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Training and Adoption of AI Technology for Sustainable Career in Vulnerable Employment Groups: A Mixed-Method Netcoincidental Analysis

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Abstract: This mixed-methods study investigates the acceptance of artificial intelligence (AI) among vulnerable employment groups (freelancers, gig workers, low-skilled workers) and the role of training in shaping their attitudes and behaviors. Based on an extended Technology Acceptance Model (TAM), we surveyed 39 individuals from vulnerable employment backgrounds and conducted in-depth interviews with 6 participants. Quantitative data were analyzed using descriptive statistics, independent t-tests, and reticular coincidence analysis (RAC) to visualize significant associations among TAM dimensions, training experience, and demographic variables. Qualitative data provided contextual insights into participants' perceptions. Results show generally positive attitudes, with perceived usefulness ($M = 5.41$) and intention to use ($M = 5.49$) rated highest, while actual use lagged ($M = 4.93$). Training experience was associated with higher perceived ease of use ($p < 0.05$) and behavioral intention. RAC networks revealed that positive attitudes cluster together, forming a profile of younger, experienced, trained individuals; negative attitudes were rare and linked to older age and lack of training. Interview narratives confirmed that training reduces anxiety, builds practical skills, and enhances career prospects. These findings underscore the importance of targeted AI training programs for vulnerable groups to promote digital inclusion and employability, contributing to SDG 8 (Decent Work and Economic Growth) and SDG 10 (Reduced Inequalities).

Keywords: AI adoption; vulnerable employment groups; AI training; reticular coincidence analysis; mixed methods; AI literacy; SDGs

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1. Introduction

The rapid advancement of artificial intelligence (AI) is reshaping labor markets worldwide, offering productivity gains but also posing significant risks of job displacement for lowskilled and vulnerable workers(George & George, 2023)[1]. Vulnerable employment groups—including freelancers, gig workers, temporary workers, and individuals with low educational attainment—often face heightened challenges in adapting to technological change due to limited access to training, resources, and social protection(Bekker et al., 2025)[2]. While the Technology Acceptance Model (TAM) has been extensively applied to study AI adoption in educational and organizational settings(Davis, 1989; Venkatesh et al., 2003)[3,4], research focusing on vulnerable employment populations remains scarce. Moreover, the role of formal AI training in shaping acceptance among these groups is underexplored.

This study addresses this gap by examining how training influences AI acceptance among vulnerable employment groups. We adopt an extended TAM framework that incorporates personal innovativeness, tasktechnology fit, perceived organizational support, AI literacy, and career sustainability (Dahri et al., 2024; Venkatesh et al., 2003)[5,4]. Using a convergent mixedmethods design combining survey data (N =3 9) with indepth interviews (N = 6), we apply reticular coincidence analysis (RAC) to visualize significant associations among TAM dimensions, training experience, and demographic characteristics(Escobar & Martinez-Uribe, 2020)[6]. The research questions are:

(1) What are the levels of AI acceptance among vulnerable employment groups across TAM dimensions?

(2) How does training experience relate to these dimensions?

(3) What patterns of association emerge among TAM dimensions and individual characteristics?

(4) How do participants describe their experiences with AI training and its impact on their careers?

By answering these questions, we aim to provide evidencebased recommendations for designing effective AI training programs tailored to vulnerable populations, thereby promoting digital inclusion and reducing the digital divide.

2. Literature review

2.1. Technology Acceptance Model (TAM) and AI Adoption

The Technology Acceptance Model (TAM), first proposed Davis (1989)[3], identifies perceived usefulness (PU) and perceived ease of use (PEOU) as two core factors that shape individuals' acceptance of new technologies. Later developments, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), further expand this framework by including social influence, facilitating conditions, and individual innovation characteristics (Venkatesh et al., 2003)[4].

In recent years, TAM has been widely applied to research on emerging AI tools such as ChatGPT and Deepseek. Empirical evidence consistently shows that perceived usefulness and perceived ease of use significantly predict users' intention to adopt and actual usage behavior(Zhang et al., 2023)[7]. Within educational environments, tasktechnology fit (TTF) and perceived organizational support (POS) have also been identified as important variables that moderate technology acceptance (Dahri et al., 2024)[5]. Despite these advances, limited empirical attention has been paid to how these mechanisms operate among vulnerable employment groups.

2.2. AI and Vulnerable Employment

As defined by the International Labour Organization, vulnerable employment typically involves unstable work arrangements, low earnings, inadequate social protection, and weak bargaining power in the labour market (Bekker et al., 2025)[2]. The rapid development of artificial intelligence and automation presents a doubleedged challenge for these workers. On the one hand, increased automation may replace routine tasks and threaten job stability. On the other hand, many vulnerable workers lack the necessary capabilities to use AI for career development or new employment opportunities (Fuchs, 2023)[8].

Existing research highlights a persistent digital skills gap that deepens existing social and economic inequalities (Kanwal et al., 2023)[9]. For freelancers and gig workers, AI tools can improve efficiency and create alternative income sources, but their effective adoption usually depends on adequate training and confidence building (Yu, 2023)[10].

2.3. The Role of Training in AI Acceptance

Targeted training programs can reduce anxiety toward new technologies and strengthen users' selfefficacy, which in turn promotes technology acceptance (Ali et al., 2023)[11]. In educational contexts, training has been found to improve perceptions of both usefulness and ease of use (Yilmaz et al., 2023)[12]. However, a few studies note that overly technical training may occasionally reduce confidence by exposing users to AI's practical limitations (García Alonso et al., 2024)[13].

For vulnerable employment groups, foundational AI training is especially critical for lowering entry barriers and clarifying misconceptions about intelligent systems. This study therefore hypothesizes that training experience is positively associated with key TAM constructs among vulnerable workers. Therefore, this research framework proposed ad **Figure 1** shows.

