

Shared and Contested Beliefs About Generative AI Among Korean as a Foreign Language Instructors Evidenced by Q Methodology

Huan-yi Liu

yoohy@skku.edu

Sungkyunkwan University

Qian-xiong Jin

Sungkyunkwan University

Keum-hee Lee

Sungkyunkwan University

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Abstract

Institutional pressure for generative AI (GenAI) adoption is reshaping language teaching; however, instructors' beliefs regarding this shift remain substantially underexplored. This study employed Q methodology to reconstruct the belief structures of Korean as a Foreign Language (KFL) instructors. For this purpose, we developed a 54-statement pool through a systematic review of peer-reviewed literature coupled with Latent Dirichlet Allocation (LDA) topic modeling. With 30 instructors sorting the statements, the analysis extracted three factors that together accounted for 49% of the study variance: Human-Centric AI Utilizers (Factor 1), Institutional and Ethical Advocates (Factor 2), and Relational AI Optimists (Factor 3). In the context of language education, there is broad consensus among instructors on three dimensions: affirmation of teachers' centrality, recognition of the need for critical evaluation of GenAI outputs, and willingness to innovate classroom instructional practices. This consensus demonstrates that the three groups diverge not over whether to embrace GenAI but over how to respond in the GenAI era. This convergence within divergence anchors a differentiated professional development model that starts from shared beliefs and tailors complementary AI literacy to each factor. For settings such as KFL, where institutional adoption precedes the formation of stable pedagogical norms, the model embeds professional support within instructors' internal reasoning about GenAI.

1. Introduction

In 2024, South Korea's Ministry of Education announced the introduction of AI-integrated digital textbooks in public schools, and by March 2025, this policy had been implemented across a limited set of subjects and grades [1]. The plan, however, soon ran into setbacks. Teachers objected forcefully, leading to the program being downgraded to a voluntary trial; subsequently, the National Assembly struck the materials from the official textbook catalogue [2]. This policy reversal is less indicative of a policy than as a diagnostic signal. When institutions adopt generative AI (GenAI) faster than the profession can establish stable norms, teachers are compelled to make high-stakes judgments about tools they have had insufficient time to evaluate.

Korean as a Foreign Language (KFL) teaching falls outside the scope of this policy, yet the same top-down push reaches its educators through institutional expectations rather than law, and an explicit definition of responsible AI use remains unavailable in the field. That gap establishes KFL teachers as a revealing early case. Language teaching also entails a complication not present in math and science. GenAI's core output is fluent target-language text—exactly what learners seek to acquire. The previous tasks of drafting, translating, and language modeling, which were usually handled by teachers, can now mostly be accomplished independently by GenAI. This functional overlap is redefining the boundaries of the teacher's role [3, 4]. This study centers on how KFL instructors respond to this pressure in the absence of consensus or settled norms.

Research on GenAI in language education has been developing rapidly, exploring both its affordances and risks [3–6], with teacher-centered work expanding alongside it [7, 8]. We now know much about

teachers' attitudes, knowledge, and self-reported practices. However, it is still not clear how these elements are integrated with each other. Borg [9] argues that teacher cognition is not a checklist of variables but an organized system that requires the organic integration of what teachers think, know, and believe with what they do. However, research on GenAI has not fully reconstructed the complexity of that system. Perception, knowledge, acceptance, and practice are often studied as separate variables, an approach that fails to examine how institutional pressure organizes the belief structures that bind them together. Recent research on teacher education tends to treat professional GenAI competence as a uniform skill set to be trained [10]. However, what we aim to investigate is a more fundamental question: whether that competence is instead differentiated by the belief structures instructors already possess. The distinction matters, because professional development strategies built on average scores struggle to serve teachers with varying belief structures.

This paper seeks to reconstruct, rather than measure, KFL instructors' belief structures toward GenAI under external pressure. That aim requires a method built to handle whole configurations of belief, and Q methodology is an optimal fit [11, 12]. Q methodology works from each participant's pattern of agreement and disagreement across a set of statements. Its logic is abductive, proceeding from the overall configuration of a sort to the qualitative differentiations that distinguish one belief structure from another. We pursue this through two questions:

RQ1. What distinct belief structures do KFL instructors exhibit toward integrating GenAI into teaching under institutional pressure?

RQ2. What shared cognitions connect these belief structures, and what might they imply for professional development?

2. Literature Review

2.1. Teacher Cognition and Belief Structures

Three decades of research have established teacher beliefs—about students, subject matter, tools, and institutional roles—as among the strongest predictors of classroom behavior [9, 13, 14]. These beliefs are not isolated but operate as parts of an integrated system in which, as Buehl and Beck [15] argue, each belief takes its meaning from its place in the whole. For instance, a conviction that human judgment is irreplaceable shapes how a teacher interprets GenAI feedback, which in turn governs which uses of GenAI are regarded as professionally legitimate. Once the system is decomposed into separate scale items, the structure that governs practice disintegrates.

This belief structure is not fixed. When institutions require teachers to adopt unfamiliar practices within a constrained timeframe—in the absence of established norms or adequate support—existing belief structures may reorganize in qualitatively different ways [15]. Teachers neither fully retain their original beliefs nor abandon them outright. Instead, they construct new models of responsible participation.

Institutional pressure, then, is not a distraction to be eliminated but a condition that shapes how belief structures form. For KFL instructors in South Korea, that condition is precisely GenAI.

