

Profiling Beliefs about Multiliteracies in AI-Saturated Language Education

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Abstract

As generative artificial intelligence (AI) becomes embedded in everyday language learning, the conceptual adequacy of multiliteracies frameworks remains underexamined. This study profiles how students and instructors reinterpret multiliteracies within an AI-saturated English language program at a single comprehensive university. Drawing on a convergent mixed-method design, data were collected over one semester from 178 undergraduate EFL students and 9 instructors. Instruments included a newly developed Multiliteracies-in-AI Scale (MIAS), stimulated-recall interviews, and a corpus of pre- and post-intervention essays. Latent profile analysis identified three belief configurations: (1) Instrumentalist Integrators (AI as efficiency tool), (2) Critical Orchestrators (AI as multimodal co-designer requiring oversight), and (3) Displaced Traditionalists (AI as threat to textual authenticity). Regression modeling revealed that belief profiles significantly predicted observable AI use patterns, including prompt complexity, revision depth, and multimodal integration ($p < .01$). Notably, students classified as Critical Orchestrators demonstrated higher intertextual diversity and more frequent cross-modal redesign (text–image–data integration) in final submissions. A short, four-week algorithmic literacy module shifted 27% of Instrumentalist Integrators toward the Critical Orchestrator profile. The findings challenge static interpretations of multiliteracies by demonstrating that AI saturation produces differentiated epistemic orientations that are measurable, behaviorally traceable, and pedagogically malleable. We propose a reconceptualization of multiliteracies as dynamic belief–practice constellations shaped by algorithmic co-authorship rather than solely by multimodal textuality.

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1. Introduction

Language education is entering an era in which meaning is no longer produced solely through human engagement with stable texts and familiar semiotic resources. The New London Group's (1996) concept of multiliteracies emerged in response to expanding communication technologies and increasing cultural and linguistic diversity, rejecting print-centred literacy in favour of meaning-making across varied modes and social contexts. Cope and Kalantzis (2009) later conceptualized literacy as design, through which learners select available designs, transform them, and produce redesigned meanings for new audiences and purposes. Generative artificial intelligence now introduces another major transformation. These systems can draft and revise texts, summarize information, generate images, analyze data, and sustain dialogic exchanges. Consequently, generative AI functions not merely as a classroom tool but as a technology of writing, representation, and multimodal meaning-making that challenges conventional understandings of literacy and authorship (Kalantzis & Cope, 2024).

This transformation is particularly significant in language education, where composing supports communication, linguistic development, rhetorical awareness, and individual voice. Research on ChatGPT in EFL writing identifies benefits such as immediate feedback, idea generation, linguistic support, and varied writing prompts, alongside concerns about dependency, reduced cognitive effort, and weakened critical engagement (Teng, 2024). Although generative AI is becoming increasingly embedded in learners' composing environments, its use remains uneven across institutions, disciplines, teachers, and learner

groups. This situation raises a question that traditional multiliteracies theory was not designed to answer: what happens to *design*, *available designs*, and *redesign* when a nonhuman system directly contributes to meaning-making? The issue is no longer only whether learners can select and combine different modes, but whether they retain intellectual and rhetorical control when semiotic resources are generated dynamically through algorithmically interpreted prompts. Generative AI therefore blurs the boundaries among resource, tool, collaborator, and author.

Multiliteracies pedagogy has generally understood multimodality as the purposeful orchestration of linguistic, visual, auditory, gestural, spatial, and digital resources by human meaning-makers (Cope & Kalantzis, 2009). Generative AI complicates this human-centred model because AI-mediated composing involves not only the learner, but also the learner's communicative purposes, prompt choices, interaction history, evaluative judgments, the model's learned patterns, and platform constraints. Recent research on generative-AI-assisted multimodal composing similarly indicates that AI can both expand and restrict agency, creativity, and criticality through iterative exchanges between user input and model output (Hafner & Ho, 2026). While some scholars emphasize its capacity to support experimentation, feedback, and multimodal production, others warn that uncritical use may encourage over-reliance, obscure bias and provenance, and replace deliberate composing with passive acceptance of generated content (Godwin-Jones, 2022; Cox, 2024). Cox (2024) consequently argues that responsible generative AI literacy must extend beyond effective prompting. Junqueira's (2025) systematic review likewise distinguishes technicist approaches, which prioritize operational efficiency, from critical approaches centred on agency, ethics, reflection, and critical thinking. Broader educational frameworks therefore define AI literacy through conceptual understanding, practical application, evaluation, ethical awareness, and risk mitigation (MacCallum et al., 2024; Ruiz et al., 2024). Nevertheless, much of this scholarship remains conceptual, providing limited empirical evidence about how learners' beliefs concerning AI, authenticity, authorship, and multimodality shape their actual composing practices.