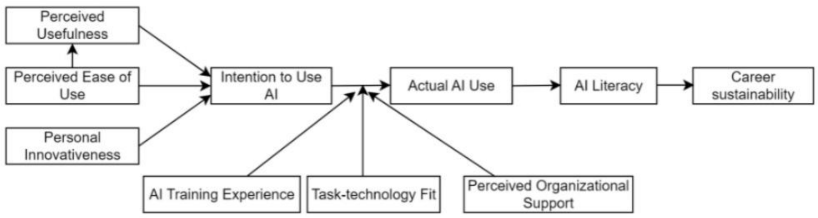

Figure 1. Research framework

3. Methodology

3.1. Design and Procedures

This study employed a convergent mixedmethods design (Schoonenboom & Johnson, 2017)[14]. Quantitative data were collected via an online survey administered between July and September 2025. Participants were recruited through community networks, online platforms, and youth training programs targeting vulnerable employment groups in China. Inclusion criteria were: currently in internship, formal employment (≤ 2 years), or flexible employment (freelancers, gig workers). Prior to participation, informed consent was obtained, and anonymity was guaranteed. All statistical analyses were conducted using Python.

Qualitative data were collected through semistructured interviews with six survey respondents who volunteered for followup. Interviews lasted 10–25 minutes, were audiorecorded, and transcribed verbatim. Topics included initial perceptions of AI, training experiences, practical applications, and perceived impact on career.

3.2. Participants

Table 1 presents the sample characteristics (N = 39). Gender was nearly balanced (46.2% male, 53.8% female). Age groups ranged from 18 to 60 years, with the largest proportion aged 18–25 (48.7%). Most participants had some AI usage experience: 25.6% had used AI for less than 6 months, 30.8% for 6 months to 1 year, 25.6% for 1–2 years, and 17.9% for over 2 years. Selfreported AI expertise was predominantly beginner (71.8%), followed by intermediate (20.5%), with only 2.6% advanced and 5.1% knowing nothing. Regarding AI training, 38.5% had received no training, 53.8% had relevant subject training or selfstudy, and 7.7% had received professional training.

Table 1. Sample characteristics of vulnerable employment groups

Variable	Category	N = 39
Gender	male	46.2% (18)
	female	53.8% (21)
Age	18-25	48.7% (19)
	26-30	7.7% (3)
	31-40	28.2% (11)
	41-50	10.3% (4)
	51-60	5.1% (2)

Table 1 (Continued)

Variable	Category	N = 39
AI Usage Duration	less than 6 months	25.6% (10)
	6 months to 1 year	30.8% (12)
	1 year to 2 years	25.6% (10)
	2 years and above	17.9% (7)
AI Expertise Level	know nothing	5.1% (2)
	beginner	71.8% (28)
	intermediate	20.5% (8)
	advanced	2.6% (1)
AI Training Experience	No training	38.5% (15)
	Have relevant subject training or self-study	53.8% (21)
	Received professional training	7.7% (3)

Note: Values are presented as percentage (frequency).

3.3. Quantitative Measurement

The survey included established scales for nine constructs as shown in **Table 2**: Personal Innovativeness (PI, 4 items), Perceived Usefulness (PU, 4), Perceived Ease of Use (PEOU, 4), Intention to Use (BI, 5), Actual Use (USE, 5), Career Sustainability (CS, 12), TaskTechnology Fit (TTF, 4), Perceived Organizational Support (POS, 4), and AI Literacy (AIL, 5). All items were measured on a 7point Likert scale (1 = strongly disagree, 7 = strongly agree). Cronbach's alpha for the overall questionnaire was 0.899, indicating good reliability.

For the RAC analysis, continuous dimension means were categorized into four ordinal groups based on the 7 point scale: Negative (≤ 3.0), Indifferent (3.01–4.0), Positive (4.01–5.0), and Very Positive (5.01–7.0). This categorization follows the practice of García Alonso et al. (2024).

Table 2. Operationalization of AI perception and usage measurement

Dimension	Number of Items	Cronbach's α	Response Range
Perceived Usefulness	4	0.95	1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neutral, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree
Perceived Ease of Use	4	0.923	
Personal Innovativeness	4	0.81	
Intention to Use	5	0.943	
Task-Technology Fit	4	0.965	
Perceived Organizational Support	4	0.792	
Actual Use	5	0.86	
AI Literacy	5	0.881	
Career Sustainability	12	0.968	

Note: All continuous items measured on a 7-point Likert scale.

3.4. Data Analysis

Quantitative analysis: Descriptive statistics (means, standard deviations, frequencies) were calculated for each dimension. Independentsamples ttests were used to compare mean scores across subgroups (gender, age, usage duration, expertise, training) against the rest of the sample. Statistical significance was indicated with asterisks (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Reticular Coincidence Analysis (RAC): RAC identifies statistically significant cooccurrences of categorical responses. For every pair of dummy variables (e.g., "PU = Very Positive" and "PEOU = Very Positive"), a 2×2 contingency table is constructed. The adjusted residual (AR) is computed as $AR = (observed - expected)/\sqrt{(expected \times (1 - p\_row) \times (1 - p\_col)}$, which follows a standard normal distribution. Pairs with $|AR| > 1.96$ ($\alpha = 0.05$) or > 1.645 ($\alpha = 0.10$) are considered significant and are connected by an edge in the network. are considered significant and are connected by an edge in the network. Node size is proportional to the frequency of that response; edge thickness reflects the absolute AR value. We used Python (pandas, numpy, scipy, networkx) to compute ARs and generate network graphs. Two thresholds were applied: $\alpha = 0.05$ (stricter) for networks with ample sample size, and $\alpha = 0.10$ (more sensitive) for networks with sparse negative responses.

