

Article

# The Future of Postsecondary Education in the Age of AI

Alfred Essa

AI-FutureMinds Inc., Windermere, FL 34786, USA; aessa@ai-futureminds.com

**Abstract:** This paper examines a *possible future* for postsecondary education in the age of AI. The consensus view among economists is that AI is a general purpose technology (GPT), similar to the steam engine, electricity, and the internet. As a GPT, AI will be the main driver of innovation for the foreseeable future in most sectors of the economy, including education. As AI evolves, it holds the promise of fundamentally redefining the educational landscape, influencing not only current practices in institutional management and pedagogy but also shaping future trends in learning, evaluation, and accreditation. While traditional college-aged students have received significant attention in educational studies, this paper emphasizes the needs of *adult learners as lifelong learners* and explores how *AI-driven innovations* can enhance their educational experiences, offering personalized and flexible learning solutions. This paper also argues that a dramatic breakthrough is needed in the *cost–value equation* for education to support workforce development and lifelong learning.

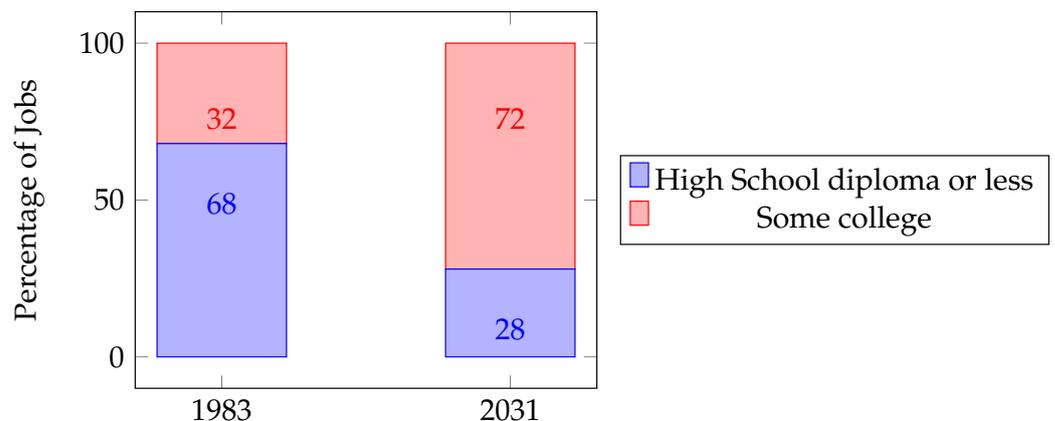
**Keywords:** artificial intelligence; adult learners; adaptive learning; generative AI; learning analytics

## 1. Introduction

Creating an educated workforce is a global challenge. According to a recent study of the US economy by *Georgetown University’s McCourt School of Public Policy Center on Education and the Workforce*,

“Postsecondary education is no longer just the preferred pathway to middle-class jobs—it is, increasingly, the only pathway”. [1]

The report goes on to note that the workforce is rapidly upskilling and 72% of all jobs by 2031 will require workers to have at least some postsecondary credential or training beyond high school, see Figure 1.



**Figure 1.** In 1983, 32% of jobs required some college. By 2031, the number is projected to increase to 72%. Source: Georgetown University Center on Education and the Workforce.

The shift in demand for highly skilled workers coincides with rising inequality. The gap is widening at an alarming rate with economies increasingly dominated by a



**Citation:** Essa, A. The Future of Postsecondary Education in the Age of AI. *Educ. Sci.* **2024**, *14*, 326.

<https://doi.org/10.3390/educsci14030326>

Academic Editor: Anthony G. Picciano

Received: 18 January 2024

Revised: 26 February 2024

Accepted: 6 March 2024

Published: 19 March 2024



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“winner-takes-all” scenario, where a mere 1% of the population controls the vast majority of wealth, power, and freedom [2–4]. A revitalized approach to education, therefore, holds the key not only to meeting workforce needs but reversing the trend of inequality.

It is apparent that the supply of affordable and effective learning has not kept pace with demand. The problem is especially acute for adult learners and their need for lifelong learning. The market reasons for the mismatch are complex. However, several things are clear. First, incentives and institutions are aligned to meet the needs of traditional learners taking traditional courses in traditional disciplines. Second, a “known known” in learning science is that we “learn by doing, not viewing” [5]; yet most instruction, including in complex subjects, encourages passivity: listening to lectures, watching videos, and reading textbooks. Third, middlemen in the education value chain (e.g., publishers and edtech) contribute to rising costs but have failed to adapt to new market needs and opportunities [6,7].

Can AI be a force of *creative destruction* [8] in education?

This paper is divided into four sections. First, I begin with a problem statement defining some key *educational challenges*. The problem statement also sets the stage for examining how AI can help to solve these challenges. Second, I discuss why AI is important. AI is not a run-of-the-mill technology but what economists call a general purpose technology (GPT). GPTs historically are the hallmark of creative destruction across the entire economy. Third, I examine the practical economics of lifelong learning. I pose the following question: *Is lifelong learning currently affordable to those who need it most?* Finally, I outline how AI can address the key educational challenges laid out in the first section. I do so by outlining a new open-source project, created by the author, called **AI-Learn**.

Having outlined the broad challenges and opportunities presented by AI in postsecondary education, let us delve into specific problems this technology can address.

