Data-Directed Education:
The Future of AI in Education

NSF Convergence Accelerator Ideation Workshop: Final Report

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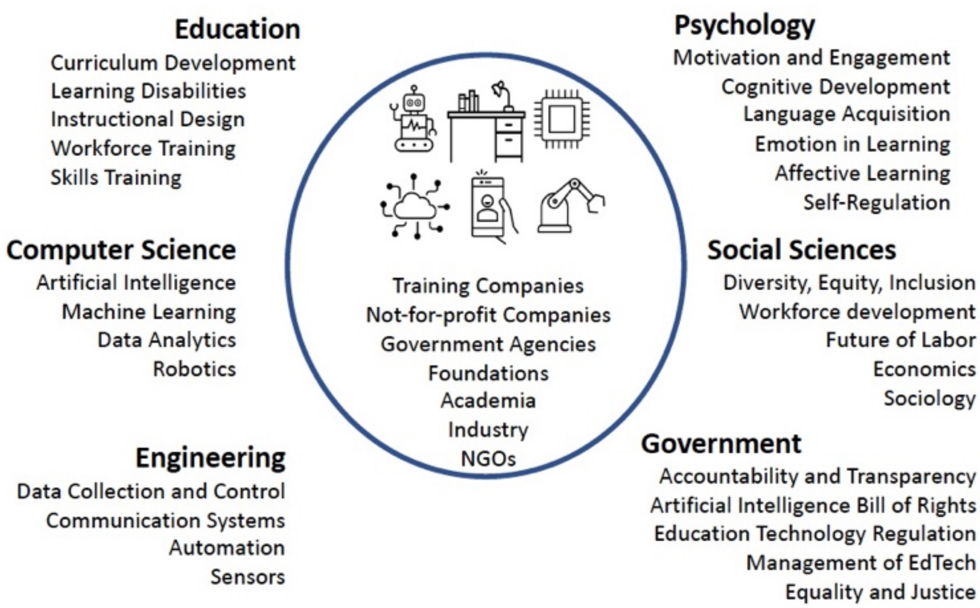
1.0 Executive Summary

A funding track is proposed for *Data-directed Education* within the NSF Convergence Accelerator Program that will transition basic education research into practice within three years and will deliver tangible social benefits. The current educational research paradigm tends to separate out the threads of this field without experiencing the full tapestry that those threads might create. The field remains slow, low-scale and data-poor, compared to other fields (e.g., communication, transportation). The proposed Convergence Accelerator *Data-directed Education Track* will enable researchers to *think about* and *access* multiple approaches to teaching and learning simultaneously, thus facilitating and accelerating convergence of different viewpoints, technologies, theories and strategies. For example, the field needs to examine what happens when numerous learning/teaching platforms and tools interact with one another. This track will address national scale educational challenges and produce *connected, open,* and *accessible* products will include a number of domains, e.g., *artificial intelligence*, *learning science, social sciences, instructional theory* and *psychology* (Figure 1).

Figure 1. Multidisciplinary Domains Involved in Data-directed Education



To explore these issues, an ideation workshop was held Oct 18-19, 2022, and Oct 24-25, 2022 (see the Ideation Workshop Website for complete information including recordings of presentations). Workshop experts explored *theories, algorithms, big data,* and *systems* that optimized many points in the education process to *understand* students, *organize* what they learn, and *optimize* how they learn. The workshop coupled *use-inspired* research with foundational AI and Learning Science research in a virtuous cycle and forged new partnerships among diverse stakeholders including *engineers, technologists, and designers*, from two or more disciplines (Figure 1). The workshop placed laser focus on projects that presented well-defined deliverables with fast tracked time-to-deploy cycles. Integrative teams will accelerate convergence toward a networked AI educational economy and will rapidly deploy and evaluate new data-directed projects.

2.0 Convergence: The Challenge of a Data-directed Education Track

2.1 The Challenge of Convergence.

The challenge of a *Data-directed Education Track* is a challenge of convergence – the need to bring together multiple components of a system (along with respective stakeholders) to create a transformative difference. The impact includes overcoming learning loss, providing more rapid skilling, more job readiness and reducing instructional time and educational disparities. The proposed *Data-directed Education Track* will recognize the scope of the field and encourage convergence across the large and interdisciplinary nature of the landscape. The track will support thinking about interdisciplinary behavioral sciences as well as learning engineering and collaboration among different experts (computer scientists, educators, psychologists, sociologists) necessary to build platforms and tools (Figure 1). Multi-disciplinary experts will contribute specific expertise and knowledge to the network of systems, thus finding ways to bring separate areas of knowledge together – in collaboration – to converge on big solutions for education.

Proposals submitted to the track will address aspects of a basic *challenge question*: How can we benefit the *full range* of national educational components (teaching, learning, access, support, and management) by *enhancing* the *quality* and *expanding* the capacity of *AI* and *data sciences* for education. Specifically, how can we leverage *basic research* in teaching and learning online? *Quantify positive impacts*? *Explore, organize, monitor, and distribute* AI in Education at scale in authentic education settings (online, hybrid, and on-the-job)? Meet the needs of *diverse learners* and address the *disconnected, fragmented, and often closed nature of education sectors* (educators, parents, commercial ventures, not-for-profit organizations and communities)? *Understand, model, infer,* and *respond* to students using technology to learn online? Inform *best practices* in design, generate future *development* and *testing*, and leverage technology and new modes of platform design? Leverage the growing power of computers in education? Train the next generation of scientists, engineers and educators to work in interdisciplinary teams to solve real-world educational problems?

2.2 Converging on Multiple Concerns.

The proposed track will support solutions that converge five interwoven concerns to address these challenges:

- ***Societal needs embedded in the educational system****:*
    - Personalize education for specific populations that are otherwise underserved in the traditional educational settings (e.g., neuro-diverse learners);
    - Advance the best and the brightest regardless of socio-economic status, culture, language, or disability;
    - Address safety and security of student data;
    - Reverse learning loss;
- ***Develop AI and Data Science technologies for Education:***
    - Large data sets;
    - Scale up;
    - Identification of projects that are ready to go to the next step;
- ***Revise the current education technology research paradigm as a convergent process:***
    - Create a collaborative culture among developers;
    - Share knowledge (e.g., who's doing what);
    - Establish a cooperative context (non-competitive; egoless);
    - Embrace stakeholder (user) input in design and development;
    - Open channels of access for stakeholders seeking solutions;

- ***Revise the teaching / learning paradigm as an ecosystem:***
    - Reexamine the classroom setting;
    - Study the role of the teacher;
    - Re-evaluate assessment strategies;
- ***Identify mechanism(s) that facilitate/accelerate convergent development and expedite access to Ed Tech technologies, platforms, apps, and large data sets:***
    - Compile (inventory) existing research and trends;
    - Match users to solutions;
    - Enable user access to research data, platforms, apps;
    - Advocate for convergence (e.g., encourage developer collaboration).

2.3 Convergence with NSF-Funded AI Institutes.

NSF has funded three National AI Institutes that pertain to education and address basic AI research issues and are long term (~ five years) and involve large amounts of funding (~$20M). These institutes focus on issues that may take years to develop new scientific knowledge and fundamental advances for AI in education:

- The *AI Institute* on *Adult learning* (Garn, Dede), Georgia Research Alliance, addresses adult learning (especially in the workplace) that is often open-ended, ill-defined, task-specific and self-directed. One goal is to make adult education more equitable through enhanced availability, greater affordability, and enhanced potential for success.
- *The AI Institute* on *Student-AI teaming* (D'Mello) views AI as a social, collaborative partner that helps students work and learn more *effectively, engagingly, and equitably*. AI innovations will be made in computational agents that interact naturally with students and teachers through *speech, gesture, gaze,* and *facial expression* and are designed in close collaboration with educators to support students to develop STEM competencies, disciplinary practices, and 21st century skills (collaborative problem solving, critical thinking).
- *The AI institute* on *Engaged Learning, narrative learning environments* (Lester) will design, develop, and investigate data-driven *narrative learning* that can create *story-based, collaborative problem-solving experience* and will focus on foundational AI research in *natural language processing, computer vision, and machine learning.* It will investigate *multimodal processing, natural language understanding, affective computing, and knowledge representation* to develop AI models that can autonomously monitor learning discourse at multiple levels – understanding the content, the conversational dynamics, gestures, and social signals– and learn to generate appropriate dialog moves to be effective partners in learning conversations.

The proposed Convergence Accelerator track differs from these AI Institutes in that the *Data-directed Education Track* will focus on delivery of transitional products and changes to education and workforce training. *Convergence approaches*, *human-centered design,* and *team science* will bring together *researchers* and users of data-driven educational products (teachers, students, stakeholder, entrepreneurs, government officials) to address national-scale educational challenges, to *transition* technology into practice and to rapidly deliver *tangible solutions* that have a *societal impact*. Two leaders from *AI Institutes were participants in our workshop* (Garn and Dede). The institutes operate on a five-year timeline and our track focuses on transitional projects that provide well-defined deliverables with fast tracked time-to-deploy cycles. Integrative teams in our track can rapidly deploy and evaluate new projects, dramatically accelerating the access and use of AI technology in education, see Appendix E.

3.0 The Ideation Workshop and Its Process

To explore these issues, an ideation workshop was held Oct 18-19, 2022, and Oct 24-25, 2022. See Appendix C and the Data-driven Education Workshop website, for a description of the program agenda (speakers, topics, etc.), breakout brainstorming sessions, and recordings of keynote presentations.

3.1 Workshop Design.

Workshop experts explored theories, algorithms, big data, and systems in connection with many aspects of the education process, to understand students, organize what they learn, and optimize how they learn. The workshop coupled use-inspired research with foundational AI and Learning Science research in a virtuous cycle and forged new partnerships. It focused on convergent projects that presented well-defined deliverables with the intention and capability of accelerating implementation. AI educational teams were prepared to forge partnerships as they bridged the expertise of educational and computer science researchers to solve real-world problems with practitioners, engineers, technologists, and designers. Such integrative teams will accelerate convergence toward a networked AI educational economy.

