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Role Perceptions of EFL Learners in Human-GenAI Collaborative Revision: A Q-Methodological Study

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Abstract— *Generative artificial intelligence (GenAI) is increasingly being used as a cognitive partner rather than merely an auxiliary writing tool. Previous research has largely examined learners' evaluations of GenAI functions and perceived risks, whereas role perceptions in human-GenAI collaborative writing revision have received limited systematic attention. Using Q methodology, this study identifies two role-perception types among EFL learners: the Open Collaborative Type and the Prudent Autonomous Type. Both groups value integrating GenAI suggestions with their own ideas and reject delegating all revision decisions to GenAI. However, they differ in their views of feedback evaluation and uptake, revision-goal setting, and control over the revision process. These findings offer evidence on how learners understand cognitive responsibilities in GenAI-supported L2 writing revision.*

Keywords— ***Role perceptions; Q methodology; human-GenAI collaborative revision***

I. INTRODUCTION

The increasing use of generative artificial intelligence (GenAI) in L2 writing has changed how learners obtain and respond to feedback during revision. Unlike conventional feedback, which often takes the form of predefined suggestions, ChatGPT allows learners to discuss writing problems, seek clarification, and refine their texts through ongoing interaction. As learners engage with GenAI in revision, they must also determine what each party should contribute, who should evaluate and adopt feedback, and who should retain control over revision decisions. These understandings of human and AI roles and responsibilities are central to learners' role perceptions (Gao et al., 2026).

Existing research on GenAI-assisted L2 writing has primarily examined learners' attitudes toward the technology, its potential risks, and its effects on writing performance (Tam, 2025). Studies have also explored the roles of GenAI in broader collaborative contexts. Less is known, however, about how L2 learners perceive their own roles in relation to GenAI during writing revision, particularly the different ways in which they understand the division of responsibilities. The present study therefore employs Q methodology to identify distinct patterns of role perception in human-GenAI collaborative writing revision. Follow-up interviews provide further insight into the reasoning behind learners' Q-sort decisions and the characteristics of each identified type.

II. LITERATURE REVIEW

Mental models provide a useful perspective for understanding how individuals interpret and interact with complex systems. Johnson-Laird (1983) conceptualized them as internal representations that enable individuals to understand and reason about the world. Although mental models have been defined and operationalized in different ways, users' perceptions offer one approach to examining how they understand and interact with AI systems (Bodamer et al., 2026).

Research on GenAI-assisted writing has largely focused on learners' perceptions of its benefits and potential risks. Amani and Bisriyah (2025), for instance, found that 40 English learners valued AI assistance with grammar, vocabulary, and spelling, but continued to seek support from teachers and peers when more substantive writing guidance was needed. Similarly, Duong et al. (2024) reported positive

attitudes toward GenAI-assisted writing, alongside concerns about its limitations and implications for academic integrity. Beyond these general perceptions, researchers have also examined how human and AI roles are understood in collaborative settings. McComb et al. (2023) distinguished AI roles according to the focus and mode of interaction, while Dreyer et al. (2026) documented varied perceptions of human and AI roles in design co-creation. In the context of L2 writing, Huang and Wang (2025) found that learners retained control over writing decisions while drawing on ChatGPT to generate ideas, develop arguments, and refine language.

These studies suggest that learners' perceptions of GenAI involve more than judgments about its usefulness or limitations. They may also reflect how learners understand the respective contributions and responsibilities of humans and AI, an aspect that remains underexplored in L2 writing revision (Gao et al., 2026). Drawing on the perspective of mental models, the present study defines role perceptions as learners' subjective understandings of their own and GenAI's roles and decision-making responsibilities during collaborative revision. This includes how learners position GenAI as a source of writing support and how they understand responsibility for evaluating feedback, deciding whether to adopt suggestions, and managing the revision process. Q methodology is employed to identify shared patterns in these perceptions and explore how they differ across learners.

III. RESEARCH METHODOLOGY

1. Participants and Research Context

This study was conducted in a general English writing course at a comprehensive university in eastern China. A convenience sample of 105 non-English-major master's students was recruited from disciplines such as information technology, fisheries development, law, and biological sciences. All participants had studied English for over ten years and had prior experience using GenAI for writing revision. Before data collection, they were informed of the study's purpose and how their data would be used. Informed consent was obtained, and anonymous codes were assigned to protect their identities.

