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Fostering AI Literacy through SDG-Oriented Hands-On Learning Activity for Non-CS Students

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Abstract

This study examines how AI learning activities can be designed to help non-computer science students apply AI tools to address real-world problems aligned with the United Nations Sustainable Development Goals (SDGs). A one-day hands-on workshop was implemented as the project in an introductory AI course, guiding students through goal setting, service design, prototype implementation, and ethical reflection. Students used Google Teachable Machine and Dialogflow Essentials to build AI-enabled prototypes that combined image and language understanding. To assess the outcomes, a survey was administered to first-year students, measuring AI conceptual understanding and perceptions of AI application authenticity. While no statistically significant differences in AI capability self-assessment were found, the students participating the workshop demonstrated more cautious and realistic views of AI applications. These findings suggest that experiential, interdisciplinary AI education can enhance critical engagement with AI technologies and support the development of socially responsible learners.

Keywords: AI education, AI literacy, Sustainable Development Goals.

1 Introduction

The world today faces increasingly complex and urgent challenges—from climate change to unequal access to healthcare. These global issues are articulated in the United Nations' Sustainable Development Goals (SDGs), which call for collaborative, innovative, and interdisciplinary solutions [1]. For students across all fields, engaging with SDGs provides a meaningful opportunity to connect academic learning with real-world impact.

In the era of rapid technological advancement, artificial intelligence (AI) is no longer a distant concept but a powerful force shaping how we live, learn, and work. As an emerging technology, AI presents new possibilities for addressing the global challenges. Understanding AI has become essential for students across all disciplines. Learning its core concepts and applications helps students make sense of the technologies and prepares them to apply these tools creatively and critically. Integrating AI education with real-world problems helps students develop the skills and mindset to use technology responsibly [2].

This paper aims to explore how AI learning activities can be designed to support non-computer science students in understanding and applying AI tools to address SDG-related challenges. By integrating real-world problems into the learning process, the study seeks to make AI education more relevant and engaging for learners [3]. This approach may shift students from AI users to AI creators through interdisciplinary education [4].

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2 Activity Design

In order to put AI concepts into meaningful practice, a one-day hands-on workshop was designed to replace the final four sessions of an introductory AI course. As a course project, students worked in groups to conceptualize a future AI service aimed at solving SDG-related challenges. Each group was required to design a prototype that incorporated functionalities involving both image and language understanding. In addition, students were asked to identify and reflect on the potential limitations associated with their proposed designs. The experience served not only as an opportunity for technical exploration, but also as a platform for ethical reflection and interdisciplinary thinking.

Based on the theory of self-regulated learning [5], the activity included the following steps: goal setting, design planning, prototype implementation, and reflection on limitation.

2.1 Goal Setting

The workshop began with a goal-setting phase, during which students were guided to identify a clear and achievable direction for their proposed AI-based smart health service. Although smart health is most directly aligned with SDG 3 (Good Health and Well-being), students were encouraged to explore a broader range of topics related to physical, psychological, or environmental health in both humans and animals. Depending on the context of their proposed services, these topics could also align with other Sustainable Development Goals, such as SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life Below Water), and SDG 15 (Life on Land). The phase included the stages of idea generation and evaluation.

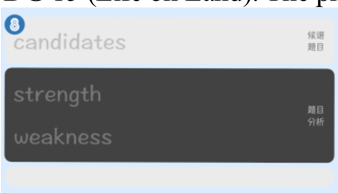

Figure 1: Goal Setting

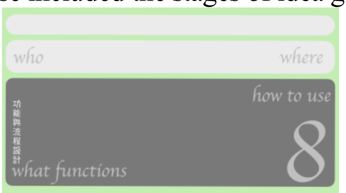

Figure 2: Design Planning

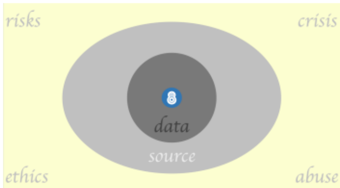

Figure 3: Reflection

During the idea generation stage, students engaged in an open-ended brainstorming task, where each team member proposed potential project ideas based on their prior knowledge, interests, and social concerns. Each group collaborated using a shared Google Jamboard (Figure 1), which enabled simultaneous contributions and helped visually organize emerging ideas. This phase promoted divergent thinking before narrowing the scope.

During the idea evaluation stage, to support deeper reflection, the instructor prompted students to consider several key dimensions of their proposals, including relevance to smart health, overall importance, and feasibility within the one-day workshop timeframe. Students then evaluated the proposed ideas directly within the Jamboard, analyzing their strengths and weaknesses. To conclude the phase, each group selected and presented a formal name for their smart health service.

