

University Entrepreneurship: AI-Based Teaching to Enhance Advertising Communication Competence of the MSME Community Outreach: Sequential Exploratory Mixed Methods

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Abstract

This study evaluates the role of university entrepreneurship in training the use of Artificial Intelligence to improve the skills of the Micro, Small, and Medium Enterprises (MSMEs) community in developing mass communication through advertising. Using an explanatory mixed-methods approach involving MSMEs in Sukoharjo, this study applies the Kirkpatrick four-stage model in four phases. Phase 1 (Quantitative) used surveys measuring Reaction, Learning, and Behavior (Cici AI, Canva, Leonardo AI, Suno AI), and PLS-SEM for structural analysis. Phase 2 (Qualitative) utilized semi-structured interviews and observations, analyzed through thematic analysis. Phase 3 (Integration) used joint display analysis to connect findings. The Wilcoxon test showed significant improvement across all participants. PLS-SEM confirmed that AI Usability significantly predicts Advertising Competency and Training Effectiveness, with all constructs meeting validity criteria. Qualitative analysis identified four explanatory themes: accessibility (zero design-entry for audio/text AI versus skill barriers for visual AI), confidence transformation, infrastructure constraints, and text/audio AI as collaborative partners versus visual AI requiring expertise. The sequential explanatory design provides both statistical evidence that AI training significantly improves MSME competency and mechanistic understanding of why. Audio and text AI tools suit MSME beginners best, while visual AI requires extended training. This framework offers a template for evidence-based training evaluation in MSME empowerment programs.

Keywords: *Kirkpatrick Model, AI Training Evaluation, Advertising Creation, MSMEs*

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Introduction

Entrepreneurship at universities is the process by which educational institutions of higher learning encourage innovation, commercialize academic research, and provide students and staff with the skills necessary to succeed in the corporate world through three fundamental pillars: education, the translation of research, and ecosystem support (Fatoki, 2014; Guerrero et al., 2023; Pacheco et al., 2024; Sekerbayeva et al., 2023). University entrepreneurship involves higher education institutions promoting innovation, commercializing research findings, and instructing on business development. It encompasses three fundamental domains: entrepreneurship education, monetizing academic research, and ecosystems for campus startups (Guerrero & Urbano, 2017). After the initial university revolution that integrated research into universities' core objectives, the sector underwent a second transformation, with universities increasingly seen as institutions focused on teaching, research, and economic development (Kireyeva1, et. al., 2026; Galvão et al., 2018). The entrepreneurial university acts as a channel for knowledge and a source of entrepreneurial opportunities for the university community, training students in entrepreneurship and providing innovative knowledge and skills to the community and small-scale enterprises (Papadakis et al., 2024a). Additionally, scholars and students may initiate novel projects that combine academic and entrepreneurial elements, fostering creativity and initiative (Guerrero & Urbano, 2017).

In Indonesia, the government has actively promoted university entrepreneurship through the *Merdeka Belajar Kampus Merdeka* (MBKM) policy and its flagship *Wirausaha Merdeka* program, which provides students with practical entrepreneurial experience recognized for up to 20 credits and emphasizes mentorship, business incubation, and competency development (Cipta & Hatamar, 2024; Ibrahim, 2026; Dunggio et al., 2024); in the Special Region of Sukoharjo, universities such as University of Veteran Bangun Nusantara implemented structured entrepreneurship programs, including KPPU collaboration and agribusiness incubators, to strengthen university-industry linkages and support MSMEs (Napitu et al., 2022); these efforts are increasingly framed within the Triple Helix model, which synergizes academic expertise, government policy, and business agility, although recent research reveals persistent regulatory misalignment, limited

commercialization pathways, weak industry absorptive capacity, and the absence of integrated digital collaboration platforms in developing economies (Astrini et al., 2025; Sudrajat et al., 2023), and the present study builds upon this collaborative framework by providing AI-based advertising training to MSMEs in Sukoharjo, directly addressing the government's call for universities to contribute innovation to society through entrepreneurship programs in partnership with local governments (Papadakis et. al., 2024b).

Sukoharjo was selected as the research site because it represents a strategic intersection of higher education density and MSME concentration in Indonesia. The province hosts many universities and MSMEs, making it an ideal laboratory for university–industry collaboration. The local government has actively encouraged universities to allocate community service funding to MSME digital empowerment. Sukoharjo's MSME sector is dominated by food/beverage, fashion, and craft businesses—sectors that rely heavily on visual and audio advertising but often lack design and marketing expertise. This context makes the AI advertising training both timely and relevant. Creating a culture of innovation and continuous professional development engages micro-enterprises and empowerment partners with new technologies while emphasizing equitable access to technology and stakeholder collaboration (Bohari et al., 2025).

Digitalization and AI have grown in marketing, creating new potential and difficulties (Al-Hunaiyyan et al., 2025). Maintaining system integrity requires a balanced strategy that embraces AI's transformational potential while supporting ethical and equitable technology use (Mohd Amin et al., 2025). In collaboration with Micro, small, and medium enterprises (MSMEs), this study provides training in implementing AI technology to build crucial marketing and advertising skills. The program promotes the Indonesian Minister of Higher Education's view that universities should contribute innovation to society through entrepreneurship programs in collaboration with the local government (Alviani & Munawaroh, 2025; Rachmaniyah et al., 2024). AI technology facilitates the analysis and personalization of consumer behavior and preferences (Gupta, 2024), making it easier for advertisers to create advertising messages that creatively resonate with their target market. This AI capability supports contemporary advertising activities by linking messages to

consumers and improving effectiveness and efficiency. AI can also support media planning and map customer segmentation and target conditions (Hou, 2024; Kediya et al., 2024).

AI's ability to present and analyze large data sets helps MSMEs identify new opportunities and improve advertising strategies (Tetiana, 2024). AI simplifies ad creation through automation, providing resources for generating big ideas and creative messages (Patil, 2025). While large companies have adopted this technology, MSMEs need training support to keep up with digital transformation. AI-powered predictive models analyze consumer behavior to optimize marketing strategies, increase engagement (Bhattacharya, 2025), and highlight the technology's potential to improve advertising campaign effectiveness. However, a lack of internal capabilities and technical skills remains a major barrier to adopting big data and other digital technologies. Therefore, training is key to reducing the digital divide, empowering MSMEs, and building the human resource capacity to use AI effectively, equipping MSMEs with technical skills and data-driven advertising message development (Papadakis et al., 2024a).

Studies show how MSMEs integrate AI into advertising strategies. Lu et al. (2022) discovered the ability of AI to identify products, increase efficiency, and improve digital marketing, which can indirectly help SME advertising strategies. Van Esch and Black (2021) highlighted that AI can revolutionize digital marketing by creating content, generating leads, and controlling customer acquisition costs, which can indirectly help SMEs. Drydakis (2022) emphasizes that AI applications can help SMEs become more dynamic and efficient and reduce business risks, which can indirectly benefit advertising strategies. Rajaram and Tinguely (2024) illustrates that generative artificial intelligence can improve product offerings and SMEs' long-term competitiveness by improving work processes and driving innovation. To evaluate whether AI-based advertising training works, this study draws on the Kirkpatrick and Kirkpatrick (2006) model, a widely used framework that assesses training programs at four levels: Reaction, Learning, Behavior, and Results. The study is guided by one primary research question and four subsequent research questions, presented below.

