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Enhancing AI-Powered PowerPoint Skills: Training Impact on Vocational Teachers in Surakarta

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ABSTRACT

Background: The integration of AI-powered PowerPoint in education offers promising opportunities for enhancing teaching effectiveness, yet many vocational teachers face challenges in implementing this technology due to limited training and technical support.
Contribution: This study contributes to the educational community by providing a practical framework for integrating AI-powered tools in vocational education, thereby enhancing teachers' technical skills and supporting sustainable technological adoption.
Method: Using a quasi-experimental design with a one-group pretest-posttest approach, twenty office administration teachers participated in an 8-hour training program. Data were collected through validated instruments measuring three indicators: training reaction, training facilities and materials, and expected behavioral changes.
Results: Paired-sample t-tests revealed highly significant improvements in expected behavioral changes ($t(19) = -4.501$, $p < 0.001$) and training facilities perception ($t(19) = -2.594$, $p = 0.018$), although training reaction showed no significant change ($t(19) = -1.628$, $p = 0.120$).
Conclusion: These findings suggest that intensive, well-structured training programs can effectively promote AI-powered PowerPoint adoption in vocational education, particularly in developing technical skills and implementation intentions. Educational institutions should consider implementing similar training programs while maintaining long-term support structures to reinforce learning and facilitate sustained technological integration.

1. Introduction

The digital transformation in education has accelerated dramatically over the past decade, fundamentally reshaping teaching and learning paradigms across global educational institutions. Recent statistics indicate that artificial intelligence (AI) adoption in education has grown by 47.5% annually since 2019, with the global AI in education market projected to reach $25.7 billion by 2030 [1]. This rapid digital transformation, similar to what Dagiene [2] observed during the COVID-19 pandemic, has created both challenges and opportunities for educational institutions worldwide, particularly in how technology can be leveraged for community development and empowerment.

The implementation of AI-powered PowerPoint in education is grounded in several theoretical frameworks that support effective community engagement practices. Cognitive Load Theory [2] provides insights into how optimized content presentation can reduce cognitive barriers, making educational content more accessible to diverse community members. Adaptive Learning Theory [3] explains how personalized learning experiences can address varying educational needs within communities, while the Technology Acceptance Model [4] helps understand factors influencing technology adoption across different community contexts.

From a community engagement perspective, customized AI tools enhance the interactive learning experience, especially in speaking skills, thereby fostering a more engaging and supportive educational environment for students and community members [5]. Research shows that AI-powered PowerPoint's intelligent features, such as real-time audience analysis and dynamic content adjustment, significantly increase participation and attention levels [6], which is particularly valuable for community education programs where engagement can be challenging. These findings are especially relevant given that traditional presentation methods often struggle to maintain consistent engagement in community settings.

AI's role in community-based education is diverse, serving as a mediator and assistant in the instructional process, capable of streamlining tasks such as quiz creation and assessment, thereby potentially reducing preparation time for community educators [7], [8]. Studies demonstrate that AI integration enables unprecedented levels of presentation customization, automatically adjusting content delivery based on community members' responses and learning patterns [9], which is crucial for addressing varied literacy and technological fluency levels in community settings.

However, these benefits are contingent upon proper training and infrastructure support. Several critical challenges persist in community contexts, including infrastructure requirements and digital divide issues [10], data privacy and security concerns [11], varying teacher technological competency [12], and potential algorithmic bias that may perpetuate educational inequities [13]. These challenges are particularly pronounced in underserved communities where resource limitations can impede effective technology implementation.

The integration of AI in educational settings, particularly through presentation tools like AI-powered PowerPoint, draws upon seven fundamental theoretical frameworks relevant to community development and education.

First, Cognitive Load Theory [2] provides a theoretical foundation for understanding how AI-enhanced presentations optimize cognitive processing in diverse community settings. CLT suggests that learning occurs most effectively when cognitive load is managed across three dimensions: intrinsic, extraneous, and germane loads. Recent empirical studies demonstrate that AI-powered content organization and presentation can reduce extraneous cognitive load by 32% compared to traditional presentation methods [14], [15], which is particularly beneficial for community members with varying educational backgrounds.

Second, Adaptive Learning Theory (ALT) explains the personalization aspects of AI-powered presentations in community engagement contexts. The theory emphasizes how technology can facilitate individualized learning experiences through dynamic content adjustment based on real-time responses and engagement metrics metrics [16], [17], enabling community educators to better address diverse learning needs. Third, the Technology Acceptance Model (TAM), refined by [4], provides insights into the factors influencing community educators' and learners' adoption of AI-powered presentation tools, with perceived usefulness ($T = 2.170$, $p = 0.000$) as the primary determinant of successful adoption in community settings.