3.2 Workshop Themes.

During the Ideation Workshop we discussed each of five themes through topical presentations by keynote speakers (all well-known subject matter experts), a follow-up question/answer period, and breakout sessions (see Appendix B for complete description of each theme). NOTE: Recordings of all presentations, and related slide decks where available, can be viewed on the Ideation Workshop Website. The following outlines the themes and their respective topics and keynote presenters.

Theme A: Design, Develop and Test Digital Education Artifacts

- *Robots as Social Learning Companions* (Erin Walker)
- *Online Adult Learning: AI Institute* (Myk Garn)
- *AI for Orchestration in the Classroom* (Jennifer Olsen)

Theme B: Assessment of Educational Research

- *Social Analytics* (Carolyn Rosé)
- *How AI Can Empower Component-Based Educational Research* (Chris Dede)
- *Opportunities Matter: Hybrid Human-Computer Tutoring Toward Educational Equity* (Ken Koedinger)

Theme C: Learning at Scale

- *Future of Stealth Assessment* (Val Shute)
- *Data-driven Item Selection and Generation in Assessments and Learning* (Andrew Lan)
- *Crowdsourcing Paves the way for Personalized Learning* (Neil Heffernan)

Theme D: Ethical and Equitable

- *Rapid Workforce Development* (Lewis Johnson)
- *Bilingual Tutor* (Ivon Arroyo)

Theme E: Entrepreneurial, Not-For-Profit, And Government Digital Learning Systems

- *Aligning Curricula with Skills and Jobs* (Robby Robson)
- *Foreign Language Learning* (Lewis Johnson)
- *Intelligent Game-based Assessment and Tutoring* (Danielle McNamara)
- *Large Scale Commercialization* (Steve Ritter)
- *The EdTech Investment Climate* (Max Woolf)

4.0 AI in Education: Problems and Opportunities

4.1 Introduction.

Education is a vital contributor to the country's overall *economic, intellectual* and *political* health and should enable all citizens to achieve their *highest potential* as individuals, serve effectively in their society, and successfully compete in a *changing global marketplace*. Education should prepare students for the *real world* and produce *learners* who can *think deeply* and *solve problems.* It should create *authentic learning environments* in which students can solve real-world challenges and come up with meaningful solutions (Bakia et al., 2012). To fulfill this vision of education and to sustain the vision of the NSF Convergence Accelerator Program as it applies to education, we propose a funding track to support truly interdisciplinary convergent projects that will support data-directed education and focus on one of the most critical ground pillars of society. We intend to leverage exciting AI advances and encompass a wealth of theories about how humans learn, think, communicate, socialize, and collaborate. For example, one transformative effect of AI could be to augment human cognition in learning (e.g., Molenaar, 2022; Tuomi, 2018). Several exciting projects whose primary purpose is to dramatically *accelerate* online education *development* and *increase access* and *use* of AI technology in education were described during the workshop, see Sections 7-8 and Appendix E.

> . . . invest our efforts into producing technologies that are easy to use, adoptable by all, and capable of promoting cultural changes without affecting our quality of life (ASLERD, 2016).

4.2 Situational Analysis.

Education technology is a complex landscape (Figure 2), with many different aspects feeding into its design and development (e.g., platforms, processes and tools). For example, students' learning and affective outcomes (motivation, engagement) are impacted by *individual factors (e.g., age, gender, psychology)* and *contextual factors (e.g., instructional design, learning context, online feedback, analytics)*. The field of EdTech attempts to refine *contextual* factors, e.g., to meld and improve features of the instructional context. For example, AI can *predict* individual *factors* (students' activities, speed, requests for help) as well as students' *learning and affective outcomes*. By placing research within this constantly changing framework, stakeholders can explore how platforms might improve learning, e.g., by using *stealth assessment* (constant evaluation of student outcome) or *predictive algorithms* (AI to predict student outcomes).

Figure 2. Taxonomy of AIED

STUDENT-FOCUSED AIED
- Intelligent Tutoring Systems
- AI-assisted Apps (e.g., math, text-to-speech, language learning)
- AI-assisted Simulations (e.g., games-based learning, VR, AR)
- AI to Support Learners with Disabilities
- Automatic Essay Writing
- Automatic Formative Assessment
- Dialogue-based Tutoring Systems
- Exploratory Learning Environments
- AI-assisted Lifelong Learning Assistant

TEACHER-FOCUSED AIED

Smart Curation of Learning Materials
AI Teaching Assistant (including assessment assistant)
Classroom Orchestration

INSTITUTION-FOCUSED AIED

Admissions (e.g., student selection)
Course-planning, Scheduling, Timetabling
School Security
Identifying Dropouts and Students at risk

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. European Journal of Education, 57, 550. https://doi.org/10.1111/ejed.12533

Significant technology exists; however, it does not fully take advantage of *the growing power of computers and of stakeholder needs*. Commercial ventures create real and immediate solutions, which is what they are in business to do. But what's needed are solutions that take into account stakeholder needs and are informed by research and data. That won't happen without communication among education sectors, e.g., educators, parents, commercial ventures, not-for-profit organizations, and researchers. These group that are often *disconnected, fragmented,* and *closed off* need to talk with each other.

4.3 Societal needs embedded in the educational system.

Education has failed to serve the United States and the typical reasons to explain this failure (poverty, family instability, large class size, and insufficient spending) do not explain why the scores of high performing students declined at least as much as those of low performing ones (Gorman, 2022). Additionally measures of students' inferential ability and problem solving declined more than those of simpler tasks such as arithmetic computation (Gorman, 2022). Suspension of face-to-face instruction in schools during the COVID-19 pandemic led to consequences for students' learning (Moscoviz & Evens, 2022; Enzell et al., 2021). Following the outbreak and spread of COVID-19 in 2020, schools around the world closed for significant periods of time. Two years after schools began shutting down, research has identified learning losses using at least 40 empirical studies. Learning loss was much higher among students with lower socioeconomic status in high-, middle-, and low-income countries, even in contexts with little or no average learning loss. In other words, the pandemic consistently boosted learning inequality. Students made little or no progress while learning from home and learning loss was most pronounced among students from disadvantaged homes.

Additionally, in the U.S., student outcomes began to decline in the 1960s and this led to a decline in the growth of US productivity by the 1980s (Gorman, 2022). After rising every year for fifty years, student scores on a variety of achievement tests dropped sharply in 1967 and continued to decline through 1980. The decline was so severe that students graduating in 1980 were said to have learned "about 1.25 *grade-level equivalents* <u>*less*</u> than those who graduated in 1967" (Bishop, 1989). The recovery has been weak and student achievement has yet to regain 1967 levels.

Competencies among K-12 students in *reading* and *mathematics* are *abysmal*; serious economic issues exist along with mental health, neurodiversity and social ethical issues that are not addressed. US students have failed to achieve international standards (Barshay, 2019) and teachers have been slow to transform the ways they teach, despite the influx of new technology in classrooms. The *Covid Pandemic* brought the inevitable transformation towards *virtual education* and kicked distance learning into high gear. The ensuing need for *scalable*, *personalized* learning systems has led to an unprecedented demand for understanding the role played by *AI* and *large-scale data* in online instruction.

The U.S. is also in a nationwide college completion crisis. Between 40 to 60% of college students now need remedial math, or English, or both (Xu & Dadgar, 2018). Only 58% of students who started college in 2012 had graduated 6 years later (Shapiro et al., 2018). More than 4 out of 10 college students wind up in remedial math or English courses, and those that do are *even less likely* than other students to finish college (Hanford, 2016). At a time when 9 out of 10 new jobs are going to those with a college degree, a teaching method that helps underprepared students move back on track academically could boost the prospects for millions and raise productivity in our country and elsewhere. The U.S. ranks 36th out of a comparison group of 79 countries in math proficiency, according to the 2018 Programme for International Student Assessment (Barshay, 2019).

Additionally, the workplace is changing. Innovations from robotics to AI have dramatically improved productivity and created millions of jobs, while other jobs have disappeared (Holtzer, 2022). However, new jobs are being created more quickly than people can be trained to fill them. Elevating the technology skills of our workforce and fostering workplace flexibility is critical to developing pathways to new careers. This can be accomplished through tech-adapted workforce development programs. *Personalized workforce development technology* has impacted the workforce. *Job seekers* have new ways to find relevant, attainable opportunities; trainees can learn new skills and gain certificates without completing full courses (Van Horn et al., 2015) and workers can directly connect with employers, without first joining the workforce. We need to look differently at *skills, competencies* and *credentials*.

Technology enables development of platforms that make available *standardized, cross-industry competency assessments* to help improve the mobility and efficacy of our workforce. Employees or job seekers can get a baseline of their current skill set and discover programs available to obtain the skills required for better paying, more fulfilling jobs.

4.4 Development of AI and Data Science Technologies.

> . . . sustain the development of smart learning ecosystems by fostering the development of a fully interoperable tech-sphere to avoid barriers against innovation (ASLERD, 2016).

Numerous AI in Education (AIED) products are available and many more are on the way, but they are developed as discrete research projects with little *collaboration* and *convergence* across the full spectrum of research fields and user applications – this slows down the *process* of *development* and *impact*. Products are not easily accessible to those who will use them (teachers) nor those who will benefit from them (learners) – this slows down *implementation*.

4.5 Education Reform and The Ed Tech Research Paradigm.

In general, modern education reform movements have done little to meet the needs of the current *demographic, social,* or *technological changes*; nor the demands of the *future workforce* (Toldson, 2021), and there are significant issues on the horizon that have not been fully addressed (Figure 3).