2.2 GenAI in Language Education

GenAI's capabilities, such as generating language, supplying adaptive feedback, and simulating dialogue, overlap with the core work of language teaching [3, 5, 6, 16, 17]. It is precisely this overlap that makes adopting GenAI a professional decision rather than a purely technical one, a distinction particularly important in the context of Korean language education. The decision calls for careful judgment about teaching responsibilities and the boundary between human and GenAI contribution, yet such judgment remains understudied in prevailing teacher education programs [4]. Researchers are increasingly focusing on how language teachers make these decisions, documenting their attitudes, self-assessed knowledge, and self-reported practices across different settings [8, 18]. A more recent line of research extends the focus to the preservation of teacher agency and the evolving responsibilities of teacher educators [7, 10, 19].

Korean language education presents a highly enlightening case. The earlier national episode, which experienced rapid, top-down adoption, was rolled back within months amid sustained teacher resistance [1, 2], marking implementation running ahead of professional readiness. Although KFL instructors fall outside the policy's scope, they continue to make consequential judgments about tools whose educational implications remained unsettled, under institutional and normative pressures, not by statutory mandate. Survey evidence suggests low uptake and modest perceived effectiveness in KFL integration, a finding that reflects not teacher indifference but the absence of stable professional frameworks for confident engagement [7]. This is likely not a regional anomaly but an early instance of what occurs whenever institutional adoption outpaces stable norm formation. The literature documents teachers' reported thinking and practice, yet rarely examines them as a coherent system.

2.3 From Research Questions to Q Methodology

This study places two demands on the method: first, it must surface qualitatively distinct configurations of professional beliefs without fixing their number or form in advance; second, it must identify the shared cognitions across them. These are not merely about frequencies or individual narratives. Rather, they concern the organized whole of professional subjectivity—the internal logic that sustains each belief structure together, and the stable foundations that persist across structures. Capturing that whole is what Q methodology is designed to do [11, 12]. Its constitutive feature lies in treating the unit of analysis as each participant's full relational pattern of Q-sort placements, that is, the whole configuration, rather than any single item. A single analytical framework can serve both tasks: allowing distinct belief structures to be derived from the data (RQ1) and detecting cross-factor consensus statements (RQ2).

That fit has been validated in related research. Yang and Stefaniak [20] applied it to instructional designers' views on ChatGPT and revealed three distinct belief structures that Likert-scale aggregation would have flattened into a single mean. In the field of language education, Wang et al. [21] reconstructed how Chinese learners of English as a Foreign Language (EFL) perceive GenAI-mediated

informal learning, whereas Chaaban et al. [22] extended the method to teachers' professional development. Overall, these studies support its applicability for research on professional beliefs. The present study extends that line into a previously unexplored domain: KFL instructors working under institutional GenAI implementation—a context that constrains belief formation significantly differently from the voluntary-adoption settings of earlier Q methodology research.

3. Methods

3.1. Design of the Study

This study follows the standard Q methodology procedure, structured in three core stages: concourse development and Q-sample construction, P-set selection, and the Q-sort task.

3.1.1. Concourse development and Q-sample construction

A concourse refers to the comprehensive discourse space formed by a particular community around a given topic [23]. We developed our concourse based on peer-reviewed literature on Korean language education indexed in the Korean Citation Index (KCI). To ensure source transparency and methodological rigor, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [24].

After initially identifying 1,210 records and refining them to 900 through pre-processing (Fig. 1), we applied Latent Dirichlet Allocation (LDA) to this corpus to identify its latent topic structure [25]. Topic-representativeness screening then yielded 249 records as the source for the Q sample. It should be noted that LDA did not replace researcher judgment; rather, it supplied a structured, corpus-based framework to guide the drafting of statements. Validation metrics converged on a ten-topic solution (Fig. 2), the thematic content of which detailed in Appendix A.

Drawing on the 249 articles across the ten topics, two researchers independently extracted candidate statements relevant to Korean language education. They reviewed these after consultation, removing unsuitable items and refining the wording. The content validity of the remaining statements was then evaluated by a Korean language education expert, yielding a final Q sample of 54 (Appendix B). Through the pairing of systematic retrieval with an empirically derived topical structure, the resulting statement set remains grounded in the authentic discourse of KFL education. This reflects a structured-sampling principle of Q sample construction, in which the discourse is represented by statements systematically rather than selectively [12, 26].

3.1.2. P-set Selection

In Q methodology, participants function as variables rather than as a statistical sample [27]. Within this framework, what matters is not demographic representativeness but whether participants can make discriminating subjective judgments on the Q statements drawing on their own knowledge and

experience [12]. Following these principles, a P-set was assembled through purposive sampling, spanning the range of professional perspectives among KFL instructors on GenAI integration under institutional pressure. Participants had to meet three conditions simultaneously: (1) holding or currently pursuing a master's degree or higher in Korean language education or a related field; (2) having hands-on experience with GenAI tools; and (3) currently teaching or preparing to teach Korean, whether as a preservice or in-service instructor.

