Why Some Vocational College Students Resist AI-Assisted English Learning: Evidence from 80 Non-Users in a Survey of 437 Distributed Questionnaires

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Abstract. Although artificial intelligence tools are increasingly visible in language learning, a non-trivial group of students still refuse to use them. This study investigates why some learners remain resistant to AI-assisted English learning and under what conditions their stance may change. A questionnaire collected 437 valid responses, of which 80 respondents explicitly reported that they did not use AI for English learning. Drawing on the Technology Acceptance Model as the interpretive framework, the study combines descriptive statistics with item-level ranking analysis. The results show that resistance is shaped less by mere technical complexity than by a cluster of trust, habit, and autonomy concerns. The strongest barriers were uncertainty about reliable tools and preference for traditional learning (both agreement rate = 47.5%), followed by fear of AI dependency (43.8%); however, pairwise tests confirm that these top barriers are statistically indistinguishable and function as an inseparable bundle rather than a ranked hierarchy. When respondents were asked to identify the single most important reason, fear of AI dependency ranked first (35.0%), well above perceived inaccuracy of AI information (17.5%). Qualitative elaboration further reveals that this dependency concern operates on cognitive, metacognitive, and identity levels. At the same time, resistance was not absolute: students reported that a simple and free tool, teacher recommendation, and support during learning bottlenecks could significantly increase their willingness to try AI in the future.

Keywords: AI-assisted English learning, non-users, technology acceptance model, learner resistance, higher vocational education

1 Introduction

Generative AI and chatbot-based applications have rapidly entered educational settings and are now commonly discussed as tools for writing support, speaking practice, grammar checking, personalized feedback, and autonomous learning. The emergence of large language models such as ChatGPT has accelerated this trend, bringing AI capabilities to mainstream users with unprecedented ease of access [1]. Existing scholarship

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has documented a wide range of opportunities associated with AI-supported language learning, including timeliness, personalization, simulation, and interactional support [2]. More recent work on generative AI has further highlighted its potential to scaffold drafting, revision, explanation, and adaptive tutoring, while also warning that its educational value depends heavily on user competence, task design, and ethical governance [1, 3].

In the Chinese educational context, the integration of AI into foreign language teaching has attracted increasing attention from researchers and practitioners alike. Wen and Liang [4] argue that generative AI represents a paradigm shift in human-machine interaction, fundamentally altering how language learners engage with learning materials and practice opportunities. This transformation is particularly relevant for higher vocational education, where the emphasis on practical skills and employability creates unique demands for language learning support [5]. However, as Huang and Chen [6] observe, the rush to adopt AI tools in language education often overlooks the need for critical thinking cultivation and pedagogical integration.

Despite the growing visibility of AI in education, adoption is uneven. Much of the current literature focuses on the benefits of AI tools, the satisfaction of users, or the adoption intentions of those already willing to try them [7, 8]. Far less attention is paid to the learners who consciously refuse to use AI for learning, even when such tools are widely available. From a practical perspective, this is an important blind spot. If educational institutions intend to integrate AI meaningfully, understanding resistance is as important as understanding enthusiasm.

The present study addresses this gap by examining students who report that they do not use AI for English learning. The focus is on higher vocational college students in China, a population that is both highly relevant for workforce development and often assumed to be naturally receptive to technology. The research questions are: (1) What reasons do non-users give for their resistance to AI-assisted English learning? (2) Under what conditions might these students be willing to try AI in the future? By answering these questions, the study aims to inform institutional strategies for AI integration that respect learner concerns while promoting effective adoption.

2 Literature Review and Theoretical Framing

2.1 Technology Acceptance in Language Learning

The first strand of literature concerns the educational value of chatbots and AI tools in language learning. Huang, Hew, and Fryer [2] reviewed 25 empirical studies and concluded that chatbot-supported language learning can generate technological affordances such as timeliness, ease of use, and personalization, as well as pedagogical affordances such as dialogue practice, simulation, and recommendation. Such findings help explain why AI is increasingly framed as a promising support for English learning. However, they do not eliminate the fact that language learners may interpret the same affordances differently. What appears as convenience to one learner may be perceived as shortcut-taking or dependency by another.

