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Socratic Mediation Patterns in AI–Student Interactions: A Content Analysis of a Conversational Agent in Distance Higher Education

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Abstract

This study identifies and characterises the Socratic mediation patterns enacted by MIA, an AI-based conversational agent used in distance higher education. A deductive content analysis was conducted on 737 conversations using six categories: exploration of prior knowledge, contextual adjustment, linkage to experiences, autonomy-oriented prompts, dialogic progression, and verification prompts. The categorical framework achieved full expert content-validity agreement (S-CVI/Ave = 1.00). Contextual Adjustment (77%), Verification Prompts (76%), and Autonomy-Oriented Prompts (74%) were the most frequently observed categories. Sixty of the 64 theoretically possible category combinations occurred in the corpus, and Linkage to Experiences appeared more frequently in personal conversations (33.7%) than in academic conversations (18.3%). The distribution of categories also varied according to conversation length, with longer exchanges containing a broader range of coded dialogic moves. These findings describe the conversational repertoire through which MIA operationalised features associated with Socratic mediation. Because the study did not include independent measures of student satisfaction, learning, engagement, or self-regulation, the results should not be interpreted as evidence of educational effectiveness or causal effects. The study contributes an operational framework for analysing Socratic features in AI–student interactions and identifies directions for outcome-based research.

Keywords: artificial intelligence in education; Socratic mediation; conversational agents; human–AI interaction; content analysis; distance higher education; dialogic patterns



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1. Introduction

Digital technologies have gradually transformed higher education, forcing a rethinking of practices rooted in paradigms that no longer serve current or future societies. This transformation brings with it the urgency to abandon standardized systems in favour of developing essential competencies such as critical thinking, innovation, and the resolution of complex problems [1,2].

As a result of this digital transformation, personalised learning has become an influential orientation in contemporary education, particularly in initiatives seeking to accommodate differences in learners' needs, prior knowledge, interests, and learning contexts. Traditional methodologies reveal significant limitations: they are characterized by a vertical transmission of knowledge where the student is a passive recipient, a structure that

fails to address the diversity of cognitive styles and socioemotional contexts [3]. This homogenization persists even in digital environments, where sophisticated LMS platforms paradoxically often reproduce the traditional model through linear videos and standardized assessments [4], which fail to harness the adaptive potential of digital environments.

The increasing use of artificial intelligence in educational settings has expanded the technical possibilities for supporting approaches such as self-regulated learning [5] and dialogic scaffolding [6], among others. It is common for universities to have systems that analyze large amounts of data in real time and can make immediate adjustments [7]. Platforms like Coursera or EdX, for instance, do this frequently, profoundly transforming the educational experience, as noted by Xie et al. [8], from selecting resources based on individual interests to creating environments that consider cultural and emotional diversity, as discussed by Sadaf et al. [9].

Personalised learning seeks to adjust pace, content, and methods to individual needs [10]. Previous studies have examined whether such adjustments may support student agency, academic performance, and metacognitive development. These potential outcomes, however, require independent empirical measurement and cannot be inferred solely from the presence of adaptive conversational features, as mentioned by Lee et al. [11], and suggested by Luckin et al. [12], who emphasize balancing automation and humanization, where technology complements the critical and creative dimensions of the educational process.

1.1. The Role of Socratic Dialogue and AI in This Study

For this study, Socratic dialogue is defined as an educational inquiry process that uses a chain of questions to foster critical thinking. This conceptualization of the Socratic method aligns with the historical evolution of educational personalization, as noted by Walkington and Hayata [3], which acknowledges diversity in its various meanings, scales content according to interests and knowledge, and provides individualized pedagogical paths from different perspectives.

The practical implementation of personalization has evolved from an approach centred on the teacher as a designer of personalized instruction [1] to an emphasis on the student's role in the process [2], as an agent who engages in their learning process or active learning. As Xie et al. [8] note, this new approach allows not only for content adjustments but also for behaviour anticipation and instant feedback, significantly expanding the pedagogical scope. It is not merely about providing content or materials to have a personalized process, and AI plays an essential role in this aspect. This conceptual evolution of Socratic dialogue and educational personalization lays the theoretical groundwork to examine how artificial intelligence can enhance these approaches, fundamentally transforming the nature of learning experiences.

Just as streaming platforms and social media adapt content to individual interests, educational environments are experiencing a similar transformation, but with deeper pedagogical purposes and consequences. Hosseini et al. [7] described how learner-modelling approaches can support personalised e-learning, while Lim et al. [13] examined how students engage with real-time personalised scaffolds. Together, these studies illustrate the development of adaptive support based on learner information and ongoing activity. Although AI has shown potential for educational personalization, a gap remains in the detailed understanding of how conversational agents implement complex dialogic strategies such as Socratic dialogue. Educational technology has evolved from passive to adaptive, offering unprecedented personalized experiences [14]. It no longer indicates static content routes; instead, content appears adaptively depending on student interaction, a common feature in language learning platforms, for example, which identify learning behaviour

patterns and, as noted by Winkler and Söllner [15], adapt instruction to overcome the limitations of traditional methods.