In the Western U.S., (predominantly) indigenous and Hispanic students experienced subpar learning conditions while Black students suffered the brunt of inequitable learning conditions in the south and east (Frankenberg, 2009; McCormick & Ayala, 2007; Menchaca & Valencia, 1990; Wollenburg, 1974). Recent census projects indicate that the U.S. will be a *"minority white"* population by the year 2045 (Frey, 2018). Radical changes are needed in education due to these and other profound changes in *racial demographics* (Cilluffo & Cohn, 2019; Poston, 2020), increased *social awareness* (Minnesota Department of Education, n.d.; Praslova-Forland, 2002), and *technological advancement* (Cole & Weber, 2019; Tolson, 2021).

Figure 3. Prominent Roadblocks on the AI Highway

Ethics

"Most AIED R&D has happened without serious engagement with the potential ethical consequences."

Personalization

"AIED tools aim to ensure that students fit in the right box…, prepared for their designated role in the world of work."

Efficacy and impact

"Very rarely does AIED research consider the wider implications of AI in classroom settings and its broader impact on teachers and students."

Techno-solutionalism

"Deeper social and cultural factors are rarely addressed as they are difficult to change without a broad participation of the stakeholders and policy change."

Commercialization of education

"Commercial AIED organizations are not only shaping individual learners but are also beginning to influence governance and national policies… [this] is fraught with both practical and ideological issues."

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. European Journal of Education, 57, 557-562. https://doi.org/10.1111/ejed.12533

For example, the U.S. has serious problems teaching a diverse student population using English as the only language. *Over 30% of U.S. public school children (in 2025) will be Hispa*nic and these children often need specialized extra help learning English; yet extra funding is often not supported, due to education budget cuts (Frey, 2018). Also *student mental health challenges* provide another growing concern that affects school students (Horowitz & Graf, 2019, Bitsko et al., 2022). A 2018 study showed that nearly two-thirds of *college students* experienced overwhelming *anxiety*; anxiety has been reported in younger students as well (Bitsko et al., 2018). Awareness of *mental health issues* is increasing, but a stigma exists that prevents many students from seeking care.

The new educational paradigm is moving beyond teaching only academics and toward nurturing the *whole student, including social-emotional learning (SEL).* This movement is based on the growing consensus that schools have a responsibility to protect and develop students' *social* and *emotional* learning in addition to their cognitive *skills.* SEL helps students to *manage their emotions, show empathy, set goals, identify their strengths* and *make responsible decisions*. Person to person training in SEL results in reduced *antisocial behavior*, improved *academic achievement* and *long-term health* (CASEL, 2022; Durlak, et al., 2011; Taylor et al, 2017).

With two notable exceptions, the current education research approach tends to conduct very small studies that focus on one or two factors (e.g., 30 treatment subjects and evaluation of student interest or skills). Stakeholders tend to separate out the threads of this field without experiencing the full tapestry that those threads might create. Typically, the field has not leveraged sufficiently large datasets to look at the large scale of what happens when teaching and learning factors interact with each other.

However, two large digital learning platforms that use *AI in Education* invite researchers to use their large data sets to increase the efficiency and reliability of conducting educational research at scale, leading to more rigorous education research. The *first large scale study* is based on an existing and well vetted platform, ASSISTments (Gosh et al., 2020; Erikson et al., 2020) that enables researchers to compare alternative educational strategies and provides tools and templates to increase the efficiency and reliability of conducting large data in educational research. The platform automates statistical analyses, improves usability of existing data reporting tools, and applies educational data mining algorithms (e.g., deep knowledge tracing) on student data collected before, during, and after experimentation. The platform automates the creation and data analysis of randomized controlled experiments, addressing two components of the infrastructure that have been resource-intensive bottlenecks in prior research. The *second large scale study* is SEERNet, a hub of five platforms used in either K-12 or higher education by more than 100,000 users that enables third-party researchers to explore, develop, and test improvements (Ritter et al., 2022; Zacamy & Roschelle, 2022). For example, researchers might conduct equity-relevant research studies by developing scenarios and personas in one or more platforms to help envision equitable and inclusive usage.

These two large scale projects have the potential to facilitate large-scale learning in education research, reaching hundreds of schools and thousands of students that will help developers, researchers, and educators share ideas, build knowledge, and strengthen dissemination. Compared to typical field-generated education research projects, research conducted on large digital learning platforms can be more *agile, efficient, replicable, and cumulative* to better connect research to practice and help include diverse research perspectives to minimize bias. Large digital platforms can achieve deeper and broader national impacts by leveraging extensive, existing networks of education partners, researchers, and other educational stakeholders.

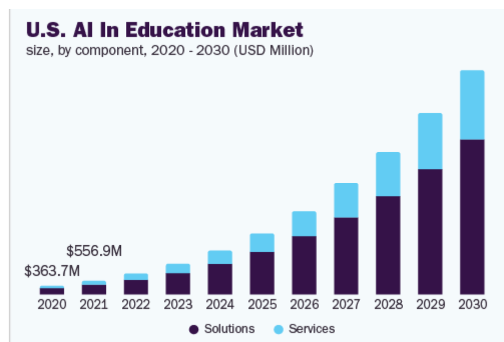
On the other hand, teachers have been *slow to transform* the ways they teach, despite the influx of new technology into their classrooms and *limited evidence exists to show that technology* and online learning are improving learning outcomes for most students. Academics and parents alike have expressed concerns about digital distractions, ways in which unequal access to and use of technology might widen achievement gaps, and more.

4.6 AIED in Classrooms.

Artificial intelligence has quietly entered the classroom (Holmes et al., 2019; Luckin et al., 2016). Intelligent, adaptive, or personalized learning systems are increasingly being deployed in schools and universities (Beker et al., 2008) around the world, gathering and analyzing huge amounts of student big data, and significantly impacting the lives of students and educators (Holmes et al., 2018). More recently, companies as influential as Amazon, Google and Facebook have invested millions of dollars developing AIED products, joining well-established multimillion dollar funded AIED companies, such as Knewton (2022) and Carnegie Learning (2022) while the $15 million Global Learning XPrize (2018) called for software that empowers children to take control of their own learning (AIED by another name). Meanwhile, AI is being introduced into some mainstream schools as a curriculum in its own right, is being developed to improve online tutoring (Yuanfudao, 2018) and is being researched as a way of enhancing teacher training. Not only is the market growing exponentially (E-school, 2017), it is growing at a rapid annual growth rate of 36% (Figure 4). Following a $300m investment, the Chinese online tutoring company Yuanfudao set up a research institute for artificial intelligence, which aims to train its homework application to be smarter. In short, the application of AI in educational contexts and by 2024 is predicted to become a market worth almost $6-8 billion (AIED Market, 2022).

AIED when used in classrooms can "gauge" a student's learning style and pre-existing knowledge to deliver customized support and instruction. AI can help grade exams using answer keys, compile data about how students performed and even grade more abstract assessments such as essays. It can dive into student responses and identify missing information or concepts, so educators can produce targeted improvements. It can provide feedback on course quality, e.g., if many students answer a question incorrectly that question should be refined. AI can provide meaningful and immediate feedback to students. Some students may be shy about taking risks or receiving critical feedback in the classroom, but using AI, students can feel comfortable to make the mistakes necessary for learning and receive needed feedback for improvement.

Figure 4. AI in Education Market Size, Grand Review Research, 2022



4.7 Hybrid Learning.

Hybrid learning (involving both classroom and online learning) is here to stay. The world is now irreversibly hybrid. Businesses, civic organizations, entertainment venues, and social relationships that used to be primarily *face-to-face* are now often or even predominantly online. Hybrid learning will not go away. Half of all college students report taking an online class in the last 12 months with education institutions have been leading the charge to establish distance learning. 77% of US companies used online learning in 2017, a number that has been trending consistently upward for years.

4.8 Ethics in Online Learning.

Unconscious bias can creep into online instructional systems based on how data is 'sliced' and 'diced', how raw data is transformed and processed using various filters and how criteria are selected about what data to ignore and what to emphasize (Gupta & Saxena, 2021; Bach 2010). The varied skill sets of data professionals also impacts assumptions that underlie data collection, use, and processing. Data does not exist independent of context and a lack of contextual knowledge about students can open the gates for assumptions about race, gender, and class. Learning Analytics (LA) is a subfield of data-directed education that monitors and collects learner data consistently for specific periods of time. LA enables educators to plan timely and targeted educational interventions based on learner habits (Princloo & Slade, 2014).

Sensitization to biases in student data begins with awareness of the existence of such assumptions and of how bias can permeate data collection, data analysis and data usage. For example, in a study by Ifenthaler (2017), only two respondents indicated that they did not want to use LA due to privacy concerns. This raises the question of whether the overwhelming majority of young adults do not think privacy is a concern or they are simply not aware of the possibility that their privacy may be encroached upon. In Canada, for instance, hesitancy was expressed about potential misuse of learner data of learners from underrepresented groups, which may be labeled for lack of participation (Nkabinde, 2017). Typically, parents are concerned about what is happening to their child's data. And people may trust the educators and still distrust the corporations that own the platforms where the data resides. Unfortunately, most learners readily offer much more sensitive personal data to internet service providers such as Google, Facebook. Very little debate exists at a time when LA is scaling up on the back of widespread online learning. The time is ripe for initiating the process of wide scale sensitization to ethical quandaries relating to bias and privacy in implementing LA (Gupta & Saxena, 2021). The field of data-driven education needs to create and implement a code of ethics to promote responsible deployment of Learning Analytics.

5.0 A Proposed Convergence-Accelerator Funding Track

5.1 The Benefits of a Funding Track for Data-Directed Education.

A proposed NSF Convergence Accelerator track that invests in Data-directed Education will produce massive impact where it matters most – with *students, adults, informal learners, and workers* (many from underrepresented backgrounds) enabling them to more successfully *learn, upskill and reskill*. Specifically, the outcomes we envision that lead to success include enabling more learners to: 1) learn successfully and rapidly, 2) reduce inequities, 3) help overcome learning loss, and 4) learn for upskilling and reskilling. These of course are not the only benefits, but these are the challenges that we currently face in recovering from the pandemic and increasing workforce competitiveness.