Qualitative analysis: Interview transcripts were analyzed using thematic analysis. Initial codes were generated inductively, then grouped into broader themes that captured participants' experiences and perceptions. These themes were used to triangulate and enrich the quantitative findings.

4. Results

4.1. Descriptive Statistics

Table 3 presents the frequency distribution of the nine dimensions after categorization, along with means and standard deviations. Overall, participants held positive views: the proportions of "Very Positive" responses ranged from 35.9% (AIL) to 61.5% (BI). Mean scores were all above the midpoint (4.0), with the highest for BI (M = 5.49, SD = 1.06) and PU (M = 5.41, SD = 1.08), and the lowest for USE (M = 4.93, SD = 1.01) and AIL (M = 4.89, SD = 1.05). Notably, the "Negative" category was almost absent for most dimensions, except for PEOU (5.1%), TTF (2.6%), POS (7.7%), and AIL (2.6%). This indicates that outright negative attitudes toward AI are rare in this sample.

Table 3. Frequency table of the dimensions of the index

Categories Grouped According to Likert Scale						Statistics		
Dimension	**Negative**	**Indifferent**	**Positive**	**Very Positive**	**Total**	**N**	**Mean**	**SD**
Perceived Usefulness	0.0% (0)	17.9% (7)	30.8% (12)	51.3% (20)	100%	39	5.41	1.08
Perceived Ease of Use	5.1% (2)	12.8% (5)	38.5% (15)	43.6% (17)	100%	39	5.26	1.10
Personal Innovativeness	0.0% (0)	12.8% (5)	41.0% (16)	46.2% (18)	100%	39	5.28	1.03
Intention to Use	0.0% (0)	15.4% (6)	23.1% (9)	61.5% (24)	100%	39	5.49	1.06
Task-Technology Fit	2.6% (1)	25.6% (10)	23.1% (9)	48.7% (19)	100%	39	5.22	1.12
Perceived Organizational Support	7.7% (3)	20.5% (8)	25.6% (10)	46.2% (18)	100%	39	5.01	1.08
Actual Use	0.0% (0)	28.2% (11)	33.3% (13)	38.5% (15)	100%	39	4.93	1.01
AI Literacy	2.6% (1)	20.5% (8)	41.0% (16)	35.9% (14)	100%	39	4.89	1.05
Career Sustainability	0.0% (0)	17.9% (7)	25.6% (10)	56.4% (22)	100%	39	5.31	1.04

Note: Categories based on 7-point scale: 1-3 = Negative, 4 = Indifferent, 5 = Positive, 6-7 = Very Positive.

Figure 2 displays boxplots of the raw dimension scores. The median values hover around 5.2–5.5, with interquartile ranges relatively narrow (approximately 1 point). Outliers are few, suggesting homogeneous perceptions. The boxplots visually confirm that USE and AIL have slightly lower central tendencies.

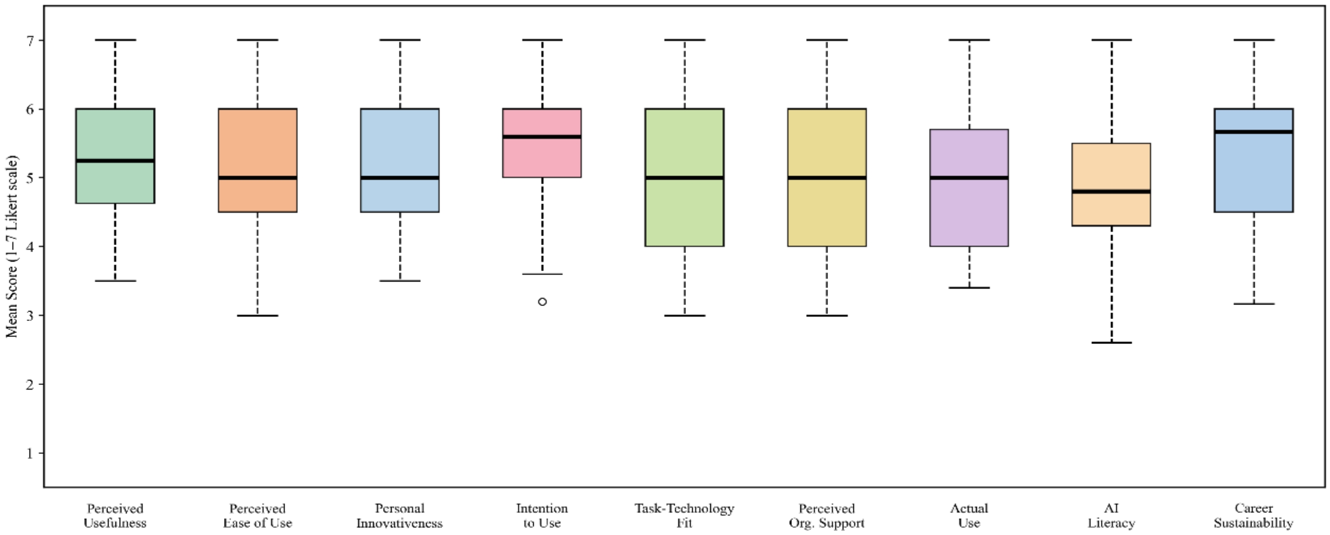

Figure 2. Dimensions of perception and usage of AI tools among vulnerable employment groups.