This application presents ethical and pedagogical challenges, such as the risk of excessively prescriptive evaluation frameworks that sacrifice creative problem-solving [12]. To avoid this, systems must be designed based on solid pedagogical traditions and equitable approaches that promote metacognitive development [5].

This study involves MIA (Intelligent Mentor of Accompaniment), an agent designed for the “Distance 4.0” learning model at one of the largest private universities in Colombia, based on principles of Socratic questioning. MIA was designed to pose reflective questions rather than provide exclusively direct answers, following principles associated with Socratic inquiry [6]. Tools such as MIA provide an opportunity to examine whether conversational agents can operationalise dialogic moves associated with critical inquiry, autonomy-oriented prompting, and the social construction of knowledge [16]. However, questions remain regarding the effective implementation of Socratic dialogue in digital environments, requiring an articulated methodological framework. This study examines the observable dialogic moves enacted by MIA in its interactions with university students. Rather than evaluating whether these interactions produce personalised learning or improve educational outcomes, the analysis identifies how six theoretically grounded dimensions of Socratic mediation are distributed and combined across the conversational corpus. In this dynamic, MIA does not directly impart knowledge but guides the student through reflective questions to help them discover, articulate, and evaluate knowledge themselves [17–19].

The interpretation of MIA’s interactions is structured according to six variables of the Socratic method that represent complementary dimensions of the dialogical process and serve as core analytical categories in this study: Prior Knowledge, Contextual Adjustment, Experiences, Autonomy, Progression, and Verification. The analysis examines how these six categories manifest in the recorded interactions and how their distribution varies across conversation types and lengths. The categories are treated as indicators of observable conversational behaviour rather than evidence of students’ learning, satisfaction, autonomy, or comprehension. Jedishkem and Jedishkem [20] and Torres-Gutiérrez et al. [21] emphasise the importance of combining experiential and human-centred approaches with AI-supported educational practices rather than reducing education to a purely technical process.

1.2. Background and Research Question

This study emerged from informal observations of interactions between students from diverse academic programs, regions, and sociocultural environments with MIA. What began as a pilot project to facilitate basic academic inquiries revealed surprisingly complex dialogic interaction patterns that warranted systematic analysis. These preliminary observations demonstrated the need to methodically investigate the mediation strategies underpinning these pedagogical exchanges.

Accordingly, the study addresses the following research question: What patterns of Socratic mediation are observable in MIA’s interactions with university students, and how do the distribution and combination of these patterns vary across conversation types and lengths? The study focuses on the conversational behaviour recorded in the corpus. It does not evaluate learning gains, student satisfaction, engagement, or the causal effects of interacting with MIA. Accordingly, the study characterises how Socratic mediation features are organised within human–agent interactions and provides an operational basis for their subsequent evaluation. MIA operates under the “Distance 4.0” model, a hybrid design (virtual–in-person) aimed at populations with difficulties attending regular in-

person classes, such as workers and single mothers. MIA functions as a permanent virtual tutor to address questions, provide academic guidance, and offer educational support within the time and space constraints experienced by this student community. Within this bounded case, the analysis offers a descriptive account of conversational mediation that can inform future comparative and outcome-based research on human–agent interaction in education.

2. Literature Review

AI-mediated personalized learning seeks to tailor the educational process to each student's specific needs [2,14], aiming to comprehensively transform the educational experience through individualized learning trajectories. “AI-based conversational agents facilitate this personalization through adaptive interactions that simulate human dialogue,” as noted by Winkler and Söllner [15], with Socratic dialogue being particularly relevant due to its ability to stimulate critical thinking through sequences of reflective questioning [18,19]. This study analyses the observable dialogic moves through which a conversational agent operationalises features associated with Socratic mediation, using six analytical categories: prior knowledge, adjustment, experiences, autonomy, progression, and verification. These categories enable a systematic examination of how Socratic mediation is represented in recorded AI–student interactions.

2.1. Socratic Dialogue as a Pedagogical Mediation Strategy

Socratic dialogue represents an approach where knowledge is built through guided exchange [22], using questions as catalysts for autonomous thinking [23]. Rapanta and Macagno [24] identify its progressive structure: exploration of initial conceptions, critical examination through challenging questions, and construction of grounded understanding. This dialectical progression underpins the dimensions of analysis used in this study. In its contemporary educational application, the Socratic method has been operationalized through various pedagogical taxonomies.

Tofade et al. [25] categorize questions based on their function (conceptual, analytical, and evaluative), while Davies and Mangan [26] document their capacity to develop transformative “threshold concepts” in university settings. Yang and Carless [27] emphasize the educator's role as the architect of “cognitive scaffolds” that operate within the learner's “zone of proximal development,” calibrating questions that challenge without overwhelming.