Thousands of instructors will benefit from open-access to *data-directed power tools* for differentiated instructional platforms, computer-aided instructions, algorithms, applications for students, adult learners, workers and parents, and timely professional development for teachers, schools and districts. Such a movement is not a threat to teachers, nor will it replace teachers, but rather it will augment classroom teaching through the support of the *design, development* and *evaluation* of instructional systems (Marr, 2019). Educational institutions will benefit from the collective use of platforms, ensuring greater continuity in teaching and thus greater likelihood of student success. Communities and industry partners will benefit from a significant increase in the number of skilled workers, convenient, timely, low-cost teaching and training, and new tools to identify and remedy skills-based workforce inequities.

Much of the potential impact centers on reducing time spent by teachers on tedious tasks to free up time for more meaningful activities. Automating administrative tasks is a potential benefit: the forecast of growth in education technology was 47.5% from 2017-2021 in the use of AI in education in the U.S. (Marr, 2019). Another goal of a proposed Convergence Acceleration track is to converge experts around fruitful near-term approaches for scaling up innovative pedagogies and to create smart and integrated platforms, devices and processes for teaching and learning. Another goal is to increase the number of trials of new products; to test more often and fail faster; to identify promising interventions and evaluate the conditions and circumstances that increase the probability of successful products. The need is greatest among educational stakeholders, e.g., academics (learning science, AI, human-computer interaction, education, psychology), industry and government workers who will need to identify barriers and solutions to the delivery of high-quality online education; they will inform best practices in design, generate future development and testing, and leverage technology and new modes of platform design.

5.2 Goals of the Track.

One goal of the Data-driven Education track is to understand the laws of teaching and learning and the techniques for applying them. A new field called Learning Engineering is focused on learning about learning (Feldstein, 2020). Rapidly produced and deployed systems will make *learning* observable, enabling researchers to *measure* students' learning progression and *observe* how they *change* while *engaged* or *disengaged*. Researchers will *experiment* with instructional models, place models into practice and use student data to improve system performance. For example, many teaching and learning approaches persist, even after being proven wrong by science. Reading back over a textbook and taking lecture notes with a *highlighter* have proven of limited merit, and in some cases even counterproductive. Yet, these methods are recommended to students. Additionally, some educators believe *mathematical notation* is easier for students to grasp than *word problems*, yet research shows that using word problems in math class is better for learning.

…foster social inclusion, civic participation, community identity and social cohesion; and the development of an entrepreneurial, lifelong, life-wide and life-deep learning mind-set (ASLERD, 2016).

Another goal of a proposed track is to investigate paths to large-scale adoption of AI-based educational platforms, systems, and tools; to investigate education and workplace solutions and to optimize every point in the educational process. During our Ideation Workshop, academics, entrepreneurs, and government leaders were supported to collaborate using team science and human-centered design to rapidly move projects toward deliverables for broad scale national impact (Sections 7-8, Appendix E). We seek affiliated projects that are in a state of readiness to deliver tangible products, resources, and processes that empower stakeholders soon after funding. We seek projects that investigate and augment human learning in all settings (classroom, remote, virtual, hybrid, and on-the-job).

5.3 Impact of the Funding Track.

This Convergence Accelerator funding track will support people who contribute across domains to understand *teaching* and *learning*. This is not a neat and explicit collection of people, but rather individuals who build, deploy, and evaluate online courses: teachers who seek more *engaging resources*; researchers who build stores of *learning data* accessed by other researchers; cognitive scientists and data scientists who design and test *algorithm*s that analyze student interactions; and designers who want to maximize student *learning* while minimizing the distractions introduced by some environments.

The funding track will support the transformation of teaching from the solo sport of "sage on the stage" to a community-based science in which teams design/build learning materials and experiences — and continually refine them (Young, 2020). Learning Engineering is a new approach to education that treats education as a science: researchers test a teaching approach, see where it fails/succeeds and further refine the mechanisms in the online system. Digital environments often leave data trails, making it possible to quickly measure how well online materials convey knowledge, or whether materials need to be *revisited* and *revised*. Proponents of this approach are building the infrastructure necessary for turbo-charging the speed and the quality of learning. Some Learning Engineers believe they can help students reach mastery of complex subject matter as much as 10 times faster than with traditional approaches (Young, 2020).

The proposed track will also support data-driven education that targets vulnerable communities, by adapting content and pedagogy to each student's individual learning needs, based on students' strengths and weaknesses. For example, personalization, meeting the needs of special students , can personalize responses, graphic vs. text, problems targeted to learning, gaming and other interactive efforts that are particularly effective for individual students.

5.4 Convergence at the Intersection of Verticals and Horizontals.

Convergent projects and *teams* in the Data-driven Education Track will span different *horizontals* (tools/initiatives that apply to more than one domain) and *verticals* (integrative solutions that focus on specific application domains). To ensure convergence, each data-driven education track proposal is expected to combine at least one horizontal (demonstrating novelty & acceleration) with one vertical (emphasizing the use-inspired nature of the work) though multi-disciplinary and/or multi-institutional teams. Given these verticals and horizontals, data-driven integrative teams are expected to deliver practical and complementary outcomes that integrate into the overarching theme of *smart, integrated,* and *connected* education tools, platforms and deliverables. Below, we highlight the various horizontals and verticals in the context of Data-driven Education.

Horizontals (tools/initiatives that apply across more than one domain):
- *Systems & Technologies:* Ethical issues (diversity, inclusion), distributed and interoperable tools for monitoring student performance (data analytics, robotics), and data analytics techniques (standards, databases, algorithms, and modeling);
- *People & Communities*: Efforts to empower communities (strategies, sustainability) and educate the workforce (training, curricula, diversity, equity, inclusion, technology commercialization);
- *User characteristics:* (age, culture, gender, nationality, social economic status, diversity, equity, inclusion, neuro features);
- *Educational support:* (organizational management/administration, enrollment management, marketing).

Verticals (integrative solutions that focus on specific application domains):
- *Content Areas*: Topic areas (e.g., STEM, language, reading, writing, social studies);
- *Technology platforms:* The nature of the activity (design, development, evaluation) and type of engagement (gamification, avatars, teaching at scale, robotics, NLP, augmented reality);
- *Traditional education*: (Pre-K12, higher ed, online, adult ed)
- *People & Communities*: Empowering communities (translation affect, culture biases, social-emotional learning) and public policy (ethical considerations, research biases);
- *Workplace/workforce:* (job skilling, training, professional development, placement, career, safety training, curricula, technology commercialization).

Many educational industries (e.g., publishers, entrepreneurial companies) are involved in the design and development of systems that are deeply hierarchical or focused on simple goals in a single domain; information and practices become siloed and are not communicated and shared within organizations or communities. The Data-directed Educational track will seek affiliated projects that are convergent, require multi-disciplinary leaders, and are in a state of readiness to deliver tangible products within *three years* following funding.

6.0 Convergent Solutions, Partnerships, and Mechanisms

Convergent *solutions enabled by AI* will deliver platforms, tools and products that help the community digest the large and interdisciplinary nature of the landscape, and help stakeholders *working in partnership* move forward to provide personalized education. We envision several *data-driven mechanisms* whose primary purpose is to dramatically accelerate online education development and to increase the access and use of AI technology in education.

6.1 Solutions.

Convergent solutions will incorporate open convergence accelerator mechanisms, focused on platforms, processes and tools. Solutions will require public-private *partnerships,* engaging convergence teams from all areas of education, data science, engineering, and science domains to support creation of nonproprietary shared knowledge infrastructures. Solutions will encompass interoperable educational technologies, including well vetted teaching systems (pre-K12, higher ed, adult learning), databases and visualization tools for building new teaching systems, and algorithms and AI tools for reasoning, inference, and decision-making about teaching and learning. Solutions will be *inclusive, open,* and *community*-based resulting in nonproprietary knowledge infrastructures that can facilitate and empower a host of applications and can initiate new research avenues, including the ability to create new *trustworthy teaching* and *training* modules. The community has begun to build multidisciplinary and multi-institutional teams needed to identify the development paths for such mechanisms with a particular focus on education and training.

> … transform learning ecosystems into drivers of social innovation and regional development, capable of filling the gaps between traditional educational agencies - school, parents and territorial stakeholders - and of integrating them with… the web and its virtual communities (ASLERD, 2016).

Convergent proposals submitted to the Convergence Accelerator track will be based on *AI solutions, educational context, instructional knowledge, machine learning (ML), data enriched* with extensive information about the underlying objects, and *natural language systems* that link words and sentences to descriptions meaningful for human users. Proposals will suggest *personalization*, higher *engagement* among students, enhanced ability to keep *content updated*, and *greater interactivity* and adaptivity to (or responsiveness for) individual learners. Key characteristics of such activities will include (i) *dynamic structures*, reflecting updates and changes to teaching and training modules as they occur, (ii) *open systems*, to accommodate input from a variety of sources, and (iii) *linkages* among entities, to enable linking across disparate content and contexts. Access to research data, will also link to, but not publish, controlled information (e.g., private student data) and will open the gates to a new generation of powerful data-driven platforms serving educational needs. Furthermore, researchers will develop expressive frameworks to capture knowledge and will design user centered instructional interfaces to access knowledge at scale for real applications. Organizations, including universities, pre-K12 districts, companies, government, and non-government organizations will take advantage of this networked infrastructure to provide better services and products.