2. Data Collection

Data collection took place over three weeks. In the first week, the researchers developed the Q-set and organized a training session on human-GenAI interaction. Guided by mental-model research, they reviewed literature on learners' attitudes, beliefs, cognitive division of labor, and perceived responsibilities in collaborative revision (e.g., Chen & Liu, 2026; Dreyer et al., 2026). This process yielded an initial pool of 28 statements (McKeown & Thomas, 2013). Three experts in foreign language education and applied linguistics, all familiar with educational technology, reviewed the statements for clarity, relevance, distinctiveness, and coverage. Following their feedback, overlapping statements were combined or removed, leaving a final Q-set of 20 statements.

A forced-distribution Q-sort grid was created in Excel (Figure 1), with columns ranging from "most disagree" to "most agree". Positions within each column represented the same level of agreement. Participants then attended a one-hour online training session covering the use of ChatGPT, human-GenAI interaction strategies, and academic integrity. An open question-and-answer session was held to clarify the procedure. After the training, participants were given 40 minutes to write an argumentative essay of at least 300 words on a topic selected from the College English Test Band 6 (CET-6).

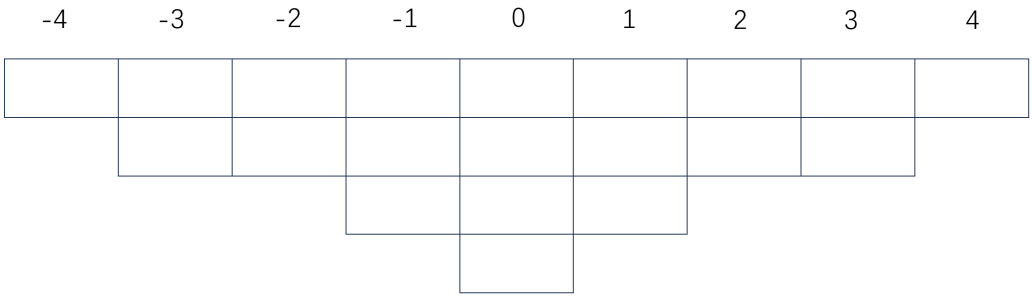


Fig.1: Q-sort

In the second week, participants used ChatGPT to revise their essays through self-directed interaction. During the third week, they completed paper-based Q sorts within 48 hours of submitting their final drafts. Each participant ranked the 20 statements on the forced-distribution grid according to their level of agreement, placing each statement number in a single position. The completed Q sorts were analyzed using KADE, and participants were selected for follow-up interviews based on their factor loadings. The interviews focused on the reasoning behind their rankings,

particularly the statements placed at the two extremes of the distribution.

3. Data Analysis

Of the 105 Q sorts collected, seven were excluded as invalid, leaving 98 for analysis. Principal component analysis (PCA) initially yielded eight factors with eigenvalues greater than 1 (Table 1). The scree plot showed a steep initial decline followed by a more gradual decrease. On this basis, a two-factor solution was retained and subjected to varimax rotation (Watts & Stenner, 2005, 2012).

Factor loadings were evaluated using the significance threshold of $2.58/\sqrt{N}$, where N represents the number of Q statements (N = 20), giving a threshold of approximately 0.577. Participants whose Q sorts loaded significantly on only one factor were treated as defining sorts, yielding 32 for Factor 1 and 33 for Factor 2. The two factors were then interpreted by examining their idealized Q sorts, standardized factor scores (Z-scores), and distinguishing and consensus statements. Interview accounts provided additional context for interpreting the factor arrays and naming the resulting role-perception types.

Table 1: Eigenvalues and cumulative explained variance

No.	F1	F2	F3	F4	F5	F6	F7	F8
Eigenvalues	42.514	7.832	6.187	5.838	4.432	3.706	3.541	3.093
Explained variance (%)	43	8	6	5	5	4	4	4
Cumulative explained variance (%)	43	51	57	62	67	71	75	79

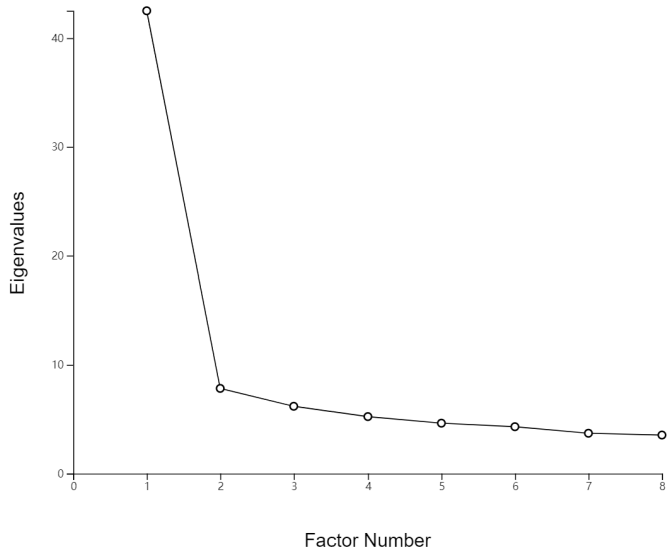


Fig.2: Scree plot of the extracted factors

IV. FINDINGS

The following sections first examine the two role-perception types separately and then compare their distinguishing statements. Of the 98 valid Q sorts, 65 met the defining-loading criteria: 32 loaded on Factor 1 and 33 on Factor 2.

