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Development and evaluation of a modular experiential learning curriculum for promoting AI readiness

Irene Kahvazadeh[1] · Edwin Jose[1] · Alvis C. Fong[1] · Ajay K. Gupta[1] · Steve M. Carr[1] · Shameek Bhattacharjee[1] · Michael Harnar[2]

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Abstract
Information systems are increasingly using artificial intelligence (AI). However, AI can be tricked into misbehaving, showing bias, or committing abuse. The root causes of these errors and uncertainties can be hidden away while parallelizing AI algorithms on high-performance computing (HPC) infrastructure. The project outlined in this paper aims to use artificial intelligence from the ground up to generate teaching materials and curricula for student-teachers. Students embark on a journey of discovery, taking calculated risks in a learning environment. The main purpose of this document is to present the primary research results of the two-year pilot project. A secondary purpose of this paper is to disseminate information about this exciting endeavor to encourage like-minded educators and researchers to participate in this project.

Keywords Information Technology · Education · Curricular initiative · Artificial intelligence trustworthiness · Experiential learning · IT education

1 Introduction

Members of the Transformative Interdisciplinary Human + AI Research Group at Western Michigan University (WMU) along with public and private partners at various US locations and beyond, have addressed a significant lack of STEM and IT workers who are aware of the profound technological and societal changes attributed to artificial intelligence (AI)(Transformative interdisciplinary human + a.i. research group, Western Michigan University). A strong AI-informed workforce is essential, according to the American AI Initiative (National Artificial Intelligence Initiative Office, 2021). The project discussed in this paper takes a convergent approach to integrate fundamental to advanced skills across STEM fields at the junction of Secure, Safe, Reliable (SSR) Computing, High-Performance Computing (HPC), and

✉ Irene Kahvazadeh
irene.kahvazadeh@wmich.edu

Extended author information available on the last page of the article

Artificial Intelligence (AI) (Fong et al., 2022). Large data sets will be handled and analyzed with ease by professors, undergrads, and graduate students.

This initiative also aims to provide a framework for the broader adoption of advanced CI training resources in the future, to have a significant impact on a large portion of the CI community. As part of this course, outreach efforts and creating and developing a talent pipeline will be undertaken from pre-university through his two-year and four-year schooling and graduate studies. The project also aims to promote AI readiness in STEM so that a broad range of STEM students can effectively use AI for solving their problems. The following are key project artifacts:

1. SSR concepts and methods are integrated into relevant computer science (CS) and IT programs that utilize cutting-edge HPC clusters.
2. Repeatable, adaptable, modular, experiential instructional components that may be added to current CS courses or used as independent study activities.

This project aims to expand participation by actively engaging local partners (community colleges, consortia) to include segments of various underrepresented groups within and outside Michigan. In addition to students and faculty from participating institutions, consortium members, and other IT professionals, the target group is community college students, undergraduate and graduate students, and consortium member faculty. Participants are further diversified through outreach activities such as workshops for local high school students. Future initiatives to integrate ubiquitous cloud-based services will ensure compatibility with modular designs and provide CI users with customized access to the workplace and pre-training training resources to support national strategies. Thus our paper contributes to the agenda of the National Strategic Computing Initiative (NSCI).

The remainder of this paper is organized as follows. SSR AI that runs on HPC CI is explained in Section 2 as well as the key challenges and opportunities that motivated this research. The project design is presented in Section 3. The deliverables of the project are described in Section 4. Section 5 presents an evaluation of the project deliverables and key findings. Section 6 concludes the paper and suggests future research directions.