## 2. Problem Statement

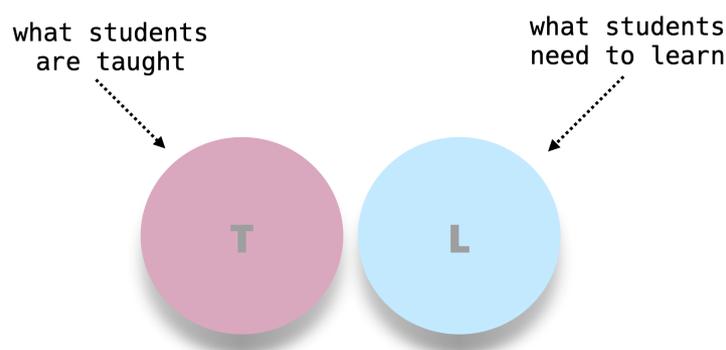
I define some key *educational challenges* faced by all learners but particularly adult learners in the modern economy. The problem statement is in the form of four premises:

1. Students are not taught what they need to learn.
2. Students do not learn what they are taught.
3. Students need to learn throughout their lives, and what they need to learn changes frequently.
4. Practical knowledge in STEM disciplines is increasingly inter-disciplinary, computational, and data-intensive.

### 2.1. Students Are Not Taught What They Need to Learn

Given the dynamic nature of the modern economy, there is an increasing divergence between *what students need to learn* and *what they are taught*.

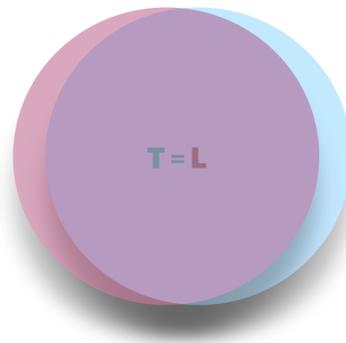
We can visualize this with a simple Venn Diagram as shown in Figure 2.



**Figure 2.** Circle T represents what students are taught. Circle L represents what students need to learn.

The target of good learning design is to achieve a strong overlap between the two circles (Figure 3).

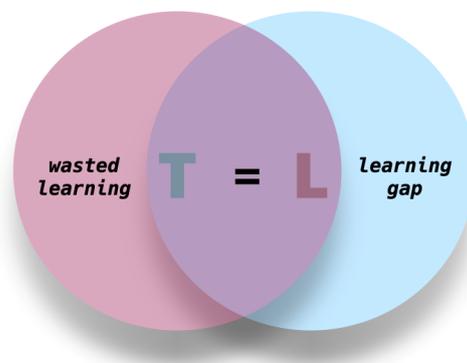
## Learning Design Target



**Figure 3.** In the target case, there is strong overlap between what is taught and what students learn, represented as  $T = L$ .

But we need to anticipate a misalignment between what is taught and what students learn. There are two primary reasons for the divergence. The first is due to poor learning design. The second is due to shifts in the knowledge domain. In the divergent case, the areas of *non-overlap* can become sizable. We should note that there are two distinct areas of non-overlap (Figure 4).

## Divergent Case



**Figure 4.** The first area of divergence represents the *skills gap* (what is not taught but students need to learn) and the second represents *wasted effort* (what is taught but students do not need to learn).

Both areas translate as a *cost* to the student. The skills gap means that the student has to bridge the gap elsewhere, needing more time, money, and effort. Wasted learning means that the student has squandered time, money, and effort. Wasted learning is an irrecoverable cost. Taken together, the real cost is what economists call the *opportunity cost*: the value of the next best alternative that an individual foregoes in order to pursue a certain action or decision.

This paper's key argument is that for adult learners, the opportunity cost of education is now prohibitively high due to new market realities; however, AI has the potential to significantly lower these costs.

## 2.2. Students Do Not Learn What They Are Taught

Even in the case where students are taught what they need to learn (the area of overlap  $T = L$ ), students do not necessarily learn it. Instructors believe they have taught what students need to learn. Students believe they have learned what instructors have taught. Instruction can be *ineffective* even when the right subject matter is taught and students make an effort to learn it. This is the *problem of inefficacy* and it manifests itself in the curriculum and teaching practices in several ways.

First, a bedrock principle of learning science, confirmed by an overwhelming number of studies, states that we learn by doing, not by viewing [5]. Yet most instructors remain wedded to the lecture format. The situation is no better online. In online environments, video lectures are often substituted for live lectures. We have simply replaced one form of passive learning with another. Similarly, instructors assign reading material from a textbook. Students read it. Both believe learning has magically occurred. But this is a mirage.

Second, traditional instruction does not take into account the fact that each learner comes to learning with different prior preparation. Those with weaker preparation begin with a handicap. In a course where everyone has the same amount of time to master the material, those who start behind must learn the material at a faster pace than those who are adequately prepared. As the course progresses, if the handicap is not addressed, small “errors” or gaps compound quickly and become irrevocable [9]. It has been shown formally that learners on their own, no matter the amount of “grit” or “mindset”, cannot close the deficit if the learning environment is not supportive [10].

Third, much of learning requires relearning. It takes repeated practice to make knowledge stick, to move it from working memory to long term memory. And it takes spaced practice and reinforcement to keep the knowledge usable [11]. Traditional instruction is based on the mistaken assumption of “teach once, learn once, and we are done”. Relearning also needs to take place not just in a course but across courses in a discipline. But given the fragmentary nature of course design at most institutions, students move on to advanced courses not having adequately learned materials from previous courses.

Fourth, traditional learning does not take into account the fact that different parts of knowledge serve different roles [12]. Much like a well-constructed building, each part plays a special role and the entire edifice must be constructed harmoniously. A building requires a solid foundation. Yet most learning design ignores the special role of foundational knowledge or underestimates its importance in sustained and successful learning.