These Socratic principles—exploration of prior conceptions, conceptual clarification, connection to experiences, promotion of autonomy, dialectical progression, and verification of understanding—form the basis of the analytical categories employed in this study. While the Socratic practice represents an integrated continuum, its decomposition into operational dimensions facilitates the systematic analysis of interactions mediated by MIA, while preserving the holistic nature of Socratic dialogue as an integral pedagogical process.

2.2. Relevance of Socratic Dialogue in Digital Environments and with Conversational Agents

Contrary to initial expectations, research shows that Socratic principles are not only compatible with digital environments but can be enhanced by them. Kulik and Fletcher [28] confirm that tutorial systems employing Socratic strategies yield significantly greater educational gains than those based on direct instruction. Advances in natural language processing have enabled conversational agents to implement Socratic dialogues to develop argumentative skills [29], offer personalized feedback at scale, and democratize access to Socratic learning experiences [30]. While challenges remain in these systems' ability to

grasp contextual nuances and adapt dialogic strategies [14], recent language models show promising developments.

The dimensions of Socratic dialogue—exploration of prior knowledge, conceptual clarification, linkage to experiences, promotion of autonomy, conceptual progression, and comprehension verification—take on specific manifestations when mediation occurs through AI agents. These features can be operationalized as analytical categories to systematically examine how MIA implements Socratic principles in its educational interactions, shaping the interpretive framework applied to analyze conversations between the agent and university students.

2.3. Interpretive Framework for Socratic Mediation in Interactions with Conversational Agents

Applying Socratic dialogue in AI-mediated environments requires a specific interpretive framework to identify its concrete manifestations. Through an inductive–deductive methodology, the study began with theoretical principles [23,24] and conducted a preliminary analysis of interactions between MIA and university students, which allowed for the recognition of recurring patterns in the Socratic dialogic process. This approach responds to the need to develop analytical tools that capture the particularities of human–computer interaction, considering that conventional frameworks are insufficient to assess AI-mediated dialogues [29].

The analysis of interactions between MIA and students is structured around six fundamental dimensions that capture complementary aspects of Socratic dialogue. These dimensions do not function as isolated compartments but as interrelated facets that together configure pedagogical mediation, and which are presented below:

Exploration of Prior Knowledge: Corresponds to the Socratic practice of beginning dialogue by examining the interlocutor’s preexisting conceptions. It appears when the conversational agent asks questions designed to explore the student’s existing knowledge, beliefs, or experiences related to the topic.

Contextual Adjustment: Linked to the Socratic ability to situate the dialogue within an appropriate referential framework. It is evident when the agent asks clarifying questions to accurately understand the student’s context and communicative intent, thereby establishing a shared foundation for subsequent exchange.

Linkage to Experiences: Reflects the Socratic principle of connecting abstract knowledge with the interlocutor’s concrete experience. It is seen when the agent invites the student to relate theoretical concepts to personal or professional situations, promoting situated and meaningful learning.

Autonomy-Oriented Prompts: This category identifies agent interventions that invite the student to make a decision, propose an explanation, evaluate alternatives, formulate a conclusion, or plan an action. The category describes the orientation of the prompt and does not establish that the student subsequently developed or exercised autonomy.

Dialogic Progression: Involves structuring the dialogue as a journey toward higher levels of conceptual complexity. It is observed in sequences where the agent builds on prior responses to progressively deepen understanding, introducing new elements that expand the initial comprehension.

Verification Prompts: This category identifies interventions in which MIA asks whether its response was clear, useful, or sufficiently complete, or invites the student to request further clarification. The presence of such a prompt does not confirm that the student understood the response, was satisfied with the interaction, or achieved a learning outcome.

These dimensions, while reflecting classical aspects of the Socratic method, have been reformulated to accommodate the particularities of the digital context and the specific capabilities of an AI-based conversational agent.

2.4. Relevance of the Dimensions in the Context of Human-Agent Interactions

The proposed interpretive framework is especially relevant for analyzing interactions between students and conversational agents for several key reasons:

Pedagogical mediation in digital environments presents distinctive challenges that the identified dimensions help to examine systematically. As suggested by Zawacki-Richter et al. [14], educational conversational agents must navigate limitations of computer-mediated communication, including the absence of non-verbal cues and potential interpretative ambiguity. Contextual Adjustment and Verification Prompts are analytically relevant because they capture attempts by the agent to clarify the exchange and request confirmation; their presence does not demonstrate that shared understanding was achieved.

Personalised learning is a central aspiration of many AI-based educational systems, but its achievement cannot be inferred from adaptive features alone. Exploration of Prior Knowledge and Linkage to Experiences provide observable indicators of context-sensitive prompting through which the agent may tailor its responses to information emerging in the conversation. Whether students experience these moves as meaningful personalisation requires independent evidence beyond the conversational corpus [2].