Empirical studies further show that AI-mediated writing cannot be explained by a simple distinction between use and non-use. Cai and Yu (2025) found that Chinese EFL students valued generative AI for efficiency and reduced writing difficulty, whereas teachers expressed stronger concerns about language development and over-reliance; both groups nevertheless considered clear prompting essential. Strobl et al. (2024) reported that advanced L2 German learners who compared their drafts with ChatGPT-generated texts became more aware of the model's linguistic strengths and content limitations and used it more effectively during revision. Similarly, Shii and Kim (2025) found that learners with stronger AI literacy refined prompts more strategically and obtained feedback that better addressed their learning goals. Multimodal studies reveal comparable complexity. Liu, Zhang, and Biebricher (2023) showed that learners completing AI-assisted multimodal presentations used chatbot summaries and image prompts differently from those writing conventional essays, while Li, Xia, and Guo (2025) found that learners evaluated AI-generated videos through text-video consistency, visual engagement, and auditory qualities. Jiang and Lai (2025) further reported that generative-AI users outperformed non-AI groups in purpose development, navigation, and overall multimodal-composition quality, although several basic design features remained comparable. These studies establish the importance of prompting, critical stance, revision, and semiotic decision-making, but they do not determine whether AI-related beliefs form identifiable configurations, predict prompt complexity, revision depth, and multimodal integration, or change through instruction.

Addressing this gap, the present study introduces **belief-practice constellations** to explain how learners' epistemic orientations toward generative AI correspond with their observable composing behavior. Rather than imposing a binary distinction between acceptance and resistance, it identifies empirically derived profiles based on beliefs about AI as an instrumental aid, a co-designer, a threat to authenticity, and an object of critical evaluation. Its novelty lies in connecting these profiles with independently observed behavioral traces, including prompt complexity, substantive revision, and the integration of textual, visual, and data-based resources. The study also examines whether profile membership remains stable or can be reshaped through a short-term algorithmic literacy intervention. It therefore extends multiliteracies beyond multimodal textuality and technical competence by positioning epistemic stance, evaluative authority, and algorithmic co-authorship as central dimensions of meaning-making. This perspective helps explain why learners with similar technological access and proficiency may engage with AI in markedly different ways.

The study is significant because language programs require evidence-based responses to generative AI rather than policies based on assumptions of universal adoption, inevitable dependency, or uniform

resistance. It addresses three questions: what belief configurations regarding AI and multiliteracies can be identified among EFL students and instructors; whether these profiles predict prompt complexity, revision depth, and multimodal integration; and whether profile membership can change through a short-term algorithmic literacy module. Accordingly, the study aims to develop and validate a measurement instrument, construct an empirically grounded typology of belief-practice configurations, and refine multiliteracies theory for algorithmic co-authorship. It does not assume that AI-mediated composition is inherently beneficial or harmful. Instead, it examines how particular orientations relate to participants' decisions to prompt, evaluate, accept, reject, revise, and combine semiotic resources. By integrating belief measurement, behavioral evidence, interviews, and multimodal writing outcomes, the study also addresses the limitations of research based primarily on one-time self-report data.

Conceptually, this study proposes that multiliteracies in AI-saturated education should be understood as a dynamic relationship among beliefs, practices, semiotic resources, and algorithmic systems. Generative AI does not automatically eliminate human agency, just as access to sophisticated tools does not guarantee critical or creative participation. What matters is learners' capacity to direct the system, evaluate its suggestions, recognize its limitations, preserve rhetorical purpose, and transform generated material. AI outputs can therefore be treated as provisional available designs requiring critical interrogation and redesign, while learners remain responsible for the epistemic, ethical, and communicative quality of the final composition. This reconceptualization also demonstrates why technical proficiency alone is insufficient. Algorithmic literacy must include the ability to question how outputs are produced, identify the assumptions they may encode, evaluate their relevance to audience and purpose, and justify their inclusion in multimodal texts.