2.2 Design Planning

Once a topic was confirmed, students moved on to the design phase, where they defined the service context and planned the core functions of their proposed smart health solution. The target context varied across groups, including healthcare institutions, home environments, community settings, or digital platforms. Guided by a structured visual template in Jamboard (Figure 2), students analyzed the characteristics of their target users and service environments to ensure their design addressed real-world needs.

Students then envisioned the key features their service would offer and mapped out the logical relationships between them. As shown in the Jamboard, each group identified at least three core functions and illustrated how these functions would contribute to the overall smart service. In parallel, students outlined a step-by-step user interaction flow, demonstrating how end users would engage with the system in practice. This process encouraged students to think critically about usability, integration, and the sequence of AI-supported tasks.

To ensure alignment with course learning goals, students were required to implement at least two of the proposed features using designated AI tools. Specifically, one function had to involve image-based understanding (e.g., image classification or pose detection via Google Teachable Machine), while the other had to demonstrate language-based interaction (e.g., voice recognition via Google Teachable Machine or chatbot development via Dialogflow Essentials). This instruction allowed students to apply AI concepts in a hands-on manner while grounding their designs in meaningful service scenarios.

2.3 Prototype Implementation

In the prototype implementation phase, each group was required to transform their conceptual design into a working prototype by utilizing AI tools that support image and language understanding. To meet this requirement, students were instructed to use Google Teachable Machine (Figure 4) and/or Google Dialogflow Essentials (Figure 5). These platforms enabled students to implement machine learning models without requiring programming skills, lowering the technical barrier while emphasizing the importance of data, labeling, and model evaluation [6, 7].

For image-based applications, students used Google Teachable Machine to build custom classifiers using image or pose recognition. During the workshop, students collected their own image data using smartphones, webcams, or online open sources, preparing examples that reflected the target features of their proposed services. One student group who targeted SDG 14 (life below water), for example, designed a prototype to detect marine debris through image recognition (see Figure 4), training their model to distinguish between ocean waste (e.g. plastic bottles) and marine organisms (e.g. fishes). This task challenged students to consider real-world visual complexity and required them to curate diverse training samples with precise labeling. This process required them to think about data quality, quantity, diversity, and label accuracy, factors that significantly affected the resulting model's performance.

For language-based applications, students used either the sound recognition module of Google Teachable Machine or Google Dialogflow Essentials to build conversational agents. In Dialogflow, students designed intent-based interactions, which required them to define a set of possible user inputs and appropriate system responses. One group who targeted SDG3 (health and well-being), for instance, developed a mental health counseling chatbot that guided users through basic emotional check-ins and suggested self-care tips based on user input (See Figure 5). This involved planning not only the structure of the conversation but also identifying semantic variations in natural language and labeling training phrases accordingly. The platform's built-in simulator allowed students to immediately test and refine their agents, providing insights into the iterative nature of dialogue design and the challenges of natural language understanding.

Throughout this implementation phase, the focus on data and labeling helped students understand core machine learning principles in an applied context. By working directly with training data, observing its impact on model behavior, and adjusting their input based on system feedback, students gained experiential knowledge of how AI systems are trained, evaluated, and refined. This hands-on experience also encouraged students to consider the ethical implications of data choices, including representativeness, privacy, and potential misuse.

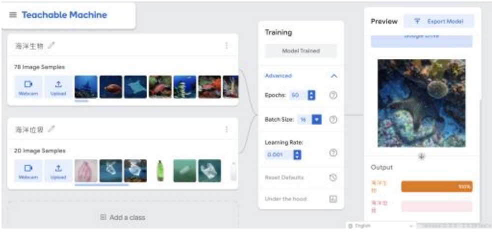

Figure 4: Google Teachable Machine

Figure 5: Google Dialogflow Essentials

2.4 Reflection on Limitation

In the final phase of the workshop, students were guided to critically examine the limitations and potential risks associated with their proposed AI-based smart health services. Each group was asked to analyze the types of data their service would require, including its source, accessibility, and permissions. This data-centered reflection served as a starting point for evaluating broader risks across four key dimensions: risks, crisis, ethics, and abuse (Figure 3).

- Potential risks referred to foreseeable but unintended negative outcomes that could arise from AI model behavior.
- Crisis referred to more severe and unpredictable threats, such as system failures or security breaches, including the possibility of cyberattacks that exploit vulnerabilities.
- Ethics referred to issues related to user privacy, data ownership, or inequality.
- Abuse referred to users applying the technology in harmful or unintended ways.

Rather than engaging in abstract discussion, students were instructed to ground their analysis in the specific design of their own projects, identifying concrete examples of how such risks could manifest and proposing initial strategies for mitigation.