The development of self-regulation and critical thinking also requires pedagogical strategies that extend beyond information delivery. Autonomy-Oriented Prompts and Dialogic Progression provide analytical categories for identifying questions theoretically associated with student agency and progressively connected reasoning [28]. Their presence, however, does not establish that these competencies were developed.

Together, the six dimensions form an analytical lens for describing the observable forms through which features associated with Socratic dialogue appear in MIA's interactions. The framework supports systematic comparison across conversations and generates hypotheses for the future design and evaluation of educational conversational agents; it is not presented as evidence that the agent achieved pedagogical effectiveness.

Next, an operational synthesis of the six identified dimensions is presented, structured in matrix form to facilitate systematic analysis. Each matrix articulates: (1) the theoretical basis supporting the dimension, summarizing the sources and concepts behind it; (2) its concrete manifestation in pedagogical mediation contexts, describing how it is observed in general educational practices; (3) the specific operationalization for analyzing MIA, detailing the criteria for identifying the dimension in studied interactions; and (4) an illustrative example extracted from the analyzed conversation corpus. This matrix organization not only synthesizes the developed theoretical-methodological framework but also provides concrete analytical tools for the coding and systematic analysis of interactions between MIA and students, supporting the transition from conceptual framework to methodological implementation.

In the present study, these dimensions function as observational coding categories. Their presence indicates that MIA generated a conversational move corresponding to a theoretically defined Socratic function. It does not demonstrate that the student acquired knowledge, experienced autonomy, developed critical thinking, or achieved understanding. Such outcomes would require external measures beyond the conversational corpus analysed here.

3. Method

This study adopts a mixed analytical approach centred on deductive categorical content analysis. It examines the Socratic mediation patterns enacted by an AI-based conversational agent in 737 interactions with undergraduate students enrolled in the Distance 4.0 model. The purpose is to identify the frequency, distribution, combination, and contextual variation of six theoretically grounded dialogic categories within an asynchronous

distance higher education environment. The following describes the research design, corpus characteristics, technological context, instruments used, coding procedures, analytical strategies, and ethical safeguards considered.

3.1. Research Design

The research employs a single case study design, centered on deductive content analysis [31]. The study aims to identify and characterize pedagogical mediation strategies that emerge in interactions between undergraduate students and the AI-based conversational agent (MIA), within the educational framework of the “Distance 4.0” model.

The analysis was supported by a pre-established categorical matrix composed of six functional dimensions associated with Socratic dialogue, which enabled the organization of the corpus based on theoretically grounded categories. From an interpretive-constructivist perspective, it is assumed that meanings are not predetermined but are constructed in situated interaction and that conversational agents constitute situated interactional environments in which meanings and dialogic sequences are constructed through successive exchanges. The categorical matrix was built from specialized literature on Socratic dialogue and digital pedagogical mediation, allowing the alignment of categories with discourse functions recognized in contemporary educational theory. The study is descriptive and observational. Its unit of evidence consists of recorded conversational interactions, and no independent measures of learning, satisfaction, engagement, self-regulation, or perceived personalisation were collected. Accordingly, the analyses identify associations and patterns within the corpus but do not support causal or effectiveness claims.

3.2. Participants and Sampling

A total of 737 conversations between undergraduate students and the conversational agent MIA were analysed and selected through convenience sampling from an institutional database. All participants were enrolled in the “Distance 4.0” model, characterised by its asynchronous flexibility and inclusive orientation towards students with limited access to face-to-face education. The sample comprised 576 conversations from women and 161 from men. Gender was retained as descriptive metadata only and was not entered into the analyses reported in this article.

Eligibility required at least two substantive MIA interventions and sufficient semantic continuity to permit conversation-level coding. Inclusion did not require the presence of any particular Socratic mediation category; consequently, eligible conversations could receive an all-zero vector when none of the six categories was observed. Fragmented interactions, technical errors, content-free exchanges, and dialogues without sufficient semantic continuity for analysis were excluded.

3.3. Educational Environment and Functional Architecture of MIA

The study took place within the educational model “Distance 4.0”, an asynchronous modality designed to support access and retention among students who face difficulties attending in-person classes. Within this setting, MIA (Intelligent Mentor of Accompaniment) was incorporated as an AI-based conversational agent intended to provide academic, emotional, and personal support through adaptive dialogic strategies.

According to the institutional system documentation, MIA operates continuously (24/7) and does not require prior user training. Its pedagogical architecture was designed around principles associated with the Socratic method, with a preference for reflective questions rather than exclusively direct answers. Technically, MIA is described as a multimodal, multi-agent system based on Transformer architectures, implemented in C# 14, Python 3.14.7, and JavaScript ES2026, and incorporating reinforcement learning with

human feedback. It also includes a recursive user-modelling component intended to infer learning preferences, interests, and selected profile characteristics from the interaction. These technical features describe the deployed system and were not variables in the present analysis; the accuracy of the internal user-profile inferences was not evaluated.