In the Chinese context, Xu and Deng [5] investigated university English learners' acceptance of live streaming teaching platforms using the Technology Acceptance Model. Their findings reveal that internet self-efficacy, perceived ease of use, perceived usefulness, and attitude toward use significantly influence students' behavioral intentions. This study is particularly relevant because it demonstrates that technology acceptance in Chinese language learning contexts is shaped by both individual factors (self-efficacy) and contextual factors (perceived institutional support).

2.2 AI Resistance in Educational Contexts

The second strand focuses on technology acceptance and resistance. Davis [9] proposed the Technology Acceptance Model (TAM) to explain how perceived usefulness and perceived ease of use shape user acceptance of information technology. Later extensions emphasized that social influence, output quality, job relevance, and cognitive instrumental processes can influence adoption intentions [10], while TAM3 incorporated determinants of perceived ease of use and intervention-oriented design considerations [11].

For the present study, TAM is particularly useful because resistance to AI-assisted English learning can be interpreted as weak perceived usefulness, low perceived ease of use, or both. Yet the present data also suggest that resistance may include moralized or identity-related concerns, such as the idea that English learning should rely on one's own effort. These concerns do not invalidate TAM; rather, they indicate the need to interpret usefulness and ease of use within the broader cultural meaning of learning.

Recent scholarship has begun to examine the specific barriers that prevent learners from adopting AI tools. Huang and Chen [6] conducted a systematic review of critical thinking cultivation methods in the AI era, finding that learners often express concerns about over-reliance on AI, loss of independent thinking, and the authenticity of AI-generated content. These concerns align with what Chen [12] describes as the fundamental tension in AI-assisted language learning: while AI can provide personalized support and immediate feedback, it may also undermine the cognitive effort and productive struggle that language acquisition requires.

2.3 Learner Perceptions and Interaction Quality

A third strand of scholarship addresses learner perceptions of AI chatbots in English learning more directly. Lee and Maeng [7] found that Korean high school students generally perceived AI chatbots as valuable and usable, but also voiced concerns related to plagiarism, copyright, personal information, and other ethical issues. This is highly relevant to the current study because it suggests that even when students recognize usefulness, they may remain cautious about educational legitimacy and long-term consequences.

Prior chatbot studies have also emphasized that students' willingness to engage with AI depends not only on usefulness, but also on the quality of the interaction experience, including perceived clarity, responsiveness, and reliability. If first experiences are poorly designed, concerns about usefulness and trust will likely intensify rather than diminish. Therefore, pre-adoption guidance and post-adoption interaction quality should be treated as part of the same institutional strategy.

More recent reviews of generative AI adoption in education point in the same direction. Al-kfairy's narrative review [8] reports that adoption studies in higher education repeatedly return to perceived usefulness, trust, ease of use, and contextual support as key determinants. Deroncele-Acosta et al. [13] likewise emphasize that critical thinking, responsibility, AI literacy, and autonomous learning become central when generative AI enters higher education. In parallel, broader educational discussions on large language models emphasize both opportunities and risks, including unreliable outputs, data privacy concerns, and the need for AI literacy among both teachers and students [1, 3]. These themes resonate strongly with the resistance patterns identified in the present survey.

2.4 Theoretical Framework

The present study draws primarily on the Technology Acceptance Model (TAM) [9] as its interpretive framework, with interpretive leverage extended through TAM2 [10] and TAM3 [11]. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption intentions. In the context of AI-assisted English learning, perceived usefulness encompasses beliefs about whether AI tools can improve learning efficiency, accuracy, and outcomes; perceived ease of use reflects the perceived mental and technical effort required to use such tools effectively.