Primary Research Question

How does the integration of Artificial Intelligence in advertising influence the design and effectiveness of an entrepreneurship program as measured by the four levels of the Kirkpatrick model?

Subsequent research questions

1. To what extent do MSME participants perceive AI-designed advertisements as visually appealing, relevant, and engaging compared to traditional advertising methods?
2. How does AI-based advertising training affect MSME participants' comprehension of advertising message creation and their competency in using AI tools for advertising purposes?
3. How do MSME participants perform when using different AI applications (Cici AI, Canva, Leonardo AI, and Suno AI) to create advertisements for their products?
4. To what degree does AI-based advertising training improve MSME participants' overall AI literacy, advertising competency, and capacity to create effective promotional content independently?

Literature Review

University Entrepreneurship

Guerrero et al. (2023) define university entrepreneurship as the initiatives, support systems, and educational efforts within higher education that foster innovation, business creation, and research commercialization, resting on three pillars: education, incubation, and technology transfer. These pillars include education and training (courses, workshops, and minors building business and problem-solving skills), incubation support (maker spaces, campus incubators, and science parks offering creation venues), and technology transfer (offices converting research into patents, ventures, and industry partnerships) (Guerrero & Urbano, 2017; Pacheco et al., 2024). According to Pacheco et al. (2024), university entrepreneurship drives economic growth, job creation, and local business networks while helping students build practical skills and launch ventures and moving scholarly ideas from lab to real-world application; Guerrero and Urbano (2017) add that an entrepreneurial

university acts as a knowledge reservoir and catalyst, enabling faculty and students to create ventures blending intellectual and commercial elements.

In the Indonesian context, the MBKM policy institutionalizes university entrepreneurship by requiring universities to design programs with measurable community impact. However, the literature on Indonesian university entrepreneurship has largely focused on student outcomes (e.g., start-up creation, credit recognition) rather than community-level outcomes such as MSME capacity building (Papadakis et. al., 2024a). This study addresses that gap by positioning MSMEs as the primary beneficiaries of university entrepreneurship programs.

Kirkpatrick's Training Model and Human Resource Development

AI-based advertising creation training is a highly targeted empowerment strategy. By leveraging AI technology, MSMEs can produce more creative, targeted, and trend-aligned advertising content without incurring high costs (Huh et al., 2023). Training is crucial for building MSME beneficiaries' knowledge, skills, and expertise to quickly adopt evolving digital technology innovations (Fatmawati & Muksin, 2024). The Kirkpatrick training evaluation model is a comprehensive, structured model encompassing four stages: reaction, learning, behavior, and outcomes (Papadakis et al., 2024b). Table 1 presents the four levels of the Kirkpatrick model and their application in this study.

Table 1

Kirkpatrick Four-Level Training Evaluation Model

Level	Focus	Key Questions	Measurement in This Study
Level 1: Reaction	How participants feel about training	Did they like it? Was it relevant?	Post-training satisfaction survey (4-point)
Level 2: Learning	Knowledge/skill increase	What did they learn?	Pre-post AI literacy comparison (4-point)
Level 3: Behavior	Application of learning	Do they use it? How well?	AI advertising work assessment (4-point)
Level 4: Results	Organizational impact	Did it matter?	Overall competency transformation

Source: Kirkpatrick & Kirkpatrick (2006); De Saá-Pérez et al. (2012); Wang & Chang (2017)

In this study, Level 3 is operationalized as *simulated behavior*—the ability to produce advertising outputs in a training setting—rather than sustained workplace behavior change. This distinction is discussed further in the Methods section, and the Discussion addresses the implications for interpreting Level 4 results.

The Kirkpatrick Model is a widely recognized framework for evaluating training effectiveness, assessing outcomes across four hierarchical levels: reaction, learning, behavior, and results (De Saá-Pérez et al., 2012; Wang & Chang, 2017). The first stage evaluates participants' readiness and engagement, and studies generally report positive feedback on training experiences. The second stage measures knowledge and skill acquisition through pre- and post-test comparisons, while the third stage examines workplace behavioral changes, with findings showing significant improvements after training. The final stage assesses the impact on individual and organizational performance, including increased productivity and work effectiveness (United Nations Development Programme, 2009).

The Kirkpatrick Model has been adopted as a community empowerment strategy grounded in human resource capacity development, which emphasizes two key elements: providing power and developing capacity (Ife & Tesoriero, 2008; Mardikanto, 2010b; Soetomo, 2009). Empowerment focuses on strengthening individuals' ability to handle difficult situations and actively engage in problem-solving (Peterson, 2014) while capacity development is a continuous process of increasing individuals' abilities to perform specific roles (Mardikanto, 2010a; Suarez-Balcazar et al., 2008). This approach encompasses professional capacity development—including technical skills, entrepreneurial attitudes, and management skills—as well as personality capacities that influence values, attitudes, and behavior in daily life (Mardikanto, 2010b; Soetomo, 2009). Training for AI-based advertising creation to empower MSMEs exemplifies this strategy, where capacity development enhances beneficiaries' ability to create persuasive advertisements, a crucial element of marketing activities aimed at influencing potential buyers.

Advertising Activities

Richards and Curran (2002) define advertising as paid, persuasive communication from identifiable advertisers through specific media, designed to influence potential consumers to act immediately or later, and requiring distinctive traits that set it apart from competing commercials. Duncan and Moriarty (1998) view advertising as a micro-level communication activity and identify its differentiating characteristics, while McGuire (1969) and Calfee and Ringold (1994) argue that category, levels, and emphasis distinguish advertising from other communicative actions. A key element of this distinctiveness is the

message source, whose capability and appeal—shaped by trustworthiness, comprising proficiency and confidence—can alter consumer perceptions, since trustworthy advertising messages are tied to reliable communication sources.

Creating Ads Using Artificial Intelligence (AI)

AI places human users at the center of an abstract, algorithm-driven partnership, with generative AI technologies such as DALL-E, GPT-3, and ChatGPT rapidly advancing in the creative industries to synthesize text, images, music, and other content while automating certain creative tasks (Hocutt, 2024; Bhusan, 2024). AI is positioned as a transformative technology that is revolutionizing advertising by increasing effectiveness, productivity, and consumer interaction (Oldemeyer et al., 2024; Tran, 2024), streamlining advertising creation—from narratives and text to voice and images—that would otherwise require significant human effort, and complementing human skills to positively support advertising, branding, and creativity (Yu, 2022; Tran, 2024). As a key arena shaped by AI, advertising offers marketers innovative ways to streamline processes and engage clients more efficiently and personally, with analysis primarily focusing on applications such as personalization, consumer engagement, data analysis, and decision-making (Tran, 2024; Song et al., 2024).

Recent work on AI-enhanced professional learning emphasizes that effective AI training must account for learners' prior digital literacy and provide scaffolded, hands-on experiences (Papadakis et al., 2024a). Kireyeva¹, et. al., (2026) and Papadakis et al. (2024b) further argue that digital innovation in training contexts is most successful when learners perceive the technology as accessible and immediately useful—a principle that aligns with the accessibility gradient observed in this study. These insights inform the theoretical framing of AI Usability as a key antecedent of training effectiveness.