30 participants in this study met the criteria, a sample size consistent with Watts and Stenner's [12] guidance that the number of participants in a P-set should not exceed the number of Q statements (here, 54). Among the 30, 23 were female (76.7%) and 7 male (23.3%). In terms of educational background, 26 held a doctoral degree (including current students; 86.7%) and 4 a master's degree (including current students; 13.3%). Ages ranged from 25 to 42 years ($M \approx 32$). Regarding nationality, 19 were Korean (63.3%) and 11 Chinese (36.7%). We included Chinese-national KFL instructors by deliberate design, since participants function as variables rather than as a population sample. These instructors constitute a professionally unique group whose institutional experiences, pedagogical socialization, and pressures arising from GenAI may shape belief structures in qualitatively different ways from those of their Korean-national counterparts. Accordingly, their inclusion ensured that the P-set covered this range of professional variation.

All participants were adult individuals who gave their informed consent and took part in this study voluntarily. The researchers fully explained the research purpose, procedures, data management protocols, as well as the relevant rights of the participants to terminate their participation at any time without reason to each participant; and each participant signed a written informed consent document before the formal data collection began. This study meets the criteria for an extremely low-risk research: it involves neither deception nor vulnerable groups, and only requires voluntary participation of working adult professionals to complete an opinion-based task. This classification is consistent with the minimum risk classification of similar professional belief Q-methodology research [20, 22].

3.1.3. Q-Sort

We conducted online Q-sort data collection using Q Method Software [28], with a time window set at ten days (August 22–31, 2025). We chose online administration because this approach enabled participants to complete the sorting at their own pace without time pressure, and such conditions are generally more conducive to collecting genuine and thoughtful feedback. Participants first divided the 54 statements into three groups: “agree”, “disagree” and “neutral”. Subsequently, the statements were redistributed across an eleven-column grid in a quasi-normal distribution, ranging from – 5 (most disagree) to + 5 (most agree), under the prompt: “Please arrange the following statements according to your degree of agreement in Korean language teaching practice” (Fig. 3).

3.2. Data Analysis and Post-Sorting Interviews

The Q-sort data were analyzed using KADE 1.3.1 [29]. Factors were extracted by centroid factor analysis [12], and the number of retained factors was determined by two criteria: eigenvalues greater than 1.00 and the inflection point on the scree plot. We then applied varimax rotation to sharpen their differentiation [30], but distinguishing the factors required a defensible significance threshold. According to Watts and Stenner's [12] calculations, the standard threshold for 54 statements at $p < .05$ was $\pm .267$. When applying this threshold, cross-loading was pervasive: only 8 of the 30 participants loaded cleanly on a single factor, while 21 showed cross-loadings on two or more factors, and one loaded on none. A stricter criterion, $\pm .450$, was adopted to secure strong, unambiguous alignment and minimize interpretive uncertainty at the factor boundaries. Applying a stricter criterion excluded the weak secondary loadings that had driven the cross-loading, thereby aligning more participants with a single factor: 24 of the 30 loaded significantly on just one (Appendix C).

Based on this factor structure, we selected one exemplar per factor for a semi-structured post-sorting interview. Rather than selecting the highest-loading participants, we chose exemplars who loaded cleanly and exclusively on a single factor, with patterns that strongly matched the respective factor's configuration and that lacked substantial cross-loadings [12, 31]. During each interview, participants explained the reasoning behind their sorting choices. The qualitative narratives thus supplied served to interpret each factor array—the composite Q-sort embodying a factor's idealized viewpoint, computed as the weighted average of the Q-sorts with significant loadings onto that factor.

4. Results

4.1. What Belief Structures Emerge Regarding GenAI Integration? (RQ1)

The factor-score correlations range from .37 to .67 (Table 1), with Factors 1 and 2 exhibiting the highest correlation ($r = .67$), followed by Factors 1 and 3 ($r = .60$) and Factors 2 and 3 ($r = .37$). Q methodology precisely predicts the coexistence of internally coherent yet qualitatively distinct viewpoints within one discursive community [12]. These figures are not quality thresholds but rather indices of the relative proximity of factors within the solution, a role different from the one that correlation plays in variable-centered methods. The coherence and distinctiveness of the viewpoints each factor represents are what interpretive adequacy rests on [32].

Table 1
Factor Score Correlations and Explained Variance

Factor 1	Factor 1	Factor 2	Factor 3
	1.00	.67	.60
Factor 2	.67	1.00	.37
Factor 3	.60	.37	1.00
% Explained Variance	20	19	10

The three factors together explain 49% of the overall variance. Factor 1 accounts for 20%, Factor 2 for 19%, and Factor 3 for 10%. These values indicate each viewpoint's relative reach in the sample. The internal logic of the statements each factor places at its extremes is what interpreting each factor depends on, and this logic is the subject of the descriptions that follow. We define each factor's belief structure by its highest (+ 4/+5) and lowest (– 4/–5) placements, which most directly reveal a viewpoint's internal logic; accordingly, post-sorting interview excerpts from each factor's representative participant reconstruct these placements through qualitative analysis. We cite Q-statements as (#statement/score), where the score indicates placement on the – 5 to + 5 grid; "D" flags statistically distinguished statements across factors; and asterisks denote significance at $p < .05$ (*) or $p < .01$ (**). We identify differentiated status where it illuminates a substantive contrast (Appendix D).

4.1.1. Factor 1: Human-Centric AI Utilizers

Factor 1 portrays human competence as GenAI's critical and unique counterpart, anchored by two statements: "In the generative AI era, those who ask better questions gain more opportunities" (#26/+5D**), and a concern about the risks GenAI may pose (#38/+5). In the words of one defining participant, "When posing questions to AI, the more specific the better; I obtain accurate outputs solely due to asking good questions."