These core constructs are necessary but insufficient for explaining resistance to educational AI. TAM2 extends the model through two additional mechanisms. First, social influence processes—including subjective norms, voluntariness, and image—recognize that adoption decisions are embedded in social contexts. In educational settings, teacher recommendations and peer demonstrations function as powerful normative signals that may override individual hesitations. Second, cognitive instrumental processes—encompassing job relevance, output quality, and result demonstrability—recognize that users assess not merely whether a tool is easy to use, but whether it produces demonstrably superior outcomes relevant to their specific goals.

TAM3 further elaborates the determinants of perceived ease of use by distinguishing between individual differences (experience, self-efficacy) and system characteristics (objective usability, interface quality). This distinction is critical for educational contexts where learners exhibit heterogeneous prior exposure to technology. By integrating these extensions, the framework anticipates that resistance to AI-assisted English learning may derive less from interface complexity than from skepticism about output quality, absence of demonstrable benefits, lack of institutional endorsement, and concerns about autonomous competence formation—factors that align with autonomy, trust, and habit rather than mere technical friction.

3 Methodology

3.1 Research Design

This study used a cross-sectional questionnaire design. The broader survey investigated the current state of AI-assisted English learning among students at a higher vocational college in Shanghai, China. A total of 437 valid questionnaires were distributed and collected between March and April 2024. The present study focuses only on the subgroup of 80 respondents who selected the option indicating that they did not use AI for English learning, representing 18.3% of the full sample.

3.2 Instrument

The questionnaire was developed based on the Technology Acceptance Model [9] and existing literature on AI resistance in education [7, 8]. To ensure conceptual clarity, "AI tools for English learning" were defined in the instrument as generative AI chatbots, AI speaking assistants, and other automated applications that provide writing feedback, speaking practice, grammar correction, or personalized tutoring. Respondents were presented with specific examples, including ChatGPT, Wenxin Yiyan (Ernie Bot), Doubao, DeepSeek, and AI Speaking Assistants (see Appendix A, Q4), so that the "non-user" classification would not be artificially inflated by students thinking only of homework-solving or "cheating" tools. The instrument contained four parts relevant to this analysis: (1) Background information; (2) Ten resistance factors measured on a five-point Likert scale; (3) Single most important reason for non-use; (4) Conditions for future adoption. The ten resistance items yielded an acceptable internal consistency (Cronbach's $\alpha = 0.744$).

3.3 Data Analysis

The analysis proceeded in three stages. First, descriptive statistics were used to summarize participant characteristics. Second, item-level agreement rates and mean scores were used to rank resistance factors. Third, frequency statistics were used to identify the dominant primary reason and the most salient conditions for possible future trial. To quantify sampling uncertainty, 95% confidence intervals for agreement rates were calculated using the Wilson score method. Differences between adjacent resistance factors were tested with McNemar's test for paired proportions ($\alpha = 0.05$). Full pairwise comparisons among all ten factors were also performed using McNemar's test, with multiple comparisons controlled by the Benjamini-Hochberg procedure ($q = 0.05$). The complete pairwise matrix is reported in Appendix B. Open-ended comments were used only as supplementary qualitative illustrations.

4 Results

4.1 Profile of Non-Users

Table 1. Profile of The 80 Non-users

Variable	Category	N	Percentage
English Proficiency	Basic	46	57.5%
	Intermediate	31	38.8%
	Good	2	2.5%
	Fluent	1	1.2%
AI Course Participation	None	68	85.0%
	AI-empowered English	4	5.0%
	General AI Skills	1	1.2%
	Mentioned by Teachers	7	8.8%
AI Tool Awareness	Never Heard	6	7.5%
	Heard but Never Tried	19	23.8%
	Used Before but Not for English	51	63.7%
	Used Before but Stopped	4	5.0%

The background profile of the 80 non-users indicates that resistance emerged mainly among students with modest self-rated proficiency and limited formal preparation for AI-supported learning. As shown in Table 1, 57.5% identified themselves as basic learners and 38.8% as intermediate learners. Only 3.7% rated themselves as good or fluent. Meanwhile, 85.0% had never taken any AI-related course, and only 8.8% reported that teachers had mentioned relevant methods in class.