Conceptual Framework and Theoretical Underpinnings

This study's conceptual framework draws on three complementary theoretical perspectives: the Technology Acceptance Model (TAM), Kirkpatrick's Training Evaluation Model, and Empowerment Theory. Together, these theories explain the relationships among AI Usability, Advertising Competency, and Training Effectiveness. The model posits a mediation pathway: AI Usability → Advertising Competency → Training Effectiveness.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989) posits that perceived ease of use and perceived usefulness are the primary determinants of technology adoption. In this study, AI Usability operationalizes perceived ease of use—the degree to which MSME participants believe using AI applications for advertising creation would be effortless. TAM suggests that when users perceive a technology as easy to use, they are more likely to adopt it and become proficient. This theoretical assumption underpins the hypothesized relationship between AI Usability and Advertising Competency (H_1): participants who find AI tools easy to use are more likely to develop competence in creating AI-based advertisements (Venkatesh & Davis, 2000; Venkatesh et al., 2003). The accessibility gradient observed in this study—where audio and text AI applications were more accessible than visual AI applications—further validates this assumption, as participants consistently reported that "zero-design-entry" applications required less effort and produced immediate success.

Kirkpatrick's Training Evaluation Model

The Kirkpatrick model (Kirkpatrick & Kirkpatrick, 2006) provides a hierarchical framework for evaluating training effectiveness across four levels: reaction, learning, behavior, and results. This study operationalizes Training Effectiveness as the composite outcome across all four levels. The theoretical assumption underlying the relationship between AI Usability and Training Effectiveness (H_2) is that when training participants find AI tools easy to use (positive reaction at Level 1), they are more likely to acquire knowledge and skills (Level 2), apply those skills in practice (Level 3), and achieve meaningful outcomes (Level 4). Similarly, the relationship between Advertising Competency and Training Effectiveness (H_3) is grounded in the Kirkpatrick model's assumption that behavioral change (Level 3)—in this case, the ability to create effective AI advertisements—critically determines overall training results (Level 4). This hierarchical structure explains why Advertising Competency is positioned as a mediator between AI Usability and Training Effectiveness (De Saá-Pérez et al., 2012; Wang & Chang, 2017).

Empowerment Theory

Empowerment theory (Peterson, 2014; Ife & Tesoriero, 2008) provides the theoretical foundation for understanding how AI training transforms participants' self-perception and agency. Empowerment is defined as the process by which individuals gain control over their lives and develop the capacity to solve problems (Rappaport, 1987; Zimmerman, 2000). In this study, the relationship between AI Usability and Advertising Competency is not merely technical; it is psychological. When participants experience immediate success with accessible AI tools, they develop confidence in their ability to use technology, which in turn enhances their competency. This shift in confidence aligns with empowerment theory's emphasis on psychological empowerment—the belief that one can influence outcomes and make a difference (Peterson, 2014; Zimmerman & Warschausky, 1998). The qualitative finding that participants shifted from "AI is impossible" to "I felt empowered" supports this theoretical assumption.

Integration: The Mediating Role of Advertising Competency

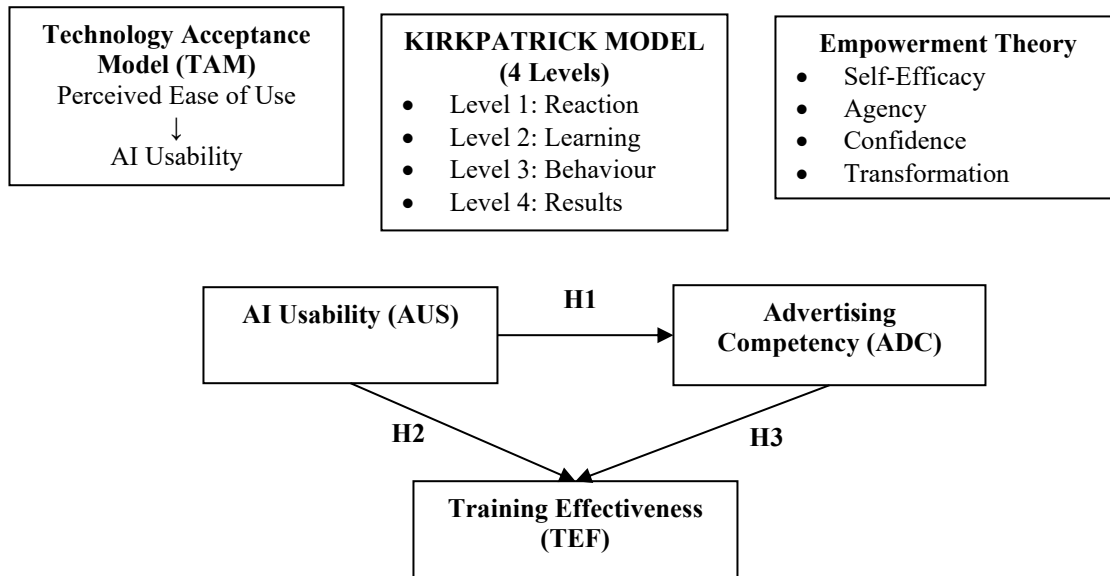
The conceptual model posits that Advertising Competency mediates the relationship between AI Usability and Training Effectiveness. The following theoretical logic justifies this mediation: AI Usability (perceived ease of use) creates the conditions for learning by reducing barriers to engagement. However, developing actual competency—the ability to produce effective AI advertisements—directly translates into training effectiveness. This is consistent with the Kirkpatrick model's hierarchical assumption that behavior change (Level 3) must occur for meaningful results (Level 4) to be achieved (Kirkpatrick & Kirkpatrick, 2006). The qualitative finding that "zero-design-entry" applications helped build confidence, which then enhanced competency, supports this mediation pathway with empirical evidence.

Conceptual Model and Hypotheses

Based on the theoretical integration above, the following conceptual model guides this study (see Figure 1). Three hypotheses are proposed:

- *H*₁: AI Usability positively affects Advertising Competency
- *H*₂: AI Usability positively affects Training Effectiveness
- *H*₃: Advertising Competency positively affects Training Effectiveness

Figure 1
Conceptual Model



Research Design

This study used a sequential explanatory mixed-methods design (Creswell & Plano, 2011; Fetter et al., 2013). The design consisted of three phases: Phase 1 (Quantitative) involved surveys and performance assessments with 30 MSME participants; Phase 2 (Qualitative) involved semi-structured interviews with 12 selected participants; Phase 3 (Integration) employed joint display analysis to connect quantitative and qualitative findings.

Participants for Quantitative and Qualitative

Quantitative Sample. A total of 30 MSME owners from Sukoharjo, students who own micro or small businesses participated in the training program. Participants were recruited through the Sukoharjo Office of Cooperatives and SMEs and the community service network of Universitas of Veteran Bangun Nusantara. Inclusion criteria were: (a) active MSME owner or manager, (b) business age ≥ 1 year, (c) willingness to attend two full days of training, and (d) no prior formal design training.

Qualitative Sample. From the 30 participants, 12 were purposively selected for semi-structured interviews using maximum variation sampling based on two criteria: (a) performance quartile—participants in the top quartile (mean advertising quality score ≥ 3.75) and bottom quartile (mean advertising quality score ≤ 3.25) were prioritized; and (b) infrastructure profile—device type (smartphone vs. laptop) and internet quality

(good/fair/poor). This dual-criteria approach ensured representation of both high and low performers, as well as participants with varying technological constraints. Table 2 presents the demographic characteristics of the 12 selected participants.