4.2. Group Comparisons

Table 4 reports mean dimension scores by participant characteristics, with asterisks indicating significant differences (ttest against all others). Several notable patterns emerged:

Table 4. Mean values of perception and usage of AI according to participant characteristics

Variable	Category	PU	PEOU	PI	BI	TTF	POS	USE	AIL	CS
	Mean	5.41	5.26	5.28	5.49	5.22	5.01	4.93	4.89	5.31
	Standard deviation	1.08	1.1	1.03	1.06	1.12	1.08	1.01	1.05	1.04
Gender	male	5.18	5.03	5.33	5.37	5.04	4.78	4.82	4.79	5.17
	female	5.61	5.46	5.23	5.59	5.37	5.21	5.03	4.97	5.44
Age	18-25	5.54	5.36	5.42	5.51	5.43	5.25	5.12	5.06	5.46
	26-30	5.08	5.17	4.00*	5	4.25	4.33	4.4	4.27	4.25
	31-40	5.39	5.27	5.64	5.71	5.18	4.84	4.85	4.78	5.45
	41-50	5.62	5.5	4.75	5.7	5.25	5.38	5.1	5.2	5.62
	51-60	4.38	4	4.88	4.4	4.75	4	4.1	4.1	4.08
AI Usage Duration	less than 6 months	5.4	5.28	5.32	5.44	5.4	5.15	4.74	4.78	5.49
	6 months to 1 year	4.85*	4.85	4.73*	4.87*	4.79	4.71	4.35*	4.28*	4.62**
	1 year to 2 years	5.68	5.3	5.65	5.88	5.08	5.05	5.26	5.34	5.71
	2 years and above	6	5.89	5.61	6.06	5.89	5.29	5.74*	5.43	5.67

Table 4 (Continued)

Variable	Category	PU	PEOU	PI	BI	TTF	POS	USE	AIL	CS
AI Expertise	know nothing	5	5.25	4.88	5.1	5	5	4.3	4.4	5
	beginner	5.17*	5.05	5.12	5.29	5.06	4.9	4.74	4.64*	5.16
	intermediate	6.16*	5.78	5.72	6.1	5.59	5.34	5.70*	5.72**	5.84
	advanced	7	7	7	7	7	5.5	5.4	6	6
Training	No training	5.05	4.75*	5	5.08	5.18	4.57*	4.57	4.57	4.91
	Have relevant subject training or self-study	5.58	5.60*	5.43	5.7	5.2	5.25	5.15	5.02	5.58
	Received professional training	6	5.5	5.58	6.07	5.5	5.58	5.2	5.53	5.44

Note: Levels of statistical significance (independent-samples t-test, each subgroup vs. all others): * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Gender: No significant differences were found.
Age: The 26–30 age group showed significantly lower PI (4.00, $p < 0.05$).
AI Usage Duration: Participants who had used AI for “6 months to 1 year” scored significantly lower on PI (4.73, $p < 0.05$), BI (4.87, $p < 0.05$), USE (4.35, $p < 0.05$), AIL (4.28, $p < 0.05$), and CS (4.62, $p < 0.01$). Those with “2 years and above” experience scored significantly higher on USE (5.74, $p < 0.05$).
AI Expertise: “Beginner” level was associated with significantly lower PU (5.17, $p < 0.05$) and AIL (4.64, $p < 0.05$). “Intermediate” level showed significantly higher PU (6.16, $p < 0.05$), USE (5.70, $p < 0.05$), and AIL (5.72, $p < 0.01$).
Training Experience: Participants with “No training” scored significantly lower on PEOU (4.75, $p < 0.05$) and POS (4.57, $p < 0.05$). Those with “relevant subject training or selfstudy” scored significantly higher on PEOU (5.60, $p < 0.05$).

4.3. Reticular Coincidence Analysis

RAC networks were generated using two significance thresholds ($\alpha = 0.05$ for most networks; $\alpha = 0.10$ for negative networks due to sparse data). Node labels are abbreviated (e.g., “PU” for Perceived Usefulness) and, in mixed networks, include category information in parentheses.

Figure 2 shows the network of “Very Positive” responses for the nine dimensions. All nine nodes are present, connected by a dense set of edges. Network 1: Very Positive responses among dimensions ($\alpha = 0.05$). The strongest coincidences (thickest lines) occur between PU and BI, PU and CS, and BI and CS. This indicates that individuals who rate AI as highly useful also tend to have high intention to use it and perceive it as contributing to career sustainability. PEOU is also strongly linked to PU and BI. The network suggests a cohesive cluster of positive evaluations, with no dimension isolated.