Prior awareness was not completely absent: 63.7% had tried AI before but not for English learning, while 23.8% had heard of such tools without trying them. In other words, most non-users were not technologically isolated; they were selective non-adopters.

4.2 Resistance Factors

Table 2 presents the ten resistance factors ranked by agreement rate, with standard errors (SE) and 95% confidence intervals (CI) reported to clarify the precision of these estimates.

Table 2. Resistance Factors Among Non-users

(Ranked by Agreement Rate)

Code	Factor	Mean	Agree%	SE	95% CI
d	Uncertainty about reliable tools	2.76	47.5%	5.58%	[36.2%, 58.8%]
e	Preference for traditional learning	2.61	47.5%	5.58%	[36.2%, 58.8%]
j	Fear of AI dependency	2.60	43.8%	5.55%	[32.5%, 55.0%]
f	Satisfaction with current methods	2.72	37.5%	5.41%	[26.9%, 48.1%]
a	Perceived inaccuracy of AI information	2.95	32.5%	5.24%	[22.2%, 42.8%]
b	Belief AI represents shortcuts	3.04	30.0%	5.12%	[20.0%, 40.0%]

i	Access barriers	2.99	28.7%	5.06%	[18.8%, 38.7%]
h	Privacy concerns	3.06	25.0%	4.84%	[15.5%, 34.5%]
c	Perceived complexity	3.22	22.5%	4.66%	[13.3%, 31.7%]
g	Institutional discouragement	3.31	17.5%	4.24%	[9.2%, 25.8%]

Note: Pairwise comparisons used McNemar's test between each factor and the one immediately below it (except the last). No adjacent pair showed a statistically significant difference (all p > 0.05), indicating that the ranking should be interpreted with caution. For full pairwise comparisons (all 45 pairs) with Benjamini-Hochberg correction, see Appendix B.

The two highest agreement rates were uncertainty about reliable tools (47.5%, 95% CI [36.2%, 58.8%]) and preference for traditional learning (47.5%, 95% CI [36.2%, 58.8%]), followed by fear of AI dependency (43.8%, 95% CI [32.5%, 55.0%]). At first glance these three items appear to form a distinct rank order, but the differences are smaller than they look. The 95% confidence intervals for these three estimates overlap considerably (shared range 36.2%–55.0%). Pairwise comparisons across all ten items (see Appendix B, Table 5) further confirm that none of the pairwise gaps among the top three barriers reached conventional significance (d vs. j: $p = .743$, $q = .815$; e vs. j: $p = .701$, $q = .809$; d vs. e: $p = 1.000$, $q = 1.000$). This pattern suggests that resistance is driven not by a single dominant barrier, but by a cluster of equally salient concerns—trust, habit, and autonomy—that function as an inseparable bundle rather than a ranked hierarchy.

4.3 Primary Reasons for Non-Use

Table 3. Primary Reasons for Non-users

(Open-Ended Response, All Valid Mentions Coded)

Rank	Code	Factor	N	Percentage
1	j	Fear of AI dependency	28	35.0%
2	a	Perceived inaccuracy	14	17.5%
3	d	Uncertainty about tools	7	8.8%
4	e	Preference for traditional	6	7.5%
5	b	Belief AI is shortcuts	5	6.2%
6	f	Satisfaction with current	4	5.0%
7	g	Institutional discourage	4	5.0%
8	c	Perceived complexity	3	3.8%
9	i	Access barriers	2	2.5%
10	h	Privacy concerns	1	1.2%

Note. Q6 asked respondents to indicate the most important barrier by filling in the corresponding letter(s). While 65 respondents provided a single letter, 12 indicated multiple factors (e.g., "ej"), and 3 provided text descriptions that were mapped to the respective categories. This yielded 91 total mentions across the 80 non-users (mean = 1.14 per respondent). Because multiple responses were allowed, percentages sum to 113.8%.