6.2 Partnerships.

The workshop forged new partnerships among diverse stakeholders including *engineers, technologists, and designers*, from two or more disciplines (Figure 1, Appendix A). Team members are prepared to forge partnerships as they bridge their multi-discipline expertise to solve real-world educational problems. Integrative teams will accelerate convergence toward networked AI educational ecosystems. Active partnerships were initiated from several groups.

- **Academic Partners.** AI in Education platforms were represented at the workshop (e.g., Mathia, OpenStax, ASSISTments, Quil). Many were originally developed by academia partners, have supported hundreds of thousands of students and continue to be tested with new students each year. Several universities (CMU, Arizona, UMass, WPI, Harvard, UPitt, Vanderbilt, Florida State) have dedicated research hubs that that advance cognitive and behavioral sciences and instructional design, and develop content, internet usage and trends. Academic centers can help curate data and define measurement tools for research and development.

- **Technology Company Partners.** Companies that develop AI in education products were represented at the workshop (e.g., Eduworks, Cognitive Learning, Alelo, ETS, WestEd, TERC, Concord Consortium, Bamboo Learning, Skillprint). Other technology companies were represented (Apple, ETS, Elsevier). Companies are important partners in developing and evaluating the AIED industry, which is booming with corporate titans (e.g., EdX, Coursera) and small startups alike vying for a slice of an $8 billion-plus yearly market for hardware and software. Much attention is also paid to the “early adopters”—those districts, schools, and teachers who seek out new ways to teach. This theme will bring AI and the data revolution to businesses, non-profits, and government organizations. Information-sharing efforts across tech platforms is often easier to achieve than across other industries.

- **Government Partners.** Government organizations were represented at the workshop (U.S. Dept of Education, European Parliament, NSF). They are important partners in this space. Governments will shape regulation and laws that define how AIED platforms can operate and will need to be involved in conversations around how best to bring tools effectively and efficiently into classrooms. Attention must be paid to regulation; while overregulation could stifle innovation, under regulation can lead to inappropriate teaching and privacy breakdowns. Currently AIED platforms are left to police themselves, a rarity in any industry. Legislative and regulatory organizations need to be designed, similar to the U.S. Food and Drug Administration, to help incentivize AIED platforms to operationalize tools that efficiently support teaching and security.

- **Non-Governmental Organization Partners.** Several NGOs were represented at the workshop **(**Digital Promise, Education Technology Consortium). A range of NGOs support education technology whose work is relevant for design, development and assessment of instructional systems, think tanks and institutions that focus on policy-relevant research provide an important bridge between industry and government.

6.3 Mechanisms.

We envision proposals to the track that produce data-driven mechanisms – each created over a three-year time frame-- whose primary purpose is to dramatically *accelerate development* and *increase access and use* of AI technology in education, see Appendix E, Convergent Products. These mechanisms will support *stakeholders* to create and search *networked libraries;* to employ *affordable* and *accessible tools* for engaging public participation in STEM; to engage with others in *hubs* for retrieving material, and to locate *curricula* for policy, diversity, mentorship, and technology translation. Mechanisms will provide techniques to search and deploy each platform and have a systemic view of data science and AI in education. Workshop participants discussed the affordance of several mechanisms.

- Compile data and research provided by a broad spectrum of researchers, users and supporters;
- Search and analyze the full range of tools using AI technology (data mining, natural language processing, machine learning, social analytics, etc.);
- Target urgent societal needs (e.g., personalized learning, learning loss, data security, socio-ethical considerations);
- Encourage high levels of collaboration and convergence among researchers;
- Engage the full range of stakeholders;
- Facilitate collaboration and convergence for new directions that could not otherwise be accomplished in the current research paradigm;
- Encourage development of *policies* and *standards* for applications development that target societal needs that research interests on their own would not likely address (e.g., diversity, equity, inclusion, learning loss, etc.).

7.0 Track Funding A: Convergent Mechanisms

The brainstorming section of the workshop identified several convergent mechanisms that encourage high levels of collaboration, support the compilation of data and research, target urgent societal needs, and encourage development of *policies* and *standards* for applications development. A brief summary of these solutions is included below.

7.1 The "Library."

One model of a Network Library, rather than being an entity or mechanism, is of a hub that sits as an intermediary between the requester and the body of learning modules. The proposed hub, where all material resides, instead of cataloging, would provide listings more akin to the nutritional value labels on food products that informs users about various components. In this scenario, AIED labels would show reliability and validity and salient statistics that have been collected on products, e.g., a rating system for each product (perhaps one by teachers and another by users). Products with more stars are likely to survive and flourish while others with fewer stars fall out of the pile.

7.2 Scaling Up Tutoring for a Collective Outcome.

Expert human tutors are a valuable resource. Past research has shown that they can be highly effective in improving student learning outcomes (Nickow et al., 2020) by providing either scheduled or on-demand support through tutoring activities. However, this effectiveness cannot yet reach all students in need since the number of expert human tutors is limited and many students, especially those financially or socially disadvantaged, do not have access to high-quality human tutors. Therefore, there is a need to develop AI-based solutions to scale up and augment the capabilities of expert human tutors.

Numerous promising research directions have been explored along these lines. It is possible to develop AI-based agents to support tutoring activities between tutors and students by providing content-, affect-, and strategy-targeted feedback. It is also possible to use AI during tutor training to develop more expert tutors. Most of these directions are made possible by recent development in *natural language processing*, especially chatbots (Thoppilan et al., 2022). It is also possible to use *reinforcement learning* to learn effective dialogue strategies and mimic effective human tutors. These ideas are made possible by collecting and analyzing a large amount of textual data during tutor-student interactions.

7.3 Immersive Performance Assessments.

Data-driven education offers the opportunity to develop an industry centered on *virtual performance simulations* that develop people's abilities to work productively with others. Advances in artificial intelligence and immersive learning now enable "digital puppeteering" systems in which one simulation specialist can control up to six or seven virtual avatars. As an example, a person could learn and practice negotiation skills under various conditions (the number of people involved in the negotiation, the objectives of the interaction, the demographic characteristics of participants). Beyond benefiting from the repetitions of practicing any skills involved in working with others, human mentors and AI-based coaches could aid the learner in improving their performance, assisted by next-generation *natural language processing*. Further, the *metavers*e could serve as a showcase for people to experience and improve various types of skill-building performance simulations, enabling better collaboration and leadership as well as identifying and reducing biased behaviors.

7.4 Hybrid Learning.

We brainstormed about an industry based on infrastructures, tools, and training to enable hybrid work, civic participation, and learning. The world is now irreversibly hybrid. Businesses, civic organizations, entertainment venues, and social relationships that used to be primarily face-to-face are now often or even predominantly online. Most employees who have the option of working from home, part or all the time, are delighted by this new flexibility. Many people who accept new jobs far from their current location can now negotiate to avoid relocating by instead working across distance. Businesses that can accommodate remote work find their expenses for physical offices declining, increasing profits by reducing costs. Many workers have shifted to occupations providing remote services that were previously face-to-face, and quite a few find their new form of employment better than their old job. Older people and those with comorbidities to COVID appreciate having their meals and groceries delivered. Politicians, pundits, and entertainers delight in the scope and reach of social media with global impact via enhanced digital infrastructures. Through mobile apps, families can keep close contact with remote friends and relatives. All of these audiences could benefit from an industry that provides infrastructures, tools, and training to actualize the dual face-to-face and online interactions they seek. To fuel this industry, a rich source of case studies celebrating online and hybrid education are being explored (Dede et al., 2022).

7.5 Learner-Data Ecosystems.

The following factors currently stand in the way of making effective use of learner data. Available types of data, e.g., question responses, keystroke and clickstream data, are often not only difficult to interpret because they are incomplete but also challenging to correlate with learning outcomes and predictors of learning success. For example, it is important to know not just whether learners completed computer-based exercises correctly, but also what learner characteristics we can use to predict correct responses and whether online performance correlates with in class performance and in summative student assessments. Available data are often not available for use by outside researchers and developers. Moreover, data may contain personal identifiable information, so sharing it raises privacy concerns. This is particularly true of eye tracking data and audio and video data, which can reveal a lot about a learner's mental state but which could be used to identify students. Finally, stakeholders do not always trust platform developers to make ethical use of data and not sell it to advertisers and others who are not acting in the learners' best interests.

8.0 Track Funding B: Complementary Project Ideas

During the workshop nearly a dozen novel data-driven education projects were proposed by participants (Appendix E). These projects couple use-inspired AI research with foundational AI and Learning Science research and forge new partnerships among diverse stakeholders. They describe well-defined deliverables that can be submitted to a potential track, explore new theory, algorithms, big data, and systems and can be completed within three years. These projects optimize many points in the education process from *understanding* students' learning, *organizing* what they can learn, and *enhancing* how they learn. These convergent projects are listed below, and several are described in detail in Appendix E.

Artificial Intelligence in Education for Assessing Human Learning Constructs

- AI-Assisted Authoring of Conversational Tutors and Avatar
- Digital Puppeteering Systems Enable AI-Enhanced Simulations for Learning Psychosocial Skills
- Developing Foundational Literacy, Math, and Critical Thinking Through Conversational AI
- Using Science to Train Preservice Teachers to Create Effective and Motivating Explanations to Teach STEM
- Helping Student Ask Questions in Math Class
- Quill.org: AI for Literacy Skills for 7 Million Students
- Assistive Technology Templates: Artificial Intelligence for Neurodiversity (ATTAIN)
- The Cyclical Ethical Effects of Using Artificial Intelligence in Education
- A Data-driven Orchestration Tool to Help Promote Best Teaching Practices and Optimize Learning
- Toward an Equitable Computer Programming Practice Environment for All

9.0 Summary and Conclusion

The challenge of a *Data-directed Education Track* is a challenge of convergence – the need to bring together multiple components of a system (along with respective stakeholders) to create a transformative difference. The impact includes overcoming learning loss, providing more rapid skilling, more job readiness and reducing instructional time and educational disparities. To achieve the vision of *data-directed education*, the community must make best use of available data from learners interacting with data-directed educational systems. Developers of learning platforms increasingly recognize the value of learner data, platforms and tools and many devices serve as data collection platforms as much as learning platforms. However, important categories of data are still not consistently captured, and data that is captured tends to be siloed and not accessible to other developers and researchers. Thus, the field is not yet able to take full advantage of the data sets that exist. The proposed *Data-directed Educational* funding track aims to overcome these limitations, by fostering a learner-data ecosystem that encourages capturing, processing, and safe use of learner data.