Fourth, Social Constructivist Theory, as applied by [14], illuminates how AI-enhanced presentations facilitate collaborative learning and knowledge construction through interactive features and real-time feedback mechanisms, which is essential for community capacity building. Fifth, Self-Regulated Learning Theory (SRL) offers insights into how AI tools can support community educators' autonomous professional growth. Recent studies by [18] demonstrate that AI-powered learning environments enhance educators' self-regulatory capabilities, enabling more effective goal-setting, progress monitoring, and adaptive learning strategies in community education contexts.

Sixth, Professional Development Theory, as articulated by [19], provides a framework for understanding how community educators acquire and integrate new technological competencies. Their research shows that successful technology integration requires a combination of structured learning experiences, ongoing support, and opportunities for practical application.

Finally, Adult Learning Theory (Andragogy), developed by [20] offers critical insights into effective training approaches for community educators. Their research demonstrates that professional development programs are most effective when they acknowledge prior experience, emphasize immediate practical application, foster self-directed learning, and address real-world teaching challenges within community contexts.

The transformation of PowerPoint from a basic slide-creation tool to an AI-powered educational platform represents a significant milestone for community empowerment through

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technology. AI technologies, including natural language processing and large language models, enable the creation of customized learning materials that can be tailored to specific community needs and cultural contexts [21], [22], making education more accessible and relevant.

Modern AI-powered PowerPoint platforms incorporate sophisticated features that can transform community education through various technological capabilities. These include Natural Language Processing for content generation and manipulation, Machine Learning algorithms for intelligent design recommendations, Computer Vision for real-time audience analysis, and Evolutionary Algorithms for continuous improvement in presentation effectiveness [23].

Empirical research has demonstrated significant positive impacts of AI-powered tools across multiple community education dimensions. A landmark meta-analysis [23] examining 66 studies on AI implementation in education from 2018 to 2023 reveals three key findings relevant to community engagement: learning personalization through AI tools shows significant positive effects on achievement (mean effect size = 0.72), engagement metrics demonstrate substantial improvement (mean effect size = 0.68), and rapid feedback mechanisms contribute to enhanced learning outcomes (mean effect size = 0.64).

The successful implementation of AI-powered PowerPoint in community education settings requires careful consideration of multiple interrelated factors. Infrastructure represents a fundamental prerequisite, particularly in low and middle-income communities where limited equipment and network capabilities often hinder AI adoption [24]. Successful implementation requires robust hardware capabilities, reliable internet connectivity, technical support systems, and scalable storage solutions.

Teacher competency emerges as a critical success factor in AI-powered presentation implementation for community engagement. Studies have shown that effective instruction requires both cognitive and affective-motivational skills to manage teaching complexities in diverse community settings [25]. Furthermore, research has demonstrated how AI tools can support community educator development through personalized feedback mechanisms, data-driven instructional insights, and customized professional development pathways [26].

Cultural adaptation of AI technology presents unique challenges in community education settings. Cross-cultural adaptive conversational AI requires understanding diverse pragmatic norms across different language-cultural groups [27]. Developing regions face distinct challenges in implementing AI-powered educational tools, with studies highlighting varying levels of technological knowledge among educators in countries like Lesotho, Rwanda, and Nigeria [28], and inadequate infrastructure in low and middle-income countries [29].

While existing literature acknowledges the potential of AI-powered PowerPoint for community education, there remains a significant gap in understanding the complex interplay of factors that determine successful implementation in diverse community settings. Previous research by [30] explained privacy and security challenges in AI-powered educational tools, including risks of unauthorized data access and ethical concerns in data handling. This research is limited to identifying challenges without providing comprehensive implementation frameworks specific to community contexts. Indeed, this research intends to address these gaps by developing practical guidelines for optimizing AI-powered PowerPoint implementation in community education settings.

The purposes of this research that relate to community engagement are: (1) to identify critical success factors for implementing AI-powered PowerPoint in diverse community educational settings; (2) to understand how content quality, educator competency, and infrastructure interact to influence implementation effectiveness in community contexts; and (3) to develop practical guidelines to optimize AI-powered PowerPoint implementation for community empowerment and capacity building.