## 2.3. Students Need to Learn throughout Their Lives and What They Need to Learn Changes Frequently

Traditional education is based on an outdated linear pattern: we are born, go to school, work, raise a family, retire, and then we die. Modern society, and the economic life on which it rests, no longer fits this pattern. In order to survive and thrive, we now need to learn and update our skills throughout our life. As new technologies and economies emerge, what we need to learn also changes frequently.

We have already cited the study by Georgetown University’s Center on Education and the Workforce, which indicates that “by 2031, 72 percent of all jobs will require workers to have at least some postsecondary credential or training beyond high school” [1]. In one of the newest global surveys on reskilling, McKinsey notes that “the need to address skill gaps is more urgent than ever. A majority of respondents (58 percent) say that closing skills gaps in their companies’ workforces has become a higher priority since the pandemic began”. The results also suggest that “this commitment to skill building represents more than a one-time investment”. For most companies, closing “skill gaps were a pressing and critical issue”.

Some have raised the specter of AI replacing humans. But a more likely scenario is one where specific tasks will be automated by AI, not the wholesale automation of entire jobs. This means that in order to become more productive and competitive in the marketplace,

workers will have to learn to perform new tasks, tasks which are out of reach of automation and AI.

The rapidly evolving job market, propelled by advancements in artificial intelligence and automation, demands a shift from traditional education models to continuous learning pathways. To remain relevant and competitive, individuals must engage in lifelong learning that is adaptive and responsive to changing industry needs. The integration of AI-driven platforms can facilitate personalized learning experiences, offering courses and materials that evolve in real time with job market trends. This ensures that learners are always equipped with the most current skills and knowledge, bridging the gap between education and employment requirements.

The future of lifelong learning is not just about individual upskilling but also about creating collaborative ecosystems where individuals, educators, industries, and AI technologies interact seamlessly. Such ecosystems would leverage AI to analyze learning outcomes and job market trends, recommending learning paths not just for individuals but also for communities, thereby fostering a culture of collective intelligence. By enabling shared learning experiences and insights, AI can help construct a more inclusive and efficient educational landscape that prepares all learners for the challenges and opportunities of the future workforce.

#### 2.4. Practical Knowledge in STEM Disciplines Is Increasingly Inter-Disciplinary, Computational, and Data-Intensive

STEM disciplines are the driving force behind modern economies. However, the general public and policy makers' understanding of how these disciplines have evolved and operate has not kept pace. In many cases, academic practice also lags behind in how the disciplines are taught.

There have been three *scientific paradigms* and we are in the midst of a fourth [13,14]. The *first* scientific paradigm was largely *empirical*. Approximately a thousand years ago, humans began to systematically collect and record data to describe natural phenomena. The Mayans, for example, created detailed calendars for tracking astronomical phenomena, like solar and lunar eclipses, planetary movements, and solstices. The Qimin Yaoshu ("Essential Techniques for the Welfare of the People") is an extensive agricultural manual on agronomy, horticulture, afforestation, sericulture, animal husbandry, veterinary medicine, brewing, cooking, and storage, as well as remedies for barren land [15].

The *second* scientific paradigm, represented by *theoretical science*, emerged during the last few hundred years. The key breakthrough was the use of models to summarize, explain, and predict natural phenomenon. Notable examples include Kepler's Laws, Newton's Laws of Motion, Maxwell's equations, and Darwin's theory of natural selection.

The last few decades have seen the emergence of the *third* scientific paradigm. Its defining characteristic is *computation* and *simulations* to model natural phenomena. As theoretical models grew too complicated to solve analytically, scientists began to devise numerical solutions. Then, these numerical techniques were extended and applied to complex phenomena such as weather patterns through the use of simulations. Simulations have become powerful instruments for modeling complex phenomena, but they also allow us to investigate multiple alternative possibilities and how each one might play out in the natural world.

In recent years, even before the explosion of artificial intelligence, we have reached a fourth scientific paradigm. Jim Gray, the Turing Award Winner, labeled this fourth paradigm "eScience". Its hallmark is the data-intensive unification of theory, experiment, and simulation.

The techniques and technologies for such data-intensive science are so different that it is worth distinguishing data-intensive science from computational science as a new, fourth paradigm for scientific exploration. . .

If you look at ecology, there is now both computational ecology, which is to do with simulating ecologies, and eco-informatics, which is to do with collecting and analyzing ecological information. Similarly, there is bioinformatics, which

collects and analyzes information from many different experiments, and there is computational biology, which simulates how biological systems work and the metabolic pathways or the behavior of a cell or the way a protein is built [14].

AI has accelerated eScience as the *fourth paradigm* of scientific discovery and invention. It unifies theory, experiment, and simulation with data-intensive computation. Among practitioners, the fourth paradigm requires inter-disciplinary knowledge (e.g., domain knowledge, statistics, programming, data analysis, and visualization) along with a thorough understanding of the scientific method.

Understanding these educational challenges sets the stage for exploring how AI, as a transformative general purpose technology, can be leveraged to address them.

### 3. Why Is AI Important?

Let us turn now to AI to better understand how it is emerging as the driving force of the new economy. The consensus view among economists is that AI is a “general purpose technology” (GPT). The GPT here is not the “GPT” of “ChatGPT”, which stands for “Generative Pre-trained Transformer”. What economists really mean by GPT is a “Technology with Superpowers”.

GPT is a technology with Superpowers.

GPTs are rare, and when they come on the scene, they cause significant, widespread impacts across an economy, affecting multiple industries and sectors. GPTs are not innovations that improve efficiency or effectiveness in a specific area; rather, they are *foundational technologies* that transform economies and societies at scale. Historical examples of GPTs include the steam engine, electricity, and the internet. For better or worse, we are now in the **Age of AI** as a GPT.