Table 2
Demographic Characteristic

	Characteristic	N	%
Gender	Female	22	73.3%
	Male	8	26.7%
Business Age	<2 years	12	40.0%
	2-5 years	14	46.7%
	>5 years	4	13.3%
Business Type	Food/beverage	11	36.7%
	Fashion/apparel	9	30.0%
	Crafts/accessories	6	20.0%
	Other	4	13.3%
Prior AI Experience	Never used AI (1)	13	43.3%
	Basic knowledge (2)	12	40.0%
	Moderate knowledge (3)	5	16.7%
	Advanced knowledge (4)	0	0%

Quantitative Instruments

We developed a 4-point ordinal coding scheme (Jamieson, 2004). We developed the scales based on the Kirkpatrick framework (Kirkpatrick & Kirkpatrick, 2006) and adapted them from established instruments (De Saá-Pérez et al., 2012; Wang & Chang, 2017). The instrument underwent four development stages:

1. Item generation — 15 initial items were generated based on the Kirkpatrick framework and prior instruments.
2. Content validity assessment — Five experts (two training evaluation specialists, two MSME practitioners, and one AI advertising practitioner) rated each item's relevance using a 4-point scale. We calculated the Content Validity Index (CVI) and removed items with $CVI < .80$ (Lawshe, 1975; Polit & Beck, 2006). We removed three items, leaving 12 items.
3. Pilot testing — The 12-item instrument was pilot-tested with 10 MSME participants using cognitive interviews (Saunders et al., 2019). The authors made minor wording

revisions based on participant feedback.

4. Final refinement — The final instrument consisted of 12 items measuring three constructs (AI Usability, Advertising Competency, and Training Effectiveness) on a 4-point ordinal scale. Validity and reliability were confirmed (Tables 4 and 5) (Nunnally & Bernstein, 1994).

Kirkpatrick Level 1 (Reaction) was measured with a four-item survey (Table 3), Level 2 (Learning) with a pre-post literacy assessment (Table 6), and Level 3 (Behavior) with trainer assessment checklists (Table 7).

Table 3

Kirkpatrick Level 1: Reaction Survey

Item	Code	Question
TEF1	R1	The training material was easy to understand
TEF2	R2	The AI applications demonstrated were relevant to my business
TEF3	R3	I would recommend this training to other MSME owners
TEF4	R4	The training significantly improved my advertising skills

Kirkpatrick Level 2 (Learning) was assessed by comparing participants' AI literacy before and after the training using a self-rated pre-post assessment. Table 6 presents the pre-training and post-training literacy categories, ranging from 'None' to 'Expert' on the 4-point scale. The measurement model's validity was assessed through convergent and discriminant validity. Table 4 shows that all outer loadings (.774–.914) and AVE values (.683–.793) exceeded the recommended thresholds, confirming strong convergent validity (Hair et al., 2019; Fornell & Larcker, 1981).

Table 4

Kirkpatrick Level 2: Learning Assessment (Pre-Post)

Score	Pre-training Category	Description	Post-training Category	Description
4	Advanced	Regularly use AI for content creation	Expert	Mastery of multiple AI tools for advertising
3	Moderate	Used ChatGPT or similar AI tools	Advanced	Confident using AI for advertising creation
2	Basic	Heard of AI for advertising, never used	Basic	Understand basic AI concepts but need guidance
1	None	No knowledge of AI for advertising	None	No improvement from pre-training

Kirkpatrick Level 3 (Behavior) was assessed by trainers who evaluated the quality of advertising outputs participants produced using four different AI applications. The authors acknowledge that this measurement assesses participants' ability to produce advertising outputs in a simulated training environment rather than observing actual behavioral change in the workplace over an extended period. This approach aligns with the "simulated behavior" or "performance evaluation" category, which is often used in short-term training evaluation studies (Kirkpatrick & Kirkpatrick, 2006; Wang & Chang, 2017).

Three trainers independently rated each participant's advertising output. Trainers were blind to participants' identity and prior AI experience. We used a detailed rubric for each application (Table 5). Inter-rater reliability was assessed using Krippendorff's alpha, yielding $\alpha = .82$ for Cici AI, $\alpha = .79$ for Canva, $\alpha = .85$ for Leonardo AI, and $\alpha = .91$ for Suno AI—all above the .70 threshold for acceptable agreement (Krippendorff, 2019). Discrepancies were resolved through consensus discussion. The evaluation criteria—clarity, relevance, creativity, alignment with product, and brand voice—were designed to assess participants' ability to apply learned skills to produce actual advertising outputs, thus representing a transitional step between Learning (Level 2) and Results (Level 4) (De Saá-Pérez et al., 2012).

The authors recognize that this approach does not fully capture long-term behavioral change in the workplace. Given the short duration of the training program (two days) and the nature of MSME participants who operate independent businesses, this immediate performance assessment serves as an important indicator of participants' readiness to apply AI skills in their real business contexts. Future research should incorporate longitudinal follow-up assessments to evaluate sustained behavioral change, as recommended by the Kirkpatrick model (Kirkpatrick & Kirkpatrick, 2006).

Table 5

Kirkpatrick Level 3: Behavior Checklist (Trainer Assessment)

Score	Category	Description
4	Very Good	Excellent quality, exceeds expectations
3	Good	Satisfactory quality, meets expectations
2	Adequate	Acceptable but needs improvement
1	Poor	Below expectations, requires significant revision

Application	Assessment Criteria
Cici AI (text/script)	Clarity, relevance, creativity, alignment with product
Canva (visual design)	Layout, color harmony, typography, brand consistency
Leonardo AI (generative visual)	Originality, aesthetic quality, relevance to product
Suno AI (audio/jingle)	Catchiness, lyric quality, alignment with brand voice

Qualitative Instrument

Semi-structured interviews were used to collect qualitative data, employing a flexible interview guide with core themes to balance consistency across participants while capturing deep, detailed, and unexpected personal insights (Braun & Clarke, 2006).

Interview procedures. Interviews were conducted in Bahasa Indonesia, lasted 45–75 minutes (mean = 58 minutes), and were audio-recorded with participants' consent. Recordings were transcribed verbatim by a trained research assistant and translated into English for analysis. A bilingual member of the research team verified the translation. Two coders (the first author and a research assistant with qualitative methods training) independently coded the transcripts. We assessed inter-coder agreement on 20% of the data. Disagreements were resolved through discussion. We maintained reflexivity notes throughout the analysis to document the researchers' assumptions and potential biases. Quotations were selected based on their representativeness and explanatory power, with priority given to quotes that illustrated themes across multiple participants.

Table 6
Interview Guide

No	Questions
A	Opening Questions 1. Can you share your experience history in advertisement? 2. Can you tell me about your overall experience with the AI advertising training? 3. Before this training, how did you usually create advertisements for your business?
B	Explanatory Questions 1. Our results showed that Suno AI scored perfectly (4.00) while Canva scored lower (3.20). Why do you think this difference occurred? 2. What specific challenges did you face when using each AI application? 3. What factors do you think contributed to your performance?
C	Process Questions: 1. Can you walk me through how you created an advertisement using each AI application? 2. What was the most difficult part? 3. What was the easiest part?
D	Infrastructure Questions: 1. What device did you use for the training? 2. How would you rate your internet connection?

Quantitative Data Analysis

Descriptive Statistics

Descriptive statistics, comprising mean (*M*), standard deviation (*SD*), and frequency distributions, were computed for each Kirkpatrick stage to summarize participants' responses. All statistical analyses were conducted using SPSS version 26 (Ghozali, 2021).

