# Work in progress: Experiential Learning Modules for Promoting AI Trustworthiness in STEM Disciplines

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***Abstract*—Artificial Intelligence (AI) has experienced a strong revival recently. From autonomous vehicles to smart factories, AI is increasingly being used in STEM fields beyond computer science (CS). While AI is regularly taught in CS curricula, treatment of AI varies in other STEM disciplines. This paper describes an on-going project aimed at elevating AI knowledge and skills of non-CS STEM students and professionals. It emphasizes trustworthiness as a key factor of effective AI usage for large scale data analysis. Specifically, ten initial modules, which take an experiential learning and problem-solving pedagogical approach, have been developed and are now being piloted in fall 2021. They have been designed to be used both in a traditional classroom setting and as self-guided learning aid. This paper reports on the findings to date and aims to disseminate this exciting venture broadly for like-minded researchers to consider.**

***Index Terms*—STEM, artificial intelligence, experiential learning, 21st century skills development**

## I. Introduction

Recent advances in statistical machine learning (ML), especially development of deep neural networks (DNNs), has broadly renewed people's interest in artificial intelligence (AI). From autonomous vehicles and drones to smart X (X = home, factory, healthcare, etc.), near-instantaneous multilingual translation and convincing deep fakes, it seems like nothing is impossible with AI. Recent studies [1] have reinforced the view that the trend of widespread AI adoption across industries will not only continue but will in fact accelerate.

Beneath the glitzy headlines lies the fact that current-generation AI technologies, which rely heavily on statistical ML, have their limitations [2]. Contemporary ML (including DNNs) often perform well when measured statistically but can be unreliable individually. Furthermore, their failure mode or output generation process is not always well understood by humans. On-going research efforts in areas like explainable and trustworthy AI [3], and commonsense reasoning [4], all contribute to better AI.

AI, and especially ML, is increasingly being used by non-computer science (CS) professionals and students for solving their domain-specific problems. Examples include optimal circuit designs [5] and smart transportation [6]. However, AI is not regularly taught in sufficient depth beyond CS. Piecemeal non-uniform treatment of AI can hamper effective application of AI by non-CS STEM professionals and students.

Although non-CS learners can take regular AI and ML courses alongside their CS peers, this "one size fits all" approach can be counterproductive for several reasons. First, non-CS learners often lack the strong programming skills of their CS counterparts, which can limit their abilities to fully engage and exploit the many opportunities that exist. Second, non-CS learners would benefit from solving problems specific to their needs, e.g., CPU/GPU design or smart routing. Third, the question of how to instill trust between human users and AI remains an open question even for computer scientists. This issue is even more acute when users from diverse disciplines and backgrounds are considered. The specific research question (RQ) is as follows.

**RQ**: How to elevate trustworthiness of AI for a range of STEM users of AI?

Specifically, it is hypothesized that it is possible to cultivate and strengthen trustworthiness of AI technologies for STEM professionals and students who use AI through contribution to both curricular initiatives and pedagogical tools. The rest of the paper is organized as follows. Section II details the methods used to test the hypothesis in an on-going study. It describes efforts made to contribute toward both curricular initiatives and pedagogical tools. Section III explains the experimentation used to validate the hypothesis. Preliminary results to date are

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also presented. Finally, Section IV concludes the paper with information on the next stage of the project.

## II. Approach

The primary approach in this research is the development of innovative pedagogical tools in the form of modular experiential learning modules. These tools complement rather than compete with existing resources, such as ACM Curricula, JTF on Cybersecurity Education, MOOC, e.g., Udacity [7], Edx [8], and industry efforts, e.g. [9], [10]. Specifically, the project applies safe, secure, and reliable (SSR) computing principles as vehicles that support trustworthiness when these principles are applied to the development of AI technologies for different STEM disciplines. The innovative aspects can be summarized as thus:

1) Holistic view of convergent SSR computing principles and AI; two-way nexus where SSR theory and practice influence (and is influenced by) AI. The aim is to progress toward an emergent society increasingly becoming interwoven with big data AI.
2) The design is informed by influential sources, e.g., [11], which shape current and future debate.
3) Intensive, multifaceted, modular, experiential learning units designed to rapidly upgrade the skills of a range of STEM learners, so they can apply new skills to their tasks. The versatile modules can be integrated with existing courses and/or taken as standalone self-directed learning units. The latter have been found effective [12].
4) Sandbox environment to encourage learners to take measured risks toward solving problems in their respective domains. With guidance and gradual increase in scope and level of difficulty (both within module and across multiple modules), learners gain confidence and see tangible results of their effort.
5) Lessons learned, and best practices will be codified into blueprints for widespread future adoption across STEM disciplines.

The 5th innovative feature is the platform from which the research term will launch their curricular initiative. Best practices identified will be applied toward curricular updates.

### A. Development of Pedagogical Tools

Active learning, which encapsulates the idea of learning by doing, is the cornerstone of the pedagogical tools developed in this project. In addition, experiential learning, informed by domain experts and topical issues, lends realism to the learning process. Learners can relate their learning experiences and education material to their respective disciplines. By taking a modular approach, educational content can be flexible in how it is delivered to learners. Manageable segments within each module allow learners to develop a sense of ownership and incremental successes, thereby building confidence to tackle more difficult problems. Modular design also allows for full integration into existing courses or delivered as standalone mini courses.

The learning modules are organized in three levels of difficulty: Foundational (which can be integrated into CS1 and CS2 and suitable for many STEM students), Intermediate (which can be integrated into Data and File Structures and Database courses), and Advanced (which can be integrated into Secure Software Development, Artificial Intelligence, Advanced Artificial Intelligence, and Machine Learning courses). Evidently, they focus on the emerging needs of fundamental research communities and resolving bottlenecks in the convergent area of SSR AI. There is an emphasis on keeping the modules agnostic in programming languages. Learners can choose their preferred language, e.g., Python, R, but are in any case encouraged to use open-source libraries and resources. Examples and data will be drawn from real-world sources, e.g., social media and news outlets and/or discipline-specific problems, so learners can relate their study to matters that they care about. For consistency, each learning module is designed based on the following format:

1) Background information presented by course instructor (if integrated) or domain expert.
2) Guided exploration leading to awareness and comprehension of a problem; how it fits in the bigger picture.
3) Implement an instance of the problem to gain insight; it becomes "real" no matter how incredible it seemed initially.
4) Using in-course knowledge and/or other resources, develop a countermeasure strategy / design based on set goal and problem (solving in principle).
5) Implement and evaluate the countermeasure (solving in practice).
6) Reflect on the outcome: could anything have been done differently / better?

Advanced modules cover all six steps; other modules will give more emphasis on some aspects than others. For example, more emphasis will be put on exploration leading to awareness than solving a problem in the foundational modules. The reason is that early-stage learners are not expected to possess a significant amount of knowledge to perform substantive problem-solving tasks. They will instead focus on experimenting with strategies toward problem solving based on the theory they have learned (solving in principle vs. solving in practice).

Although the modules are be designed to run in a series, they are not tightly coupled. This means learners can select modules (or sequence of modules) they find most relevant or interesting, in any order they desire. Further, because in-class modules are fully integrated into existing courses with a balance between theory and practice and between learning and applying, there is no net increase in time to degree completion for students.

Apart from formal classroom learning and informal mini-series self-directed learning for undergraduate and graduate students, the educational material is also developed with "train the trainers" in mind. Through outreach activities, consortia members and other practitioners will benefit from the experiential learning activities.