3.4. Analysis Categories—Dimensions of Socratic Dialogue

The analysis categories previously introduced in the literature review section were manifested and operationalized in this study as follows:

3.4.1. Exploration of Prior Knowledge

The educator asks questions that invite the student to express their initial conceptions, previous experiences, or beliefs about the topic, seeking to make the student's conceptual framework explicit to identify epistemological obstacles or favourable anchor points. The operationalization of this category in MIA is reflected in conversational turns where MIA poses questions aimed at inquiring about prior knowledge, concepts, or experiences. This includes questions like "What do you know about...?", "Have you studied... before?", or "What do you understand by...?"

3.4.2. Contextual Adjustment

The agent intervenes to clarify the context and scope of the student's questions or statements. This includes lexical clarification questions, disciplinary specification requests, or confirmations about communicative intent. In MIA, this category is operationalized in interventions where MIA asks questions to establish referential context and determine a clear epistemic location. Examples include resolving ambiguities, clarifying polysemic terms, or defining a specific disciplinary framework. For instance: Student: "I want to know more about movements." MIA: "Are you referring to movements in physics, like the motion of objects, or to social and cultural movements? Which one would you like to explore more?"

3.4.3. Linkage to Experiences

The agent invites the student to relate theoretical concepts to personal, professional, or academic experiences. This includes questions about practical applications, requests for examples based on personal experiences, and reflections on how the concept appears in everyday life. In MIA, this category is operationalized through interactions where MIA asks questions that aim to connect the topic with the student's prior experiences. These interventions include requests for personal examples, inquiries into practical applications, or invitations to reflect on the contextual relevance of the topic. For example: Student: "I'm learning about stress coping strategies."

MIA: "Have you ever applied a specific stress management technique in your life? What were the results?"

3.4.4. Autonomy-Oriented Prompts

The agent poses interventions that progressively transfer responsibility to the student. This includes questions that promote decision-making, invitations to evaluate alternatives, encouragement to propose solutions, and requests for planning actions. In MIA, this category is reflected in interventions designed to foster agency, self-regulation, and proactivity. These include turns where MIA invites the student to draw their conclusions, make informed decisions, or take actions that demonstrate knowledge ownership.

3.4.5. Dialogic Progression

This category was coded when two or more connected MIA turns formed a coherent sequence that moved from description or clarification towards comparison, evaluation, or further elaboration. The coding captures the structure of the agent's questioning, such as movement from the concrete to the abstract or from the descriptive to the evaluative. It does not demonstrate that the student's conceptual understanding actually deepened. For example:

MIA: "Didactics is fundamental because it influences how students learn and retain information. Have you ever noticed that one teaching method worked better for you than another?"

Student: "Yes, I learn better when I do things myself or write, rather than just watch or listen."

MIA: "Interesting observation. It seems your learning style aligns with active didactics, which emphasizes 'learning by doing' and personal knowledge construction. Have you thought about how you might leverage this preference in your study strategies?"

3.4.6. Verification Prompts

This category includes interventions in which MIA asks whether a response was clear, useful, or sufficiently complete, or invites the student to request further clarification. It records an agent-generated attempt to verify the exchange; it does not confirm student understanding, satisfaction, fulfilment of informational needs, or metacognitive evaluation. Examples include "Does this answer your question?", "Would you like us to go deeper into any aspect?", and "Is there anything that wasn't clear?"

In summary, the theoretical-methodological framework links the tradition of Socratic dialogue with the analysis of AI-based conversational agents in educational contexts. The six operationalised dimensions—Exploration of Prior Knowledge, Contextual Adjustment, Linkage to Experiences, Autonomy-Oriented Prompts, Dialogic Progression, and Verification Prompts—provide complementary lenses for examining MIA's observable conversational repertoire. The framework enables systematic categorisation and comparison across interactions and offers hypotheses for future design and evaluation. Its application does not, by itself, establish pedagogical effectiveness.

3.5. Coding Framework, Content Validation, and Analytical Trustworthiness

The analytical instrument consisted of a categorical framework comprising six functional dimensions of Socratic mediation: Exploration of Prior Knowledge, Contextual Adjustment, Linkage to Experiences, Autonomy-Oriented Prompts, Dialogic Progression, and Verification Prompts. The categories were derived from the literature on Socratic dialogue and digital pedagogical mediation and were operationalised to identify observable functions in MIA's conversational behaviour. The framework underwent content validation by three expert judges, who assessed each category in terms of sufficiency, clarity, coherence, and relevance using a Likert-type scale. Content-validity indices were calculated following Lynn [32] and Polit and Beck [33]. The validation produced I-CVI values of 1.00 for all items, an S-CVI/Ave of 1.00, and an S-CVI/UA of 1.00, indicating complete agreement among the experts regarding the conceptual relevance and clarity of the framework.