2 Literature survey: Challenges, guidelines and opportunities

2.1 Challenges in teaching machine learning to non-CS majors

The goal of machine learning is to develop systems that can learn from data and make predictions or decisions based on that data. The challenge, however, is to teach machine learning to non-majors, since it requires a solid foundation in probability and statistics, as well as linear algebra and calculus. The instructors of machine learning courses for non-majors reported in a study by (Sulmont, 2019) that it was not the algorithms themselves that were difficult to teach, but rather the fundamental concepts of probability and statistics. Among these concepts are random variables, distributions, hypothesis testing, confidence intervals, and Bayesian inference. In addition, students often struggle with the mathematical concepts that underlie machine learning, such as linear algebra and calculus. Several concepts are covered, including matrices, vectors, dot products, eigenvalues, eigenvectors, differentiation, integration, and optimization. Before introducing machine learning algorithms and applications, instructors should provide background and motivation for these concepts. A study (Sulmont et al., 2019) examines the challenges of teaching machine learning to non-majors. According to the authors, higher-level design decisions were difficult to teach, while lower levels of the Structure of Observed Learning Outcomes (SOLO) taxonomy were easy to teach. Learning that higher-SOLO learning goals are harder to teach can have a significant impact on course design, public outreach, and the design of educational tools (Bornstein, 2016; Sanusi et al., 2022).

2.2 Guidelines to teach machine learning

According to (Cheong, 2022) there are several ways to improve teaching machine learning through the use of recommendation systems (RS) in e-learning systems, which are as follows:

- Use a personalized learning path for the students by automatically identifying their preferences and the situations of learning.
- Different specialties should adopt different recommendation algorithms, to achieve the desired teaching effect since different students have a concept of cognition and have a specific learning styles.
- The classical E-commerce recommending algorithms can't be directly applied to an RS on CS learning. Two of the main reasons are: firstly, some of the recommended items provided by RS are uncertain to the students, even the corresponding lectures, and with the learning process, it will constantly change the items and directions of the recommendation; secondly, to achieve the better recommendation purpose, the students, lecturers, and database need to communicate constantly,
- The context of the test is important to the students, such as the purpose of the course outline and the learning style.
- The context of CS course activities is needed to be arranged to ensure that the prerequisites of some courses are met.
- An adaptive learning route is needed to help the student gain knowledge continuously.

2.3 What is SSR AI running on HPC CI and why?

To achieve trustworthy and human-friendly AI, we consider safety, security, and reliability essential ingredients. Multiple Dimensions in AI are perception, reasoning, abstraction, learning, actuation, etc. In recent years, deep learning (DL) has made significant advances, leading to machine learning (ML) (Yang & Liang, 2018; Young & Ringenberg, 2019), which evolved out of AI. To define SSR AI, we draw inspiration from the thematic pillars of the Partnership on AI (Partnership on AI, 2023), the first of which says AI tools in safety-critical areas must be safe, trustworthy, and ethically sound. The scope of our working definition is broader, encompassing not only safety-critical AI applications, but all deployments of AI in both cyberspace and the real world (Saeedi et al., 2021). Safely interacting with chatbots, both online and offline is a problem (including self-destructive and/or life-threatening) as it can affect a user's mood and behavior. In addition, in alignment with the second thematic pillar (Partnership on AI, 2023), SSR AI aims to minimize biases for disparate user groups across the political and socioeconomic spectrums. Furthermore, we model SSR as three pillars that support trust in the use of AI.

While it is possible to design SSR AI algorithms that solve real-world problems in principle, these algorithms must be implemented in architectures to solve the problem. SSR-AI, running on advanced HPC CI, aims to build trust between humans and AI, making human users of AI feel comfortable, safe, and confident in all kinds of human-AI interactions (Kania & Kramer, 2011).

2.4 Opportunities

In some cases, AI systems can be tricked into exhibiting unwanted behavior, showing bias, or being abusive (Saeedi et al., 2021). It's hard to understand AI failure models. These misbehaviors and uncertainties can be multiplied by HPC CI to the point that the root causes are even harder to trace. These problems can be mitigated by advanced SSR technology.

Two significant challenges are being addressed in this project. The first is the development of experiential and modular learning materials to empower AI users in various STEM fields. Practicing AI Bias allows the learner to experience first-hand the limitations of her AI and what it can and cannot do concerning STEM problem-solving. As learners develop mitigation strategies, they become aware of problems and limitations. Advanced learners implement mitigation strategies and then test them. Learners can relate STEM examples from different disciplines to different domains. Mechanics students build artificial intelligence models that predict fuel consumption, and computer engineers balance power grids or CPU and GPU loads.

Through guided exploration, learners formulate goals and develop strategies to mitigate problems. It builds on basic knowledge, but advanced modules guide learners to implement solutions and evaluate these solutions against set goals (real-world solutions). Modules can be used as self-directed online learning or integrated into existing courses. Non-CS students can also take the CS Fundamentals course if the module is to be used as self-directed online learning. STEM curriculums should incorporate AI early, so students understand what AI can and cannot do.