## B. Curricular Initiatives

This project aims to update curricula and develop new training material to educate CS students about the power of AI, as well as its limitations and potential pitfalls from the outset. They first become aware of the issues and secondly practical considerations are integrated into theory classes to give relevance to the theory. SSR computing theory and practice will in turn improve future AI techniques and algorithms. The materials are developed as experiential learning modules that can be integrated into existing classes, starting with fundamental CS 1 and CS 2 courses so that students are exposed to the ideas early in their undergraduate curriculum, to instill curiosity and excitement.

To facilitate an enriching learning experience for students, there is an emphasis on hands-on exercises to complement theory. Specifically, each module begins with the description of a SSRAI problem that needs theory and knowledge they learn in class, plus other resources, to address. In addition to the promises of AI, learners experience firsthand what lapses and vulnerabilities look like. They are guided toward formulating a goal and problem mitigation strategy, which in the more advanced modules are actually implemented and evaluated against the set goal.

Although the learning modules build on top of fundamental knowledge, the modular learning units are not tightly coupled. This light coupling allows learners to choose how they wish to use the modules, which offer multiple entry points for learners.

Finally, lessons learned from the launch of learning modules and best practices identified in the field tests (described in the next section) will be codified and used to inform future curricular development. An opportunity exists, in particular, as the ACM/IEEE-CS/AAAI CS Task Force has initiated the process of soliciting input on CS202X curricular recommendations. Specifically, the ACM and IEEE Computer Society together produce a CS Curricula volume every decade to provide recommendations and curricular guidelines for baccalaureate programs in CS. Past versions were published in 1968, 1978, 1991, 2001, 2008 and 2013. The taskforce is currently in the process of revising the most recent volume that was published in 2013, in collaboration with the AAAI. This provides the project team with an opportunity to inform the process using the findings of this project.

# III. Evaluation

## A. Experimental Setting

An initial set of learning modules have been developed and are currently being trialed in an integrated mode this fall semester. Table I summarizes these modules. Among the first modules to be piloted is Module 4 (M4), which has the following description.

**M4. Data Structures for SSR AI** (intermediate)
*Synopsis*: Application of data and file structures for SSR AI that can parallelize big data processing.
*Learning Outcomes*: Understanding of the connections between data and files structures and SSR AI that runs on high performance computing (HPC) infrastructures. Ability to design and implement moderately complex data and file structures that support SSR AI on HPC infrastructures.

M4 is integrated within a level 3 Big Data (BD) course for students to develop the specific knowledge and skills described above. There are two components: learning and research. Participation in one or both components is voluntary. Students in the BD class can choose to participate only in the learning component (i.e., just using M4). In addition, they can choose to participate in the research component by completing pre- and post- intervention questionnaires designed by an independent evaluator. After an introductory session, students are given one week to complete the module.

TABLE I
INITIAL LEARNING MODULES

| M# | Title | L[a] |
|---|---|---|
| 1 | Math Toolkit for SSR AI | F |
| 2 | Algorithmic Exploration & Exploitation of AI's weakness | F |
| 3 | Modular & Structured Software Development for SSR AI | F |
| 4 | Data Structures for SSR AI | I |
| 5 | Deep learning with HPC | I |
| 6 | SSRAI Software Development for HPC deployment | I |
| 7 | Vulnerabilities of Statistical Machine Learning | A |
| 8 | Beyond current generation AI | A |
| 9 | Adversarial ML and Robust Trust Scoring Models | A |
| 10 | Societal Impact of AI | A |

[a]Level = **F**oundational, **I**ntermediate, or **A**dvanced.

## B. Panel of Experts

Apart from the four core investigators, the project team is supplemented by domain experts from across multiple STEM disciplines and institutions. These experts inform the design, implementation, and dissemination of the learning modules, and provide on-going feedback on the efficacy of the modules. Some of the experts (mostly those who work in a university environment) also pilot learning modules relevant to their disciplines. The panel of experts comprises the following:

- 7 WMU faculty in different branches of engineering, statistics, and business analytics.
- 8 multidisciplinary faculty from across the US.
- 4 industry experts, e.g., pharmaceutical.
- 4 government agency experts, e.g. NIST, US Army.