3 Pilot Study

3.1 Background

This pilot study was conducted in the context of a required introductory AI course at a medical university in northern Taiwan. To bridge theory and practice, the instructional activities described in the previous chapter were implemented as part of the course's final project. Beyond conceptual design, students were expected to engage in hands-on experimentation with AI tools. In doing so, they took on roles similar to data scientists, collecting real-world data, labeling it appropriately, and training models to support their service ideas.

As an exploratory pilot study, this study aimed to investigate whether such learning activities could support non-computer science students in developing a better understanding of core AI concepts, as well as their perception of AI authenticity. A total of 60 first-year undergraduate students, all from non-technical disciplines, participated in the study.

3.2 Data Collection

To evaluate their learning outcomes, a researcher-developed survey was administered at the end of the semester. The instrument consisted of two sections: AI capability self-assessment and perception of AI authenticity.

The first section focused on students' understanding of five core AI concepts: artificial intelligence, machine learning, deep learning, image recognition, and natural language understanding. For each concept, students were asked to describe their capability as one of the following levels:

unfamiliar, recognize, understand, associate, analyze, and create. The responses were numerically coded (0 to 5) for analysis.

The second section assessed students' perception of AI authenticity by asking students to evaluate ten statements commonly seen in public discussions about AI. Statements included examples such as: "There are robots today that can think independently," "AI can predict stock market fluctuations," and "Computers can understand human body language." For each statement, students rated their level of agreement using a 5-point Likert scale: from "definitely false" to "definitely true," with a neutral midpoint of "cannot judge." In the analysis stage, the responses were numerically coded (1 to 5).

3.3 Preliminary Result

3.3.1 AI capability self-assessment

Figure 1 presents the results of the AI capability self-assessment from the first section of the survey. Independent samples t-tests (Welch's t-tests) were used to compare the experimental (n = 46) and control groups (n = 14) across five core concepts. Although the experimental group consistently reported higher mean scores across all five concepts, the differences were not statistically significant. The results suggest that the workshop-based learning activities may have positively influenced students' conceptual understanding, but the observed differences were not sufficient to demonstrate statistically significant effects in this pilot study. These findings highlight the potential for future iterations to further strengthen conceptual gains through more extended or targeted interventions.

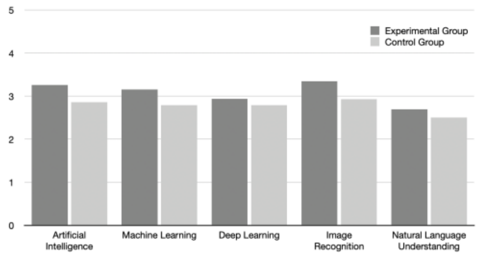

Figure 7: AI Capability Self-assessment

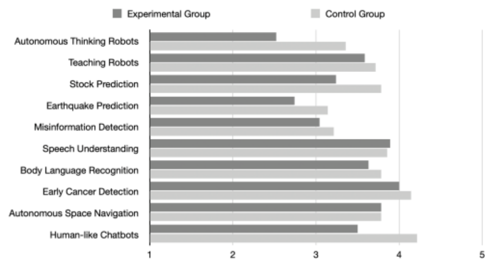

Figure 6: Perception of AI Authenticity

3.3.2 Perception of AI authenticity

Figure 6 presents the results of students' perceptions of AI authenticity. Independent samples t-tests (Welch's t-test) were performed to compare the responses between the two groups. Among the ten items, two statements showed statistically significant differences between groups. For the claim "There are robots today that can think independently," the experimental group reported significantly lower agreement than the control group ($t = -2.29$, $p = .031$), suggesting that the experimental group developed a more cautious and realistic perception of AI applications after participating in hands-on learning activities. Similarly, for the statement "Chatbots today can serve customers just like human service agents," the experimental group showed significantly lower agreement ($t = -2.77$, $p = .009$). Although the remaining items did not reach statistical significance, descriptive trends indicated that the experimental group was generally more conservative in assessing AI applications, particularly regarding applications such as stock prediction, earthquake forecasting, and distinguishing misinformation. These findings suggest that experiential AI learning activities may help students form more accurate and discerning perceptions of AI capabilities, contributing to more realistic expectations about the role of AI in society.

4 Concluding Remarks

This study explored the integration of hands-on AI learning activities into an introductory course for non-computer science students, with a focus on solving real-world challenges aligned with the Sustainable Development Goals (SDGs). While the quantitative results did not yield statistically significant improvements in conceptual understanding, the trends observed suggest that the workshop-based approach fostered more cautious and realistic perceptions of AI capabilities. These findings highlight the potential of experiential, interdisciplinary learning designs to enhance AI literacy and promote socially responsible innovation. Future studies may benefit from expanding the intervention duration, diversifying student populations, and exploring long-term impacts on ethical awareness and critical technology engagement.

Acknowledgements

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