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The AI Training Series was Washington County, Utah's first community education offering on the topic of generative AI (GenAI). The training provided community members with an overview of the capabilities and advantages of GenAI and assisted them in making informed technology adoption decisions. Utah State University Extension partnered with Dixie Technical College and Zonos, a software company, to evaluate the effectiveness of the learning experience based on anticipated outcomes. Results showed the training was effective for disseminating information and advancing knowledge on the topic of GenAI. However, students' intentions to adopt AI were lower than expected due to perceived barriers to using it effectively in their work.

Keywords: generative artificial intelligence, AI, workforce development, Extension partnerships, Theory of Planned Behavior

Introduction

Generative artificial intelligence (GenAI) represents a leap in the field of AI (Epstein et al., 2023; Toner, 2023). Large language models (LLMs) such as GPT-4 are examples of GenAI, having been trained on extensive datasets of text and code (Google, 2023). With the rise of LLMs, there has been a shift in how society communicates, learns, and operates (Chui et al., 2023). These LLM systems, including ChatGPT, Bard, and Midjourney, can craft unique content ranging from text and images to audio and music (Floridi, 2023). GenAI's rapid adoption across sectors establishes its potential, marking it as a fundamental innovation of our era (Baxter & Schlesinger, 2023; Brynjolfsson & Raymond, 2023).

As industries increasingly adopt GenAI technology into their operations, mastering its application will become essential for many professional roles (Warzel, 2023). Consequently, for a future-ready workforce, embedding GenAI skill development in both academic curricula and professional training programs is essential. Randstad (2023) reported that more than half of employees believe learning artificial intelligence skills would help them advance in their careers and 22% desired more AI-focused learning opportunities, while only 13% indicated they have access to such development.

In a collaborative effort to provide workforce development training on AI to residents of Washington County, Utah, Dixie Technical College partnered with Zonos, a software firm, to develop a new course called the AI Training Series (Dixie Technical College, 2023). The purpose of the course was to emphasize the capabilities and advantages of GenAI to the community, highlighting its broad relevance and potential for their personal and professional roles. The course was taught by the founder and CEO of Zonos over 6 weeks, starting on August 3, 2023. Weekly classes were held each Thursday from 6 to 8 p.m. at Dixie Technical College. Students paid $200 to participate, and Utah State University Extension evaluated the course.

Purpose and Objectives

The purpose of this evaluation study was to describe the outcomes of a collaborative workforce development program focused on GenAI. The study also sought to evaluate the multi-sector partnership between Dixie Technical College, Zonos, and Utah State University Extension. Guided by the Theory of Planned Behavior (Ajzen, 1991), the study's objective was to assess the program's efficacy in disseminating GenAI knowledge; measuring students' skill acquisition; and identifying key factors affecting participants' intentions to adopt GenAI technologies. The Theory of Planned Behavior (TPB) is an explanatory model used to describe the effect of an intervention or program (Montano & Kasprzyk, 2015). As the objective of this study was to measure the likelihood of adopting a new technology, not actual adoption, TPB was appropriate for assessing participants' intentions and understanding how they may adopt GenAI in the future. Evaluating the program's efficacy is important to ensuring the program effectively enhances participants' understanding and skills in GenAI, which can lead to better workforce preparedness. Identifying the key factors influencing participants' intentions to adopt GenAI technologies helps Extension professionals and workforce educators tailor programs to address these factors, ultimately increasing the likelihood of successful technology adoption and integration into various sectors.

Methods

Design

Our evaluation study used a one-group posttest-only design to gather data from participants. This is a research method in which a single group of participants is exposed to an intervention and then tested afterward to assess the outcomes without a comparison to a control group or pretest measurements (Ary et al., 2018). This was the most practical evaluation design, given the nature of the program. An exit survey was developed by the program team to assess desired program outcomes based on participants' perceptions of the AI training series. The exit survey response rate was 32% (n = 32) of the 100 participants registered for the course. TPB (Ajzen, 1991) guided the post-test assessment. Outcomes were divided into three broad components: (a) experiences and reactions, (b) factors of intentions (behavioral, normative, and control beliefs), and (c) intentions. Data were gathered after the series in September 2023 via a Qualtrics survey. This study fell under the category of applied evaluation/practice rather than research, and, as such, it did not require Institutional Review Board (IRB) approval.