Open AI's Charter (OpenAI charter, 2020) emphasizes promoting cooperation among CI users and contributors, system interoperability, and SSR standards. As advanced AI-powered AI research groups race toward artificial general intelligence (AGI), this charter recognizes the need to balance technological progress with its positive impact on people and society.

This paper stresses the importance of spreading benefits widely and establishing a cooperative framework for artificial intelligence. AGI is still a distant goal but augmented cognitive capabilities and power (Fong et al., 2019), including augmented AI, can have profound impacts on society and individuals. SSR knowledge and practices are incorporated into our experiential learning modules so that current and future CI users and contributors can benefit.

The empirical findings of AI training and learning (AITL) research have been summarized in a systematic literature review (Ng et al., 2022). This review provides a framework for AI literacy education by conducting a thematic and content analysis. Pedagogical models, teaching tools, and challenges identified contribute to today's AI literacy. Before 2021, AITL focused more on computer science education at the university level. The lack of age-appropriate teaching tools for scaffolding support prevented AI from becoming popular in K-12 classrooms at the time.

3 Project design

3.1 Innovative features

This project features the following innovative design features:

1. During our outreach studies, we continue to refine the design based on the results of course-related research. Current and future discussions are influenced by several influential sources. B. (Partnerships on AI, 2023), (Zhang & Dafoe, 2019; Brennen, 2018).
2. Intensive, multifaceted, modular, experiential learning materials designed to rapidly expand the knowledge and skills of CI workers and users. The module's versatility allows it to be integrated into an existing course or taken separately as a self-paced unit. The latter is effective (Lee et al., 2021).
3. Lay the groundwork for both future contributors and users of a fully functional experiential learning module. Users have access to these precise and fast tools to solve SSRAI-related issues.
4. Learning in a sandbox environment allows learners to take calculated risks and solve free-form problems. As a result, students feel confident in what they can achieve with AI and see tangible results in their work.

We continue to consult those already developed, e.g., ACM Curricula, JTF on Cybersecurity Education, MOOCs such as Udacity (Designing our artificial intelligence curriculum. Udacity, 2019a, b), EdX (Artificial Intelligence (AI). edX, 2023) and industry efforts, e.g. (Education. Google AI, 2023) (Overview of the Microsoft AI school. Microsoft Learn). Moreover, we are not competing with existing resources, but rather complementing them (Markdefalco n.d.).

4 Project deliverables

4.1 Pedagogical approach

An integral part of this project is active learning, embodying the idea of learning by doing. Additionally, experiential learning, including domain experts and related topics, adds realism to the journey of discovery. The SSRAI topics covered in the headings may relate to the learner's learning experience or materials. Learning content can be flexibly delivered to learners through a modular approach. The ability to divide learning content into manageable chunks within each module helps learners develop a sense of ownership and incremental success. This helps learners build the confidence they need to tackle more challenging tasks. In addition to integration into existing courses, the modular structure allows mini-courses to be run independently.

Modules can be divided into three levels of difficulty. Foundational (can be integrated into CS1 and CS2, courses taken by non-CS-STEM students), Intermediate (can be integrated into relevant high school curriculum), and Advanced (which can be integrated into graduate and senior undergraduate curriculum). Together, these modules cover all levels of literacy, from the most basic to the most advanced. The modules were developed to be self-contained.

The learning modules are designed to be programming language-independent, ensuring wide applicability. Regardless of language, learners are encouraged to use open-source libraries and resources such as Python and R. In fact, non-CS learners are not required to program (in any language) as part of the learning process. It is common for learners to be provided with code snippets that can run in a Jupyter / Colab notebook environment rather than writing their programs.

Students can relate their research to issues important to them by drawing examples and data from real-world sources relevant to the field, including Social Media and Press.

Although developed for series operation, the modules are loosely coupled. As a result, learners can choose the module (or set of modules) that is most relevant to them in any order. In-class modules are fully integrated into existing courses, so there is no net increase in the time it takes for graduate students to complete their degrees.