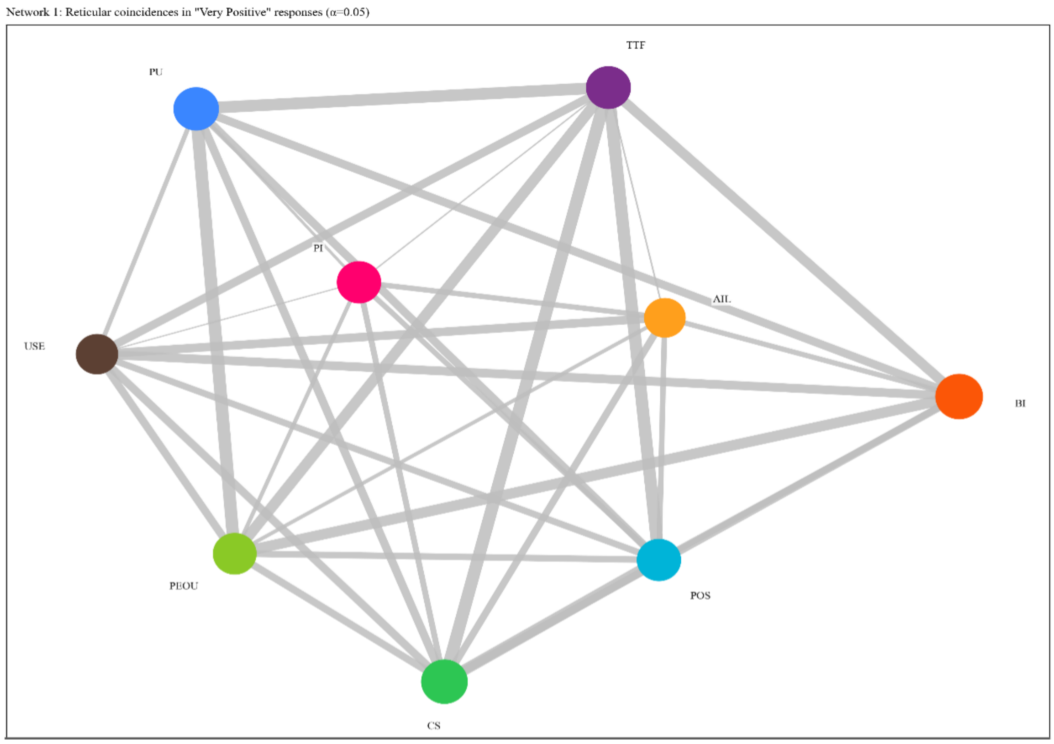

Figure 3. Network 1: Reticular coincidences in the "Very positive" response of the nine dimensions.

Figure 4 presents the network of "Negative" responses. Only five dimensions have nodes large enough to appear (PEOU, POS, TTF, AIL, and PU; the latter two with very small sizes). The only significant edge is between PEOU and POS, indicating that those who find AI difficult to use also tend to perceive low organizational support. The sparsity of the network confirms that negative evaluations are rare and not strongly interconnected.

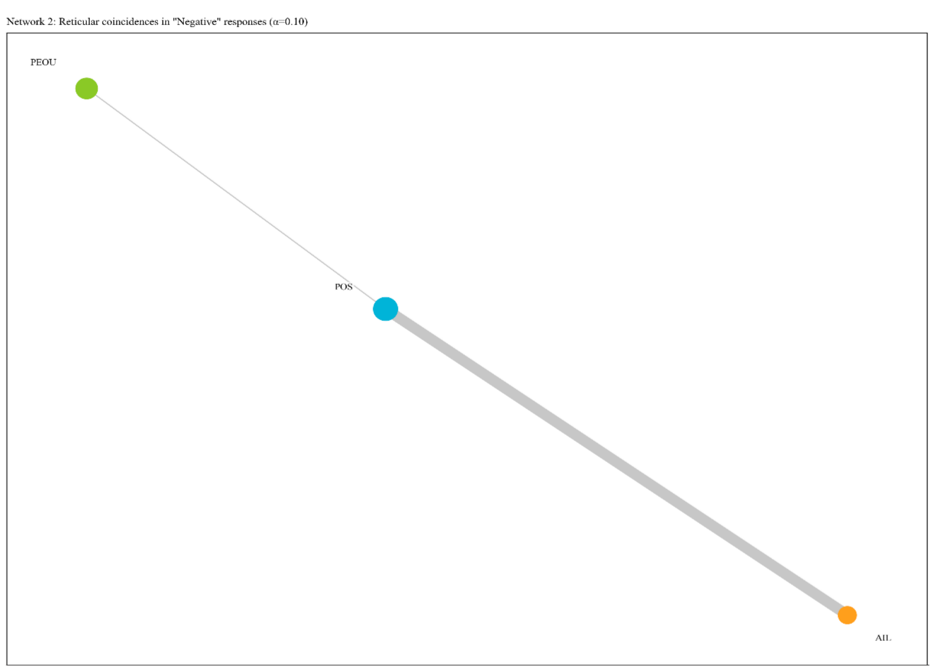

Figure 4. Network 2: Reticular coincidences in the "Negative" response of the nine dimensions.

Figure 5 integrates demographic and experience variables with the "Very Positive" dimension nodes. Several characteristics cooccur significantly with multiple positive evaluations:

AI Usage: 2 years and above is connected to PU, PEOU, BI, and CS (Very Positive).

AI Expertise: intermediate is linked to PU, PEOU, BI, USE, and CS.

Age: 18–25 is connected to PU, PEOU, BI, and CS.

Training: Received professional training cooccurs with BI and CS.

Gender: female shows a connection to PU and CS.

Gender: male is connected to PI.

This network paints a profile of the most positive subgroup: relatively young, with moderate to high AI experience and expertise, who have received professional training, and who perceive strong career benefits.