GPTs have three salient characteristics: *pervasiveness*, *accelerating improvements over time*, and the capacity to drive *complementary innovations* across industries [16]. Let us take a look at each characteristic with the example of electricity.

1. **Pervasiveness** refers to the wide-ranging applicability and use of a technology across various sectors and industries. Electricity revolutionized multiple industries and aspects of daily life starting in the 1880s. It quickly became an essential part of residential, commercial, and industrial settings. From lighting homes to powering factories, electricity’s ubiquitous presence transformed the way society functioned. It facilitated the transition from manual labor to mechanized processes, impacting everything from manufacturing to transportation and even the nature of household chores. The key period for its development and widespread adoption was primarily between the 1880s and the early 1920s.

In 1882, Thomas Edison opened the Pearl Street Station in New York City, the first commercial central power plant in the United States. Soon after, the widespread installation of electrical lighting in urban areas began, gradually replacing gas lighting. This period also saw significant advancements in electrical engineering and the development of alternating current (AC) systems, which were more efficient for long-distance power transmission than the direct current (DC) systems initially used. In the early part of the 20th century, electrification started to spread beyond lighting, powering industrial motors and public transportation systems (like electric streetcars) and leading to the development of a variety of electric appliances for homes and businesses. By the 1920s, electricity had become a critical infrastructure in urban areas in the United States and Europe, signaling its status as a GPT.

2. A hallmark of GPTs is their potential for *improvement over time*, becoming more efficient, powerful, and adaptable as the technology becomes pervasive. The evolution of electricity was marked by significant advancements in generation, distribution, and utilization. From the initial direct current (DC) systems to the more efficient alternating current (AC) systems, the technology of electricity generation and distribution underwent substantial improvements. Innovations like the transformer, the electric

motor, and the development of nationwide power grids massively enhanced the efficiency and reliability of electricity. Over time, these improvements expanded the scope and scale of electricity's applications, making it more versatile and efficient.

3. GPTs also spur *complementary innovation* that cascades across multiple industries. GPTs spur the development of new industries, technologies, and processes that complement the GPT itself. The widespread adoption of electricity led to the creation of entirely new industries and technological innovations. The electric light bulb, household appliances like refrigerators and washing machines, and, later, electronic devices like computers and telecommunications equipment are all examples of complementary innovations spurred by electricity. These inventions, in turn, created new markets, new forms of entertainment, and even new ways of working and living. The development of these complementary technologies further embedded electricity into the fabric of modern society, illustrating its role as a catalyst for broader economic and technological transformations.

#### *Artificial Intelligence as a GPT*

It is increasingly apparent that artificial intelligence is the modern embodiment of general purpose technology. It exhibits the three key characteristics that define GPTs.

1. AI's *pervasiveness* is evident in its widespread adoption across multiple domains. In healthcare, AI is now used for diagnostic procedures and personalized medicine. In finance, it powers algorithmic trading and fraud detection systems. In the automotive industry, AI is at the heart of self-driving car technology. It has also transformed consumer products through smart assistants, personalized recommendations in retail and entertainment, and more. This broad spectrum of applications across varied fields underlines AI's pervasive nature.
2. AI has seen *significant improvements over time*, especially in machine learning algorithms and neural network designs. The evolution from simple decision trees to complex deep learning models and the development of neural networks capable of processing vast amounts of unstructured data are prime examples. Each iteration brings more sophisticated, accurate, and efficient AI capabilities. The rapid advancements in AI's learning algorithms and processing power showcase its ongoing improvement and expanding potential.
3. AI has spurred a multitude of *complementary innovations* across various sectors. In the field of robotics, AI has enabled the creation of more autonomous and intelligent machines. In the realm of data analytics, AI's ability to process and interpret large datasets has led to significant advancements. AI has also fostered innovations in fields like energy management (smart grids), education (adaptive learning platforms), and even creative industries (AI in art and music composition). These innovations not only leverage AI technology but also expand its application and utility, demonstrating its role as a catalyst for further technological and industrial advancements.

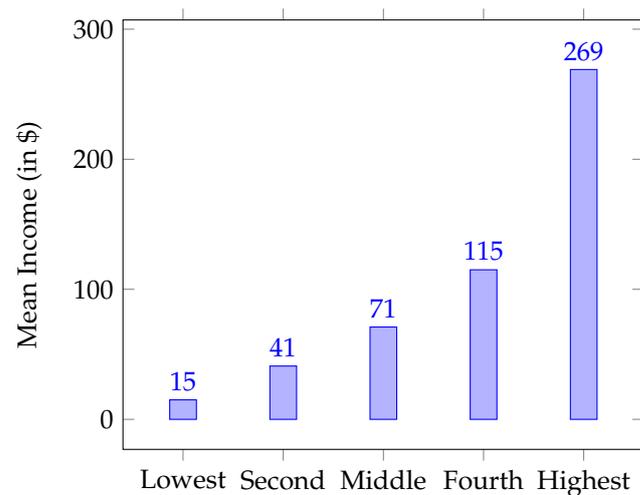
#### **4. Practical Economics of Lifelong Learning**

Having established AI's pivotal role, we now turn to examine its impact on the practical economics of lifelong learning and its accessibility. Let us pose a practical economics question:

*Is lifelong learning affordable to those who need it most?*

In the modern economy ruled by AI, lifelong learning is not a luxury but a necessity. Can those who need it most afford it?

To answer the question, let us begin by looking at US household income by quintiles. As of 2024, the US population is approximately 335 million. There are approximately 126 million households, with approximately 2.7 persons per household. Figure 5 shows the mean income (in USD) by household quintiles.