The Convergence Accelerator program can play an important role in overcoming these barriers and foster a learner-data ecosystem. First of all, the Convergence Accelerator should embrace emerging guidelines for the ethical use of artificial intelligence and data in teaching learning, proposed by the White House and the European Commission. Track funded projects should further develop plans for the safe sharing of learner data, in ways that do not infringe on learners' privacy and rights. Learners and caregivers should always have the right to withhold permission to use their data, and developers should not retain data longer than is appropriate. Guidelines for gaining appropriate economic benefits from data must be established. Data may be used to improve automated learning systems and assessments, but not for advertising or any other unrelated purpose. Each proposed project's Data Management Plan should address how the project intends to meet these goals. Moreover, the Convergence Accelerator should encourage the use of existing datasets, thereby increasing demand for data sharing. This approach could serve as a model for AIED industry and encourage broader adoption of ethics and safety guidelines.

Sharing data involves commitments of time and resources and may expose developers to liability in the event that shared data is misused. The Convergence Accelerator program can address this problem by investing in the development of interoperable tools that can integrate into learning platforms and facilitate safe sharing of data, derived data, and analytics.

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11.0 Appendices.

Appendix A: Participant Statistics and Interests

We conducted four workshops featuring 17 keynote addresses, six breakout groups, five Q&A sessions, and two brainstorming sessions. The workshops attracted a broad attendance of *160 registrants from over 100 organizations*. As shown below, participants and registrants represented stakeholders from various organizations, including academia, nonprofit (NGO) organizations, public (governmental) agencies, commercial enterprises, and investment firms, foundations, government organizations and others (see list of organizations here).

1EdTech Consortium

3M Health Information Systems

Abilene Christian University

AERDF

AI2ES

Alelo

Apple

Arizona State University

Ateneo de Manila University

AYSET

Bamboo Learning

Barbara Treacy Consulting

Berkeley

Booz Allen Hamilton

Boston College

Building State Capability, Harvard Kennedy School

Carnegie Learning, Inc.

Carnegie Mellon University

Central University of Jharkhand

Columbia University

Cornell University

Digital & Beyond

Digital Promise Global

District of Columbia Public Schools

Dublin City University

Educational Testing Service

Eduworks Corporation

Elsevier

ETH Zurich

European parliament

FFHS

Florida State University

George Mason University

Georgetown University

Georgia Institute of Technology

Harvard Graduate School of Education

Harvard Next Level Lab

Harvard University

Harvard-Westlake

HSD2

IIT Bombay

IIT Delhi

Indira Gandhi Delhi Technical University for Women, New Delhi, India

ITCILO

KIPP NYC

KLE Technological University

Know Center Gmbh

Lakehead University

MIT

Nanyang Technological University, Singapore

National Academies of Sciences Engineering and Medicine

National Louis University

National Science Foundation

NCDE

North Carolina State University

NYU

OpenStax, Rice University

Quill.org

Royal Roads University

Saint Louis University

Santa Clara county

Skillprint

SRG Technology LLC

SRI IT Consulting Limited

St John's University

TeachFX

Technical College System Of Georgia

TERC

The Concord Consortium

Trinity College Dublin

University of Massachusetts Amherst

University of Massachusetts - CICS

University of Massachusetts - College of Education

Universidad Tecnológica de Nogales

Universitas Negeri Malang

Universitat Politecnica de Valencia

University College London

University of Alberta

University of Arizona

University of British Columbia

University of Chicago

University of Craiova

University of Denver

University of Florida

University of Illinois, Chicago

University of Illinois, Urbana-Champaign

University of KwaZulu-Natal

University of Louvain

University of Massachusetts

University of North Carolina

University of North Carolina at Charlotte
University of Pittsburgh
University of Pretoria
University of San Diego
University of Sheffield
University of Southern California
University of State Manado
University of Sussex, Brighton, UK
University of Turku
University of West Georgia
UPenn
Vanderbilt University
WestEd
WPI

Appendix B: Themes Discussed During the Workshop

During the Ideation Workshop we discussed five themes during four workshops through keynote addresses and question/answer and breakout sessions.

Theme A: Design, Develop and Test Digital Education Artifacts

The first theme in the Convergent Accelerator workshop was *design, develop and test digital education artifacts.* Data-driven technology is here to stay and is moving in *many directions***,** driven by many urgent social problems, e.g., *health, transportation (autonomous vehicles), communication (SIRI and Alexa), smart cities, and finance***.** In all these domains new approaches are meeting societal needs. Education in the USA has urgent needs that can be achieved through AI. We have an opportunity to determine the path of the future of *AI driven education* rather than let it unfold unawares. Stakeholders need to get in front of *AI in Education* and determine how that result will impact society. We discussed intelligent *tutors, games, and user interfaces; new modules, interfaces or functionality. The skill set* usually includes AI, machine learning, models, UX/UI design including needs analysis, wireframing, prototyping, iterative design research, and human factors. During the Convergent Accelerator Workshop we discussed the following topics:

- *Robots as Social Learning Companions;*
- *Online Adult Learning: AI Institute;*
- *AI for Orchestration in the Classroom.*

Theme B: Assessment of Educational Research

The second theme in the Convergent Accelerator workshop was *assessment of educational research* that includes conducting experimental studies in educational settings. Two main *issues* are relevant for online assessment: *timing* and *nature* of assessment. *Timing of assessment* is no longer a process of teaching, then stopping to test, then teaching, then stopping. With AI we can evaluate complete real-time monitoring of students, detection students in trouble, frustrated and need help, as well as those who should move ahead of the class. Similarly the nature of *assessment* has changed. Previous assessment instruments typically focused on cognitive development. Now students' affect and interest can be included in students' profiles. Using AI we can detect student *emotion, motivation, behavior,* and *int*erests and to include them in student profiles. Of course, great teachers often did assess student *emotion* and *motivation*. However, now large data sets of previous students' efforts in similar situations can be used to estimate current students' *strengths* and *liabilities* compared to that of other students. Assessment studies often involve working with *teachers* and *students, analyzing data,* and *interpreting experimental findings*. Research focuses on testing educational technologies in various educational settings (e.g., classrooms, online). During the Convergent Accelerator Workshop we discussed the following topics:

- *Social Analytics;*
- *How AI Can Empower Component-Based Educational Research;*
- *Opportunities Matter: Hybrid Human-Computer Tutoring Toward Educational Equity*
- *Intelligent Game-based Assessment and Tutoring*

Theme C: Learning at Scale

The third theme in the Convergent Accelerator workshop was learning at scale and big data. Big data refers to vast amounts of data across disparate locations and includes digital tools, platforms, applications, and the communication among people about large data sets. Big data technologies aim at harnessing the power of extensive data in real-time. The characteristic attributes of big data have been referred to as volume (amount of data), variety (diversity of sources and types of data), velocity (speed of data transmission and generation), veracity (the accuracy and trustworthiness of data), and value (the price of the data). Key research advancements resulting from big data in education are associated with assessment and individualized learning (both covered in our first workshop day) and precision education. Model-driven data analytics approaches are growing quickly to guide development, interpretation, and validation of algorithms. However, research from educational analytics should be applied with caution, due to issues of ethics, privacy and security. Biased data, for example, comes from large datasets that were established with biased data and were not inclusive, e.g., did not include information from underrepresented people. Privacy issues arise if a visitor can identify an individual student based on “triangulating” data from several data bases or by identifying individual students by "connecting the dots." However, large data bases are helpful to identify students’ current behavior, draw inferences about their future behavior, and eventually develop deep and detailed profiles of their lives and preferences. Security issues might involve theft or loss of confidential information about students in case this data falls into unreliable hands. This theme includes large-scale research, better understanding of learning, prediction of learning outcomes, and enhancing learning at scale. The skill set includes expertise in conducting and analyzing experimental studies, A/B/n experimental design, database management, advanced statistical methodologies, and learning analytics (e.g., machine learning), use of machine learning to address issues of personalization, equity, cost, customization, usability. During the Convergence Accelerator Workshop we discussed the following topics:

- *Future of Stealth Assessment*
- *Data-driven Item Selection and Generation in Assessments and Learning;*
- *Crowdsourcing Paves the way for Personalized Learning*

Theme D: Ethical and Equitable

The fourth theme in the Convergent Accelerator workshop was *ethical* and *equitable*. The ethical considerations in artificial intelligence in education are profound, as they are when using AI in any setting. AI lacks a so-called “moral compass,” so AI programming is “as ethical as its developer” (Hoes, 2019). Clearly the field needs to build *ethics* into how *AI technology for education* is developed and to monitor/check/police the outcomes of each piece of technology to fully understand its behavior and make sure that it’s not violating our (human) moral compass, including fairness, privacy, and liability and proposed regulations that provide individuals with a right to explanation when decisions made by an AI agent affect them. Stakeholders should reasonably expect that AIED systems deployed use AI in a *safe, equitable,* and *appropriate* manner, as outlined in the OSTP's Blueprint for an AI Bill of Rights (WhiteHouse OSTP, 2022). Convergent Accelerator proposals should indicate how their planned deployments will safeguard these rights. The blueprint does not have force of law or regulation, but it is reasonable to suppose that developers should be prepared and get in front of this issue. Developers who fail to do so risk encountering stakeholder resistance when they deploy their systems. During the Convergence Accelerator Workshop we discussed the following topics:

- *Rapid Workforce Development*
- *Bilingual Tutor*

Theme E: Entrepreneurial, Not-For-Profit, And Government Digital Learning Systems

The fifth and final theme in the Convergent Accelerator workshop was *entrepreneurial, not-for-profit,* and *government digital learning systems.* The AIED industry is booming with corporate titans and small startups alike vying for a slice of an $8 billion-plus yearly market for hardware and software and will start recapping ideas that entrepreneurs have been testing in schools and workplaces. The AIED market size was valued at USD $106 billion in 2021 and is expected to reach USD $127 billion in Jan 2022. The AIED market is predicted to grow rapidly: worldwide, more than thirty multi-million-dollar-funded AIED corporations exist and the market is expected to become worth more than US$ 20 billion within five years (GMI, 2022). Much attention is also paid to the “early adopters”—those districts, schools, and teachers who are engaging new forms of teaching. This theme will bring AI and the data revolution to businesses, non-profits, and government organizations. and will start recapping ideas that entrepreneurs have been testing in schools and workplaces. Public schools in the United States now provide at least one computer for every five students. They spend more than $3 billion per year on digital content. Led by the federal government, the country is in the midst of a massive effort to make affordable high-speed Internet and free online teaching resources available to even the most rural and remote schools.