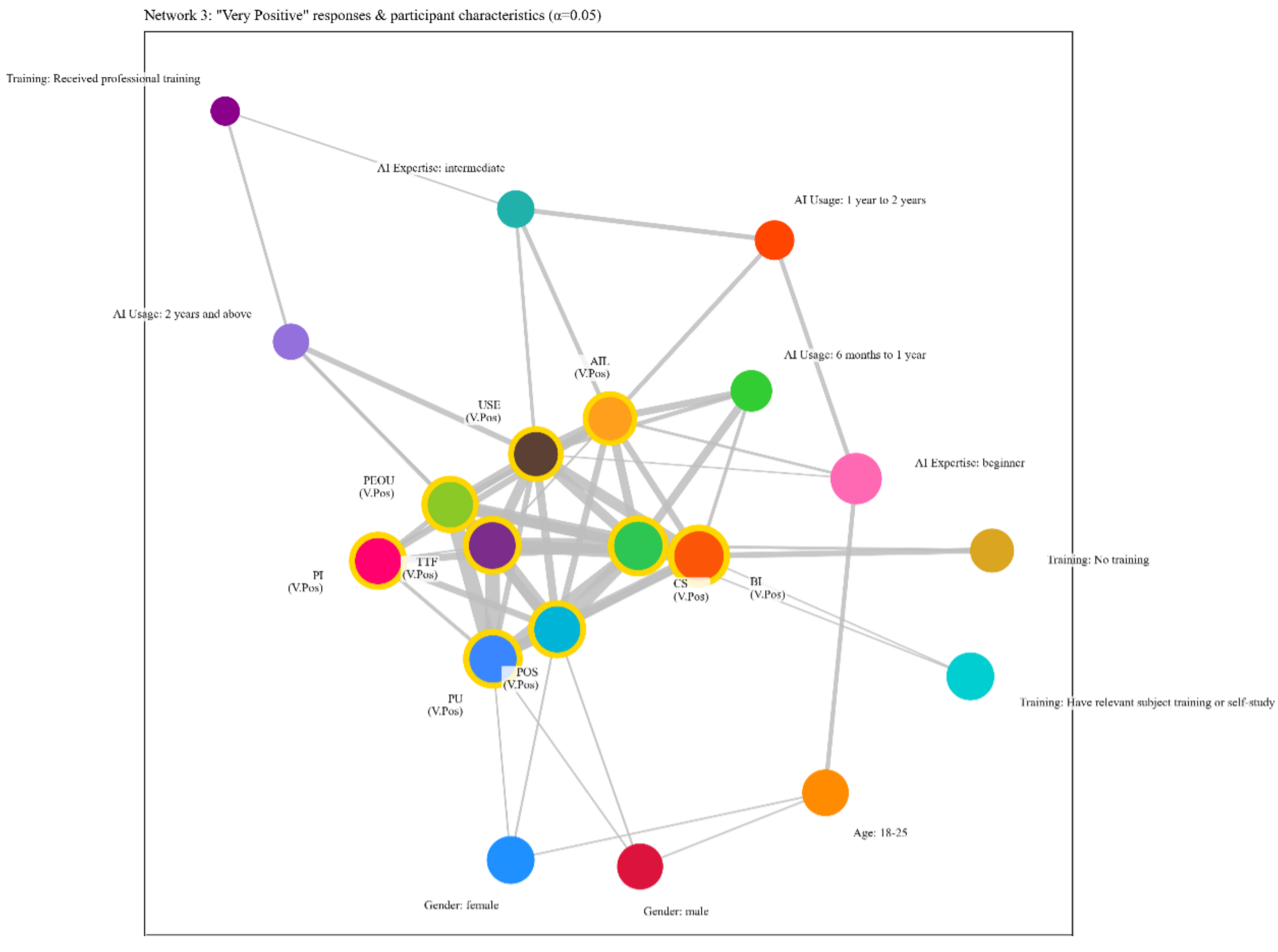

Figure 5. Network 3: Reticular coincidences in the "Very positive" response according to participant characteristics.

Figure 6 displays the negative counterparts. The negative nodes (PEOU, POS) are connected to a few characteristics:

Age: 51–60 is linked to PEOU (Negative).

AI Expertise: beginner cooccurs with PEOU (Negative).

AI Usage: 1 year to 2 years is connected to POS (Negative).

The network is sparse, but it suggests that older age, beginner status, and certain usage durations are associated with negative perceptions, particularly regarding ease of use and organizational support.