**Figure 5.** US household mean income by quintile.

The same data are shown in tabular format in Table 1.

**Table 1.** US household mean income by quintile.

Quintile	Mean Income (USD K)
Lowest	15
Second	41
Middle	71
Fourth	115
Fifth	269

Next, let us estimate living expenses for a household in a city where the cost of living is neither too high or too low (e.g., Minneapolis, MN, USA). Table 2 shows living expenses for an average household with one child.

**Table 2.** Living expenses for an average household (2 adults, 1 child) in an average city. Source: MIT Living Wage Calculator (<http://livingwage.mit.edu> (accessed on 8 January 2024)).

Category	Amount
Food	9159
Child care	10,401
Medical	8332
Housing	11,780
Civic	6565
Other	9905
Annual taxes	12,908
Required annual income before taxes	85,101

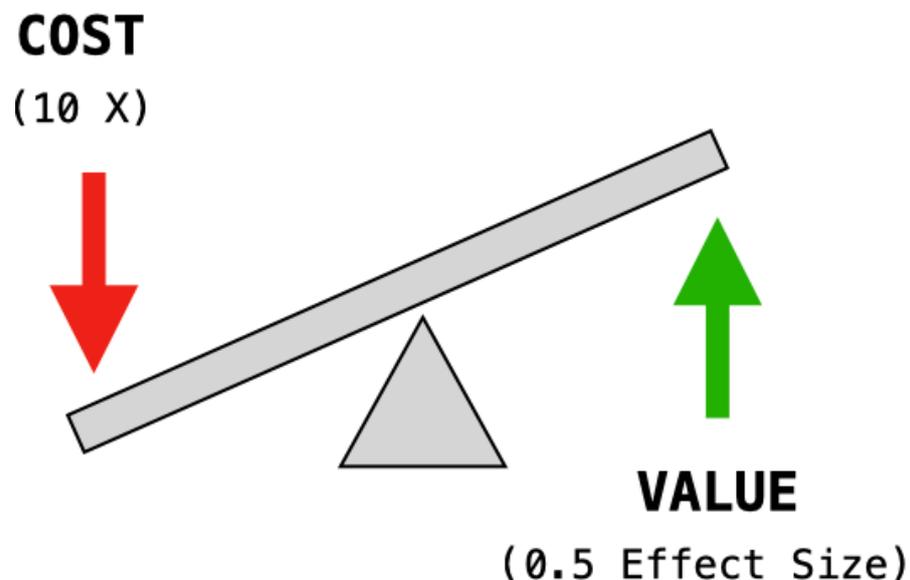
If we compare living expenses with income quintile groups, our simple estimate, based on a conservative calculation, illustrates that lifelong learning is likely to be out of reach for the majority of households.

## 5. AI-Learn

With the groundwork laid for understanding AI's role in education and the economic considerations of lifelong learning, we now introduce **AI-Learn** as a potential solution. The current educational system faces several challenges in delivering affordable, accessible, and quality skills-based training to a diverse range of learners. These challenges include the following:

- **High development costs:** Traditional curriculum development is labor-intensive and costly, limiting access to high-quality educational resources for institutions with limited budgets and, ultimately, their learners. We have seen through our quick estimate that unless there are significant breakthroughs in curriculum development, lifelong learning will be out of reach for those who need it most.
- **Inefficient processes and untimely content:** Conventional methods for creating and updating curriculums are time-consuming and often struggle to keep pace with the rapidly evolving job market and technological advancements. We have this in the potential mismatch between what students need to learn and what they are taught.
- **Lack of personalization:** One-size-fits-all educational approaches often fail to address the unique learning needs of individuals, particularly those from historically marginalized communities, leading to suboptimal learning outcomes.
- **Limited collaboration:** Inefficient knowledge sharing and collaboration among educators, researchers, and institutions hinder the exchange of best practices, stifling innovation and progress in curriculum development.

If every citizen is to have access to affordable, high-quality education, then the cost-value equation needs to change dramatically. Although a number of factors make up cost and value, we can isolate two important variables where AI can potentially contribute to a breakthrough in the near term. Our goal should be to reduce the *cost* of education by at least a factor of 10 while enhancing educational outcomes or *efficacy*, including those from historically marginalized communities, with a minimum of a 0.5 effect size (Figure 6).



**Figure 6.** Cost-value equation for education.

In this section, we outline **AI-Learn**, an open-source project, which aims to do just this using AI. We offer **AI-Learn** as an example of the types of solutions that need to emerge in the marketplace if we are to make substantial progress in lowering the cost of education and increasing learning outcomes (Figure 7).

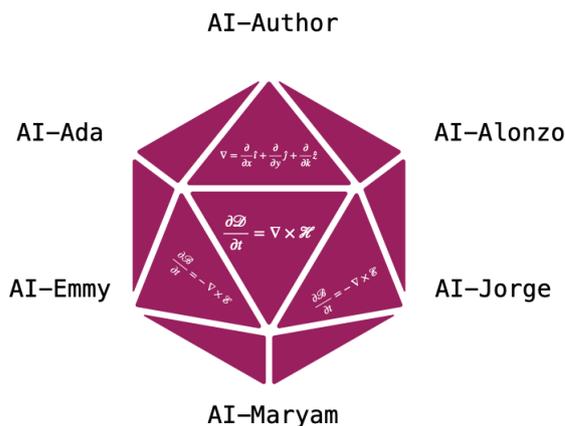


Figure 7. ALA platform components.