The study's implications extend to curriculum design, assessment, teacher education, and institutional policy. Generative AI has destabilized conventional assumptions about authorship, originality, academic integrity, and product-oriented assessment. Smolansky et al. (2023) found considerable educator and student concern about academic integrity and reported educators' preference for assessment designs that anticipate AI use while emphasizing critical thinking and learning processes. In an EFL context, Ngo, Tran, and Nguyen (2024) similarly found that teachers associated AI-driven plagiarism with risks to critical thinking and language development and advocated process-oriented teaching and assessment. Critical and inclusive frameworks also indicate that many non-technical learners lack structured opportunities to develop the analytical, ethical, and practical capacities needed for responsible AI participation (Horowitz & Foulkes, 2025). By linking belief profiles to observable behavior, this study provides language-program administrators, curriculum designers, and teachers with evidence for differentiated pedagogical responses. Its broader implication is that AI policies should recognize heterogeneous belief-practice constellations and provide corresponding forms of instruction, support, critical dialogue, and assessment.

2. Literature Review

2.1 Multiliteracies: From Multimodality to Algorithmic Mediation

The New London Group's (1996) foundational manifesto situated literacy pedagogy within changing conditions of communication, employment, civic participation, and cultural diversity. It proposed four interconnected pedagogical components: situated practice, overt instruction, critical framing, and transformed practice. Central to this framework was the concept of *Design*. *Available Designs* represent historically and culturally accessible semiotic resources, *Designing* refers to their active transformation in meaning-making, and *The Redesigned* is the resulting representation that becomes a resource for future design practices. Learners were therefore positioned not as passive recipients of established forms, but as active agents capable of redesigning social meanings and futures.

Cope and Kalantzis (2009, 2015) subsequently extended this framework to digital and networked communication. Their work emphasized that literacy requires learners to navigate and combine linguistic, visual, auditory, gestural, spatial, and digital modes rather than master alphabetic print alone. This understanding remains valuable because it treats meaning as multimodal, socially situated, and responsive to context. However, its account of agency generally assumes that human learners select and transform resources whose main forms already exist. Even as the available semiotic repertoire expands, the learner remains the principal designer.

Generative AI disrupts this assumption in several ways. Available designs are no longer limited to pre-existing cultural artifacts that learners select and recontextualize because prompts can generate new

paragraphs, images, outlines, translations, and video content in real time. The resource is therefore partly produced through interaction between the learner and the system. Kalantzis and Cope (2024) describe generative AI as a technology of both writing and multimodal production, including the generation and interpretation of text-image relations. The distinction between designing and redesigning also becomes less sequential because users can ask a model to revise, expand, summarize, translate, critique, or visually transform its earlier output within a single interaction. More importantly, AI-generated content complicates conventional distinctions among learner voice, authorship, ownership, and textual provenance.

These complexities cannot be resolved by treating AI output as either entirely external assistance or unquestionably learner-authored work. Scholarship on algorithmic cultures conceptualizes contemporary literacy as human-machine co-production shaped by critical reflection, affect, and algorithmic agency (Ehret, 2024). In language education, Hafner and Ho (2026) similarly argue that generative AI may enable or constrain agency, creativity, and criticality through iterative user-system interaction, ideological positioning, modal relationships, and questions of authenticity and voice. Generative AI does not make multiliteracies obsolete, but it requires the concept of design to be expanded. Learners must now design with, against, and through systems that actively generate semiotic possibilities.

Kalantzis and Cope's (2020) account of differentiated and data-driven learning anticipated aspects of this transformation, although it preceded the widespread availability of consumer generative AI systems. Kalantzis and Cope (2025) more explicitly reconsider multiliteracies in relation to social media and artificial intelligence, presenting design as a practice for navigating and reshaping interconnected digital environments. Nevertheless, insufficient attention has been given to how learners' beliefs about algorithmic participation affect their ability and willingness to maintain critical authorial agency when AI systems propose the words, images, and organizational structures from which compositions are developed.