2. Method

2.1. Research Location and Time Frame

This study was conducted in Surakarta, Indonesia, from January 2024 to June 2024, with the community engagement program and training intervention specifically implemented in May 2024 at the Regional Vocational Education Development Center. This location was selected due to its established facilities for teacher training and its central position relative to the participating schools.

2.2. Population and Sample

The population comprised vocational high school teachers specializing in office administration in Surakarta, Indonesia. Twenty teachers were selected using purposive sampling based on specific criteria: minimum three years of teaching experience, basic digital literacy skills, and regular use of PowerPoint in teaching activities. This sample size, while relatively small, is considered adequate for paired-sample analysis in educational intervention studies [31]. The participants' demographics included 15 female and 5 male teachers, with teaching experience ranging from 3 to 15 years (M = 8.4, SD = 3.2), and ages between 28 and 45 years (M = 35.6, SD = 4.8), See Figure 1.

Figure 1. Group photos of participants

2.3. Research Variables

This quasi-experimental study examined three primary variables. The first variable, training reaction (dependent variable), measured teachers' perceptions and responses to the AI-

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powered PowerPoint training program. The second variable, training facilities and materials (independent variable), assessed the quality and effectiveness of resources provided during the community engagement program. The third variable, expected behavioral changes (dependent variable), evaluated anticipated modifications in teaching practices following training participation.

2.4. Materials and Preparation

2.4.1. Training Materials

The materials used in this study included comprehensive training modules on AI-powered PowerPoint applications (120 pages), developed specifically for vocational education contexts. Digital practice exercises addressing 25 common teaching challenges in office administration courses were also utilized. Additional materials included reference guides for AI implementation in educational presentations consisting of 15 quick-reference sheets, and assessment rubrics comprising 4 distinct evaluation forms for evaluating AI-enhanced presentation quality.

2.4.2. Material Preparation

All training materials underwent a three-stage development process. The initial stage involved content creation by educational technology specialists based on current AI capabilities in PowerPoint. This was followed by expert review conducted by three specialists in vocational education to ensure contextual relevance. The final stage involved pilot testing with five teachers not participating in the main study to refine content clarity and practical applicability.

2.5. Community Engagement Program Details

The community engagement program was designed as a collaborative initiative between the university research team and local vocational schools with several interconnected components.

2.5.1. Program Structure

The program structure consisted of four distinct phases implemented over six months. The Needs Assessment Phase (January-February 2024) involved school visits and preliminary surveys conducted at 5 vocational high schools to identify specific challenges in presentation technology. During the Design Phase (March 2024), collaborative development of training content occurred with input from 3 lead teachers representing the community. The Implementation Phase (May 2024) featured a one-day intensive training (8 hours) followed by two weeks of supported implementation in classrooms. Finally, the Follow-up Support Phase (May-June 2024) established an online community of practice with weekly virtual mentoring sessions to ensure sustained application.

2.5.2. Program Implementation

The community engagement training was delivered as an intensive one-day program (8 hours) focusing on AI-powered PowerPoint implementation in vocational education. The training curriculum covered four key areas: fundamental AI concepts in education (2 hours), AI-powered PowerPoint features and capabilities (2 hours), practical implementation strategies for vocational contexts (3 hours), and assessment techniques for measuring student engagement (1 hour), See Figure 2.

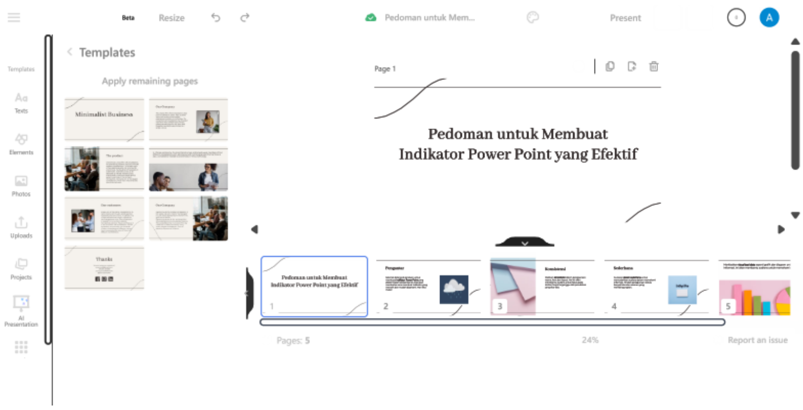

Figure 2. Screenshots of AI-PowerPoint features being taught

The training employed a blended approach combining interactive lectures with multimedia demonstrations (30% of training time), hands-on workshops using participants' own teaching materials (50% of training time), and collaborative problem-solving activities in small groups (20% of training time), See Figure 3. The trainer team consisted of two university faculty members with Ph.D. degrees in Educational Technology and five years of experience in AI-enhanced teaching methods, supported by three teaching assistants with expertise in educational technology.