5.1. AI-Learn Components

The open-source AI-Learn platform consists of six major components:

- **AI-Learn Author** is an authoring wizard and design canvas for creating a skills-based curriculum.
- **AI-Learn Ada** is an AI-based extraction engine for automatically generating a recommended curriculum based on topics.
- **AI-Learn Alonzo** is an AI-based analytics engine for generating advanced insights and evaluating learning efficacy.
- **AI-Learn Emmy** is an AI-based intelligent tutoring system for delivering a personalized curriculum to each learner.
- **AI-Learn Jorge** is a “crowd-sourced” searchable digital repository of pre-configured curriculum materials with robust IP management.
- **AI-Learn Maryam** is AI-Learn’s digital infrastructure, including cloud-based services for security, scalability, and integration.

Each component of AI-Learn plays a unique role in transforming educational delivery, as we will further explore in the subsequent section on pedagogical design. We describe each of these components and their role in the section on workflow. Prior to that, we review the pedagogical design of AI-Learn based on aligned learned activities or ALAs.

5.2. Pedagogical Design: Aligned Learning Activities

The cornerstone of AI-Learn’s pedagogical design is smart, learning atoms called aligned learning activities (ALAs). An ALA is an aligned semantic triple consisting of (a) a learning objective, (b) assessments, and (c) learning activities. The assessments and learning activities are aligned to a particular learning objective (Figure 8).

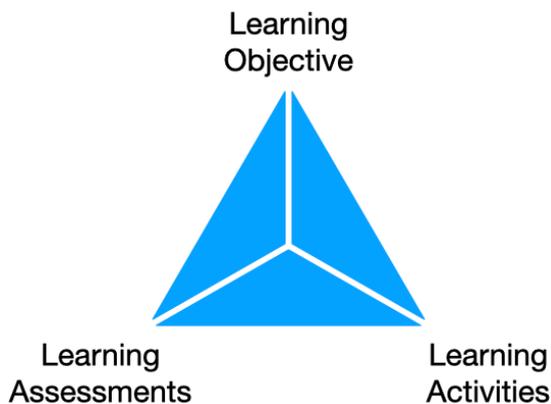
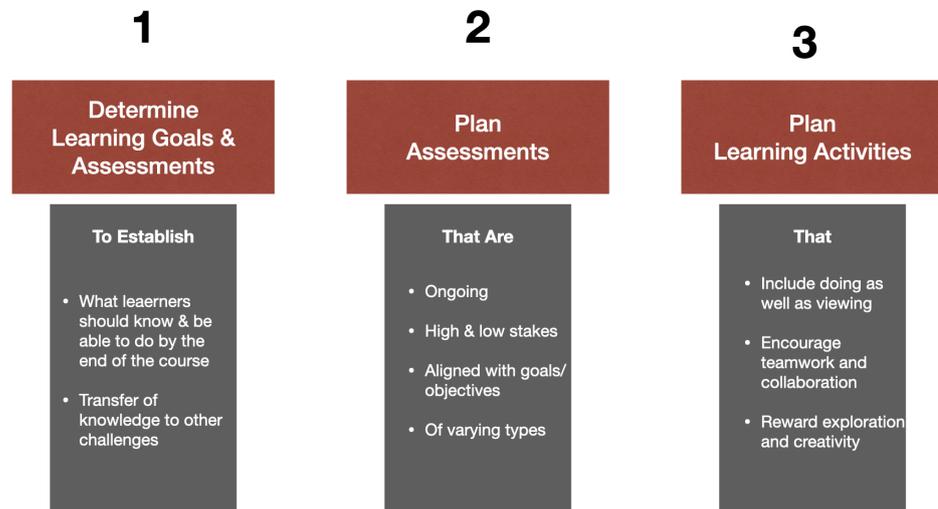


Figure 8. AI-Learn’s pedagogical design is based on aligned learning activities (ALAs).

Traditional learning design is based on a “forward design” process. Instructors typically begin with learning materials such as a textbook, develop assessments (primarily quizzes and test), and then eventually get around to learning goals (Figure 9).



**Figure 9.** AI-Learn’s backward design process.

The research evidence strongly suggests that learning outcomes can be improved by a backward design process [17]. In backward design, learning objectives are formulated first. A learning objective states the knowledge or skill a student is expected to master. The second stage defines the evidence, in the form of assessments, that will be used to know whether a student has achieved a learning objective and to what degree. The assessments are ongoing and primarily formative. Unlike quizzes and tests, formative assessments are designed to provide actionable feedback to both the learner and the instructor. In backward design, the instructional activities and learning materials are formulated last. The final stage defines how students are expected to master a learning objective. Students learn by doing, not viewing. Learning activities should go beyond passive learning (e.g., reading a textbook and watching a video) to include active and collaborative learning (e.g., solving problems and peer learning). In short, an aligned learning activity (ALA) captures the backward design process as a modular learning atom.

### 5.3. Workflow

Now that we have a preliminary understanding of AI-Learn’s components and pedagogical design, let us examine its workflow to understand how these elements come together in practice. How does AI-Learn work? The AI-Learn tool and platform can be used to design, deploy, evaluate, improve, and share a skills-based learning curriculum (Figure 10).



**Figure 10.** AI-Learn workflow.

To develop a skills-based curriculum, an educator begins with the **AI-Author** workbench and design wizard. AI-Author is a versatile design workbench that streamlines the curriculum creation process. With AI-Author, educators can harness AI-Learn’s Large Language Models (LLMs) to automatically generate learning modules or full curriculums based on simple prompts. The platform allows for seamless editing, deployment, assessment, improvement, and sharing of Aligned Learning Activities (ALAs), fostering a dynamic and effective educational ecosystem (Figure 11).