Apart from these purposeful prompting skills, Factor 1 addresses the risks of GenAI through two priorities. On the one hand, it strongly opposes the idea that an ideal GenAI can be constructed merely by removing offensive terms (#32/–5). "Artificial intelligence is a tool; as long as the outcome is correct, discussing its ethical implications is meaningless," one defining participant plainly stated. From this viewpoint, ethics is not an attribute inherent to the tool itself. Second, Factor 1 supports novel legal and ethical mechanisms (#30/+4), as they secure human authority over technological tools and prevent the transfer of control to the technology. What anchors this stance, then, is not regulation but a belief in human control—an autonomy no technological device can provide.

This human-centered, instrumental logic has extended to practice. Factor 1 argues that GenAI will not replace human intellectual work (#18/+3D**), that it can act as an educational tool (#9/+3), and that Korean language education must keep pace with the times (#50/+4). These placements constitute a coherent stance of instrumental appropriation: GenAI counts as an educational resource, so long as

teachers retain autonomy and critical oversight. This position is further strengthened by a strong affirmation of the role of teachers (#14/+4).

4.1.2. Factor 2: Institutional and Ethical Advocates

Factor 2 is grounded in the core belief that introducing GenAI requires institutional governance (#30/+5), and this same conviction manifests at the negative pole, where the factor expresses the strongest opposition to the idea that merely filtering out immoral words could yield an ideal, fully humanlike AI (#32/-5). Both positions derive from a single premise: humans and machines are not governed by the same language-generation mechanisms (#16/-5D**). In light of this categorical distinction, Factor 2 argues that accountability cannot be achieved merely through internal fixes such as word filtering; rather, it should be grounded in a systemic regulatory structure at the institutional level.

This structural concern extends to consequences most factors leave aside. Factor 2's highest-scoring distinguishing statements address the potential loss of nonmainstream languages (#45/+4D**) and the GenAI literacy gap (#48/+4D**). Taken together, they frame GenAI as a problem of structural social inequality, not merely one confined to the classroom. The representative participant stated explicitly: "It is insufficient to promote AI education and competitiveness alone. If AI is applied indiscriminately in the absence of defined standards, it becomes difficult to verify the authenticity of information; institutional constraints on GenAI use in critical social fields must be established." Regarding GenAI's specific educational applications, Factor 2 remains neutral. Indeed, it takes no firm position on whether GenAI can function as an educational tool (#9/0D**), whether it enhances teachers' efficiency, accuracy, and insight (#52/0D**), or whether Korean language learners' efficiency will be enhanced by it (#49/0D*).

Factor 2 neither uncritically accepts nor wholly rejects GenAI's advantages in language education; it views GenAI as a conditioned tool whose instrumental value is contingent upon a more extensive regulatory and ethical framework. On this view, a fundamental prerequisite for adoption is developing that framework and its systematic regulation. The same logic accounts for why Factor 2 devalues prompt-design skill as a pivotal competency (#28/-2D**), in marked contrast to Factor 1, which frames prompt mastery as a defining human capability in the GenAI era (#26/+5D**).

4.1.3. Factor 3: Relational AI Optimists

Factor 3 views GenAI as a highly competent, near-human partner to be embraced rather than guarded against, refusing to dismiss GenAI as nothing more than a myth (#7/-5), affirming instead its genuine presence, and firmly rejecting that the technology is frightening (#6/-5D**)—a benchmark of acceptance exclusive to this factor. These rejections give way to assertions of competence. Factor 3 rejects the assertion that GenAI is more proficient at data processing than at language understanding and generation (#4/-4D**), acknowledging the system's genuine linguistic competence, and it negates Factor 1's core tenet that human intellectual contributions are not replaceable (#18/-3D**). A representative participant stated plainly: "Artificial intelligence is more logical than I am. Its writing is logically compelling, and I embrace its results."

From a pedagogical standpoint, Factor 3 advocates for accumulating cross-genre analyses of GenAI translation errors to enhance translation quality (#36/+5D*). It emphasizes the necessity of professional GenAI education and training (#35/+4D**) and affirms that learners can achieve greater efficiency through GenAI (#49/+4D**). The factor goes further still, asserting that GenAI can sharpen teachers' efficiency, accuracy, and insight into language use (#52/+3D*).

Factor 3 did not weigh the risks and benefits of GenAI, and instead kept its distance from those questions. Factors 1 and 2 viewed GenAI's urgent social implications—bias, misinformation, hallucination, and copyright infringement—as demanding attention. Factor 3 remained neutral (#38/0D**). It showed no unease about deferring to GenAI's judgment in specialized fields, a deference the other two factors refuse (#19/0D**). Indeed, one participant described treating ChatGPT as a friend and bringing personal problems to it. Such openly anthropomorphic engagement is consistent with the factor's muted concern for GenAI risk.