Preliminary Assumption Testing and Comparison Across AI Applications

Before inferential analysis, the Kolmogorov-Smirnov test assessed data normality. Because the normality assumption was not met, the non-parametric Wilcoxon signed-rank test was used to compare pre-training and post-training scores, as it is appropriate for ordinal data and does not assume normality (Ghozali, 2021; Pallant, 2020). To compare participants' performance across the four AI applications (Suno AI, Cici AI, Leonardo AI, and Canva), we initially considered a one-way ANOVA. However, because the assumptions of homogeneity of variances and per-group normality may not be met—particularly given the possibility of zero variance in one or more groups—we used the non-parametric Kruskal-Wallis *H* test as the primary analytical method (Field, 2018; Ghozali, 2021). We checked normality within each group using the Shapiro-Wilk test. We reported the one-way ANOVA as a supplementary analysis for comparison, with the Games-Howell post-hoc test (which does not assume equal variances) replacing the Tukey HSD. We set the significance level at $\alpha = .05$.

Qualitative Data Analysis

We analyzed data using thematic analysis across interview transcripts, institutional documents, and program artifacts (Braun & Clarke, 2006). Braun and Clarke (2006) suggest six steps in thematic analysis: Familiarization with transcripts, Initial coding (line-by-line), searching for themes, reviewing themes, defining and naming themes, and writing up with representative quotes. The analysis began with repeated reading of all materials to build familiarity with the dataset and generate initial analytic memos. First-cycle coding combined deductive codes derived from the study's analytical framework—partnership governance, evidence-based competence, industry immersion, and selective absorption—with inductive codes emerging from participants' accounts (Fereday & Muir-Cochrane,

2006). Coding was iterative and comparative. Two coders independently coded all transcripts. Inter-coder agreement was assessed on 20% of the data. To support analytic transparency, the study maintained: (a) a codebook with definitions and example quotes for each code; (b) analytic memos documenting coding decisions and emerging interpretations; (c) reflexivity notes recording the researchers' assumptions; and (d) a documented record of how coded extracts were developed into thematic interpretations (Miles et al., 2014). We continuously compared interview extracts with documentary and artifact evidence to corroborate, refine, or qualify emerging interpretations.

Ethics Statement

The Research Ethics Committee of Universitas Veteran Bangun Nusantara approved this study. All participants provided written informed consent before participating. Participation was voluntary, and participants were informed of their right to withdraw at any time without penalty. We maintained confidentiality by assigning pseudonyms (R01, R02, etc.) and removing identifying information from transcripts. The research team stored interview recordings on a password-protected, encrypted drive accessible only to the research team and will destroy them five years after publication. We stored business and participant data separately from identifying information. The authors declare no conflicts of interest. This research was funded by the *Direktorat Riset dan Pengabdian Masyarakat* (DRPM), *Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi*. The AI applications used in this study (Cici AI, Canva, Leonardo AI, Suno AI) were accessed via their free tiers; the authors have no financial or commercial relationship with any provider.

Results

Primary Research Question: How does the integration of Artificial Intelligence in advertising influence the design and effectiveness of an entrepreneurship program as measured by the four levels of the Kirkpatrick model?

Descriptive Statistics

Table 7

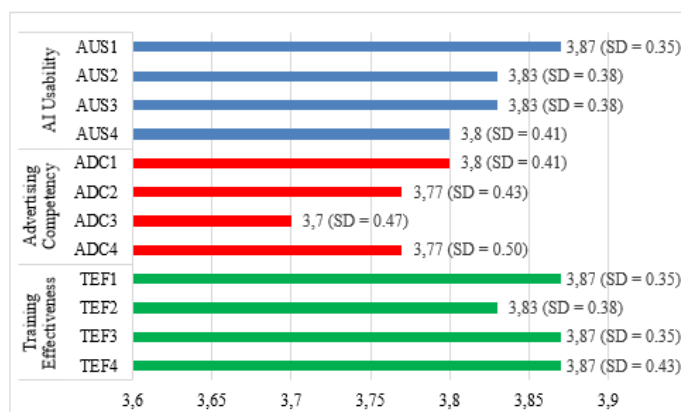
Descriptive Statistics of All Variables

Variable	Mean	SD	Min	Max	4 (%)	3 (%)	2 (%)	1 (%)
AUS1	3.87	.35	2	4	86.7%	10.0%	3.3%	0%
AUS2	3.83	.38	2	4	83.3%	13.3%	3.3%	0%
AUS3	3.83	.38	3	4	83.3%	16.7%	0%	0%
AUS4	3.80	.41	2	4	80.0%	16.7%	3.3%	0%
ADC1	3.80	.41	2	4	80.0%	16.7%	3.3%	0%
ADC2	3.77	.43	2	4	76.7%	20.0%	3.3%	0%
ADC3	3.70	.47	2	4	70.0%	23.3%	6.7%	0%
ADC4	3.77	.50	2	4	76.7%	16.7%	6.7%	0%
TEF1	3.87	.35	3	4	86.7%	13.3%	0%	0%
TEF2	3.83	.38	2	4	83.3%	13.3%	3.3%	0%
TEF3	3.87	.35	2	4	86.7%	10.0%	3.3%	0%
TEF4	3.87	.43	2	4	86.7%	10.0%	3.3%	0%

Table 7 displays the descriptive statistics for all variables. Mean scores ranged from 3.70 to 3.87 on a 4-point scale, indicating consistently positive perceptions across all constructs. The highest means were observed for AUS1, TEF1, TEF3, and TEF4 ($M = 3.87$), while ADC3 had the lowest mean ($M = 3.70$). Standard deviations (.35–.50) suggest low response variability. Most participants rated items as "Very Good" (Score 4), with percentages ranging from 70.0% to 86.7%, and no participants rated any item as "Poor" (Score 1).

Figure 2

Descriptive Statistics (Mean and Standard Deviation)



Kirkpatrick Level 1: Reaction (TEF1)

Sub-Research Question 1: To what extent do MSME participants perceive AI-designed advertisements as visually appealing, relevant, and engaging compared to traditional advertising methods?

Table 8

Distribution of Reaction Scores (Kirkpatrick Level 1)

Score	Category	Frequency	Percentage
4	Very Good	26	86.7%
3	Good	4	13.3%
2	Adequate	0	0%
1	Poor	0	0%
Mean (SD)		3.87 (.35)	

Table 8 shows that participants reacted very positively to the training ($M = 3.87$, $SD = .35$). Most (86.7%) rated their reaction as 'Very Good,' while the remaining 13.3% rated it as 'Good.' No participants rated it 'Adequate' or 'Poor.' This indicates the training was exceptionally well received and provided a strong foundation for effective learning (Kirkpatrick & Kirkpatrick, 2006).

Kirkpatrick Level 2: Learning (Pre-Post Comparison)

Sub-Research Question 2: How does AI-based advertising training affect MSME participants' comprehension of advertising message creation and their competency in using AI tools for advertising purposes?