Most teachers have been slow to transform the ways they teach, despite the influx of new technology into their classrooms. There remains limited evidence to show that technology and online learning are improving learning outcomes for most students. And academics and parents alike have expressed concerns about digital distractions, ways in which unequal access to and use of technology might widen achievement gaps. Digital instructional content is the largest slice of the (non-hardware) K-12 educational technology market, with annual sales of more then $3 billion. That includes digital lessons in math, English/language arts, and science, as well as “specialty” subjects such as business and fine arts. The market is still dominated by giant publishers who have scrambled to transition from their *print-centric* legacy products to more *digital offerings*. But newcomers with one-off products or specific areas of expertise have made inroads, and some apps and online services have also gained huge traction inside of schools. During the Convergence Accelerator Workshop we discussed the following topics:

- *Aligning Curricula with Skills and Jobs;*
- *Foreign Language Learning;*
- *Large Scale Commercialization;*
- *The EdTech Investment Climate*
- *Innovative Education Technology from the US Department of Education;*

Appendix C: List of Keynote Addresses and Sessions
(Workshop Schedule)

This is the schedule and links for Convergence Accelerator Education Workshop Days 1-4 that featured keynote addresses, Q/A, and breakout sessions. The links provided at the website, https://learning-pal.org/ include videos of each keynote talk. The last two days, Oct 24, 25, 2022, featured ideation of convergent themes for the future of AI in Education. Videos for each keynote speaker are included here.

SESSION 1: Tuesday, October 18, 2022 1:00 PM - 5:00 PM EST

THEME A: DESIGN, DEVELOPMENT, AND TESTING

Welcome to the NSF Convergence Accelerator Ideation Workshop By Beverly Woolf, PI
Robots as Social Learning Companions By Erin Walker
Online Adult Learning: AI Institute By Myk Garn
AI for Orchestration in the Classroom By Jennifer Olsen
Q&A and BREAKOUTS Moderators: Keynote Speakers and Chad Lane
Theme Re-Cap Moderator: Beverly Woolf, PI

THEME B: ASSESSMENT OF EDUCATIONAL RESEARCH

Social Analytics By Carolyn Rosé
How AI Can Empower Component-Based Educational Research By Chris Dede
Opportunities Matter: Hybrid Human-Computer Tutoring Toward Educational Equity By Ken Koedinger
Q&A and BREAKOUTS Moderators: Keynote Speakers
Theme Re-Cap Moderator: Beverly Woolf, PI

SESSION 2: Wednesday, October 19, 2022 1:00PM - 5:00 PM EST

THEME C: LEARNING AT SCALE

Welcome By Beverly Woolf, PI
Future of Stealth Assessment By Val Shute
Data-driven Item Selection and Generation in Assessments and Learning By Andrew Lan
Crowdsourcing Paves the way for Personalized Learning By Neil Heffernan
Q&A and BREAKOUTS Moderator: Andrew Lan
Theme Re-Cap Moderator: Beverly Woolf, PI

THEME D: ETHICAL AND EQUITABLE

Rapid Workforce Development By Lewis Johnson
Bilingual Tutor By Ivon Arroyo
Q&A and BREAKOUTS Moderator: Andrew Lan
Theme Re-Cap Moderator: Beverly Woolf, PI

SESSION 3: Monday, October 24, 2022 1:00PM - 5:00 PM EST

THEME E: ENTREPRENEURIAL, NOT-FOR-PROFIT, AND GOVERNMENT DIGITAL LEARNING SYSTEMS

Welcome By Beverly Woolf, PI
Aligning Curricula with Skills and Jobs By Robby Robson
Foreign Language Learning By Lewis Johnson

Intelligent Game-based Assessment and Tutoring By Danielle McNamara
Q&A and BREAKOUTS Moderators: Keynote Speakers and Chad Lane
Theme Re-Cap Moderator: Beverly Woolf, PI
Large Scale Commercialization By Steve Ritter
The EdTech Investment Climate By Max Woolf

RECAP OF PROJECT IDEAS (PART 1)

Facilitated Brainstorming Session (Keynote Speakers and Participants):
Exploring Project Possibilities, Collaboration and Synergy, Engaging Users
Panelists: Beverly Woolf and selected Keynote Speakers
Facilitator: Burt Woolf, Ed.D.

- **Promising Possibilities***: What projects and/or ideas for AI in Education have you heard, are thinking about, or are aware of that would benefit from an NSF Con-Accel Funding Track?*
- **Collaboration and Synergy***: Which projects overlap or where are we working toward similar impact? What combinations (integration, blending, piggybacking, dovetailing) of research efforts would amplify the impact of AI in education and learning?*
- **Realizing our Shared Transformative Vision***: In what ways might we engage users to help address and overcome inherent limitations, barriers and biases in our research efforts so that we might be more effective in realizing our vision for AI in the world of education and learning?*

SESSION 4: Tuesday, October 25, 2022 1:00PM - 4:00 PM EST

SPECIAL PRESENTATION

Innovative Education Technology from the US Department of Education By Ed Metz

RECAP OF PROJECT IDEAS (PART 2)

Facilitated Brainstorming Session (Keynote Speakers and Participants):
Exploring Project Possibilities, Collaboration and Synergy, Engaging Users
Panelists: Beverly Woolf and selected Keynote Speakers
Facilitator: Burt Woolf, Ed.D.

Appendix D: Convergent Workshops

During all four days of the workshop we engaged in highly dynamic and engaging conversations through breakout sessions and brainstorming sessions to address the challenges, formation of multi-disciplinary teams and expected deliverables within three years through NSF Convergence-Accelerator projects.

Workshop Theme	Breakout Sessions
Design, Develop, and Test Artifacts	Robots as Social Learning Companions Online Adult Learning AI for Classroom Orchestration
Assessment of Educational Research	Social Analytics Intelligent Game-based Assessment Component-based Educational Research
Learning at Scale	Future of Stealth Assessment Data-driven Item Selection and Generation Crowd-sourcing for Personalized Learning
Ethical and Equitable	Rapid Workforce Development Bilingual Tutor Human-Computer Tutoring towards Educational Equity
Entrepreneurial/Gov't Digital Learning Systems	Aligning Curricula with Skills and Jobs Foreign Language Learning Large scale Commercialization EDTech Investment Climate US Dept of Education SBIR Investment

During Day 3-4, panelists and participants explored three convergence questions:

- **Promising Possibilities**: What projects and/or ideas for AI in Education have you heard, are thinking about, or are aware of that would benefit from an NSF Con-Accel Funding Track?
- **Collaboration and Synergy**: Which projects overlap or where are we working toward similar impact? What combinations (integration, blending, piggybacking, dovetailing) of research efforts would amplify the impact of AI in education and learning?
- **Realizing our Shared Transformative Vision**: In what ways might we engage users to help address and overcome inherent limitations, barriers and biases in our research efforts so that we might be more effective in realizing our vision for AI in the world of education and learning?

Appendix E: Sample Data-directed Education Projects

Workshop participants presented several projects that involve data-directed education and well-defined deliverables with fast tracked time-to-deploy cycles. Integrative teams can rapidly deploy and evaluate these projects, dramatically accelerating the access and use of AI technology in education. We summarize several of these projects below.

1. Equitable Programming Practice Environment

Carl Haynes-Magyar

Goal: Improve programming environments for learners with cognitive disabilities; help diverse students develop programming skills; deliver insights into developmental processes related to learning disabilities; 22.6% of programmers are neurodiverse (invisibly disabled), 3.48% are physically (visibly) disabled, 10.6% have concentration and/or memory disorder, 10.3% anxiety disorder, and 9.7% mood or emotional disorder. These values have increased since 2021. LGBTQIA+ students often think about dropping out because of a lack of belonging.

AI in Education: Develop adaptive scaffolding of problem types, feedback, and support; eliminate pseudocode, boring code-reading, tracing with paper and pencil, and code-writing from scratch use less frustrating Parsons code (code blocks placed in order); provide support for computing as a social practice or culturally relevant pedagogy; be responsive to student identities.

Convergent Topics: AI, machine learning (ML), personalize learning; data analytics, data mining, learning disabilities, motivation & engagement; cognitive development; emotion in learning; instructional design, motivation and engagement, cognitive development, diversity, ethics.

2. Puppeteering

Chris Dede

Goal: Support pre-service teacher training using avatars; train implicit bias, work effectively across a wide variety of developmental levels and demographic characteristics.