An initial pilot was conducted on 10% of the corpus (N = 75) to examine the interpretive consistency of the preliminary coding rules. Three raters independently coded the pilot conversations, and Fleiss' kappa was calculated. The resulting coefficient was low ($\kappa = 0.111$), indicating that the initial category definitions and decision rules did not yet

support sufficiently consistent independent application. Pairwise examination revealed particular ambiguity in categories such as Contextual Adjustment, including $\kappa = -0.01$ between two raters. The pilot coefficient was therefore treated as a diagnostic finding rather than as evidence of acceptable intercoder reliability.

In response to the pilot findings, the research team conducted structured calibration sessions. Divergent cases were reviewed in relation to the complete conversational context, category boundaries were clarified, inclusion and exclusion rules were expanded, and examples of ambiguous cases were incorporated into the operational codebook. The revised framework was subsequently applied to the complete corpus by two researchers through a negotiated-consensus procedure. When different interpretations arose, the researchers examined the relevant conversational sequence and the operational criteria until an agreed classification was reached. The final decisions and modifications to the coding rules were documented in a traceability record.

The trustworthiness of the analysis was therefore supported through the convergence of several procedures: expert content validation, diagnostic pilot coding, iterative calibration, investigator triangulation, negotiated consensus, documentation of coding decisions, and analytical triangulation across complementary forms of analysis. These procedures strengthened the credibility, dependability, and confirmability of the interpretations, although they do not constitute a statistical estimate of post-calibration intercoder reliability.

3.6. Procedure

The analytical procedure comprised five interconnected stages. First, the conversational corpus was extracted from the institutional system and anonymised by removing direct and indirect identifiers while preserving the semantic continuity required for analysis. Second, the inclusion and exclusion criteria were applied to identify conversations containing sufficient dialogic interaction for categorical analysis.

Third, three raters independently coded an initial pilot sample of 75 conversations. The low agreement obtained at this stage was used diagnostically to identify ambiguities in the preliminary framework. Calibration sessions were then conducted to review divergent interpretations, refine operational definitions, clarify category boundaries, establish inclusion and exclusion rules, and expand the codebook with examples of difficult cases. Fourth, two researchers applied the revised codebook to the complete corpus through negotiated consensus. Coding decisions were examined at the level of the complete conversational sequence rather than as isolated statements. When disagreement occurred, the relevant context and operational criteria were reviewed until a shared classification was reached. The evolution of category definitions and the treatment of ambiguous cases were recorded in an audit trail to support procedural transparency and analytical traceability.

Fifth, the consensus-coded corpus was examined through complementary descriptive, contextual, configurational, structural, and relational analyses. The findings generated by these procedures were compared to identify convergence, complementarity, and dissonance across analytical perspectives. This integration formed the basis of the analytical triangulation described in the following section.

3.7. Analytical Strategy and Triangulation of Findings

The analysis followed a deductive categorical content approach complemented by descriptive, contextual, configurational, and relational procedures. Because all analyses were conducted on the same conversational corpus, the integration process is described as analytical triangulation rather than data-source triangulation. Its purpose was to examine whether findings converged across different analytical perspectives, whether

they provided complementary explanations, or whether they revealed dissonant patterns requiring further interpretation.

The first analytical perspective examined the absolute and relative prevalence of each Socratic mediation category across the complete corpus. The second examined contextual variation by comparing category distributions across academic, personal, and support conversations and across short, medium, and long interactions. Conversation length was operationalised using predefined descriptive bands based on character count: short (<5000 characters), medium (5000–15,000 characters), and long (>15,000 characters). These bands distinguished brief, sustained, and extended exchanges; they were not derived as latent classes or interpreted as thresholds of learning quality. The third perspective examined configurational variation through the frequency of the binary combinations formed by the six categories. The fourth examined directional conditional co-occurrence. For each ordered pair of categories A and B, the percentage was calculated as $P(B|A) = [N(A \cap B)/N(A)] \times 100$. Each cell therefore represents the percentage of conversations containing the row category A that also contained the column category B. Because the row categories have different prevalence levels, the resulting matrix is asymmetric by definition and should not be interpreted as joint prevalence across the complete corpus.

As a fifth exploratory analytical perspective, hierarchical clustering was used to organise conversations with similar binary category configurations. The input matrix comprised 737 rows, representing individual conversations, and six binary columns indicating the presence or absence of the six Socratic mediation categories. Jaccard distance was selected to emphasise shared category presences rather than shared absences, and agglomerative hierarchical clustering with complete linkage was applied. The 21 conversations with an all-zero vector were retained and reported as a distinct modal configuration; because these vectors contain no positive category features, their grouping was interpreted descriptively. The six-cluster solution was retained because it provided an interpretable summary of the dominant modal configurations, not because it was established as statistically optimal. No formal optimisation criterion, resampling-based stability assessment, or external validation was applied. The clusters were therefore used only to organise configurational variation within this corpus.