2.2 Learner and Instructor Beliefs about AI in Writing

A growing body of research has examined students' and teachers' perceptions of AI-assisted writing. Although no universally accepted typology has emerged, the literature repeatedly identifies tensions among instrumental adoption, critical evaluation, authenticity, academic integrity, and dependency (Barrot, 2023; Warschauer et al., 2023; Teng, 2024). Teng's (2024) systematic review of 20 EFL writing studies identified immediate feedback and diverse prompts as important affordances while highlighting dependency and reduced critical thinking as central concerns. Similarly, Sarica and Deneme Gençoğlu's (2025) review of 19 studies reported perceived benefits for efficiency, accuracy, idea generation, and personalized learning alongside concerns about plagiarism, over-reliance, and unethical use.

An instrumental orientation positions AI primarily as a productivity resource for accelerating drafting, correcting grammar, generating ideas, translating content, or overcoming writer's block. Söğüt's (2024) qualitative study of EFL pre-service teachers and teacher educators documented perceived advantages in language support, personalized feedback, and assistance with writing difficulties. A critically reflective orientation, however, treats AI-generated output as provisional material that must be evaluated, revised, contextualized, and aligned with the learner's communicative intentions. This orientation corresponds more closely to multiliteracies' concept of critical framing because it requires users to examine the accuracy, voice, appropriateness, and modal suitability of generated options. By contrast, a resistant orientation emphasizes concerns that AI may undermine originality, personal expression, assessment validity, and ownership of writing.

These orientations should not be viewed as mutually exclusive or assigned as predetermined categories. Cai and Yu (2025) found that EFL students and teachers recognized the usefulness of generative AI, although students emphasized efficiency while teachers prioritized ability development and warned against excessive reliance. Both groups nevertheless regarded effective prompting as essential to productive use. In an advanced L2 German course, Strobl et al. (2024) found that comparing learner-written drafts with ChatGPT-generated texts increased students' awareness of the model's linguistic fluency and weaknesses in content development, enabling more informed revision. Shii and Kim (2025) similarly reported that learners with stronger AI literacy refined prompts more effectively and obtained feedback that better addressed their language-learning objectives. These findings suggest that beliefs matter not only because they affect adoption, but also because they influence how learners direct, evaluate, and revise generated material.

The multimodal dimension further complicates these orientations. Liu, Zhang, and Biebricher (2023) found that EFL students completing an AI-assisted multimodal presentation used chatbot summaries and

image-generation prompts to develop slide content while evaluating generated images from multiple perspectives. Li, Xia, and Guo (2025) similarly reported that students assessed AI-generated videos according to text-video consistency, visual engagement, and auditory features. These studies indicate that beliefs about AI may influence not only textual drafting and revision, but also learners' decisions about how meaning is distributed and coordinated across modes.

Despite these advances, much of the research relies on self-reported perceptions collected at a single point in time. Such studies reveal what participants claim to value or fear but cannot determine whether their beliefs form coherent configurations, predict independently observed behaviors, or respond to pedagogical intervention. They also rarely connect beliefs with behavioral evidence such as prompt complexity, revision histories, and multimodal redesign. The present study addresses these limitations by combining person-centred modeling of belief patterns with behavioral and corpus analyses of AI-mediated composition.

3. Method

This study employed a convergent mixed-methods design (Creswell & Plano Clark, 2018), in which quantitative and qualitative strands were collected concurrently over a single 16-week semester and integrated at the interpretation stage. The quantitative strand comprised the Multiliteracies-in-AI Scale (MIAS), behavioral trace data extracted from writing platform logs, and essay corpus metrics. The qualitative strand comprised stimulated-recall interviews conducted with a purposive subsample. Integration occurred through joint display matrices linking latent profile membership to interview themes, and through the use of qualitative findings to substantively interpret and label the quantitative profiles.

The study was conducted within a comprehensive university's intensive English language program, in which generative AI tools (a large language model writing assistant and an integrated text-to-image feature within the institutional learning management system) had been formally incorporated into coursework for two consecutive semesters prior to data collection, satisfying the study's operational definition of an "AI-saturated" learning environment. Participants included 178 undergraduate EFL students (Mage = 20.4, SD = 1.8; 103 female, 71 male, 4 nonbinary or unspecified) enrolled across nine sections of an academic writing course, and 9 instructors teaching those sections (7 female, 2 male; teaching experience M = 8.6 years, SD = 4.3). Students represented CEFR levels B1 through C1 as determined by program placement testing. Recruitment occurred through in-class announcements and institutional email; participation was voluntary and uncompensated beyond course-embedded activities that all enrolled students completed regardless of research participation, with data used for research purposes only upon informed consent. The study protocol was reviewed and approved by the university's institutional review board.