AI in Education: use virtual humans in mixed reality digital puppeteering simulations; avatars can assume many physical forms (e.g., a small girl, a grown man); enable simulation specialists to control avatars' interactions with realistic verbal and nonverbal capabilities (e.g., voice volume, tone, and prosody; nonverbal facial expressions, postures, gestures); provides algorithmic assistance for a simulation specialist to inhabit a 3D (virtual reality) or 2D (mixed reality) digital environment.

Convergent Topics: AI, data science, module blends specialist's input ––including head motion, morphing the voice of the simulation specialist to a wide range of options, and lip-syncing—with the avatars' unique body language and facial expressions.

3 Academic Writing for Neurodiverse Students

Ibrahim

Goal: Assist neurodiverse learners (ADHD or autism) in academic writing, specifically difficulty in the mechanics of writing; help organize and abstract ideas into larger concepts.

AI in Education: Use natural language generation algorithms (such as GPT-3); students provide comments in response to basic writing prompts; AI tools create outline templates for student writing that serve as structures, producing outlines that help flesh out critical analyses.

Convergent Topics: AI, ML, data analytics, learning disabilities, motivation & engagement; cognitive development; emotion in learning; diversity, equity and inclusion, , instructional design.

4. AI Literacy for Low Income Students

Peter Gault

Goal: Help low-income 3rd-12th grade students become strong writers and critical thinkers by providing personalized learning plans; assess a range of student writing skills.

AI in Education: Use 100 different algorithms to provide real-time coaching and feedback on literacy activities; support students to quickly develop and revise writing skills; provide a personalized learning plan for students through a diagnostic assessment.

Convergent Topics: AI, ML, data analytics, target motivation, engagement and cognitive development; emotion in learning; diversity, equity, inclusion; instructional design.

5. Authoring Tools for AI Platforms

Lewis Johnson

Goal: Create tools that easily change avatar-based content to new topics**;** accelerate content creation and drive down production costs; improve tool ability to provide feedback and progressively learn as used; enable stakeholders to leverage already created course content and convert slides into interactive avatar-driven content.

AI in Education: Improve a platform's ability to ingest and understand each author's learning content and quickly transform it into avatar-based content; e.g., create Socratic questioning exercises based on information extracted from PowerPoint slides or textbooks; learners will respond in a wide variety of ways; use data mining to analyze and classify learner responses; add content to dialogue models.

Convergent Topics: Natural language processing, data science, data mining, ML, psychometricians, PowerPoint plug-ins; creators of learning content; psychometricians using conversational avatar technology to measure learning.

6. Cyclical Ethical Effects of Using AI in Education

Edward Dieterle

Goal: Explore structural biases that lead to inequity; study ethical questions about learning and teaching associated with generating, analyzing, and interpreting data with AI; probe the ethical effects of algorithms; train stakeholders to plan for and mitigate bias; train instructors to create, evaluate, and improve life-wide, lifelong learning experiences.

AI in Education: Predict learning outcomes and automate low-level instructional decisions; discover relationships and patterns among ethical divides: *algorithm* (do algorithms represent learners or do they reflect human biases)*, access* (who has access to hardware, software, and connectivity), *representation* (factors that make data representative of the total population or bias understanding), and *interpretation* (how stakeholders understand the outputs of algorithms); analyze large datasets to promote evidence-based decisions.

Convergent Topics: AI, ML, data science, learning analytics**,** machine learning, educational data mining, diversity, equity, inclusion.

7. Foundational Learning Through Conversational AI

Irina Fine

Goal: Address the worsening literacy crisis; language development and reading fluency; close the deepening achievement gap in reading comprehension; provide adaptive learning experiences.

AI in Education: Provide personalized, scaffolded reading journeys that result in gains in language development and reading fluency; conversational form of learning; algorithm-based generation of customized comprehension questions based on students' interests, abilities, and progress.

Convergent Topics: Voice recognition technology, conversational AI, evaluate students' free-form voice responses to open-ended comprehension questions, "serve and return" conversations.

8) Help Students to Ask Questions in Math Class

Neil Heffernan

Goal: Provide a library of automatic coaching tools for pre-service teachers that support students while solving online math problems; tools ask students questions and provide feedback -- coached-problem-solving; leverage design patterns as a framework to learn about what patterns help pre-service teachers apply effective coaching moves.

AI in Education: Build and evaluate software coaching tools that replicate coaching moves of experienced teachers; work with pre-service teachers to study the activities (teachers walking around a room) and capture it (~20 second interaction of teacher with student) in an online system, e.g., ASSISTments; study new teacher's actions and test efficacy in randomized controlled trials (RCTs) collected by and conducting small RCTs that compare selected coaching moves.

Convergent Topics: Natural language processing (through NLP models); computer science (in the development of student- and teacher-facing interfaces and tools); machine learning and models of design patterns that represent effective ways for teachers to coach students.

9. Intelligent Orchestration Dashboard

Lewis Johnson

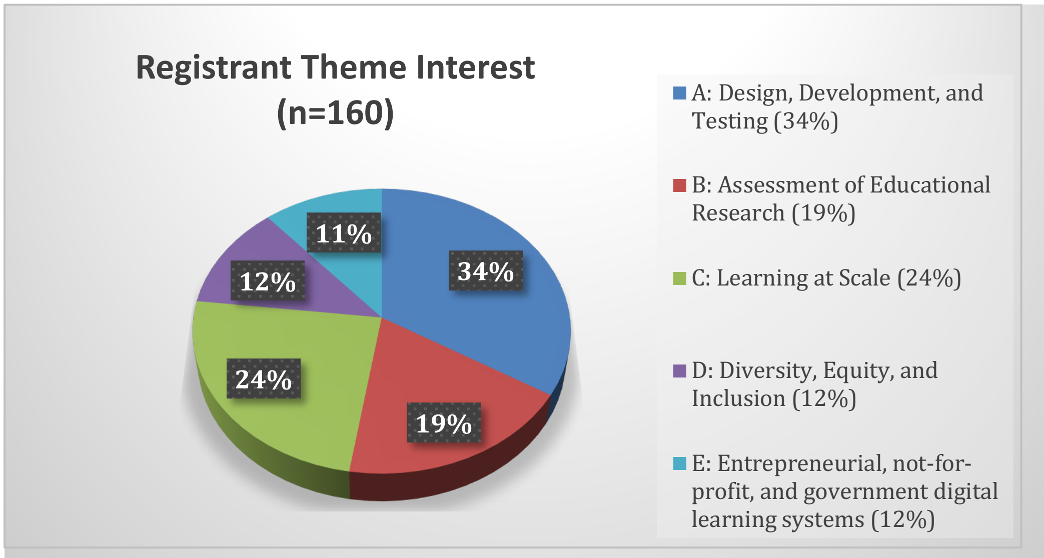
Goal: Track learners' progress and manage personalized learning tools through intelligent orchestration dashboards; identify learners not on track; meet target outcomes set by the teachers; understand how good teachers contribute to classroom success; personalize learning experiences informed by learner data.

AI in Education: Enable other stakeholders to access research data for experimentation; support rapid testing (Learning Engineering); identify alternative instructional materials and sequencing; support teachers to adopt best practice and optimize personalized learning algorithms; examine how students' progress toward mastery, both individually and as a class; determine which practices are used by teachers; help other teachers and automated tools learn from those practices.

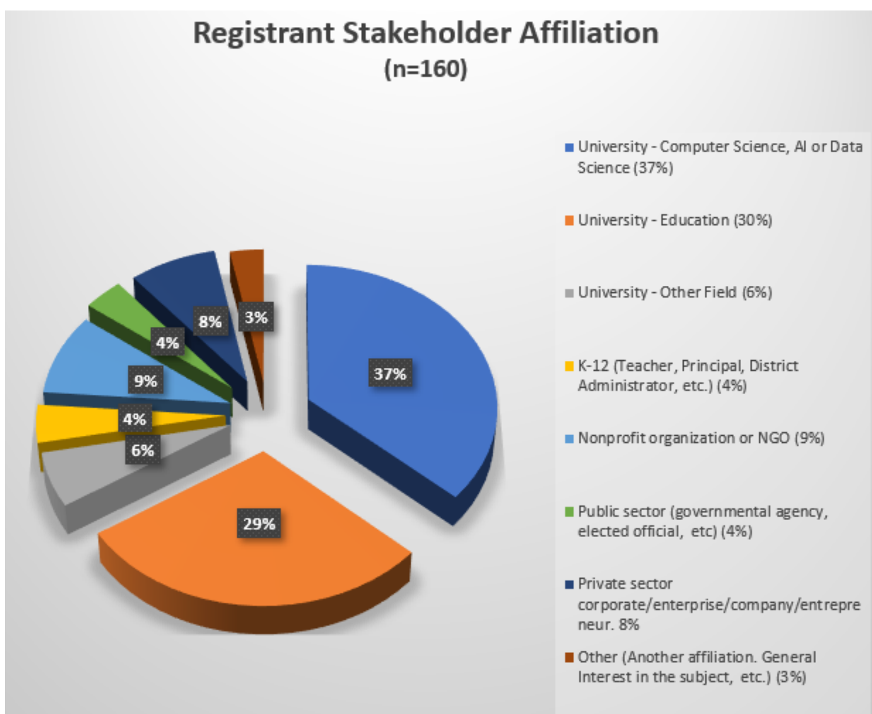
Convergent Topics: AI, ML, data science, educational data mining, interoperability; data analytics, instructional design.

Appendix F: Registrant Profiles
(n=160)

Which Workshop Theme (sub-topic) is of greatest interest to you?



What affiliation best indicates your stakeholder relationship to the workshop?



Geographic distribution of registrants

Non-USA	32
MA	30
PA	14
CA	13
OR	9
NY	8
TX	8
FL	7
AZ	6
DC	6
IL	5
NC	4
GA	3
VA	3
AL	2
CO	2
NJ	2
UT	2
MD	1
MN	1
MO	1
SC	1
TN	1
WI	1