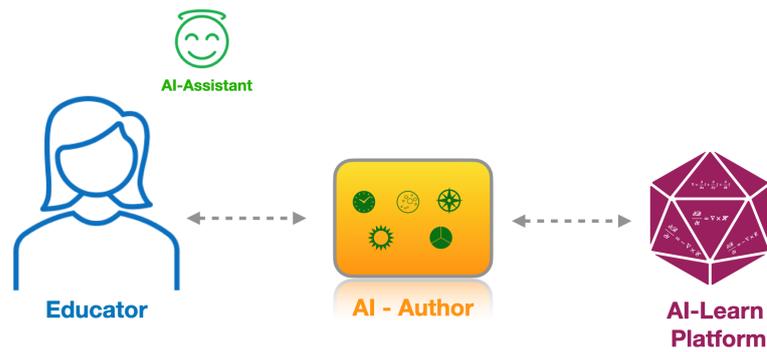


Figure 11. AI-Author workbench.

### 5.3.1. Extract Mode

The AI-Learn workflow begins with the *extract mode*, where an educator *automatically* generates a curriculum by issuing a series of guided prompts. AI-Learn then automatically generates the curriculum in the form of an ALA. The work of extraction is performed behind the scenes by AI-Ada, an AI engine based on Large Language Models (LLMs). The extracted curriculum is populated in the design canvas for review and editing. AI-Learn can automatically extract 50–75% of the curriculum for most STEM fields without prior training. AI-Learn can also extract ALAs from proprietary digital materials or Open Educational Resources (OERs) with additional modest training (Figure 12).

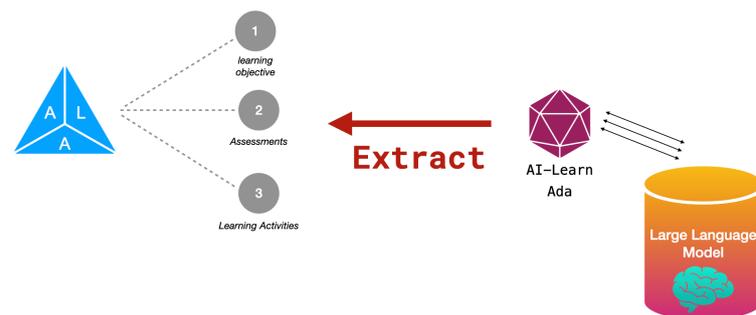


Figure 12. Extract mode.

### 5.3.2. Edit Mode

In *edit mode*, an educator uses AI-Author to edit and modify the curriculum elements generated in extract mode by the Large Language Model. Although AI-Learn automates much of the tedium of creating a skills-based curriculum, it is not meant to replace the domain expert or learning designers. It is meant to support and enhance their work (Figure 13).

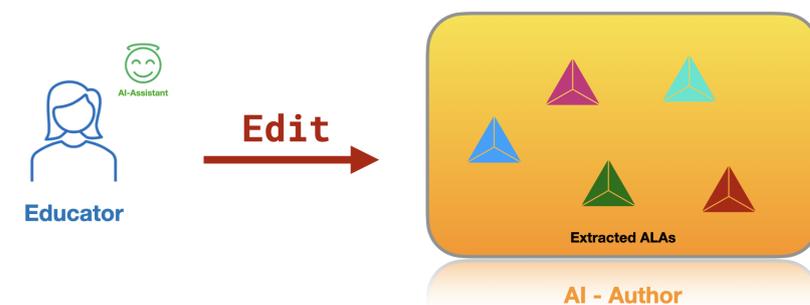


Figure 13. Edit mode.

### 5.3.3. Discover Mode

In discover mode, an educator performs advanced search and discovery against a digital repository <https://ailearncloud.github.io/ailearnweb/jorge.html#page-jorge> (accessed on 8 January 2024)—AI-Jorge. AI-Jorge contains pre-configured ALAs contributed by the educational community and curated by domain experts. The discovered ALAs are populated in the design canvas for review and editing (Figure 14).

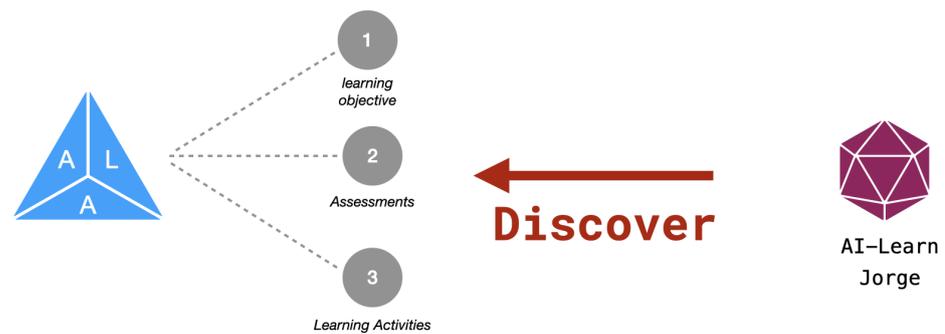


Figure 14. Discover mode.

### 5.3.4. Deploy Mode

In deploy mode, an educator deploys ALAs to intelligent tutoring systems and learning management systems using standard protocols, such as 1EDTECH’s <https://www.msglobal.org/activity/learning-tools-interoperability> (accessed on 8 January 2024)—Learning Tools Interoperability (LTI). ALAs can also be deployed to <https://ailearncloud.github.io/ailearnweb/emmy.html#page-emmy> (accessed on 8 January 2024)—AI-Emmy, a next-generation intelligent tutoring system (Figure 15).