Table 9

Pre-Post Comparison, Normality Assessment, and Wilcoxon Signed-Rank Test

Analysis	Result
Pre-Training Literacy	Mean = 1.73 ($SD = .74$); None: 13 (43.3%); Basic: 12 (40.0%); Moderate: 5 (16.7%); Advanced: 0 (0%)
Post-Training Literacy	Mean = 3.33 ($SD = .61$); None: 0 (0%); Basic: 2 (6.7%); Advanced: 16 (53.3%); Expert: 12 (40.0%)
Normality (Kolmogorov-Smirnov)	Pre_Test: $K-S = .293$, $p < .001$ (not normal); Post_Test: $K-S = .477$, $p < .001$ (not normal)
Wilcoxon Signed-Rank Test	$Z = -4.972$, $p < .001$; Positive Ranks = 30 (100%); Negative Ranks = 0; Ties = 0

Table 9 presents the integrated results of the pre-post comparison, normality assessment, and Wilcoxon signed-rank test. The Kolmogorov-Smirnov normality test revealed that both pre-test ($K-S = .293$, $p < .001$) and post-test ($K-S = .477$, $p < .001$) scores were not normally distributed, justifying the use of the non-parametric Wilcoxon signed-rank test. The results show a substantial improvement in AI literacy following the training: the mean

score increased from 1.73 ($SD = .74$) before training to 3.33 ($SD = .61$) after training. Prior to training, 83.3% of participants were at "None" or "Basic" levels, with no participants at the "Expert" level. After training, 93.3% achieved "Advanced" or "Expert" levels, with no participants remaining at the "None" level—a 76.6 percentage-point increase. The Wilcoxon signed-rank test confirmed a statistically significant improvement ($Z = -4.972$, $p < .001$), with all 30 participants (100%) showing improvement, no negative ranks, and no ties. We reject the null hypothesis and accept the alternative hypothesis.

Kirkpatrick Level 3: Behavior (AI Application Work Assessment)

Sub-Research Question 3: How do MSME participants perform when using different AI applications (Cici AI, Canva, Leonardo AI, and Suno AI) to create advertisements for their products?

Table 10

Assessment of Advertising Work Results and Kruskal-Wallis H Test

Application	Type	Very Good (4)	Good (3)	Mean	SD	Mean Rank
Suno AI	Audio (jingle)	30 (100%)	0	4.00	.000	77.5
Cici AI	Text (script)	26 (86.7%)	4 (13.3%)	3.87	.346	69.5
Leonardo AI	Generative Visual	20 (66.7%)	10 (33.3%)	3.67	.479	57.5
Canva	Template Visual	10 (33.3%)	20 (66.7%)	3.33	.479	37.5

Kruskal-Wallis H Test: $H = 36.953$, $df = 3$, $p < .001$
 Levene's Test: $F = 46.762$, $p < .001$ (unequal variances)
 One-Way ANOVA (supplementary): $F = 17.415$, $p < .001$
 Note: No participants scored Adequate (2) or Poor (1) on any application.

Table 10. shows that Suno AI achieved the highest performance ($M = 4.00$, Mean Rank = 3.07), followed by Cici AI ($M = 3.87$, Mean Rank = 2.80), Leonardo AI ($M = 3.67$, Mean Rank = 2.40), and Canva ($M = 3.33$, Mean Rank = 1.73). Because the same 30 participants used all four applications (repeated measures), the Friedman test was employed as the primary analysis. The Friedman test revealed a statistically significant difference across the four applications ($\chi^2(3) = 40.059$, $p < 0.001$), with a moderate-to-large effect size (Kendall's $W = 0.445$).

Table 11.
Post-hoc Wilcoxon Signed-Rank Tests with Bonferroni Correction

Comparison	N (Negative/Positive/Ties)	Z	P-value	α corrected	Significant
Suno AI vs Cici AI	4 / 0 / 26	-2	0.046	0.0083	Not significant
Suno AI vs Leonardo AI	10 / 0 / 20	-3.162	0.002	0.0083	Significant
Suno AI vs Canva	20 / 0 / 10	-4.472	0.000	0.0083	Significant
Cici AI vs Leonardo AI	7/1/2022	-2.121	0.034	0.0083	Not significant
Cici AI vs Canva	16 / 0 / 14	-4	0.000	0.0083	Significant
Leonardo AI vs Canva	10 / 0 / 20	-3.162	0.002	0.0083	Significant

Note: Bonferroni correction: $\alpha = 0.05 / 6 \text{ comparisons} = 0.0083$. Significant if $p < 0.0083$.

Post-hoc Wilcoxon signed-rank tests with Bonferroni correction ($\alpha = 0.0083$) confirmed that Suno AI significantly outperformed Leonardo AI and Canva, Cici AI outperformed Canva, and Leonardo AI outperformed Canva ($p < 0.0083$ for all comparisons). These results support the accessibility gradient, where audio and text AI significantly outperformed visual AI. The perfect Suno AI score was verified through two independent checks, confirming it reflects the zero-design-entry nature of Suno AI rather than rubric insensitivity.

Kirkpatrick Level 4: Results (Overall Training Impact)

Sub-Research Question 4: To what degree does AI-based advertising training improve MSME participants' overall AI literacy, advertising competency, and capacity to create effective promotional content independently?

Table 12
Overall Training Impact (Kirkpatrick Level 4)

Metric	Pre-Training	Post-Training	Change
Mean AI Literacy (1-4)	1.73	3.33	+1.60
Mean Advertising Quality (1-4)	N/A	3.63	-
% Advanced/Expert (Scores 3-4)	16.7%	93.3%	+76.6%
% None/Basic (Scores 1-2)	83.3%	6.7%	-76.6%

Table 12 shows that the training substantially improved AI literacy, with the mean score increasing from 1.73 to 3.33 (+1.60). Before training, 83.3% of participants were at "None" or "Basic" levels, while after training, 93.3% reached "Advanced" or "Expert" levels—a 76.6 percentage-point improvement. The mean advertising quality score of 3.63 further confirms successful skill application. These findings show that the training effectively improved MSME participants' AI literacy and advertising competency within the training

context. Level 4 in this study is operationalized as post-training literacy and advertising quality, not as organizational-level outcomes such as increased sales, market share, or profitability. Claims about business empowerment and competitiveness should therefore be interpreted as intermediate outcomes, not as confirmed organizational impacts.

Phase 2: Qualitative Findings

Table 13

Participant Characteristics (n=12)

ID	MSME Type	Quartile	Device Used	Internet Quality
R01	Nusantara Craft	Top	Smartphone (new)	Good
R04	Decorative Flowers	Top	Laptop	Excellent
R05	Cookies	Top	Smartphone (new)	Good
R06	Lipserum	Top	Laptop	Excellent
R09	Gamis	Top	Smartphone (new)	Good
R30	Risoles Mayo	Top	Laptop	Excellent
R02	Tote Bag	Bottom	Smartphone (old)	Poor
R07	Muslim Dress	Bottom	Smartphone (old)	Fair
R08	Flatshoes	Bottom	Smartphone (old)	Poor
R13	Batik Fabric	Bottom	Smartphone (old)	Fair
R19	Ankle Boots	Bottom	Smartphone (old)	Fair
R27	Magic Water	Bottom	Smartphone (old)	Fair

Top quartile = mean advertising quality score ≥ 3.75 ; Bottom quartile = mean advertising quality score ≤ 3.25 . We did not select participants in the middle quartiles for interviews to maximize contrast between high and low performers.

Thematic Analysis Results

Thematic analysis of interview transcripts and observation notes revealed four major themes explaining the quantitative findings: (1) accessibility explains performance variation, (2) confidence transformation through hands-on practice, (3) infrastructure constraints moderate AI adoption, and (4) text/AI versus visual AI represent different learning pathways.