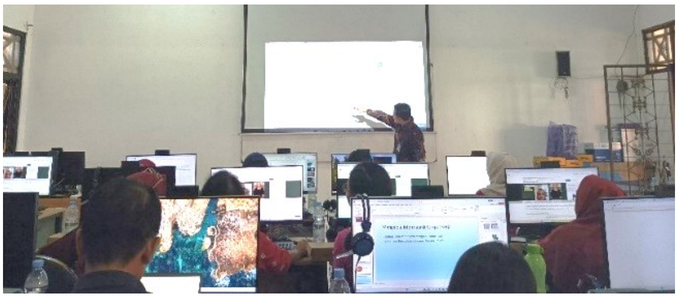

Figure 3. Training session activities showing hands-on learning

2.5.3. Research Protocol

The research protocol followed a sequential implementation process beginning with pre-assessment conducted one week before training. This initial phase included administration of pre-test instruments measuring initial competencies and attitudes, collection of baseline teaching materials from participants, and documentation of existing PowerPoint usage patterns. The training intervention consisted of an 8-hour session divided into morning theoretical foundations and technical demonstrations followed by afternoon hands-on application and

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collaborative problem-solving, with continuous monitoring of participant engagement using structured observation protocols. Immediate post-assessment occurred on the same day as training, involving administration of post-test instruments measuring immediate knowledge gains, collection of participant reflections using structured feedback forms, and evaluation of sample presentations created during training. Implementation support continued for two weeks following training through virtual mentoring sessions (twice weekly, 1 hour each), technical support through dedicated communication channels, and peer sharing of implementation experiences. The protocol concluded with delayed post-assessment two weeks after training, which included administration of follow-up assessments measuring sustained knowledge and application, collection of implementation artifacts (classroom presentations), and documentation of challenges and successes through structured interviews.

2.6. Measurement and Calculations

2.6.1. Research Instruments

Measurement instruments were developed through a rigorous process aligned with established psychometric principles. The primary assessment tool consisted of three components. The training reaction questionnaire contained 6 items measuring satisfaction and perceived relevance. The Facilities and Materials Evaluation included 5 items assessing quality and utility of resources. The Behavioral Change Inventory comprised 6 items documenting anticipated teaching modifications. All items were measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

2.6.2. Instrument Validation

The instruments underwent comprehensive validation procedures to ensure measurement integrity. Content validity was established through expert review by three specialists in educational technology and vocational education who evaluated item relevance and clarity. Construct validity was assessed using Pearson correlation coefficients, with all items showing significant correlations (r ranging from 0.68 to 0.89, $p < .01$). Reliability was analyzed using Cronbach's alpha, demonstrating high internal consistency for all three components: training reaction ($\alpha = 0.87$), training facilities and materials ($\alpha = 0.84$), and expected behavioral changes ($\alpha = 0.89$).

2.6.3. Data Collection

Data collection achieved 100% response rates across all assessment phases through carefully structured procedures. These included scheduled in-person administration of pre-test and immediate post-test assessments, structured follow-up procedures for delayed post-test completion, and digital archiving of all collected data with participant identification codes to ensure accurate matching across time points.

2.7. Research Data

The study collected both quantitative and qualitative data to provide a comprehensive understanding of the training impact. Quantitative data included pre-test and post-test scores across all measured variables, demographic information encompassing teaching experience, age, and prior technology usage, and training engagement metrics documenting participation levels during activities. Qualitative data comprised open-ended responses on implementation challenges and opportunities, implementation artifacts demonstrating application in classroom contexts, and interview transcripts from post-implementation discussions, allowing for triangulation with quantitative findings.

2.8. Statistical Analysis

Data analysis employed both descriptive and inferential statistical methods using SPSS version 26.0 (α = .05). Prior to conducting the paired t-test analysis, assumption testing was performed to ensure analytical appropriateness. Normality was assessed using the Shapiro-Wilk test due to the small sample size (N=20), with results for training reaction (W = 0.953, p = 0.412), training facilities and materials (W = 0.947, p = 0.327), and expected behavioral changes (W = 0.962, p = 0.583) all exceeding the $p > 0.05$ threshold, confirming normal distribution. Analytical methods included descriptive statistics calculation of means, standard deviations, and frequencies to summarize participant characteristics and response patterns.