4.2. What Shared Understandings Cut across All Three Factors? (RQ2)

Notwithstanding their structural distinctions, the three factors share a set of common beliefs (Table 2). The most widely held is the conviction of human teachers' centrality in the GenAI era (#14), which links Factor 1, prioritizing human instrumental agency, to Factor 3, which most openly embraces GenAI's humanlike capacities. This implies that anthropocentrism operates as a shared epistemic ground, holding true even when underpinned by very different stances toward GenAI. The same ground underpins a further field-specific consensus: Korean language education must renew itself by embracing digitally oriented, data-driven approaches (#34). A corresponding consensus emphasizes the need for purpose-built evaluation systems and datasets for GenAI development (#33). This common foundation goes beyond affirmation to restraint. None of the three factors agrees that the uncertainty of GenAI's output is inherently advantageous to learners' thinking or creativity (#46)—a critical-reflective stance toward GenAI's products. A parallel restraint shapes their perspective on misuse: all acknowledge that GenAI's capabilities could be misused for criminal purposes, yet none treats that possibility as a core educational priority (#43).

Table 2
Consensus Statements across All Three Factors (all nonsignificant at $p < .05$)

No.	Q Statement	Factor 1 (Rank/Z)	Factor 2 (Rank/Z)	Factor 3 (Rank/Z)
14	The role of human teachers is crucial in the era of generative AI.	4 (1.35)	5 (1.44)	3 (1.26)
33	Developing evaluation systems or datasets Developing evaluation systems or datasets specifically for generative AI development is unnecessary.	-3 (-1.44)	-4 (-1.70)	-3 (-1.23)
34	Research in Korean language education applying digital data processing technology is essential in the era of generative AI.	2 (0.81)	2 (0.78)	1 (0.47)
43	The exceptional capabilities of generative AI can easily be exploited for criminal activities.	0 (0.37)	0 (0.39)	1 (0.45)
46	The uncertainty inherent in generative AI outputs enhances users' logical thinking and creativity.	-2 (-1.18)	-2 (-0.88)	-2 (-0.71)

For language pedagogy, these convergences rest on three pillars: the centrality of the human teacher (#14), a critical-reflective stance toward GenAI's outputs (#46), and the renewal of Korean pedagogy through technological methods (#34). Together they form what we term the shared epistemic ground, which is the cognitive foundation beneath the three factors' structural divergence and marks the scope within which their disagreements unfold.

5. Discussion

5.1. What Drives Differentiated Teacher Orientations Toward GenAI?

The results indicate that KFL instructors' belief structures around GenAI are organized along three dimensions, namely the use of GenAI, its systemic governance, and the human-machine relationship. This divergence in stance corresponds to Borg's [9] theory of teacher cognition, where cognition synthesizes professional experience into a coherent system rather than functioning as a standalone belief. Q methodology is well suited to exploring what conditions may contribute to the formation of these professional subjectivities, being an abductive mode of reasoning.

For Factor 1, the primary actor is the human practitioner, and what matters is precision and intent in problem formulation. Factor 1 places human-centered judgment above technical proficiency. The capacity to question, construct, and steer GenAI—critical reflection—is, from this perspective, the distinctive human competence the era demands. The factor does not deny GenAI's practical value; it

openly acknowledges the tool's constraints while asserting that human wisdom is irreplaceable, a stance resonates with proactive coping [33]. Alert to the false-empowerment risk noted by Moorhouse et al. [6], Factor 1 keeps GenAI under critical human supervision and views its outputs as resources for human evaluation. The teacher retains the authority to evaluate, interpret, and apply GenAI's outputs. This human-centered instrumentalism is grounded in a professional awareness that core teaching skills cannot be delegated: the teacher's value resides in judgment, contextual sensitivity, and metacognitive coordination—competencies GenAI cannot consistently provide.

Factor 2's viewpoint is anchored in the governance dimension of GenAI integration. It takes on the erosion of information credibility, confronts weak ethical-filtering mechanisms, and engages with the systemic risks of unregulated GenAI proliferation in education [34], resonating with calls to reinforce public regulatory frameworks [35–37]. Factor 2's sensitivity, however, reaches past governance into equity. Specifically, it centers on how the spread of GenAI influences linguistic and social inequality—the risk of intensifying the marginal status of non-dominant languages and expanding GenAI literacy disparities [19]. Such concerns emerge when GenAI implementation outpaces established educational norms. Read this way, Factor 2's sensitivity is an outward expression of the structural anxiety educators experience: bearing professional responsibility for structural conditions, they may be more prompt in identifying the governance gaps that rapid GenAI deployment reveals.

The anthropomorphic inclination and emotional engagement that mark Factor 3 are well documented in studies on chatbots and conversational GenAI [38, 39]. That literature reveals a consistent trend: as perceived GenAI anthropomorphism rises, trust in and dependence on the technology tend to grow correspondingly, while perceived risk diminishes [39, 40]. The mechanism is clear enough. When an instructor experiences GenAI primarily as a responsive, helpful, and seemingly caring dialogue agent, the tool becomes hard to perceive as a risk. This pattern further supports the link Feng et al. [5] document between GenAI dependency and the erosion of critical thinking. The stakes extend beyond the individual level. Since teacher cognition shapes learners' epistemological environments [19], the readiness of Factor 3 participants—who are themselves Korean language instructors and teacher educators—to accept GenAI's cognitive authority cannot be viewed as inconsequential. How this belief structure may affect the way learners engage with GenAI warrants close examination.