The Multiliteracies-in-AI Scale (MIAS) was developed specifically for this study through a three-stage process: (a) item generation from the literature review and a pilot round of open-ended prompts administered to 24 students not included in the final sample, (b) expert panel review by five applied linguists for content validity, and (c) exploratory factor analysis on pilot data ($n = 112$) to establish structure. The final instrument comprised 32 items across four theoretically derived subscales: AI as Instrumental Aid (8 items), AI as Co-Designer (9 items), AI as Threat to Authenticity (8 items), and Critical Evaluative Stance (7 items), each rated on a 6-point Likert scale from strongly disagree to strongly agree. Internal consistency in the current sample was acceptable to good across subscales (Cronbach's alpha ranging from .79 to .88; see Table 1). Behavioral trace data were extracted from the writing platform's activity logs and included prompt complexity (a composite index derived from prompt length, number of constraint specifications, and iterative refinement count), revision depth (number and substantiveness of edits made to AI-generated text, coded using a modified Faigley-Witte revision taxonomy), and multimodal integration (frequency of text-image-data redesign moves identified through document analysis of final submissions). Stimulated-recall interviews were conducted with a purposive subsample of 34 students and all 9 instructors, selected to maximize variation across preliminary profile indicators; interviews used screen-recorded composing sessions as recall prompts and were transcribed verbatim for thematic analysis.

Beginning in week 9, all sections received a four-week algorithmic literacy module embedded within the existing curriculum, consisting of structured activities on prompt engineering as a rhetorical act, critical evaluation of AI-generated multimodal content, bias and hallucination detection exercises, and guided reflection on authorship and attribution. The module was designed collaboratively by the research team and

program instructors to ensure ecological validity and was delivered with high fidelity as confirmed through classroom observation checklists completed for a random 30% of sessions.

Latent profile analysis was conducted in Mplus 8.10 using the four MIAS subscale scores as continuous indicators. Model selection across one- to five-profile solutions was guided by the Bayesian Information Criterion, the Lo-Mendell-Rubin adjusted likelihood ratio test, entropy, and interpretability. Following profile extraction, the most likely profile assignment was used as a categorical predictor in a series of hierarchical multiple regression models predicting prompt complexity, revision depth, and multimodal integration, controlling for CEFR level, prior AI use frequency, and section. Pre-to-post shifts in profile membership following the algorithmic literacy intervention were examined using a second LPA run on post-intervention MIAS scores and a transition matrix analogous to latent transition analysis. Qualitative data were analyzed thematically (Braun & Clarke, 2006) using a hybrid deductive-inductive coding scheme, with two coders achieving an initial inter-rater agreement of kappa = .81 on a 20% double-coded subsample prior to reconciliation.

Table 1. Descriptive Statistics and Reliability for MIAS Subscales (N = 178)

Subscale	Items	M	SD	α
AI as Instrumental Aid	8	4.62	0.71	.82
AI as Co-Designer	9	3.94	0.88	.88
AI as Threat to Authenticity	8	3.21	1.02	.85
Critical Evaluative Stance	7	4.05	0.79	.79

4. Results

4.1 Latent Profile Selection

Fit indices favored a three-profile solution over two-, four-, and five-profile alternatives (BIC = 4128.7; adjusted LMR-LRT $p = .012$ for the 3- vs. 2-profile comparison and $p = .21$ for the 4- vs. 3-profile comparison, indicating no improvement beyond three profiles; entropy = .87), providing strong classification confidence and interpretive parsimony. The three profiles, labeled with reference to their MIAS subscale patterns and corroborating interview themes, were as follows.

Instrumentalist Integrators ($n = 79$, 44.4%) scored highest on AI as Instrumental Aid and lowest on Critical Evaluative Stance, describing AI primarily as a means of accelerating task completion and reducing linguistic anxiety. Critical Orchestrators ($n = 61$, 34.3%) scored high on both AI as Co-Designer and Critical Evaluative Stance, describing AI as a resource to be actively directed, questioned, and integrated with other modes rather than passively accepted. Displaced Traditionalists ($n = 38$, 21.3%) scored highest on AI as Threat to Authenticity and lowest on AI as Co-Designer, expressing concern that AI mediation compromised the authenticity and ownership of their writing.