1. The Open Collaborative Type (Factor 1)

Learners associated with Factor 1 valued human-GenAI collaboration and were relatively open to ChatGPT feedback. In terms of functional positioning, they most strongly endorsed combining GenAI suggestions with their own ideas (S10: +4) and viewed revision with GenAI as collaborative thinking rather than merely correcting linguistic errors (S3: +3). P93 explained: "The version revised by ChatGPT is usually more logically connected than mine. It also helps me notice things I had not thought of. Revising with it is more efficient than working on my own."

Table 2: Extreme statements for Factor 1

No.	Statement	Z-score	Q-sort Value
S10	I prefer to combine parts of GenAI suggestions with my own ideas.	1.612	+4
S3	Revising with GenAI feels more like collaborative thinking than simply correcting mistakes.	1.532	+3
S4	I don't carefully examine GenAI feedback before deciding whether to use it.	1.343	+3
S20	Even when GenAI feedback looks convincing, I may not adopt it.	-1.463	-3
S18	I consider GenAI feedback sufficient for my revision decisions without consulting teachers or peers.	-1.605	-3
S5	I won't revise my prompts to make GenAI suggestions better fit my own writing style or intentions.	-1.646	-4

In evaluating and adopting feedback, these learners were relatively willing to decide whether to use GenAI suggestions without closely scrutinizing each one (S4: +3). They also disagreed with the statement that seemingly convincing feedback might nonetheless be rejected (S20: -3). P97 commented: "I think ChatGPT is like a native English speaker. Later in the interaction, I sometimes just skimmed its feedback. If it did not distort my meaning and sounded reasonable, I used it." Nevertheless, they strongly rejected an approach that disregarded their own writing style and intentions (S5: -4). P51 described asking ChatGPT to simplify revisions that contained overly complex and unfamiliar vocabulary: "The sentences looked sophisticated, but I would not be able to use them in my own writing next time, so I asked it to generate simpler and clearer suggestions." They also disagreed that GenAI feedback alone was sufficient for revision decisions and acknowledged the need to consult teachers or peers when necessary (S18: -3).

Overall, Factor 1 learners valued GenAI as a source of collaborative thinking, integrated its suggestions with their own ideas, showed a relatively open approach to feedback uptake, and actively adjusted prompts to meet individual writing needs. This factor was therefore labeled the Open Collaborative Type.

Table 3: Extreme statements for Factor 2

No.	Statement	Z-score	Q-sort Value
S10	I prefer to combine parts of GenAI suggestions with my own ideas.	1.332	+4
S2	When GenAI suggestions change my intended meaning, I decide whether to accept those changes.	1.263	+3
S20	Even when GenAI feedback looks convincing, I may not adopt it.	1.062	+3
S9	I tend to let GenAI guide the sequence of steps in my revision process.	-1.480	-3

No.	Statement	Z-score	Q-sort Value
S18	I consider GenAI feedback sufficient for my revision decisions without consulting teachers or peers.	-1.551	-3
S14	I sometimes follow GenAI suggestions that I do not fully understand because I trust GenAI's judgment.	-1.677	-4

2. The Prudent Autonomous Type (Factor 2)

Factor 2 learners also placed the highest value on combining GenAI suggestions with their own ideas (S10: +4). However, they emphasized retaining personal authority when suggested revisions changed their intended meaning (S2: +3). Even apparently convincing AI feedback might be rejected (S20: +3). Their caution was particularly evident in feedback evaluation: they strongly disagreed that they would adopt suggestions they did not fully understand simply because they trusted GenAI (S14: -4). As P61 explained: "GenAI is only a tool for supporting writing revision. It sometimes generates irrelevant or contradictory suggestions, so I have to think independently about whether the feedback makes sense. If I always follow it, I may gradually lose my writing ability."

These learners also strongly rejected allowing GenAI to determine the sequence of revision steps (S9: -3). P73 described planning to revise content and logic before refining language, based on previously identified weaknesses in argument support and paragraph cohesion, rather than following the order in which ChatGPT generated suggestions. Although they recognized the value of collaborative thinking beyond error correction (S3: +2), they did not regard GenAI feedback alone as sufficient for all revision decisions (S18: -3). Overall, Factor 2 emphasized independent feedback evaluation, revision planning, and control over the revision process. It was therefore labeled the Prudent Autonomous Type.