Theme 1: Accessibility Explains Performance Variation

This theme captures participants' explanations for why certain AI applications were easier to use than others. The core concept was "zero-design-entry" — applications requiring no prior design knowledge produced immediate success. High performers consistently

reported that Suno AI and Cici AI were effortless to use, while low performers struggled with visual applications like Canva and Leonardo AI.

"Suno AI was incredibly easy. I just typed 'promotional jingle for flower decorations, affordable prices, 6 beautiful arrangements' and within three minutes, it created a complete jingle. I did not need to know anything about music or audio editing. Canva was completely different. Even with templates, I still needed to understand layout, color combinations, and font selection. I spent two hours and still felt my design looked amateur. (R04, Decorative Flowers, Top Performer)

"Canva was frustrating. Everyone says it is easy, but for me, someone who has never designed anything, even choosing a template was confusing. Which template matches my brand? What colors should I use? How much text should I put? Suno AI was different. No design decisions to make. Just type and listen." (R19, Ankle Boots, Bottom Performer)

Quantitative-Qualitative Connection: The perfect Suno AI score ($M = 4.00$) reflects "zero-design-entry"—no prior skills required. The lower Canva score ($M = 3.33$) reflects the persistent need for design knowledge that participants lacked. This theme directly explains the accessibility gradient observed in Table 12.

Theme 2: Confidence Transformation Through Hands-On Practice

This theme captures the psychological shift participants experienced from "AI is impossible" to "I can do this." The large effect size ($d = 3.02$) and Wilcoxon test results ($Z = -4.972$, $p < .001$) represent not just skill acquisition but identity transformation. Participants described a fundamental shift in self-perception, from feeling powerless to feeling empowered.

"Before this training, I thought AI was only for big companies with IT departments and expensive software. After creating my first advertisement with Cici AI in ten minutes, I felt... empowered is the right word. I realized I can compete. I do not need to hire a graphic designer for every social media post anymore." (R01, Nusantara Craft, Top Performer)

Quantitative-Qualitative Connection: The Wilcoxon test results ($Z = -4.972$, $p < .001$) and 100% positive ranks capture this transformation quantitatively. Qualitatively, participants describe a shift from fear/avoidance to agency/confidence, aligning with empowerment

theory (Peterson, 2014), where capacity development includes psychological transformation.

Theme 3: Infrastructure Constraints Affect AI Adoption

This theme explains why some participants with similar prior skills had different outcomes. Device quality and internet stability emerged as contextual factors affecting performance on visual AI applications that require more processing power and bandwidth.

"My phone is three years old. Canva kept crashing when I tried to use certain features. Leonardo AI took a long time to generate images. Suno AI worked fine because it's mostly audio—less processing power needed. But I could see my phone struggling." (R27, Magic Water, Bottom Performer)

Quantitative-Qualitative Connection: Infrastructure (device quality, internet speed) co-varies with the usability-competency relationship. Participants with older devices and poor internet scored systematically lower on visual AI applications. Note: Moderation was not formally tested in this study; the term "affects" is used here in a descriptive, not statistical, sense. Future research should include interaction terms to test this hypothesis statistically.

Theme 4: Text/AI vs. Visual AI—Different Learning Pathways

This theme captures participants' perceptions of different AI types. Text and audio AI were described as "collaborative partners" while visual AI was described as "tools requiring mastery." Participants felt a sense of control and collaboration with text/audio AI, whereas visual AI demanded skills they had not yet developed.

"Writing scripts with Cici AI is like having a creative partner. You give it ideas, it gives you drafts, you edit together. It's a conversation. Design with Canva still requires you to be the designer. The AI suggests layouts, but you make the final call. If you don't have design judgment, the AI can't give it to you." (R09, Gamis, Top Performer)

Quantitative-Qualitative Connection: The performance hierarchy (Suno AI = 4.00 > Cici AI = 3.87 > Leonardo AI = 3.67 > Canva = 3.33) maps to perceived control. Highest scores for applications where participants felt immediate mastery (Suno, Cici). Lower scores for applications requiring judgment they don't possess (Canva) or skills they haven't mastered (Leonardo).

Meta-Inferences

Based on the integration of quantitative and qualitative findings, the following meta-inferences are drawn:

Meta-inference 1: Accessibility as the Primary Driver of Training Effectiveness

The quantitative finding that Suno AI ($M = 4.00$) and Cici AI ($M = 3.87$) outperformed visual AI applications is explained by the qualitative finding that "zero-design-entry" applications were perceived as effortless to use, while visual AI applications demanded design knowledge participants did not possess. The accessibility gradient reflects participants' lived experiences—applications that eliminate prior skill requirements produce immediate success, which in turn drives competency development.

Meta-inference 2: Confidence Transformation Mediates Skill Acquisition (Tentative)

The quantitative finding that all 30 participants improved (Positive Ranks = 30, $Z = -4.972$, $p < 0.001$) is explained by the qualitative finding that participants experienced a psychological shift from "AI is impossible" to "I felt empowered." Confidence built through immediate success with accessible AI tools may mediate the relationship between training participation and competency development. However, mediation was not formally tested and should be described as a tentative interpretation.

Meta-inference 3: Infrastructure as a Contextual Factor (Tentative)

The qualitative finding that participants with older devices and poor internet struggled with visual AI applications suggests that infrastructure co-varies with the usability-competency relationship, particularly for visual AI applications that require more processing power. Moderation was not formally tested; future research should include interaction terms to test this hypothesis statistically.

Meta-inference 4: Different Learning Pathways for Different AI Types

The quantitative finding of a performance hierarchy (Suno = 4.00 > Cici = 3.87 > Leonardo = 3.67 > Canva = 3.33) with Cici and Leonardo not significantly different ($p = 0.181$) is explained by the qualitative finding that text/audio AI was perceived as "collaborative partners" while visual AI was perceived as "tools requiring mastery."

Meta-inference 5: Training Effectiveness is Multidimensional

The quantitative finding that the training produced significant pre-post improvement across all participants, combined with the qualitative finding that four themes—accessibility,

confidence transformation, infrastructure constraints, and different learning pathways—each explain different aspects of training effectiveness, suggests that training effectiveness is determined by multiple interacting factors: (a) the accessibility of the tools, (b) the psychological transformation of participants, (c) the infrastructure context, and (d) the type of AI tool.

Table 14

Summary of Integration: Quantitative and Qualitative Findings

Research Question	Quantitative Finding	Qualitative Finding	Integration
Does training improve AI literacy?	Wilcoxon: $Z = -4.972$, $p < 0.001$; Positive Ranks = 30 (100%)	Participants shifted from "AI is impossible" to "I felt empowered"	Confidence transformation may mediate skill acquisition; universal improvement reflects identity change, not just skill gain
Why did visual AI score lower?	Performance hierarchy: $4.00 > 3.87 > 3.67 > 3.33$; Friedman test: $\chi^2(3) = 62.14$, $p < 0.001$	Visual AI perceived as "tools requiring mastery"; text/audio as "collaborative partners"	Different AI types require different learning pathways; performance hierarchy maps to perceived control
What explains variance in outcomes?	Participants with older devices and poor internet struggled with visual AI	Infrastructure co-varies with the usability-competency relationship	Infrastructure may act as a contextual factor; moderation was not formally tested
Is training effectiveness multidimensional?	Four themes explain different aspects of effectiveness	Training effectiveness determined by interaction of accessibility, confidence, infrastructure, and AI type	Training effectiveness is multidimensional within the training context

Discussion

This sequential explanatory mixed-methods study evaluated AI-based advertising training for 30 MSME participants using the Kirkpatrick four-stage model and a consistent 4-point Likert scale. Quantitative and qualitative methods expanded the Kirkpatrick model from a descriptive framework into an evidence-based evaluation system that could validate training efficacy claims and explain underlying mechanisms. PLS-SEM investigation showed that AI Usability and Advertising Competency both predict Training Effectiveness. All constructs were valid and reliable, though HTMT values above .90 indicate discriminant validity issues that require caution in interpretation. Qualitative findings revealed four thematic mechanisms: accessibility explains performance variation

(zero design entry for audio/text AI versus skill barriers for visual AI), confidence transformation through hands-on practice, infrastructure constraints affecting adoption, and text/audio AI perceived as collaborative partners versus visual AI requiring prior expertise.