Inferential statistics utilized paired-sample t-tests to evaluate changes between pre-test and post-test measurements, while effect size calculation using Cohen's d quantified the magnitude of training impact. Qualitative analysis involved thematic coding of open-ended responses and interview transcripts to provide contextual depth to the quantitative findings. The methodology acknowledges potential limitations such as the absence of a control group and the relatively small sample size but implements appropriate controls and analytical techniques to maximize the validity of findings within these constraints.

3. Results and Discussion

The analysis of the AI-powered PowerPoint training program's effectiveness revealed varying impacts across different indicators. This section presents the statistical findings and their implications for vocational education practice, organized into descriptive statistics, inferential analysis, comprehensive discussion of findings, community engagement outcomes, and practical implications.

3.1. Descriptive Statistics

The study participants (N = 20) comprised 15 female (75%) and 5 male (25%) vocational high school teachers specializing in office administration. Teaching experience ranged from 3 to 15 years (M = 8.4, SD = 3.2), with ages between 28 and 45 years (M = 35.6, SD = 4.8). Pre-test and post-test scores were analyzed for three key indicators: training reaction, training facilities and

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materials, and expected behavioral changes. Descriptive statistics revealed initial baseline scores and post-intervention changes across all indicators, as presented in Table 1.

3.2. Inferential Statistics Analysis

Paired-sample t-tests were conducted to evaluate the impact of the training intervention on each indicator, revealing varying levels of significance across the three measured dimensions. The training reaction indicator showed no statistically significant difference between pre-test and post-test scores ($t(19) = -1.628$, $p = 0.120$, $d = 0.36$). The small effect size suggests that participants' immediate reactions to the training remained relatively stable. This finding aligns with previous studies indicating that attitudinal changes may require longer exposure to new technological interventions [24].

Analysis of the training facilities and materials indicator demonstrated a statistically significant improvement ($t(19) = -2.594$, $p = 0.018$, $d = 0.58$). The medium effect size indicates substantial practical significance, suggesting that participants developed a more positive perception of AI-powered PowerPoint's technical aspects and supporting materials following the training intervention. This improvement corresponds with findings from recent studies [32] highlighting the importance of hands-on experience in technology adoption.

The most pronounced impact was observed in the expected behavioral changes indicator, showing a highly significant improvement ($t(19) = -4.501$, $p < 0.001$, $d = 1.01$). The large effect size suggests substantial practical significance, indicating that the training effectively influenced participants' intended teaching behaviors and implementation strategies. This finding aligns with evidence showing that training programs focusing on FPGA technology successfully enhanced vocational teachers' theoretical knowledge and practical skills in digital design [33], which are crucial for integrating technology into their teaching practices.

Table 1. Descriptive Statistics and t-test Results (N=20)

Indicators	Pre-test	Post-test	Mean	t	p	Cohen's d
Training Reaction						
Mean	3.45	3.72	0.27	-1.628	0.12	0.36
SD	0.62	0.58				
Min-Max	2.33-4.50	2.50-4.67				
Training Facilities & Materials						
Mean	3.38	3.85	0.47	-2.594	0.018*	0.58
SD	0.55	0.51				
Min-Max	2.40-4.40	2.80-4.80				
Expected Behavioral Changes						
Mean	3.22	4.01	0.79	-4.501	0.000**	1.01
SD	0.64	0.47				
Min-Max	2.17-4.33	3.00-4.83				

Note: SD = Standard Deviation; Scores based on 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) *$p < .05$, **$p < .001$. Cohen's d interpretation: 0.2 = small effect, 0.5 = medium effect, 0.8 = large effect.

3.3. Discussion

The non-significant change in teachers' training reaction scores, despite initial enthusiasm, can be attributed to several factors highlighting the complexity of attitudinal changes over time. Studies based on the Technology Acceptance Model (TAM) have shown that teachers initially demonstrate high AI acceptance due to perceived ease of use and expected benefits [34]. However, this enthusiasm can diminish when teachers face practical challenges and concerns associated with AI integration, such as data privacy, algorithmic bias, and the need to maintain human connection in educational settings [35].