As a complementary relational procedure, an exploratory multivariable binary logistic regression was conducted at the conversation level. The dependent variable represented the presence or absence of Verification Prompts. The five remaining Socratic mediation categories were entered as binary explanatory variables, conversation type was entered as a three-level factor with academic conversations as the reference category, and the number of MIA turns was entered as a continuous explanatory variable. The model estimated conditional associations after simultaneous adjustment for the other included variables. Because the dependent and explanatory variables were coded from the same interaction, the model was not interpreted as establishing temporal prediction, causal influence, student satisfaction, successful interaction, or learning effectiveness.

The findings were integrated by comparing the results obtained through these complementary procedures. A pattern was regarded as convergent when it appeared consistently in at least two analytical perspectives. Findings were considered complementary when different analyses illuminated distinct dimensions of the same pattern, and dissonant when an overall tendency differed from the pattern observed in a particular context or subgroup. Dissonant results were retained and interpreted rather than excluded. For example, the relatively low overall prevalence of Linkage to Experiences was examined alongside its higher occurrence in personal conversations, while the lower overall prevalence of Dialogic Progression was considered in relation to its greater presence in longer interactions.

Investigator triangulation complemented this analytical integration. Three re-searchers participated in the diagnostic pilot, and two researchers applied the revised codebook to the complete corpus through negotiated consensus. Ambiguous cases were interpreted in relation to the surrounding conversational context and the operational rules contained in the codebook. The decisions resulting from this process were documented to preserve traceability between the theoretical framework, the coding criteria, and the final classifications.

All quantitative summaries and visualisations were generated in R Studio 2025.09 using specialized libraries such as dplyr, tidyr, ggplot2, corrplot, vcd, reshape2, flextable, and officer, regarding the coded presence or absence of each category at the conversation level. These procedures were used to describe patterns within the consensus-coded corpus rather than to test educational effectiveness or causal relationships. The convergence of findings across analytical procedures strengthened the internal coherence and confirmability of the interpretation. Nevertheless, because the analyses originated from the same consensus-coded dataset, analytical triangulation does not independently establish whether other coders would reproduce the classifications.

To make the integration procedure explicit, Table 1 summarises the analytical perspectives used to examine the corpus and the distinctive contribution of each one to the interpretation. The table shows how overall prevalence, contextual variation, conversation length, category configurations, relational patterns, and investigator interpretation were considered jointly. Rather than treating convergence as independent statistical confirmation, the framework was used to identify whether the different analytical procedures produced consistent, complementary, or dissonant views of the same conversational phenomena.

Table 1. Analytical triangulation framework used to integrate the findings.

Analytical Focus	Evidence Examined	Contribution to Interpretation
Overall prevalence	Frequency and percentage of each category in the complete corpus	Identified the most and least recurrent dialogic moves
Contextual variation	Category distributions across academic, personal, and support conversations	Identified context-sensitive differences
Variation by conversation length	Category distributions across short, medium, and long interactions	Examined whether dialogic moves varied with interaction length
Configurational patterns	Frequencies of binary combinations of the six categories	Identified recurrent arrangements of dialogic moves
Directional relational patterns	Conditional co-occurrence percentages, $P(\text{column category} \mid \text{row category})$	Examined how frequently each additional category appeared among conversations containing a given focal category
Investigator interpretation	Calibration discussions, negotiated consensus, and documented decisions	Connected theoretical definitions with context-sensitive coding decisions
Integrated interpretation	Convergence, complementarity, and dissonance across analyses	Supported the overall interpretation while retaining divergent findings
Multivariable relational analysis	Binary logistic model of the presence of Verification Prompts	Estimated conditional associations among conversational categories and characteristics without interpreting Verification Prompts as satisfaction or learning
Exploratory structural grouping	Hierarchical clustering of conversation-level binary category configurations	Organised conversations with similar configurations into descriptive groups without treating them as a validated or stable taxonomy

3.8. Ethical Considerations

The study was approved by the Ethics Committee of the university where the research was conducted. The research was carried out in accordance with the ethical principles governing research involving human participants and with institutional guidelines for the analysis of anonymised secondary data.

The units of analysis consisted of conversations previously stored in MIA's institutional system. Prior informed consent was obtained from the participants for the collection, storage, anonymisation, and research analysis of these conversations. Before the corpus was made available to the research team, it underwent a rigorous anonymisation process that included the removal of proper names, telephone numbers, indirect references, and any other information that could reasonably lead to participant identification. The data were treated as strictly confidential, stored on secure institutional servers with restricted access, and used exclusively for research purposes. The integrity, traceability, and security of the information were maintained throughout all stages of the analysis.