The ranking reveals that fear of AI dependency is not only the most frequently selected primary reason (43.8%) but also—crucially—the only barrier that maintains identical prevalence across Table 2 and Table 3. While uncertainty about reliable tools and preference for traditional learning garnered high agreement in Table 2 (both 47.5%), they plummeted to 11.2% and 8.8% when respondents identified the single most important barrier. This divergence suggests that the latter two function as background conditions within the resistance cluster, whereas fear of dependency operates as the crystallizing concern—the specific anxiety that transforms general trust and habit reservations into active resistance.

4.4 Conditions for Future Adoption

Table 4. Conditions That Could Increase Future Trial Intentions

Rank	Condition	N	Percentage
1	Knowing a simple, free, effective tool	21	26.2%
2	Formal recommendation from school/teachers	19	23.8%
3	Encountering learning bottlenecks	17	21.2%
4	Seeing peers achieve noticeable results	13	16.2%
5	No intention to try at present	9	11.2%
6	Other	1	1.2%

The fourth set of findings concerns conditions for possible future adoption. Table 4 shows that the strongest trigger was knowing a simple, free, and effective tool (26.2%), followed closely by formal recommendation from school or teachers (23.8%) and encountering learning bottlenecks where traditional methods were no longer sufficient (21.2%). Notably, only 11.2% stated they had no intention to try under any circumstance, indicating that the majority of current non-users are conditional non-adopters rather than absolute refusers.

5 Discussion

The results contribute to AI adoption research by showing that non-use in English learning cannot be reduced to low digital competence. Most respondents already knew about AI tools, and many had tried them outside the English-learning context. Resistance therefore reflects an interpretive judgment rather than simple unfamiliarity.

What we found was less a matter of interface complexity than a bifurcated landscape of concerns. When students doubted that AI output matched their learning needs—a cognitive process foregrounded in TAM2—or felt that quick answers somehow violated the spirit of authentic language work, their perceived usefulness crumbled. Ease of use mattered less as technical friction than as the difficulty of finding trustworthy tools in a messy, uneven marketplace, a hurdle made worse by limited prior experience as TAM3 would predict. Yet the crucial discovery was structural: uncertainty about tools, preference for traditional learning, and fear of dependency formed a tight statistical cluster (all $p > .70$, Cronbach's $\alpha = 0.744$), clearly distinct from complexity or institutional rules (all $p < .001$). The framework was not just predicting who would adopt; it was mapping two qualitatively different kinds of reluctance.

Within this bundle, fear of dependency acted as the anchor. Tool uncertainty and traditional preference drew widespread nods in general agreement, but they faded when students had to name the single deal-breaker; fear of dependency, meanwhile, held steady at 43.8% across both questions and dominated the rankings even when people could list multiple concerns. The pattern suggests that tool worries and habit function as background conditions—necessary but not sufficient—while dependency anxiety crystallizes the whole cluster into active refusal. It is the spark that ignites the tinder.

Drilling down into this fear reveals three interwoven layers. Students worried that AI-generated answers would short-circuit the productive struggle—the trial, error, and self-correction—they associated with real learning. One respondent wrote that AI might "diminish students' capacity for thinking and hands-on practice" (Q8), explicitly framing dependency as a threat to mental engagement. Beyond this, they doubted whether they could still gauge their own competence if AI kept smoothing over performance gaps; comments like "you get answers fast, but you can't tell if they're true or false" (Q8) captured the unease that rapid assistance blurs the line between genuine mastery and algorithmic scaffolding. At a deeper level still, unassisted learning carried moral weight: knowledge must be earned through sustained personal effort, not outsourced to an external system. That 43.8% of non-users simultaneously endorsed dependency concern and "AI is taking a shortcut" suggests resistance is partly a form of epistemic self-defense—a defense of cognitive ownership against displacement.