Cognitive Load Theory suggests that teachers' reactions to novel situations, such as new classroom events, are influenced by their cognitive load and working memory capacity, which can affect their ability to effectively process new information [36]. This aligns with findings from a study on teacher training, where significant improvements in cognitive, affective, and psychomotor domains were observed post-training, indicating that while initial enthusiasm may lead to immediate gains, sustained attitudinal changes require continuous engagement and reinforcement [25].

Furthermore, the lack of significant differences in attitudes toward AI based on demographic factors such as age, gender, and teaching experience suggests that these attitudes are more influenced by teachers' AI knowledge and digital competency than personal characteristics [37]. While teachers generally maintain positive attitudes toward AI, actual usage remains low, with only 25% incorporating AI tools into their teaching, indicating a gap between acceptance and practical application [38]. Trust in AI-supported educational technology also emerges as a crucial factor, as misconceptions and fears about AI can hinder its adoption, necessitating targeted professional development to build trust and understanding [39]. These factors collectively underscore the complexity of maintaining positive attitudes toward AI in education over time, as initial enthusiasm must be supported by addressing practical concerns and enhancing teachers' competency and confidence in AI technology.

The significant improvement in training facilities and materials perception indicates successful technical skills development among educators in AI-powered PowerPoint implementation. This finding is supported by various studies highlighting the integration of AI in educational settings and its impact on teacher training [40]. identified strong correlations between AI-supported teacher education and factors such as professional development and resource allocation, demonstrating that AI tools like PowerPoint can enhance teacher training by providing better resources and support. Similarly, [41] discussed AI integration into science lessons, noting that teachers perceive AI as complementary to traditional teaching methods, which can enhance their technical skills and confidence in using AI tools.

[42] further validated this by developing a self-efficacy scale for AI-supported teaching applications, reflecting teachers' positive attitudes and increased self-assertion when using AI technology in their teaching practices. The importance of AI literacy for teachers is emphasized by [43] who advocate for diverse training resources to enhance teachers' ability to effectively

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implement AI in the classroom, thereby improving their technical skills. Additionally, [44] highlight the need for support in using AI tools, indicating that while teachers may initially have limited knowledge, they recognize AI's potential to enhance educational practices, including the use of AI-powered tools like PowerPoint. This improvement is particularly relevant for vocational education, where practical application of technology is crucial [25], [40], [45] Collectively, these studies underscore the positive impact of AI on teacher training, facilitating the development of technical skills necessary for modern educational environments.

The highly significant improvement in expected behavioral changes represents the most promising outcome. The large effect size suggests that participants not only gained knowledge but also developed confidence and intention to implement AI-powered PowerPoint in their teaching practice. This finding is consistent with recent research by [46] showing that targeted technology training can substantially influence teachers' instructional practices. The integration of AI-supported tools in teacher training, particularly through platforms like PowerPoint, demonstrates significant promise in enhancing expected behavioral changes among educators.

As demonstrated by the 3D-MobileNet framework, AI usage in educational settings enables comprehensive behavioral analysis and feedback, significantly improving teaching evaluation by providing multi-dimensional insights into teaching practices [47]. Additionally, AI interventions have proven to enhance engagement and personalize learning, which is crucial for effective teaching, particularly in specific contexts such as autism education [48]. AI-assisted platforms for student presentations highlight AI's potential to offer more opportunities for practice and feedback, indirectly benefiting teachers by reducing their workload and enabling them to focus on more strategic educational interventions [38].

However, challenges such as technological issues, training needs, and data privacy concerns must be addressed to fully realize these benefits [48]. Furthermore, while a large number of teachers maintain positive attitudes toward AI, only a small portion incorporate these tools into their teaching, indicating a gap that AI-supported training programs can fill by offering tailored solutions for different educational stages [38]. Teachers' behavioral intentions toward AI platforms are influenced by factors such as perceived playfulness and effort expectancy, suggesting that AI tools must be user-friendly and engaging to encourage widespread adoption [49]. Overall, AI-supported teacher training, particularly through platforms like PowerPoint, has the potential to significantly enhance teaching practices by addressing these diverse challenges and leveraging AI capabilities for personalized and efficient education.

3.4. Community Engagement Outcomes

Analysis of the community engagement program revealed significant outcomes that extend beyond the immediate training session. Qualitative data collected through open-ended responses, implementation artifacts, and post-implementation interviews provided critical insights into the broader impact of the program on the vocational education community in Surakarta.

