded in these principles and progressions, steering clear of one-size-fits-all approaches that often fall short of driving meaningful learning outcomes. Effective implementation models and collaborative efforts with technology experts and stakeholders are paramount to developing innovative solutions. Embracing change, addressing concerns, and advocating for the benefits of EdTech are essential for its successful integration in classrooms. To bridge achievement gaps and expand access to quality education, it's imperative to overcome resistance, offer adequate training, and support educators in technology integration. The ultimate goal is to ensure that every learner has the opportunity to achieve their full potential.

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