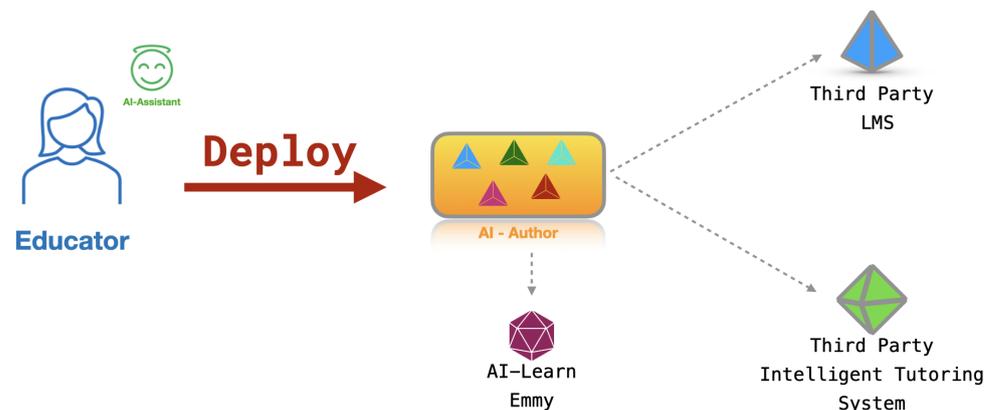


Figure 15. Deploy mode.

### 5.3.5. Evaluate and Improve Mode

In evaluate and improve mode, an educator evaluates ALAs using the AI-Learn analytics engine <https://ailearncloud.github.io/ailearnweb/alonzo.html#page-alonzo> (accessed on 8 January 2024)—AI-Alonzo. The analytics range from simple methods such as item analysis to propensity modeling and causal inferencing. AI-Alonzo can also generate recommendations for improving ALAs based on observational data. ALA “improvements” are recorded in a “scientific logbook” of modifications under the structure of hypothesis–experiment–data (Figure 16).

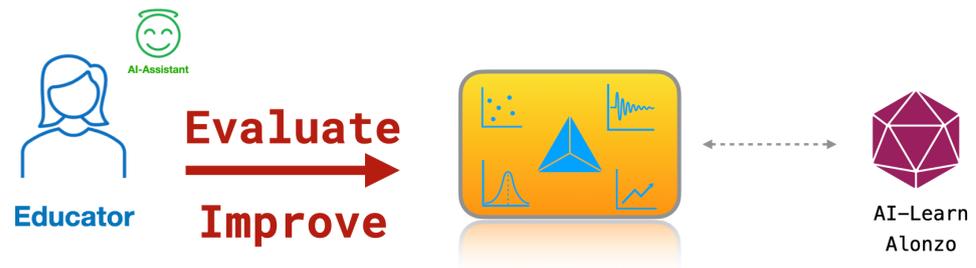


Figure 16. Evaluate and improve mode.

### 5.3.6. Share Mode

In share mode, an educator can share and license ALAs. AI-Jorge, therefore, is also a marketplace for exchanging ALAs based on license terms set by educators and institutions. Educators can also tag, rate, annotate, and recommend ALAs (Figure 17).

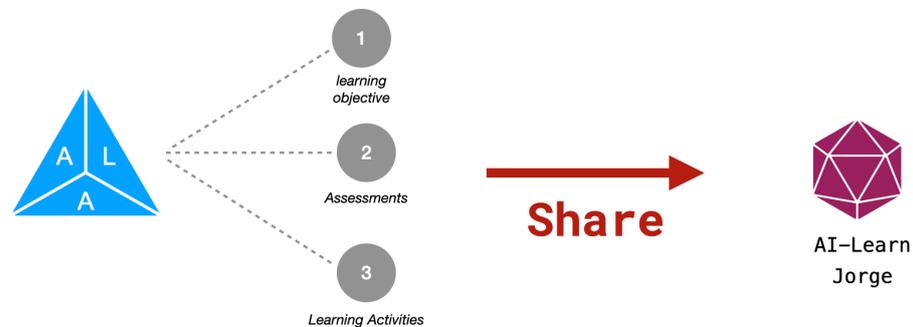


Figure 17. Share mode.

Drawing from the insights on AI-Learn and its potential impact on education, we conclude with reflections on the future of postsecondary education in the AI era.

## 6. Conclusions

In conclusion, this paper has underscored the transformative potential of artificial intelligence (AI) in redefining postsecondary education, with a particular focus on adult learners within the context of a rapidly changing economy. AI's capability to address the existing misalignment between educational offerings and the evolving demands of the workforce heralds a revolution not only in what we learn but also in how we learn. The advent of AI-Learn exemplifies a groundbreaking approach that utilizes AI to streamline curriculum development, personalize learning experiences, and deliver content more efficiently, representing a pivotal stride toward education that is more accessible, effective, and inclusive.

As we stand on the cusp of a new educational paradigm, propelled by AI's role as a general purpose technology, it is crucial for educators, policymakers, and technologists to engage in collaborative efforts to unlock its full potential. Such collaboration is essential to ensuring that education continues to serve as a potent instrument for personal growth and a vital asset for societal advancement. It is through harnessing the power of AI that we can bridge skill gaps and democratize access to knowledge, ultimately making learning a lifelong, equitable journey for individuals across the globe.

Looking ahead, the challenges and opportunities presented by AI in education demand a proactive and thoughtful approach. It is not merely about adopting new technologies but about reimagining the future of learning in a way that prioritizes ethical considerations, equity, and the human element. By doing so, we can pave the way for an educational system that not only prepares learners for the future but also shapes that future to be more inclusive, adaptive, and innovative.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Data are contained within the article.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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