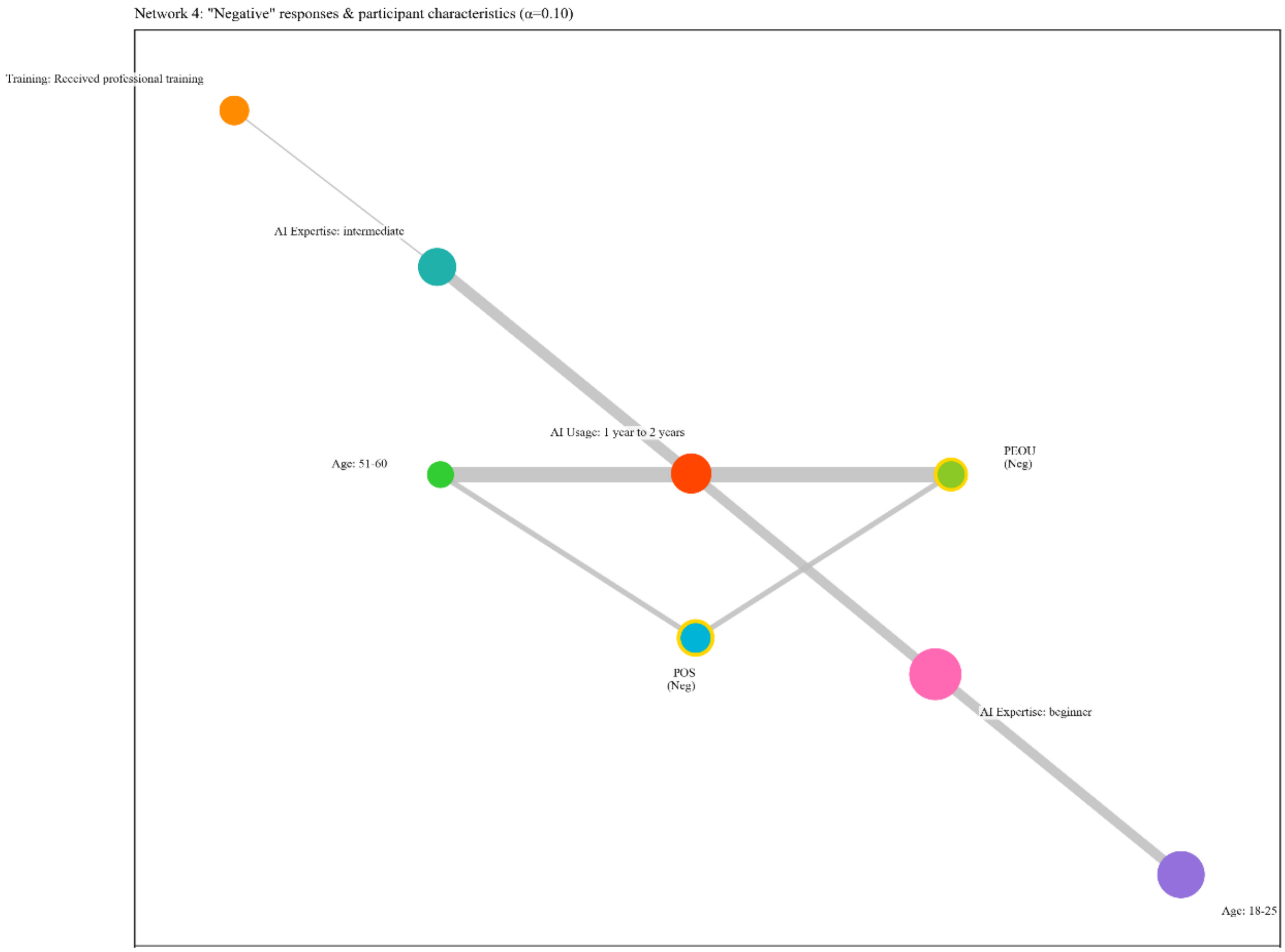

Figure 6. Network 4: Reticular coincidences in the "Negative" response according to participant characteristics.

Figure 7 focuses on training categories. "Training: No training" is connected to USE (Indifferent). "Training: Have relevant subject training or selfstudy" cooccurs with BI (Very Positive) and CS (Very Positive). "Training: Received professional training" is linked to BI (Very Positive), CS (Very Positive), and AI Expertise: intermediate. Notably, the professional training node also has an edge to AI Usage: 2 years and above, reinforcing the profile of advanced, trained users with positive intentions and career perceptions.

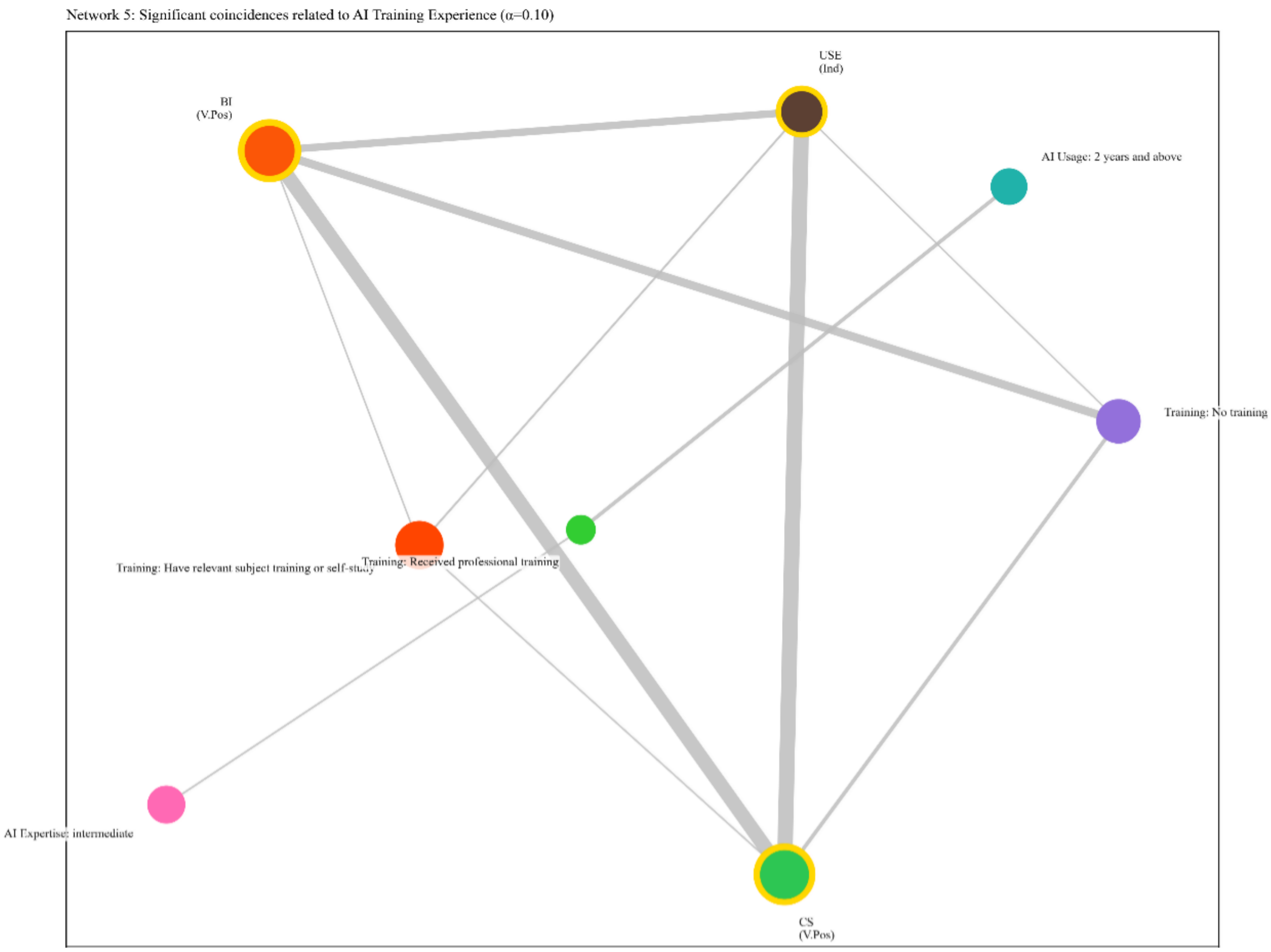

Figure7. Network 5: Significant coincidences related to AI training experience.