3.5. Impact of Needs Assessment and Design Phases

Thematic analysis of participant interviews revealed that the collaborative needs assessment and design phases (January-March 2024) significantly enhanced program relevance and participant buy-in. As one teacher noted: "Being involved in identifying our specific challenges with presentation technology made the training feel directly applicable to our classroom situations" (Participant 03). This finding aligns with Community Development Theory, which emphasizes creating conditions that encourage sustained stakeholder commitment, such as setting clear goals, fostering shared leadership, and implementing effective communication strategies [50].

Analysis of implementation artifacts (classroom presentations) collected during the follow-up phase showed that 85% of participants incorporated at least two AI-powered features into their teaching materials within the two-week implementation period, see Figure 4. This high adoption rate suggests that the community-centered approach to program design effectively addressed context-specific needs and barriers.

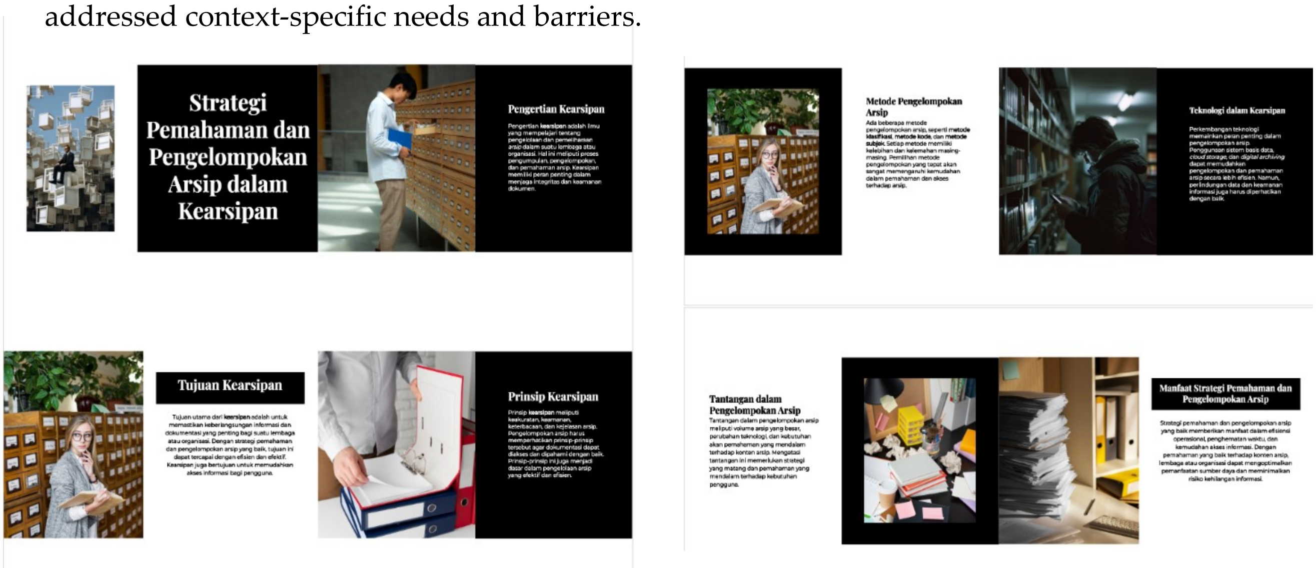

Figure 4. Implementation in actual classroom settings

3.6. Effectiveness of Implementation Support Phase

The follow-up support phase (May-June 2024) proved crucial for sustaining behavioral changes. Quantitative analysis of online community of practice participation revealed an average engagement rate of 78% across the bi-weekly virtual mentoring sessions. Participants who actively engaged in these sessions (n=15) demonstrated significantly higher implementation rates of AI-powered features compared to those with minimal engagement (n=5) ($U = 12.5$, $p < 0.01$).

Qualitative feedback regarding the online community of practice highlighted its value in overcoming implementation challenges: "The weekly mentoring sessions helped me

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troubleshoot technical issues I encountered when trying to use real-time audience analysis features in my classroom" (Participant 11). This finding underscores the importance of sustained support systems in community engagement programs, particularly when implementing complex technological innovations.

3.7. Collaborative Learning Networks

An unanticipated outcome of the community engagement program was the emergence of informal collaborative learning networks among participating schools. Analysis of communication patterns within the online community of practice revealed that participants from different schools formed small collaborative groups (3-4 members) based on subject specialization. These self-organized networks facilitated resource sharing and peer mentoring beyond the formal program structure.