Framework

Following TPB, factors of intentions were specified as short-term outcomes: (a) *Behavioral beliefs* – attitudes towards the behavior (4 Likert-type items), (b) *Normative beliefs* – subjective norms (2 Likert-type items), and (c) *Control beliefs* – behavioral control (3 Likert-type items and 1 score for self-rated ability). Self-rated ability consisted of five items: writing code/scripts, prompt engineering, creating images for marketing, analyzing data, and increasing productivity. A binary dependent variable, *Intentions*, was created using students' responses to their intentions to apply all five ability items; the score was summed, then converted to a binary variable with two states: (a) likely to use at least three AI actions, and (b) unlikely to fully integrate AI in work tasks. Construct scores were created based on students' responses to each item for the three TPB factors.

Analysis

Descriptive statistics were used to summarize all three outcomes (i.e., reactions and experiences, factors of intention, and intentions). A binary logistic regression was developed to estimate the effect of TPB factors on intentions to use AI. The logistic regression model sought to explain participants' intentions to use AI, given four independent constructs based on responses to Likert-type items aligned to *behavioral*, *normative*, and *control* beliefs.

An open-ended question on the exit survey asked students about ideas to improve the course. A basic thematic analysis was the qualitative research approach employed to identify patterns and themes emerging from the open-ended responses (Merriam & Tisdell, 2015). Responses were coded and categorized, and themes were identified to systematically analyze the data. The analysis revealed a variety of opinions, preferences, and suggestions on the course structure, instruction quality, and subject matter. The subsequent findings are delineated in Table 6 through categories and themes, providing a structured understanding of the student's feedback, fundamental to course improvement.

Participants

About 16% of participants were 18-24 years old, 28% were 25-34 years old, 16% were 35-44 years old, 22% were 45-54 years old, and about 16% were 55 years or older. The majority were white (84%), male (65%), and not Latino (97%). Most participants had either a bachelor's degree (31%) or a graduate or professional degree (31%). Most were employed full-time (72%), worked in the private sector (68%), and earned more than $100,000 annually.

Results

Section 1: Overall Experiences and Reactions

Table 1 shows students' immediate reactions to the training series. When asked if the training provided them with new insights, 88% responded "Definitely Yes." Similarly, 75% indicated the training provided them with useful information. While most students had favorable reactions to the series, some students were uncertain about how they can leverage AI to prepare for future opportunities and how to use AI in their current role. Overall, most students rated the series as "Very Good" (53%), and 22% rated it as "Excellent."

Table 1. Students Reactions to the AI Training Series

Reaction Question	**% (*n* = 32)***			
	DN	*PN*	*PY*	*DY*
Did the training provide you with new insights?	0	6	6	88
Did the training provide you with useful information?	0	3	22	75
Did you learn how AI impacts you personally?	0	6	34	59
Did you learn how AI can be applied in various job functions?	3	6	41	50
Did the training provide you with a valuable learning experience?	0	6	47	47
Did you learn how to leverage AI to prepare for future opportunities?	0	6	50	44
Did you learn how to use AI in your current role?	0	13	50	38

Note. *DN = Definitely Not, PN = Probably Not, PY = Probably Yes, DY = Definitely Yes.

Section 2: Ability and Intentions

Table 2 describes students' perceived ability to use AI for specific actions that were covered in the training series. It also shows students' intentions to use AI to execute those actions. After the series, most students rated themselves as beginners in using AI for writing code or scripts (63%), prompt engineering (53%), creating images for marketing (53%), and analyzing data (50%). About half the number of students rated themselves as intermediate in using AI to increase their productivity (53%).

As shown in Table 2, only a few students used AI before the training series. The majority did not intend to use AI for key tasks they learned in the training; only 36% indicated an intention to use AI to write code or scripts, 25% intended to use prompt engineering, and 39% intended to use it for creating images for marketing. After the training, most students stated they planned to use AI for analyzing data and increasing productivity.

Table 2. Students' Ability and Intentions Post-series

Action Item	Self-rated Ability (%)			Intentions	Prior Use
	Beginner	*Intermed.*	*Expert*	(% Yes)	(%Yes)
Writing code/scripts	63	25	13	36	18
Prompt engineering	53	44	3	25	18
Creating images for marketing	53	44	3	39	11
Analyzing data	50	47	3	57	4
Increasing productivity	41	53	6	64	7

The series addressed each item listed in Table 2. However, students' intentions to apply what they learned were lower than anticipated, a result consistent with their self-rated ability; most students left the series feeling like beginners and may require additional training before fully integrating AI into their work.