4.4. Qualitative Findings

Thematic analysis of the six interviews provided rich context for the quantitative patterns. Four main themes emerged.

Theme 1: From perceived barrier to handson empowerment (PEOU)

Before training, several participants viewed AI as inaccessible. One respondent (B, graduate student) said: "Before the training, I felt AI was a bit difficult… not something we liberal arts students could learn." Another (wcc, design student) recalled: "At first, the prompts looked intimidating; I was afraid I couldn't learn it." Training changed this perception: "On the first day, the teacher said we wouldn't learn algorithms, just how to use tools to solve creative problems. I instantly relaxed." This shift from anxiety to confidence aligns with the quantitative finding that training is associated with higher PEOU.

Theme 2: Training catalyzes the transition from awareness to active use (PU, BI)

Participants described concrete applications learned during training that they immediately adopted. For example, ysy (job seeker) highlighted the resumeoptimization session: "I had no direction when revising my resume, but that session helped me a lot. Now my resume is much better." sjh (vocational student) applied the AI agent workflow to a competition: "Learning how to build a complete workflow was very helpful for my later competition." These narratives illustrate how training translates perceived usefulness into actual behavioral intention and use.

Theme 3: AI as a lever for career development (CS)

Many respondents emphasized how AI skills enhanced their employability. sx (sales professional) noted: “AI helped me draft a yearend summary in two hours instead of a week… it frees me from repetitive work.” wcc added: “For fresh graduates like me, AI compensates for lack of experience and makes my portfolio look more professional.” Several mentioned that AI opened new career paths: “I’m now looking at jobs like AI content creator or smart media operator” (wcc). This directly supports the quantitative association between positive AI perceptions and career sustainability.

Theme 4: Training gaps and remaining challenges

Despite overall satisfaction, participants pointed out limitations. wcc noted that AIgenerated content still lacks fine detail and style control: “It’s not yet at a commercial level; you still need a lot of manual tweaking.” sjh suggested more granular instruction: “It would be helpful to know which AI is best for which task—for example, Doubao for images, Qwen for coding.” These insights echo the quantitative observation that actual use lags behind intention, and that AI literacy (AIL) scores were among the lowest.

5. Discussion

This mixedmethods study examined AI acceptance among vulnerable employment groups and the role of training. The findings reveal several important patterns that extend previous TAM research and offer practical implications.

Overall positive attitudes but an intention–behavior gap. Consistent with prior studies on ChatGPT acceptance (Yilmaz et al., 2023)[12], our participants rated perceived usefulness and ease of use highly. However, actual use scores were lower, indicating a gap between intention and behavior. This gap may be attributed to limited opportunities to apply AI in daily work, or to lingering skill deficits (as suggested by the lower AI literacy scores). Qualitative accounts confirmed that even motivated learners encounter practical hurdles.

Training as a key differentiator. Both quantitative comparisons and RAC networks showed that training experience—especially professional or selfdirected training—was associated with higher PEOU, BI, and CS. Participants with no training reported significantly lower ease of use and organizational support. This aligns with Ali et al. (2023)[11] and Yilmaz et al. (2023)[12], who found that training enhances technology acceptance. The RAC networks further revealed that "Received professional training" clustered with positive evaluations of BI and CS, suggesting that such training not only improves skills but also strengthens career optimism.

The emergence of a positive "profile". Network 3 delineated a profile of highly positive respondents: younger, with intermediate or advanced AI experience, and often having received training. This profile resonates with the diffusion of innovation theory (Raman et al., 2024)[15], where early adopters tend to be younger and more techsavvy. Conversely, Network 4 highlighted a negative profile characterized by older age and beginner status, confirming the digital divide concerns raised by Fuchs (2023)[8].

The multifaceted role of ease of use. PEOU emerged as a central node in both positive and negative networks. In the positive network, it was tightly linked to PU and BI; in the negative network, it connected to low POS and older age. This centrality underscores that ease of use is not only a direct determinant of acceptance but also a marker of broader support and demographic advantage.

Training content matters. While training generally improved perceptions, our qualitative findings suggest that overly complex topics could intimidate beginners—a nuance also noted by García Alonso et al. (2024)[13]. This may explain why some trained individuals in Network 4 still showed negative associations. Tailoring training to different skill levels could mitigate such effects.

Implications for practice and policy. These findings underscore the need for inclusive AI training programs for vulnerable groups. Such programs should: (a) demystify AI through handson, nontechnical introductions; (b) address specific workplace applications to bridge the intention–behavior gap; (c) offer differentiated tracks for beginners and more advanced users. By doing so, they can contribute to SDG 8 (decent work and economic growth) and SDG 10 (reduced inequalities).

Limitations and future research. The small sample size (N = 39) limits statistical power and generalizability. The crosssectional design precludes causal inferences about training effects. Future studies should employ larger, more diverse samples and longitudinal designs to track changes over time.

6. Conclusion

This study provides initial evidence that AI training is positively associated with technology acceptance among vulnerable employment groups. By combining survey data with RAC networks and qualitative interviews, we showed that positive attitudes cluster around individuals who are younger, more experienced, and trained, while negative perceptions are rare and linked to older age and lack of training. Training appears to enhance perceived ease of use, behavioral intention, and career sustainability. These findings highlight the importance of designing accessible, skillappropriate AI training programs to empower vulnerable workers and reduce digital inequalities, thereby contributing to the achievement of SDG 8 (Decent Work and Economic Growth) and SDG 10 (Reduced Inequalities).

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