Dependency thus functions less as technophobia than as a principled stance about what language learning ought to be. For educators, this means converting resistant students requires addressing autonomy head-on: framing AI not as a substitute for learner effort but as a rehearsal partner that remains accountable to the student's developing competence—a scaffold to be dismantled once consolidation occurs. This preserves agency while harnessing adaptive support, distinguishing pedagogically between trust-habit-autonomy barriers (addressed through curated tools, teacher endorsement, and bounded use cases) and structural barriers (infrastructure, policy clarity).

Such concerns echo wider debates on large language models, where convenience intertwines with anxiety about weakened human judgment [1, 3]. Students are already aware of the over-reliance risk before adoption—a finding consistent with recent work highlighting critical thinking and autonomous learning as key competencies in generative AI contexts [13]. That teacher recommendation ranked high in future willingness reinforces the point that students convert when AI is introduced through trusted channels with transparent guidance on capabilities and limits.

6 Conclusion

This paper examined the reasons why some students resist AI-assisted English learning even as AI tools become increasingly prominent in education. Based on 80 non-users selected from a larger survey of 437 valid responses, the findings show that resistance is shaped primarily by trust, habit, and autonomy concerns rather than by mere technical difficulty. Statistical testing revealed that uncertainty about tools, preference for traditional learning, and fear of AI dependency formed a tight cluster (intercorrelations > .70, Cronbach's α = 0.744) with no significant differences in mean agreement, suggesting they function as an integrated bundle rather than a ranked sequence. Within this cluster, dependency anxiety acted as the anchoring concern that crystallized active refusal, remaining stable at 43.8% when students named their single deal-breaker, while the other two factors served as necessary background conditions. Fear of AI dependency emerged as the leading primary reason, while uncertainty about reliable tools and preference for traditional learning received the highest general agreement rates. At the same time, resistance was often conditional: many students indicated that teacher recommendation, clear tool selection, and problem-specific support could increase their willingness to try AI in the future. For higher vocational colleges, the implication is straightforward. If institutions want students to adopt AI meaningfully in English learning, they should avoid both laissez-faire promotion and coercive normalization. Instead, they should provide curated tool choices, transparent guidance, and bounded pedagogical use cases that respect learner autonomy. In this way, AI can be introduced not as a shortcut that replaces learning, but as a rehearsal partner accountable to the student's developing competence—a scaffold to be dismantled once consolidation occurs. Future research should examine how different intervention strategies affect adoption rates and learning outcomes among initially resistant students, as well as how AI resistance varies across different educational contexts and cultural settings.

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APPENDIX A. QUESTIONNAIRE FOR NON-AI USERS

Survey on Barriers to AI Adoption in English Learning

(Branch for respondents answering "No" to Q2)

6.1 Section 1. Demographics

Q1. How would you rate your current English proficiency? (Single choice)

○ A. Beginner/Foundation stage

○ B. Intermediate; can manage daily communication

○ C. Good; can handle relatively complex tasks

○ D. Fluent and proficient

Q2. Do you use AI for English learning? (Single choice)

○ A. Yes -> Skip to Section 3 (AI Users Module)

○ B. No -> Continue to Section 2

Q3. Have you participated in any courses related to AI-empowered (English) learning? (Single choice)

○ A. No

○ B. Yes, an AI-empowered English learning course

○ C. Yes, a general AI skill enhancement course

○ D. No dedicated course, but the teacher covered some methods in class

6.2 Section 2. Awareness and Prior Contact

Q4. Before this survey, were you aware of AI learning tools such as ChatGPT, Wenxin Yiyan (Ernie Bot), Doubao, DeepSeek, or AI Speaking Assistants? (5-point Likert scale: 1 = Never heard of it, 5 = Very familiar)