Three distinct belief structure models consequently impose different requirements on Korean language teacher education. The first emphasizes critical-reflective capacity, manifested in how teachers understand GenAI: refining prompts during input and catching implicit bias or error in GenAI's outputs. Its prioritizes human-centered use over skill-based operation. The second requires awareness of institutional frameworks, with the present task being to operationalize that sensitivity into actionable classroom strategy; in the absence of such translation, teachers may experience a kind of professional paralysis. The third underscores practical competence, yet its primary demand is a balanced GenAI literacy that prevents emotional identification from undermining critical reflection. These orientations manifest in actual teaching practice. Confronted with GenAI-generated Korean, teachers in the first model verify pragmatic appropriateness prior to student use; those in the second prioritize the integrity

and fairness of assessment when GenAI is used in writing; those in the third use the tool for dialogue practice and immediate feedback—gains in speaking proficiency that, left unscrutinized, can carry subtle model errors into the student experience.

5.2. Beyond Divergence: Toward an Integrated Model Grounded in Shared Foundations

A common foundation on which three differentiated, type-matched AI literacies are built—that is what the shared epistemic ground functions as here: not as the destination of the integrated-system model but its starting point. Understood this way, the shared ground identified in Section 4.2 is a resilient orientational framework; it is durable enough to persist across varied institutional contexts, yet sensitive to professional experience and emerging challenges. This resilience aligns with the dynamic view of teacher beliefs, which expects restructuring under continuous professional pressure, experiential difficulties, and institutional constraints [13, 15]. The view of teacher cognition as an integrated system remains foundational; the shift lies in how that integration is understood, which recent work reconceives as ongoing rather than settled [41]. This capacity for restructuring bears implications for policy. The human-centered AI principles advanced by UNESCO [42] align with this shared structure, which reveals that effective policy should work with teachers' existing cognitive structures rather than impose conflicting alternatives. Shared foundations do not call for a one-size-fits-all approach: each of the three profiles presents distinct developmental concerns, and a sustainable model must accommodate all three.

Discussions of sustainable GenAI integration commonly emphasize two core needs: developing individual capability and ensuring institutional support and governance [43]. Factor 3, oriented toward technological practicality and application, responds to the first; Factor 2, centered on governance and ethical sensitivity, addresses the second. Factor 1 constitutes a dimension of its own. The distinctive contribution of this study is the straightforward claim that Factor 1's critical-thinking dimension is equally as significant as the other two, not a derivative of them. The evidence for its independence is empirical: although a critical awareness of GenAI's epistemic limits is shared position across all three factors (Section 4.2), the inclination to sustain critical-reflective distance is not universally present. Factor 1 applies that scrutiny to GenAI output itself, whereas Factors 2 and 3 do not. Factor 2 redirects it toward systemic governance; in Factor 3 it weakens [5, 6]. Since critical-reflective distance is underserved in two of the three profiles, it needs deliberate reinforcement across all: despite being shared as awareness among the factors, it must still be developed as a disposition. The three dimensions correspond to the three orientations and to the AI literacy language teachers need: practical application competence, grounded in Factor 3 [44]; institutional sensitivity and ethical judgment, rooted in Factor 2 [34, 35, 45]; and critical-reflective capacity, anchored in Factor 1 [5, 6]. Together these constitute the complementary axes of language teachers' professional AI literacy in the GenAI era. They are the components of an integrated-system model that begins from a common cognitive foundation and builds toward differentiated developmental paths for each type.

This framework carries a practical directive: teacher professional education must progress beyond unidimensional training in technology application toward integrated development spanning all three dimensions. A shared cognitive foundation provides the common starting point; diagnosis of belief type enables differentiation. Taken together, they comprise the design logic of this integrated-system model, whose growth paths are differentiated by belief type.

5.3. Limitations and Future Research

Rather than being designed to estimate how prevalent each belief type is across a population, Q methodology is designed to show that coherent, internally consistent viewpoint structures of the kinds identified here exist, and to characterize their internal logic with sufficient detail to support later inquiry [32]. The three orientations thus constitute an existence claim, not a frequency one: what this study not equipped to determine is their comparative prevalence in the broader KFL instructor population, a question suitable for large-scale survey instruments constructed using the typology provided here.

A second constraint concerns the participants. Since inclusion required practical GenAI experience, the typology represents instructors already engaged with the technology and may not apply to those who have so far avoided it; mapping the belief structures of nonadopters remains a question for future research. As belief structures can reconfigure as their shaping conditions change (Section 5.2), longitudinal designs that follow how these orientations develop—notably as institutional norms stabilize—would provide a direct test of that dynamic account and reveal whether the shared epistemic ground proves as durable as the present cross-sectional evidence implies.

5.4. Conclusion

A neglected problem addressed by this study is how KFL teachers cope with the pressure to use GenAI in the absence of clearly defined professional norms. By synthesizing LDA topic modeling and a PRISMA systematic review of the KCI corpus, we applied Q methodology to reconstruct three differentiated groups—Human-Centric AI Utilizers (Factor 1), Institutional and Ethical Advocates (Factor 2), and Relational AI Optimists (Factor 3). The three groups are distinguished by how they would use GenAI, govern it, and relate to it. All three, however, are grounded in a shared understanding. They uphold the centrality of the human teacher, adopt a critical-reflective stance toward GenAI's constraints, and support the renewal of Korean language pedagogy using digital approaches. Rather than being about GenAI itself, their disagreement centers on how educators should respond, professionally and institutionally, in an era of pervasive GenAI.