Section 3: Factors of Intention

From Table 3, descriptive results indicated students had high *behavioral* beliefs after the training series; students exhibited generally positive attitudes toward the value of using AI in their work (M = 4.30). For example, more than half the number of students strongly agreed that using AI technology would improve their productivity in various tasks and simplify tasks that are currently time-consuming. In contrast, there were lower *normative* beliefs toward AI; students did not feel that they were pressured to use AI by their supervisors (M = 3.41). As such, the majority of students neither agreed nor disagreed with the statement "I feel a strong expectation from my colleagues to use AI in our work." Lastly, students had a moderate level of *control* beliefs; they experienced some impeding factors to using AI in their work (M = 3.53). For example, slightly more than a third of the number of students neither agreed nor disagreed with the statements "The complexity of AI technology makes it difficult for me to use," and "There is a lack of clear guidance on how to effectively implement AI in my tasks."

Overall, results indicate students saw the benefit of using AI after the training series and probably attended the training on their own accord, since they did not feel pressured by their supervisors to learn AI. However, they thought several impeding factors existed in using AI, which corroborates with their lower intentions to use AI in their jobs as shown in Table 2.

Table 3. Items aligned to the Theory of Planned Behavior

Factor/Items	%				
	SD	**D**	**N**	**A**	**SD**
Behavioral beliefs (M = 4.30, SD = .57)					
Using AI technology would improve my productivity in various tasks.	0	0	9	41	50
I think using AI could simplify tasks that are currently time-consuming.	0	0	9	38	53
AI has the potential to enhance the quality of my work.	0	0	6	31	63
I feel confident in my ability to integrate AI into my daily tasks.	3	6	16	56	19

Normative Beliefs (*M* = 3.41, *SD* = .73)					
I feel a strong expectation from my colleagues to use AI in our work.	0	19	47	25	9
My supervisors or managers encourage the use of AI in our work processes.	3	9	28	47	13
Control Beliefs (*M* = 3.53, *SD* = .64)					
The complexity of AI technology makes it difficult for me to use.*	0	19	34	38	9
There is a lack of clear guidance on how to effectively implement AI in my tasks.*	0	19	37	41	3
I have access to the necessary resources and tools to effectively use AI technology.	0	6	16	56	22

Note. *Reverse-coded

Table 4 shows the logistic regression model of factors affecting students' likelihood to use AI after the series. While each item was aligned to a TPB construct, the operational constructs were not validated using existing scales or an expert panel. Therefore, the logistic regression model is only exploratory and provides a broad view of students' intentions to use AI. In addition, *a priori* alpha was set at $p < 0.10$ since the sample had limited statistical power ($n = 32$), which further affects our ability to make substantial claims about students' intentions – all results pertain only to students in the AI series.

For model fit, the overall accuracy rate increased from 50% at Step 0 in the constant-only model to 69% at Step 1 with all four (4) predictors. The null hypothesis of the Hosmer-Lemeshow test was not rejected ($\chi 2 = 5.36$, p = 0.72), indicating the data fit the model well. The model consisted of four independent variables; (a) Behavioral beliefs, (b) Normative beliefs, (c) Control beliefs, and (d) Self-rated ability (aligns to control beliefs in the TPB). From Table 4, results revealed control beliefs (or perceived behavioral control) had a statistically significant effect on students' intentions to use AI ($W = 3.30$, $p < 0.10$). Looking at the odds ratio, students who believed there were fewer impeding factors to using AI were about 4 times more likely to use it compared to others. Recall, impeding factors related to the complexity of AI, clear guidance, and having access to the necessary learning resources.

Table 4. TPB Factors of Intention to Use AI

Independent Factors	B	S.E.	Wald	df	Sig.	Exp(B)
Behavioral beliefs (Attitudes)	-0.43	0.92	0.21	1	.645	0.65
Normative beliefs (Social norms)	-0.04	0.68	0.00	1	.949	0.96
Control beliefs 1 (Perceived behavioral control)	1.68	0.92	3.30	1	.069*	5.36
Self-rated Ability (Control beliefs 2)	0.55	0.66	0.70	1	.402	1.73

The results of the logistic regression model were consistent with the descriptive summary presented in Tables 2 and 3. Students valued the course, had positive reactions toward the nature of the content, and did not feel pressured to learn about AI from their supervisors. However, after completing the course, most students still believed they were beginners in using AI and had lower-than-expected intentions to use AI.