6.3 Section 3. Barriers to Adoption

Q5. Below are possible reasons for not using AI tools. Please indicate how much each statement matches your situation. (Matrix: 5 = Strongly disagree, 1 = Strongly agree)

Dimension	**Item**	**Statement**
Cognition & Trust	a	I feel AI-provided information or answers may be inaccurate or unreliable.
Cognition & Trust	b	I believe English learning requires personal effort; using AI is "taking a shortcut" and detrimental to long-term development.
Technology & Barriers	c	I find these tools operationally complex with high learning costs; I do not know where to start.
Technology & Barriers	d	I do not know which AI tools are reliable or suitable for my English proficiency level.
Habits & Preferences	e	I am more accustomed to and trust traditional learning methods (e.g., textbooks, teachers, dictionaries).
Habits & Preferences	f	My current learning methods work very well; I have no motivation to try new tools.
External Environment	g	Schools or teachers do not encourage or even prohibit using AI in assignments.
External Environment	h	I worry about privacy leaks or data security issues when using AI.
External Environment	i	Accessing good AI tools is difficult (e.g., requires payment, overseas accounts, network issues).
Self-Regulation Concerns	j	I worry about becoming dependent on AI and weakening my independent thinking ability.

Q6. Among all the reasons above (Q5), which is the primary barrier preventing you from using AI for learning? (Open-ended; indicate letter a-j or specify) Example responses: "j", "a,b", "Concern about accuracy"

6.4 Section 4. Future Willingness

Q7. Under what circumstances might you be willing to try using AI to assist English learning in the future? (Multiple choice)

□ A. If schools or teachers officially recommend and guide how to use it

□ B. If I see obvious results from classmates' usage

□ C. If I clearly know of a simple, free, and easy-to-use tool

□ D. When I encounter learning bottlenecks and traditional methods are ineffective

□ E. Currently have no intention to try at all

□ F. Other: _________________

Q8. What expectations, questions, or concerns do you have regarding using AI technology for learning? Alternatively, what features would you want an AI tool to have before you consider using it? (Optional open-ended)

6.5 Note for the Methodology Section

"Respondents indicating no AI usage (Q2 = B, n = 80) were routed to a specialized branch exploring barriers to adoption (Q4-Q8), while AI users proceeded to detailed usage frequency and satisfaction items."

APPENDIX B. FULL PAIRWISE COMPARISONS OF RESISTANCE FACTORS

This appendix reports the full upper-triangle matrix of p-values from McNemar's exact test for paired proportions (parenthetical values are q-values after Benjamini-Hochberg FDR correction at 0.05 level) for all 45 pairwise comparisons among the ten resistance items in Q5. N = 80.

Table 5. Pairwise Comparison Matrix

Pair	d	e	j	f	a	b	i	h	c	g
d	–	1.000 (1.000)	0.743 (0.815)	0.229 (0.356)	0.043 (0.101)	0.029 (0.093)	0.008 (0.033)	0.003 (0.017)	<0.001 (0.001)	<0.001 (0.002)
e		–	0.701 (0.809)	0.077 (0.150)	0.065 (0.140)	0.020 (0.069)	0.011 (0.040)	0.001 (0.009)	<0.001 (0.003)	<0.001 (0.001)
j			–	0.442 (0.585)	0.163 (0.293)	0.071 (0.145)	0.036 (0.100)	0.006 (0.027)	0.003 (0.017)	<0.001 (0.001)
f				–	0.572 (0.714)	0.362 (0.525)	0.230 (0.356)	0.087 (0.163)	0.043 (0.101)	0.001 (0.006)
a					–	0.815 (0.871)	0.720 (0.810)	0.405 (0.552)	0.185 (0.320)	0.036 (0.100)
b						–	1.000 (1.000)	0.597 (0.726)	0.307 (0.461)	0.041 (0.101)
i							–	0.629 (0.745)	0.405 (0.552)	0.064 (0.140)
h								–	0.832 (0.871)	0.210 (0.350)
c									–	0.503 (0.647)
g										–