4.2 Twelve initial learning modules (freely available from the project website https://wmich.edu/cs/cybertraining)

Table 1 Summarizes the modules and their outcomes. These modules are available at https://wmich.edu/cs/cybertraining.

Table 1 Summary of the learning modules

No	Title	Learning outcome
1	SSRAI Math Toolkit running on HPC CI	Proficiency in math techniques and tools required for SSRAI on HPC
2	Exploring and exploiting the weaknesses of an intelligent system	High-level understanding of several practical weaknesses of intelligent systems. Using computational thinking, focus on one such issue and develop a mitigating strategy
3	Developing modular and structured software for HPC CI-based intelligent systems	Using modular and structured software techniques improves the robustness of an intelligent system
4	SSRAI data structures running on HPC CI	Understanding of the relationship between data structures and SSRAI that runs on HPC clusters.
5	Using HPC for deep learning	Awareness about Tensors. Programming skills for Python and Keras/ PyTorch deep learning algorithms running on HPC CI
6	Development of HPC CI software by SSRAI	The learning outcome is an understanding of the importance of SSRAI software development to minimize threats to AI systems. SSRAI software design, implementation, and evaluation skills
7	The vulnerabilities of machine learning	Firsthand experience in manipulating statistically accurate machine learning techniques. Effective countermeasures can be designed, implemented, and evaluated
8	The future of artificial general intelligence goes beyond current-generation AI.	Understanding how contextual data extracted from disparate data sources can be used to inform SSRAIs running on HPC clusters. The understanding of technical aspects of SSR in AGI research is often overlooked.
9	Robust trust scoring models based on adversarial machine learning	In-depth analysis of robust-by-design strategies and the types of adversarial attacks on ML algorithms.
10	Social Impacts of AI	A broad overview of current and future issues affecting human societies.
11	The challenges of applying AI to information retrieval tasks.	Understanding the pitfalls of AI applications to IR. An in-depth understanding of one of these pitfalls. An algorithmic approach to mitigating this pitfall can be formulated and tested.
12	SSRAI with HPC CI in real-time: capstone project	This course provides insight and practice in developing SSRAI for rapid decision-making.

5 Evaluation

5.1 Continuous evaluation and improvement

At the end of August 2021, after the project deliverables (experimental learning modules) were developed, we took a two-step approach to their evaluation. We started a small-scale experiment in the fall of 2021 (early September to mid-December 2021). Both Big Data (BD) and Information Retrieval (IR) the course aimed to combine two learning modules:

Module 4 for 3,000 level courses and Module 11 for 6,000 level courses. Students in BD courses mostly have lower or middle-level bachelor's degrees, with an equal number of computer science and data science students. Only graduates (master's and doctoral degrees) completed the IR.

Two separate and related components are required to assess each integrated module and course pair. An educational component (i.e. completion of a learning module) and a research component (i.e. completion of anonymized pre- and post-intervention surveys). A student's final course grade was determined by the completion of the educational component. However, completing the research portion was completely voluntary. Between the two grades, approximately 75% of the students responded spontaneously ($N = 10$). Although the composition of the two classes was very different, there was no significant difference in response rates. In our small tests, the experiential learning modules were generally well received in terms of quality. We had no complaints from the participants. However, due to the small sample size, no quantitative analysis was performed.

After a small experiment that led to fine-tuning of the content, a larger study was conducted in Spring 2022 (early January to end of April 2022). This large-scale launch involved 12 faculty members from four universities in the United States in various quantitative disciplines (CS, Mechanical Engineering, Civil Engineering, Statistics, Business Analytics, etc.). As part of an independent expert analysis conducted between May and July 2022, all participating departments conducted self-directed surveys before and after the intervention. About 200 undergraduate and graduate students chose to participate in completing the pre-/post-surveys. A further 163 students were affected but chose not to complete the surveys.

Further experiments were conducted in classes taught by the investigators in Fall 2022 and Spring 2023. All students in the affected classes contributed indirectly to the investigators' analysis of grade distributions and completion rates against historical records.