3. Distinguishing Viewpoints

To compare the two types, the idealized Q sorts were examined for distinguishing statements. KADE identified 14 statements with statistically significant differences between factors: 11 at $p<.01$ and three at $p<.05$ (Table 4).

Table 4: Distinguishing statements between the two factors

Statement	Q-sort Value of Factor 1	Q-sort Value of Factor 2	ΔZ (F1-F2)	Significance
S20	-3	+3	-2.525	$p < 0.01$
S19	-1	+1	-1.495	$p < 0.01$
S1	+1	-1	1.383	$p < 0.01$
S6	0	-2	1.183	$p < 0.01$
S3	+3	+2	0.736	$p < 0.01$
S4	+3	+1	0.710	$p < 0.01$
S13	0	-1	0.533	$p < 0.01$
S2	+2	3	-0.531	$p < 0.01$
S14	-2	-4	0.530	$p < 0.01$

Statement	Q-sort Value of Factor 1	Q-sort Value of Factor 2	ΔZ (F1-F2)	Significance
S9	-2	-3	0.462	$p < 0.01$
S12	-1	0	-0.419	$p < 0.01$
S10	+4	+4	0.280	$p < 0.05$
S8	0	0	-0.273	$p < 0.05$
S15	0	+1	-0.265	$p < 0.05$

The two types differed in their views of GenAI's functional position. Factor 1 was relatively more receptive to GenAI's expertise in improving writing (S1: ΔZ=1.383), was neutral about its being an indispensable revision partner (S6: 0), and attached greater value to collaborative thinking (S3: ΔZ=0.736). Factor 2 was less inclined to see GenAI as indispensable (S6: -2). Their strongest difference concerned feedback evaluation and uptake. S20 had the largest contrast: Factor 1 rejected the statement that apparently convincing feedback might still not be adopted (-3), whereas Factor 2 endorsed it (+3). Both types rejected adopting incompletely understood suggestions solely on the basis of trust, but Factor 2 did so more strongly (S14: ΔZ=0.530). Factor 1 was more willing to adopt feedback without close checking (S4: ΔZ=0.710), while Factor 2 placed somewhat greater emphasis on retaining the final decision when an GenAI suggestion changed the writer's intended meaning (S2: ΔZ=-0.531).

The types also differed in their control of revision. Factor 2 more strongly endorsed setting goals before requesting feedback (S19: ΔZ=-1.495), rejected letting GenAI guide the revision sequence (S9: ΔZ = 0.462), and placed less emphasis on relying on GenAI to determine revision priorities (S13: ΔZ=0.533). Together with its position on S20, these results suggest a greater preference for planning and controlling the revision process in advance. Factor 1 did not show the same pronounced orientation toward advance planning.

Importantly, S10 received the highest idealized Q-sort placement in both factors (+4), although its difference in Z-scores was statistically significant ($p<.05$). S8 and S15 also differed significantly but occupied central positions in the arrays. Accordingly, these statements were not treated as the principal basis for differentiating the types. Both types valued combining AI feedback with personal ideas and opposed delegating all revision decisions to GenAI, although their understandings of feedback verification and responsibility differed.

V. CONCLUSION

Drawing on a mental-model perspective, this study employed Q methodology to identify two role perception types among EFL learners engaged in human-GenAI collaborative writing revision: Open Collaborative and Prudent Autonomous. Both types valued integrating GenAI feedback with personal ideas and retaining responsibility for revision decisions. However, Open Collaborative learners emphasized collaborative thinking and flexible interaction, whereas Prudent Autonomous learners prioritized feedback verification, goal setting, and independent judgment. These findings highlight distinct understandings of cognitive responsibilities despite a shared preference for human-GenAI collaboration.

Pedagogically, instruction should address these differences. Open Collaborative learners may benefit from explicit feedback-verification strategies, while Prudent Autonomous learners can be encouraged to engage in exploratory, multi-turn interactions without relinquishing decision-making authority. Reflective activities can further strengthen learners' awareness of GenAI's capabilities and limitations.

This study is limited by its single-university sample of non-English-major postgraduate students with prior GenAI experience and its focus on one revision task. Moreover, Q methodology identifies shared subjective viewpoints but cannot establish their effects on revision behavior or writing outcomes. Future research could involve more diverse learners, combine Q sorts with interaction records and revised texts, and adopt longitudinal designs to examine how role perceptions evolve and relate to cognitive engagement and writing performance.

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