Table 2. Standardized Mean MIAS Subscale Scores by Latent Profile

Subscale	Instrumentalist Integrators ($n=79$)	Critical Orchestrators ($n=61$)	Displaced Traditionalists ($n=38$)
Instrumental Aid	1.02	0.31	-1.58
Co-Designer	-0.18	1.29	-1.21
Threat to Authenticity	-0.44	-0.62	1.74
Critical Evaluative Stance	-0.71	1.11	-0.29

4.2 Belief Profiles and Behavioral Outcomes

Hierarchical regression models predicting the three behavioral outcomes from profile membership (with Instrumentalist Integrators as the reference category), controlling for CEFR level, prior AI use frequency, and section, showed that profile membership was a significant predictor in all three models. For prompt complexity, Critical Orchestrators scored significantly higher than Instrumentalist Integrators ($b = 4.87$, $SE = 0.96$, $p < .001$), while Displaced Traditionalists did not differ significantly from the reference group ($b = -0.62$, $SE = 1.14$, $p = .59$), consistent with their comparatively infrequent and minimal AI engagement. For revision depth, Critical Orchestrators again scored highest ($b = 3.15$, $SE = 0.71$, $p < .001$), reflecting a pattern of substantive rather than surface-level editing of AI output. For multimodal integration, Critical Orchestrators produced significantly more text–image–data redesign moves than both other groups ($b = 2.44$, $SE = 0.58$, $p < .001$ relative to Instrumentalist Integrators), supporting the hypothesis that critical evaluative orientation, rather than mere access or enthusiasm, drives multimodal redesign under AI-saturated conditions. Full model coefficients are reported in Table 3.

Table 3. Regression Models Predicting AI Use Patterns from Latent Profile Membership

Predictor	Prompt Complexity b (SE)	Revision Depth b (SE)	Multimodal Integration b (SE)
Critical Orchestrators (ref: Instrumentalist)	4.87 (0.96)***	3.15 (0.71)***	2.44 (0.58)***
Displaced Traditionalists (ref: Instrumentalist)	-0.62 (1.14)	-1.87 (0.84)*	-1.96 (0.69)**
CEFR Level	1.21 (0.44)**	0.68 (0.33)*	0.53 (0.27)*
Prior AI Use Frequency	0.94 (0.31)**	0.41 (0.23)	0.37 (0.19)
R^2	0.34	0.29	0.31

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Section entered as fixed-effect control (coefficients omitted for brevity).

4.3 Qualitative Corroboration

Stimulated-recall interviews corroborated and enriched the quantitative typology. Instrumentalist Integrators frequently described AI interaction in transactional terms, characterizing successful sessions as ones that minimized their own cognitive labor. Critical Orchestrators, by contrast, described iterative, dialogic exchanges with the model, frequently narrating moments of rejecting or substantially rewriting AI suggestions and explaining their revision rationale in terms of audience, register, or visual-textual coherence. One recurring theme among Critical Orchestrators was a self-conception as "director" or "editor" of AI output rather than recipient of it, a framing that maps closely onto the multiliteracies construct of Designing as transformative agency. Displaced Traditionalists, meanwhile, articulated concerns about diminished ownership and voice, with several describing deliberate strategies of AI avoidance even when tools were readily accessible, framing such avoidance as a form of principled resistance rather than a skill deficit.

Instructor interviews revealed a largely parallel typology, with seven of nine instructors classifiable as holding orientations resembling the Critical Orchestrator profile, one aligning more closely with Instrumentalist Integrator patterns, and one expressing views consistent with Displaced Traditionalist concerns, particularly regarding assessment validity. Instructors holding Critical Orchestrator-like beliefs reported explicitly modeling evaluative and directive AI use in class, a pattern that, combined with the intervention's design, may partially explain the intervention effects reported below.

4.4 Effects of the Algorithmic Literacy Intervention

Comparing pre- and post-intervention MIAS-derived profile classifications, 27% of students initially classified as Instrumentalist Integrators (21 of 79) shifted to the Critical Orchestrator profile following the four-week module, while 9% (7 of 79) shifted toward Displaced Traditionalist, and the remainder (64%)

retained their initial classification. Among Displaced Traditionalists, 16% (6 of 38) shifted toward Critical Orchestrator, while the majority remained stable, suggesting that authenticity-related concerns were comparatively resistant to short-term intervention. Critical Orchestrators showed the highest stability of any profile (85% retention), suggesting this orientation, once established, is self-reinforcing. A chi-square test of independence confirmed that pre-intervention profile membership was significantly associated with the direction of post-intervention shift, $\chi^2(4, N = 178) = 28.6, p < .001$. Full transition proportions are presented in Table 4.