5.2 Evaluation instruments for pre/post-surveys

Dr. Harnar was responsible as an independent reviewer for the development of pre- and post-intervention survey instruments to assess the efficacy of the developed learning modules. Participants were asked five questions (three multiple choices, two open-ended) about their readiness and expectations for using AI in the workplace during a pre-intervention survey. The post-intervention questionnaire has 20 questions about the learner's experience (10 closed, 10 open). It takes approximately 5–10 min and 10–15 min to complete these pre-intervention and post-intervention surveys, respectively. Dr. Harnar was able to glean insightful, non-intrusive information from anonymized data. As shown in Table 2, the surveys were developed based on the Kirkpatrick model (Designing our artificial intelligence curriculum. Udacity, 2019a, b). Tables 3 and 4 gives more information on the number and type of Questions used in the Questionnaire total of 25 Questions were given to the candidates of which 5 of them were Pre and 20 of them were post-module Questionnaire (Table 5).

5.3 Evaluation procedure using surveys

This study followed a general procedure. Therefore, results from different disciplines and institutions are generally comparable. Specifically, a hybrid mode of learning was used, combining integrated in-class learning with self-directed online learning. Students were rewarded for their efforts in a flexible manner. Several faculty members incorporated a module into one of their courses and assigned a score to each student. Therefore, learning modules become an integral part of a course's assessment. Completion of a learning module can earn a student extra credit. In some cases, a mixed approach was used by combining the two approaches.

The Question of the Construct: Satisfaction was on a 5-point scale of 0–4 where 0 being "Not at all Satisfied" and 4 being "Completely Satisfied". Whereas all other Constructs were on a 5-point scale of -2 to 2, in which case -2 being "Strongly disagree" and 2 being "Strongly Agreed".

5.4 Summary of key findings – spring 2022

Participants and instructors were very satisfied with the experiential learning modules developed. Learners received clear instructions and guidance and few questions were posed in the module. In addition, some instructors improved the learning content. Tables 6, 7, and 8 quantify the post-intervention results. The results showed that both the content and implementation were generally satisfactory to the students. The lowest scores included competence and practicality (the ability to explain important concepts). There is room for improvement in these areas. The independent evaluation team conducted a t-test and found that the reported results were statistically significant. Specifically, the evaluation team applied one-tailed test on the t-distribution. They used two-sample paired t-test to look for mean difference in each population before and after the intervention.

5.5 Further evaluation and analysis

In Summer 2022, a virtual roundtable discussion was held involving all instructors who participated in Spring 2022. It was an opportunity to share experiences, and identify best practices. The instructors' opinions were overwhelmingly positive, though a few minor areas of improvement were identified. Specifically, the team

Table 2 Application of the Kirkpatrick model to measure the efficacy of the learning modules

Kirkpatrick stage	Interpretation	Construct
Reaction	The modules are relevant to the student's interest, they foster active engagement, and the ways of delivery of the modules are satisfying to the students.	Satisfaction
Learning	The participants gain knowledge or skills or experience positive changes in their attitude, confidence, or commitment to the subject.	Attitudes Knowledge
Behavior	The students see potential uses for the knowledge or skills learned during the module in other contexts or disciplines.	Application

Table 3 Kirkpatrick – Operationalization

Level	Construct	Facet	Closed	Open
Reaction	Satisfaction	Content	1	1
		Delivery	1	1
	Engagement	Motivator	1	1
	Relevance	Course Field of Study	2	0
Learning	Attitudes	Worth Confidence Practice	3 Pre/Post	3Post Only
	Knowledge	Definitions	0	2 Pre/ Post
Behavior	Application	Daily Life	1	1
		Field/Disciple	1	1

Table 4 Instrumentation pre-module and post-module questionnaire counts

Type	Item Count	Close	Open
Pre	5	3	2
Post	20	10	10

Table 5 Qualitative data acquired and their counts

Level	Construct	Facet	Data Type	N
Reaction	Satisfaction	Content	Post Q2	170
		Delivery	Post Q4	171
	Engagement	Motivator	Post Q6	170
	Relevance	Course Field of Study		
Learning	Attitudes	Worth	Post Q14	167
		Confidence	Post Q15	167
		Practice	Post Q16	167
	Knowledge	Definitions	Pre Q1 Pre Q2 Post Q9 Post Q10	184 103 169 101
Behavior	Application	Daily Life	Post Q19	165
		Field/Disciple	Post Q20	170

modified some of the examples and use cases to better match learners' aspirations. The main motivation was to help learners better apply their new knowledge in everyday situations.