Section 4: Qualitative Feedback

The analysis of the responses regarding the enhancement of the AI Training Series revealed four major categories: *Course Structure*, *Practical Application*, *Pedagogical Improvement*, and *Interaction and Engagement* (See Table 5). Within the Course Structure category, respondents advocated for an extended course duration and a more structured curriculum akin to a formal college course. Concerning Practical Application, the data suggested a desire for hands-on assignments that bridge theory to real-world application, accentuated by recommendations for finer-tuned classes targeting specific professional fields. Pedagogical Improvement emerged as a necessary domain, with respondents recommending experienced educators to facilitate learning and suggesting smaller class sizes for more personalized instruction. Lastly, the Interaction and Engagement category highlighted the value respondents placed on group activities, increased practice opportunities, and interactive learning experiences.

Table 5. Categories & Themes Regarding Course Improvement Suggestions From Students

Categories	Themes	Description
Course Structure	Extended Duration	Some respondents expressed a desire for a lengthened course with a semester-long structure, incorporating homework assignments to enhance learning.
	Structured Curriculum	Respondents indicated a need for a more structured approach with clear lesson goals, syllabi, and a lesson structure resembling a formal college course.
Practical Application	Hands-on Assignments	Suggestions for homework assignments, particularly those that entail creating and presenting projects or chatbots, were mentioned to enable practical application of the learned materials.
	Real-world Application	Respondents suggested a focus on how AI can be applied in various work situations, with finer-tuned classes targeting specific fields like marketing, sales, HR, and finance.
Pedagogical Improvement	Improved Instruction	The need for instructors with not only knowledge of AI but also pedagogical skills was emphasized to avoid off-topic tangents and provide a more conducive learning environment.
	Class Size	Smaller class sizes were suggested for a more focused learning experience and personalized attention.
Interaction and Engagement	Group Activities	Responses reflected a desire for more interactive group activities, including opportunities for students to collaborate on AI projects and present their findings.
	Increased Practice Opportunities	Respondents valued more opportunities to practice, including optional homework, at-home projects, and hands-on tasks to enhance engagement and retention of the course material.

Discussion

The findings from this evaluation study describe the outcomes of a collaborative workforce development program and provide valuable insights into the program’s efficacy and areas for improvement. Despite the limited sample size of 32 students, which impacts the statistical power of the findings, the study revealed important trends and feedback that can guide future program improvements.

Participants' overall positive reactions to the training series indicate that it was well-received, with most students finding it valuable and informative. However, the study's use of a one-group posttest-only design limits the ability to control for external factors and to measure net improvements through baseline comparisons. Future research could benefit from a more robust methodology, including pre-tests, control groups, and longitudinal tracking to assess long-term outcomes and skill retention.

The self-rated abilities and intentions to use AI revealed that many participants felt like beginners, particularly in technical tasks such as writing code, prompt engineering, and creating marketing images. This finding is consistent with their lower-than-expected intentions to apply what they learned, suggesting that additional training and support are necessary for students to feel confident in using AI in their work. The Theory of Planned Behavior (TPB) provided a useful framework for understanding these outcomes, highlighting high *behavioral* beliefs but moderate *control* beliefs and lower *normative* beliefs among participants. These moderate *control* beliefs reflect perceived barriers, such as the complexity of AI technology and lack of clear implementation guidance, which hindered participants' confidence and intention to use AI.

The logistic regression model, though exploratory due to the lack of validated constructs and limited sample size, indicated that perceived *behavioral* control significantly influenced students' intentions to use AI. Students who perceived fewer barriers were substantially more likely to intend to use AI, emphasizing the need to address these barriers in future training programs. Incorporating more hands-on learning exercises, practical content, reference guides, and quick tutorials could enhance participants' confidence and willingness to integrate AI into their work.

Qualitative feedback from participants further highlighted the importance of a structured, practical, and interactive pedagogical approach. Recommendations included extending the course duration, incorporating a more structured curriculum, providing hands-on assignments, and targeting specific professional fields for practical application. Additionally, improvements in pedagogical approaches, such as employing experienced educators and maintaining smaller class sizes, were emphasized. Increased opportunities for interactive learning and practice were also valued, reflecting a desire for a more engaging and comprehensive educational experience.