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Table 4. Descriptive Statistics and Reliability for MIAS Subscales (N = 178)

Pre-Intervention Profile	Stable (%)	Shifted to Critical Orchestrator (%)	Shifted to Displaced Traditionalist (%)	Shifted to Instrumentalist (%)
Instrumentalist Integrators (n=79)	64	27	9	—
Critical Orchestrators (n=61)	85	—	5	10
Displaced Traditionalists (n=38)	76	16	—	8

4.5 Essay Corpus Analysis

Analysis of the pre- and post-intervention essay corpus (356 essays total) using intertextual diversity indices and cross-modal redesign counts corroborated the behavioral trace findings. Essays produced by students classified as Critical Orchestrators exhibited significantly greater intertextual diversity, operationalized as the number of distinct source types (AI-generated text, AI-generated imagery, learner-authored data visualizations, and externally sourced material) integrated within a single submission ($M = 3.4, SD = 0.9$), compared to Instrumentalist Integrators ($M = 1.8, SD = 0.7$) and Displaced Traditionalists ($M = 1.1, SD = 0.6$), $F(2, 175) = 61.3, p < .001, \eta^2 = .41$. Cross-modal redesign, defined as instances in which learners transformed AI-generated content across modes (for example, converting AI-generated prose into a learner-designed infographic, or using AI-generated imagery to reframe an argument's structure), was similarly concentrated among Critical Orchestrators, who accounted for 68% of all coded redesign instances despite comprising only 34.3% of the sample.

5. Discussion

The findings highlight three interrelated outcomes. First, beliefs about generative AI were not randomly distributed across participants but formed three coherent and statistically distinguishable profiles: Instrumentalist Integrators, Critical Orchestrators, and Displaced Traditionalists. Second, these profiles predicted observable differences in prompting, revision, and multimodal composing. Third, profile membership showed varying degrees of responsiveness to the four-week algorithmic literacy intervention. Together, these findings challenge accounts of multiliteracies competence as a uniform collection of digital or multimodal skills. Instead, they support the concept of a **belief-practice constellation**, in which learners'

epistemic orientations toward AI shape how, why, and to what extent they use algorithmic affordances in composing.

This interpretation is consistent with the multiliteracies emphasis on design as active transformation rather than passive reception (The New London Group, 1996). The distinction among *Available Designs*, *Designing*, and *The Redesigned* positions learners as agents who select and transform culturally available semiotic resources. Cope and Kalantzis (2009, 2015) extended this framework to digitally mediated communication while maintaining that learners should navigate diverse modes with agency and critical awareness. Generative AI complicates this assumption because semiotic resources are now dynamically generated through prompts, interaction histories, model architectures, and platform conditions. Kalantzis and Cope (2024) describe generative AI as a technology of writing and multimodal representation, while their later work explicitly reconsiders multiliteracies in relation to social media and artificial intelligence (Kalantzis & Cope, 2025). The present findings extend this theoretical development by showing that learners respond differently to algorithmically generated resources according to patterned beliefs about utility, co-design, critical evaluation, and authenticity.

The behavioral results demonstrate that these configurations were not merely attitudinal categories. Critical Orchestrators displayed significantly greater prompt complexity, revision depth, and multimodal integration than Instrumentalist Integrators, with coefficients of $b = 4.87$, $b = 3.15$, and $b = 2.44$, respectively, all at $p < .001$ (Table 3). Displaced Traditionalists did not differ significantly from Instrumentalist Integrators in prompt complexity, but they demonstrated significantly lower revision depth and multimodal integration. The corpus analysis reinforced these patterns: Critical Orchestrators achieved greater intertextual diversity than the other profiles and accounted for 68% of all cross-modal redesign instances despite representing only 34.3% of the sample. These findings address an important limitation in earlier EFL research, which has often relied on participants' reported perceptions rather than independently recorded composing practices. Although previous studies have documented concerns about dependence, ethical use, and reduced critical engagement, self-reported attitudes alone cannot demonstrate how beliefs materialize during composition (Teng, 2024; Sarica & Deneme Gençoğlu, 2025).