In investigators subsequently conducted further experiments in their classes, e.g., AI, ML, BD, and IR in Fall 2022 and Spring 2023. Close to 200 undergraduate and graduate students were affected. In the Spring 2023 ML class alone, there were two sections of 35 students each that were affected. The investigators

Table 6 Summary of results post only: for reaction

Level	Reaction				
Construct	Satisfaction		Engagement	Relevance	
Facet	Content	Delivery		Course	Field
Mean	3.32	3.11	1.28	1.28	1.41
Median	3.00	3.00	1.00	2.00	2.00
Mode	3.00	4.00	2.00	2.00	2.00
Min	0.00	0.00	-2.00	-2.00	-1.00
Max	4.00	4.00	2.00	2.00	2.00

Table 7 Summary of results post only: for behavior

Level	Behavior	
Construct	Application	
Facet	Daily life	Course
Mean	0.67	1.35
Median	1.00	2.00
Mode	0.00	2.00
Min	-2.00	-1.00
Max	2.00	2.00

Table 8 Summary of results: for learning

Level	Learning							
Construct	Attitude						Knowledge	
Facet	Worth		Competence		Practice			
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Mean	1.67	1.71	0.06	1.04	1.14	1.18	7.64	7.64
Median	2.00	2.00	0.00	1.00	1.00	1.00	7	7
Mode	2.00	2.00	-1.00	1.00	2.00	2.00	7	10
Min	-1.00	-1.00	-2.00	-2.00	-2.00	-2.00	0	0
Max	2.00	2.00	2.00	2.00	2.00	2.00	10	10

observed more significant differences in both Attitude (Worth) and Attitude (Practice): mean difference in Fall 2022 was 0.75 and it was 0.73 in Spring 2023.

In addition, the investigators conducted analysis on three measures comparing Fall 2022 and Spring 2023 results against historical records dating back to Spring 2017. The three measures were overall class completion, overall class GPA, and distribution of the top grades (grades A and BA). Both Fall 2022 and Spring 2023 results show improvements on all three measures that cannot be explained by historical trends alone. All these results provide further evidence that the intervention was effective.

6 Conclusion and future research

Teaching AI and ML to non-CS majors has proven difficult (Sulmont et al., 2019). The purpose of this research is to influence the AI curriculum from a broader perspective. We contribute to the national educational curriculum/materials through the development of highly innovative and modern modular curricula/materials that can be integrated into undergraduate and postgraduate courses or offered as online self-paced learning. The experiential learning modules developed have been evaluated in the last two semesters and have proven their effectiveness. By participating in activities, students from different backgrounds can learn more about SSRAI running on HPC CI than others, and develop strategies for dealing with AI vulnerabilities. It is suggested that future research directions include the evaluation of experiential learning modules in more diverse modes of delivery. Our goal is to better understand whether classroom or self-directed online learning leads to better outcomes. Areas for improvement include making content more relevant to everyday life and reinforcing the learner's ability to explain important concepts. In addition, we are interested in expanding the breadth of our service (e.g. creating additional experience modules beyond the current 12) and expanding the types of learners who can benefit. High school graduates are already receiving personalized learning materials. Publicity work is already underway to promote the curriculum developed as part of this project. Among other research directions, we explore how best to deepen and expand the development of future curricula in computer science and other related research that increasingly uses AI to solve domain-specific problems and research the field.

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Data availability Not applicable.

Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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Authors and Affiliations

Irene Kahvazadeh[1] · Edwin Jose[1] · Alvis C. Fong[1] · Ajay K. Gupta[1] · Steve M. Carr[1] · Shameek Bhattacharjee[1] · Michael Harnar[2]

Edwin Jose
edwin.jose@wmich.edu

Alvis C. Fong
alvis.fong@wmich.edu

Ajay K. Gupta
ajay.gupta@wmich.edu

Steve M. Carr
steve.carr@wmich.edu

Shameek Bhattacharjee
shameek.bhattacharjee@wmich.edu

Michael Harnar
michael.harnar@wmich.edu

1 Department of Computer Science, Western Michigan University, Kalamazoo, MI, USA

2 Evaluation Center, Western Michigan University, Kalamazoo, MI, USA