In addition, an expert in evaluation serves as an independent evaluator. Apart from generating the pre- and post-intervention questionnaires, the evaluator performs formative and summative analyses to evaluate the success or otherwise of the project. Members who use the learning modules in their respective classes collect the raw data, but analyses are conducted by the evaluator. Table II highlights the AI usage of some of the non-CS STEM faculty who use the learning modules in their classes and/or work. Modules 1, 5, 7 - 10 are especially popular among them.

## C. Preliminary Results to Date

Initial trial of the learning modules is currently underway. Although it is too early to report final results, early signs

TABLE II
INITIAL LEARNING MODULES

| Area | AI Application(s) |
|---|---|
| Civil Eng | Smart transportation & smart cities |
| Mechanical Eng | hemodynamics models; vehicle fuel efficiency |
| Electrical Eng | Optimal circuit designs & CPU/GPU loading |
| Business | Analytics & decision support |
| Statistics | High-dimensional statistical inference |
| Pharmaceutics | Computational chemistry & proteomics |
| Military | Data mining & Deep Learning |

are promising. These encouraging signs come from both participating experts and student learners. First, the experts' assessment of the developed initial learning modules has been mostly positive. There have only been minor suggestions for improvement, which have all been considered and appropriately implemented. Most of the teaching faculty members involved in the project have committed to using some of the initial learning modules in their respective classes in this and/or the next semester in spring 2022. Up to 200 learners from multiple STEM disciplines will be directly affected. The experts' involvement will provide valuable data for analysis by the evaluator, who in turn will both inform further development and provide the research team with the necessary input to address the RQ.

Students' reception of the experiential learning has also been positive. Many are eager to learn to apply new skills to their tasks. Others are drawn to the prospects of a different form of learning from traditional classroom lectures: one that is flexible and experiential. Many are also interested to experience the limitations of current AI and ML algorithms, and to form realistic and informed knowledge of what AI/ML can or cannot do. All these aspects help learners generate tailored solutions to their respective, domain-specific, tasks. These observations, which have been mostly obtained through informal discussions, provide early information that can eventually help the team address the RQ. Table III relates module design features with learning outcomes that will be measured by the independent evaluator.

TABLE III
MODULE DESIGN FEATURES AND LEARNING OUTCOMES

| Design feature | Outcome(s) measured by evaluator |
|---|---|
| Experiential | Put new knowledge into practice |
| Active engagement | Enhanced internalization |
| Problem solving | Solve new problems in learner's domain |
| Relevant content | Relevant to learner's discipline |
| Core competency | Explain key concepts |

## IV. CONCLUSION

The main purpose of this work-in-progress paper is to share the research team's experiences in this exciting venture, so that like-minded researchers will consider adopting or participating in this inclusive endeavor. The paper describes effort made by the Transformative Interdisciplinary Human+AI research group at WMU and partners chiefly to develop pedagogical tools in the form of experiential learning modules for learners to rapidly gain a balanced set of relevant AI skills. A secondary aim of the project, one that is longer term in nature, is to inform the CS curriculum to better prepare CS and other STEM students with the societal impacts brought about by advances in AI. AI has already begun to transform human society in the 21st century, with its impacts felt by many. The trend is projected to continue or even accelerate in time to come.

Future work is underway to continue with the project under five main categories. 1. The extended team will continue to implement the initial modules in their classes and to collect data for analysis. 2. Some of the company and government experts will undertake trial for current professionals who apply AI to their work and data collection in non-academic settings. 3. identification and codification of best practices will be done once the trials are complete. 4. Train-the-trainers events before or after prominent conferences is a key feature of the project. The aim is to promote the project for wider adoption. 5. Other outreach activities will be conducted to reach beyond university students and professionals. For example, there are plans for engaging local high school students to start cultivating a balanced view of AI technologies at an early stage.

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