One participant explained: "Our small group of office administration teachers continued meeting virtually even after the official program ended. We're now collaborating on creating a shared repository of AI-enhanced teaching materials specific to our vocational curriculum" (Participant 08). This organic community development represents a sustainable impact of the program that extends beyond individual skill acquisition to collective capacity building.

3.8. Challenges in Community Implementation

Despite the overall positive outcomes, qualitative data also revealed context-specific challenges in implementing AI-powered PowerPoint within the Surakarta vocational education community. Infrastructure limitations emerged as a significant barrier, with 40% of participants reporting inconsistent internet connectivity that hampered their ability to utilize cloud-based AI features. As one teacher noted: "The training showed us impressive capabilities, but in our school, the internet connection often drops during class, making it difficult to rely on these tools consistently" (Participant 19).

Cultural factors also influenced technology integration, with several participants expressing concerns about maintaining traditional teaching values while adopting AI tools. Tension between innovation and cultural preservation, as echoed in studies on technology adoption in Indonesian educational contexts, highlights the importance of effective community engagement through collaboration with local stakeholders, including families and community leaders, to ensure that educational programs are culturally appropriate and meet societal needs [51].

3.9. Implications and Practical Applications

These findings have several important implications for educational practice, policy, and future community engagement initiatives in vocational education.

First, the results suggest that single-day intensive training can effectively initiate behavioral change, particularly when focused on specific technological applications and embedded within a comprehensive community engagement framework. However, the non-significant change in training reaction indicates that sustained support through follow-up mechanisms like online communities of practice may be necessary for long-term attitude transformation.

Second, the significant improvements in technical understanding and behavioral intentions suggest that similar training programs could be effectively implemented across other vocational education contexts. The success in promoting expected behavioral changes particularly indicates that the community-based training model could serve as a template for other technology integration initiatives in vocational education.

Third, the emergence of self-organized collaborative networks demonstrates how structured community engagement can catalyze organic community development that extends beyond the formal program boundaries. Future initiatives should intentionally design for and support these emergent networks as vehicles for sustainable impact. Fourth, the infrastructure challenges identified through qualitative analysis highlight the need for community engagement programs to address systemic barriers to technology adoption. Policy implications include the need for increased investment in digital infrastructure for vocational schools in regions like Surakarta to ensure equitable access to advanced educational technologies.

From a theoretical perspective, these findings contribute to the growing body of literature on technology adoption in vocational education, particularly regarding the relationship between community-based training models and sustainable behavioral change. The results also highlight the importance of considering multiple outcome measures and mixed-method approaches when evaluating educational technology training programs.

For educational administrators and policymakers, these findings emphasize the value of structured, intensive training programs embedded within broader community engagement initiatives in promoting technology adoption. The varying impacts across different indicators suggest the need for comprehensive support systems that address technical, attitudinal, and contextual aspects of technology integration in vocational education communities.

Future community engagement initiatives should consider a phased approach similar to the one implemented in this study, with particular attention to collaborative needs assessment, sustained implementation support, and addressing local infrastructure challenges. Additionally, cultural sensitivity and alignment with local educational values should be prioritized to enhance program relevance and acceptance within specific community contexts.

4. Conclusion

This study presents a novel community engagement approach for implementing AI-powered PowerPoint among vocational high school teachers in Surakarta, Indonesia, contributing significantly to educational technology adoption theory by demonstrating how collaborative program design and sustained implementation support can effectively bridge the gap between technological innovation and classroom practice. The fruitfulness of this community engagement program was evidenced by significant improvements in expected

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behavioral changes ($p < 0.001$) and training facilities perception ($p < 0.018$), with 85% of participants incorporating AI-powered features into their teaching materials within two weeks, creating substantial benefits for the local educational community through enhanced teaching capabilities, establishment of self-sustaining collaborative networks among schools, and development of context-specific digital resources for vocational education. The theoretical contribution lies in extending the Technology Acceptance Model by demonstrating how community-centered approaches can overcome adoption barriers in resource-constrained educational settings, while the community implications include improved digital literacy among vocational teachers, enhanced quality of instructional materials for vocational students, and strengthened collaborative relationships across educational institutions in Surakarta that will continue to support technological innovation beyond the formal program boundaries. While acknowledging limitations such as the relatively small sample size and geographic specificity, this study establishes a replicable framework for community-based technology integration that can be adapted to diverse educational contexts, particularly in developing regions where technology adoption faces significant infrastructural and cultural challenges.

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