Convergence within divergence has both methodological and practical significance. Methodologically, it uncovers belief structures that questionnaire studies struggle to capture, disclosing qualitative differences a mean would hide. Practically, the three orientations chart differentiated professional-development needs with respect to AI literacy: critical-reflective capacity (Factor 1), institutional sensitivity and ethical judgment (Factor 2), and practical application competence (Factor 3). Anchoring professional development within a shared cognitive framework and then routing it through type-matched, differentiated pathways constitutes a structural precondition for policy. Such policy should diagnose

teachers' belief types before prescribing training. The volatility of current AI adoption in education makes this concern increasingly acute. South Korea's experience exemplifies the point: AI digital textbooks were launched without adequate pedagogical preparation and later scaled back. That episode underscores the necessity and urgency of this research path, with implications that extend to adjacent fields such as KFL.

Declarations

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Ethics approval and consent to participate

All Q-sort tasks and accompanying questionnaires in this study were completed anonymously online, with no collection of personally identifiable or sensitive information. The study involved no medical procedures or biological samples and used no deception. No vulnerable populations were involved: participants were consenting adult professionals, and the tasks concerned professional opinions on a non-sensitive educational topic. Ethical oversight of human-subjects research at the authors' institution rests with the Institutional Bioethics Committee of Sungkyunkwan University, whose governing regulations (enacted January 1, 2009, as amended February 2, 2013) apply the Bioethics and Safety Act of the Republic of Korea and its Enforcement Rule. Under Article 13 of the Enforcement Rule, survey research that collects no personally identifiable or sensitive information from adult participants is exempt from institutional review board review. This study, whose online questionnaire and Q-sort procedures fall within that category, therefore did not require approval from an ethics committee. The research was nonetheless conducted in accordance with the research ethics guidelines of Sungkyunkwan University, relevant national regulations, and the 1964 Declaration of Helsinki and its later amendments.

Participation was entirely voluntary. All participants were informed of the purpose of the research and the anonymity of data collection, and they retained the right to withdraw at any time without consequence. Electronic informed consent was obtained from all participants, all of whom were adults, prior to their enrollment in the online study. Participants were required to indicate their agreement before proceeding to the Q-sort tasks and questionnaires.

Consent to publish

Not applicable. This manuscript does not contain identifiable images or personal data of any individual; all quoted participant responses are fully anonymized.

Data availability

The data supporting the findings of this study—the 54-item Q sample, the factor arrays, and the de-identified factor-loading matrix—are available from the corresponding author on reasonable request. They are not publicly archived to protect participant confidentiality.

Author contributions

Huan-yi Liu: Conceptualization, Investigation, Visualization, Writing-original draft, Writing-review and editing, Project administration. Qian-xiong Jin: Methodology, Software, Formal analysis, Data curation, Investigation, Visualization, Writing-original draft. Keum-hee Lee: Supervision, Funding acquisition. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Use of generative AI

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) for language translation and editing. The authors reviewed and edited all output and take full responsibility for the content of this manuscript.