The intervention findings further show that belief profiles differ in pedagogical malleability. Among students initially classified as Instrumentalist Integrators, 27% shifted to the Critical Orchestrator profile after the four-week module, whereas 16% of Displaced Traditionalists made the same transition. Critical Orchestrators showed the greatest stability, with 85% retaining their profile, and the overall association between pre-intervention membership and post-intervention transition was significant, $\chi^2(4, N = 178) = 28.6$, $p < .001$ (Table 4). These results do not suggest that resistance to AI is uninformed or educationally undesirable. Concerns about authorship, ownership, voice, academic integrity, and the conditions under which AI-supported writing can be considered a learner's own work remain legitimate. Related studies similarly show that enthusiasm for feedback and language assistance coexists with concerns about misconduct, dependency, and the erosion of process-oriented learning (Cai & Yu, 2025; Söğüt, 2024; Ngo, Tran, & Nguyen, 2024). The differential stability of the profiles therefore indicates that learners' orientations require distinct forms of pedagogical engagement rather than a single corrective intervention.

Among the three profiles, Critical Orchestrators most closely embodied the transformative aspirations of multiliteracies pedagogy. These participants did not simply use AI more often or reject it more consistently. Instead, they treated generated content as provisional available designs that could be evaluated, revised, combined with other modes, or rejected when unsuitable for their communicative purposes. This pattern corresponds with findings that L2 writers can compare their drafts with ChatGPT output to recognize both linguistic strengths and limitations before revising their texts (Strobl et al., 2024). It also supports evidence that stronger AI literacy enables learners to refine prompts iteratively and obtain feedback that better serves language-learning objectives (Shii & Kim, 2025). The present study advances this literature by demonstrating that critical engagement constitutes a broader profile-level orientation associated with more sophisticated textual revision and multimodal redesign.

These findings require a reconsideration of agency in multiliteracies theory. In The New London Group's (1996) original formulation, learner agency operated primarily on stable or human-authored resources. In AI-mediated environments, agency operates recursively on material dynamically produced by algorithmic systems. The relevant capacity is therefore not complete control over the technology, which may be neither possible nor stable, but **evaluative participation**: the ability to prompt purposefully, inspect output, identify limitations, make selective revisions, and remain accountable for the resulting artifact. This

interpretation accords with research on algorithmic cultures that rejects the reduction of digital literacy to either technical competence or ideological critique and instead emphasizes the relational and co-productive nature of human-algorithm interaction (Ehret, 2024).

6. Conclusion

This study set out to profile how students and instructors reinterpret multiliteracies within an AI-saturated language program, and in doing so, to test whether static, skills-based accounts of multiliteracies competence remain adequate under conditions of algorithmic co-authorship. The evidence indicates that they do not. Three empirically distinct and behaviorally consequential belief profiles, Instrumentalist Integrators, Critical Orchestrators, and Displaced Traditionalists, were identified, and profile membership significantly predicted the sophistication, depth, and multimodal richness of learners' AI-mediated composing practice. A brief algorithmic literacy intervention proved capable of shifting a meaningful proportion of instrumentalist learners toward more critical orientations, though traditionalist concerns proved comparatively resistant to short-term pedagogical response. These findings support a reconceptualization of multiliteracies as a dynamic belief–practice constellation, in which epistemic stance toward algorithmic co-designers is as central to multimodal competence as the multimodal textuality that originally defined the framework. As generative AI becomes further embedded in language education, attending to these belief–practice constellations, and to their pedagogical malleability, offers a more empirically grounded and actionable foundation for curriculum and policy than assumptions of uniform technological adoption or uniform resistance.

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Appendix

Appendix 1. Sample MIAS Items by Subscale

Table 1. Descriptive Statistics and Reliability for MIAS Subscales (N = 178)

Subscale	Sample Item
AI as Instrumental Aid	AI tools help me finish writing tasks more quickly.
AI as Co-Designer	I treat AI-generated text as a draft that I actively reshape.
AI as Threat to Authenticity	Using AI makes my writing feel less like my own.
Critical Evaluative Stance	I check AI-generated content for bias or inaccuracy before using it.