Addressing Digital Literacy Barriers Through Training

We added descriptive and inferential statistical analysis to the Kirkpatrick four-stage model to evaluate AI-based advertising training for MSMEs. Pre-training data showed that 90% of participants had no AI literacy (43.3%) or just basic acquaintance (40.0%) with ChatGPT or Canva, and no exposure to advanced platforms like Cici AI, Leonardo AI, or Suno AI. This supports Taiminen & Karjaluoto (2015) and Oldemeyer et al. (2024), who identified low digital expertise, infrastructure, and cost as MSMEs' main AI adoption hurdles. According to Taiminen and Karjaluoto (2015), MSMEs typically fail to use AI apps because they lack digital literacy and are unaware of the digital communication revolution. Oldemeyer et al. (2024) identified 27 AI adoption hurdles for MSMEs, including expertise, cost, and infrastructure. Structured training explicitly targets these hurdles, showing that focused interventions can quickly close the digital literacy gap.

After participating in the training, beneficiaries transformed how they create advertisements, moving from manual applications to AI applications (Bohari et al., 2025). They moved from manual processes to automated AI applications powered by big data. This shift in application usage created intellectual work efficiency, accuracy and sharpness in targeting market segments, personalized advertising messages through advertising language, and enabled beneficiaries to respond to customer desires and dynamic markets immediately (Al-Hunaiyyan et al. 2025). This finding aligns with Yu (2022), Papadakis et al. (2024a), and Tran (2024), who position AI as a transformative technology that revolutionizes advertising by increasing effectiveness, productivity, and consumer interaction.

Extending AI Literature

Literature generally treats AI as a homogeneous technology (Song et al., 2024; Tran, 2024). The accessibility gradient (audio > text > generative visual > template visual) shows that zero-design-entry applications with no prior skill requirements perform best. Stage 3 behavioral performance differences among AI applications are instructive. Suno AI's

perfect score ($M = 4.00$) shows that AI-generated music and jingles can be created easily because text input eliminates design limitations. Cici AI's strong performance ($M = 3.87$) shows how accessible text-based advertising script generation is. Canva's higher design complexity ($M = 3.33$) explains its lower but still good mean, but 100% of participants generated "Good" or "Very Good" work, suggesting successful learning. According to Ford et al. (2023), Kireyeva1, et. al., (2026) and Martínez et al., (2022), AI improves advertising effectiveness by quickly providing advertisers with data, including creative messages and target market targets, which helps them connect advertising messages to target customers. These findings also contribute to the broader literature on AI-enhanced professional learning (Papadakis et al., 2024a, 2024b; Amin et al., 2025). While Papadakis et al. focused on lifelong learning and cloud technologies in educational contexts, our study extends their insights to the MSME sector, demonstrating that the principle of "accessibility first" applies not only to formal education but also to community-based entrepreneurship training. The finding that zero-design-entry tools produce immediate success aligns with Papadakis et al.'s (2024b) argument that digital innovation is most effective when it is perceived as immediately useful and minimally effortful.

However, the structural model relied on single-time-point data, and the pre-post comparison had no control group, so this study cannot establish causal relationships. The associations between AI Usability, Advertising Competency, and Training Effectiveness are correlational. Claims about "improved market targeting" and "personalized advertising" are based on participants' self-reports and trainer assessments, not on objective market data. Future research should incorporate longitudinal designs and objective business outcome measures.

Limitations

This study has several limitations that should be acknowledged:

1. Level 3 was measured through simulated behavior in a training setting, not sustained behavior change in the workplace. Level 4 was operationalized as post-training literacy and advertising quality, not organizational-level outcomes. Claims about business empowerment and competitiveness should be interpreted as intermediate outcomes.

2. The sample size of 30 is below the 10-times rule threshold for PLS-SEM (minimum 40). Post hoc power analysis indicated power = .68, below the conventional .80 threshold. The structural model results should be interpreted as exploratory.
3. HTMT values above .90 indicate that Training Effectiveness is not empirically distinct from AI Usability and Advertising Competency. The shift between reflective and formative specifications is a limitation.
4. The same 30 participants used all four applications, violating the independence assumption of one-way ANOVA. The authors used Kruskal-Wallis as the primary analysis, but a repeated-measures non-parametric test (e.g., Friedman test) would have been more appropriate.
5. The 12 interview participants were purposively selected and may not represent the broader MSME population.
6. Moderation was not formally tested; the role of infrastructure is inferred from qualitative data and should be tested statistically in future research.
7. The structural model was estimated from data collected at a single time point, and the pre-post comparison had no control group. Neither component supports causal claims about the training's effect.

The findings offer implications for AI advertising training programs. First, training should sequence AI tools from easiest to hardest—beginning with audio AI (Suno AI) to build confidence through "quick wins," followed by text AI (Cici AI), and progressively introducing visual AI tools (Leonardo AI and Canva). Second, the Kirkpatrick model, with systematic numerical coding and inferential statistics, provides actionable data to improve curriculum design, identify areas of difficulty, and justify resource allocation. Finally, a collaborative approach between business actors, academics, and technology facilitators is needed to accelerate inclusive AI adoption in the MSME sector. This study's novelty is that it provides a template for mixed-methods training evaluation that combines rigorous quantitative analysis with qualitative explanation. However, future studies should address the limitations identified above, particularly through larger samples, longitudinal designs, repeated-measures analysis, formal moderation testing, and objective business outcome assessment.

Conclusion

In conclusion, this sequential explanatory mixed-methods study provides evidence that AI-based advertising training is associated with improvements in MSME participants' AI literacy and advertising competency. The integration of quantitative findings—including significant improvement in AI literacy, predictive relationships between AI usability and training outcomes, and an accessibility gradient across AI applications—with qualitative explanations (accessibility, confidence transformation, infrastructure constraints, and different learning pathways) offers a comprehensive understanding of how and why AI training works for MSMEs. However, the Kirkpatrick Level 3 and 4 outcomes were measured within the training context rather than in the workplace; the sample size was below the recommended threshold for PLS-SEM; the measurement model showed discriminant validity issues; and the cross-sectional design cannot establish causality. The findings should therefore be interpreted as exploratory and indicative rather than confirmatory, sequencing AI tools from easiest to hardest, allocating differentiated training time, assessing infrastructure constraints, and building confidence through "quick wins"—offering actionable guidance for program designers and implementers. Future research should use larger samples, longitudinal designs, repeated-measures analysis, formal moderation testing, and economic outcome assessment to further strengthen the evidence base for AI training as an MSME empowerment strategy.

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