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Figures

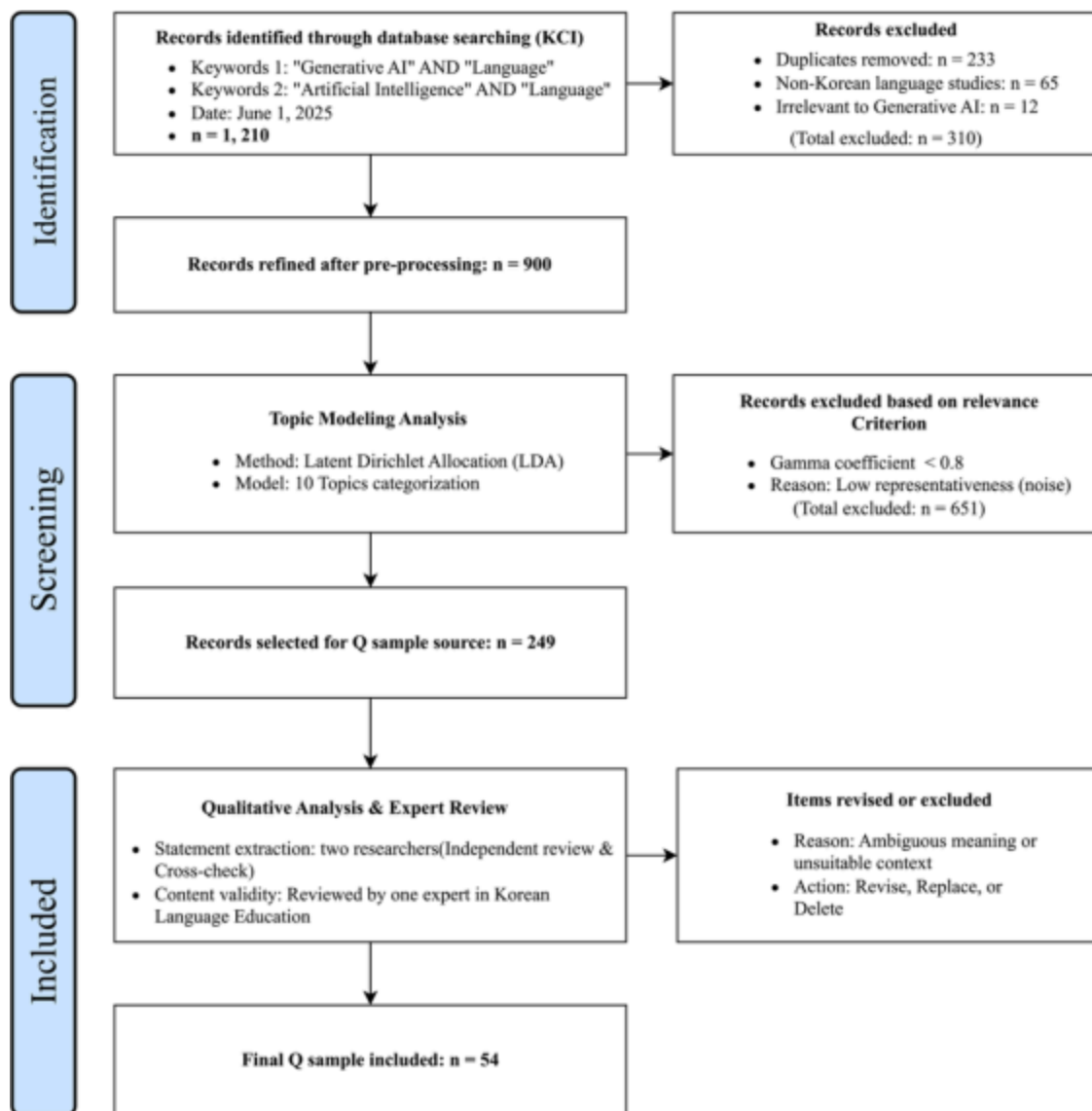


Figure 1

PRISMA flow diagram for Q sample construction via LDA

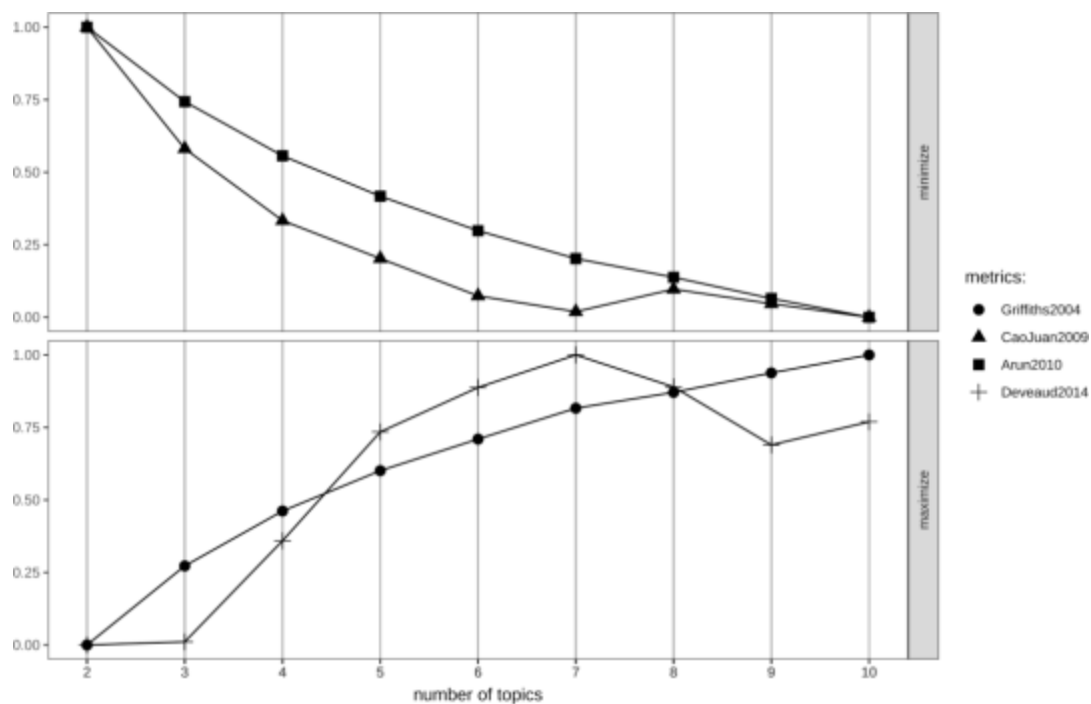


Figure 2

Validation metrics for selecting the number of topics in the LDA

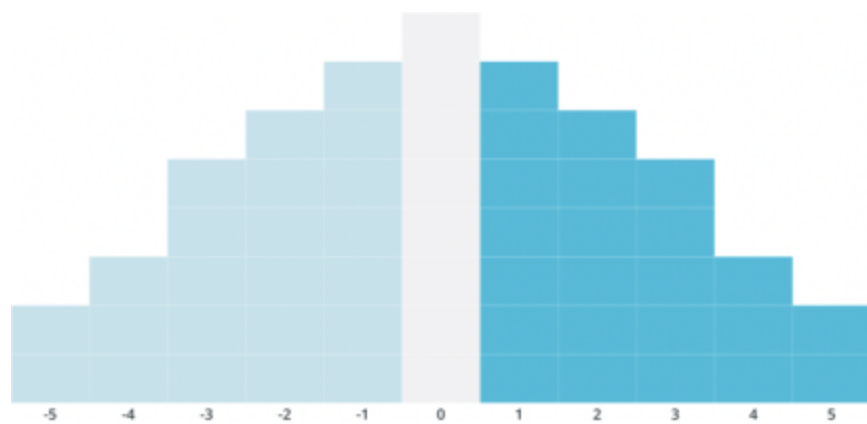


Figure 3

Sort grid

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