While the AI Training Series was positively received, the findings highlight the need for ongoing development and improvement to address the evolving needs of the Washington County workforce. By enhancing participants' abilities, addressing perceived barriers, and incorporating qualitative feedback into program design, educators can significantly improve the effectiveness of GenAI training and support the broader adoption of AI technologies in various sectors. In addition, future research could employ more rigorous methods to further validate these findings and measure long-term outcomes, ultimately contributing to the development of a highly skilled and future-ready workforce.

Conclusions and Recommendations

The study holds particular interest for Extension professionals, as the collaborative structure of this initiative can serve as a model for facilitating partnerships to support the adoption of rapidly evolving technologies. Such partnerships can optimize content delivery and set the stage for future programs, making this study useful for those involved in technological education and workforce development.

The AI Training Series in Washington County, Utah aimed to empower community members with insights and practical skills related to GenAI. The study found that the training was successful in disseminating information, with most students reporting new insights and useful information. However, the results highlight several areas for future improvement, particularly in better preparing students for the application of GenAI in various professional roles.

Students were uncertain about leveraging AI in their current roles or future opportunities. Less than half felt the training prepared them for future opportunities or aided them in their current roles. This presents an opportunity for course improvement, focusing on application-based training that goes beyond mere dissemination of information. Practical, hands-on workshops may complement the current training to bridge this gap. Despite positive reactions, many students rated themselves as beginners in GenAI-related tasks, indicating a potential gap between students' expectations and actual skill acquisition. Intentions to use AI for key tasks were lower than anticipated, which might be due to limited self-efficacy in applying GenAI. This suggests the need for more advanced modules or follow-up training sessions to foster greater confidence.

The Theory of Planned Behavior (TPB) provided valuable insights into students' behavioral, normative, and control beliefs surrounding the use of GenAI. Students exhibited high behavioral beliefs but lower normative beliefs, meaning they saw the value in using AI but felt little external pressure to do so. Addressing this could involve engagement with more industry leaders and organizations to emphasize the importance of GenAI skills in the workplace, thus increasing normative beliefs and intentions to use GenAI. Control beliefs indicated some students felt impeded by the complexity of GenAI technology and a lack of clear guidance, suggesting future courses could benefit from simplifying complex topics and providing clearer implementation guidelines.

The AI Training Series has shown initial promise while also revealing areas for development in terms of curriculum focus and student self-efficacy. Future iterations could benefit from an emphasis on practical application and industry engagement to better align with both individual and professional development needs.

The course represents an innovative effort to educate the community about the capabilities and advantages of GenAI. While it has been successful in disseminating foundational knowledge and insights, it faces the challenge of translating this information into practical application and job readiness. Findings necessitate adjustments in course curricula to emphasize real-world application and industry-specific utility.

The study further pinpoints gaps in the course that require attention, particularly in equipping students with practical skills. A notable proportion of students did not feel ready to leverage GenAI in their current or future professional roles. This is an opportunity to expand the curriculum with hands-on training and more advanced modules. By supplementing theoretical knowledge with application-based workshops, students may develop greater confidence in their GenAI skills, thus increasing their intentions to utilize GenAI in the workplace.

The demographic information collected helped to identify gaps in the course's marketing efforts. This will allow Dixie Technical College to adjust its outreach and promotion strategies for future community education programming. In addition, analyzing the demographic data provides insights into the preferences and needs of different segments of students, which will inform future learning offerings.

The outcomes of this research offer essential insights for land grant university Extension programs. First, a clear need exists for practical, hands-on training modules that go beyond mere informational sessions. This could manifest as lab exercises and projects that give students tangible experience with GenAI applications. Second, the data underscores the importance of industry collaboration. Extension programs should actively engage with industry leaders and local organizations (i.e., career and technical colleges) to better align curricula with market needs. This would not only boost the course's relevancy but also influence the community's normative beliefs about the value of GenAI, thereby potentially increasing its adoption rate.

The AI Training Series serves as an innovative initiative that lays a valuable foundation in the ever-evolving field of GenAI. Its novelty lies in not only educating the community but also in its promise for dynamic expansion and adaptation. The opportunities for hands-on experience and industry engagement present exciting avenues for further enriching the course. By addressing these opportunities, future iterations could amplify their impact, elevating both the course and similar community education courses to new levels in workforce development for GenAI.

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