4. Results

4.1. Distribution by Conversation Type

The first analysis focused on the distribution of conversations by type. As shown in Figure 1, out of the 737 conversations analyzed, the vast majority correspond to Academic interactions (82%), followed by Personal ones (12%), and finally Support interactions (6%). This distribution indicates that most conversations in the corpus were classified as academic, while smaller proportions concerned personal or technical-support matters.

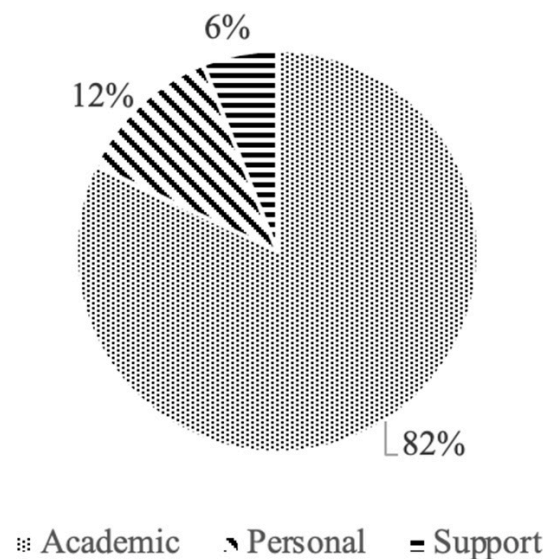


Figure 1. Distribution of conversations by type.

4.2. Presence of Categories in Conversations

The category distribution shown in Figure 2 describes the frequency with which the six coded dialogic moves appeared in the corpus. Contextual Adjustment (77.1%), Verification Prompts (76.1%), and Autonomy-Oriented Prompts (73.7%) were the most frequently observed categories, followed by Exploration of Prior Knowledge (69.5%). Dialogic Progression (33.1%) and Linkage to Experiences (20.4%) were less frequent. These percentages indicate the prevalence of coded agent behaviours and should not be interpreted as evidence that students experienced personalisation, autonomy, comprehension, or learning.

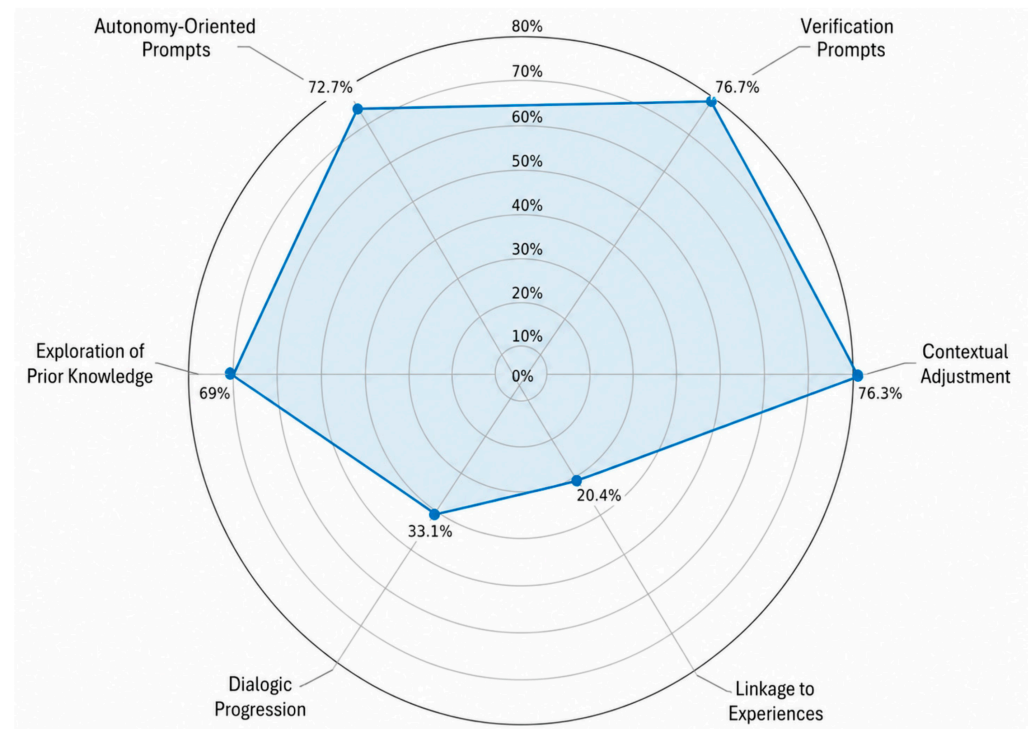


Figure 2. Prevalence of Socratic mediation categories across conversations.

4.3. Most Frequent Coding Patterns

Table 2 presents the most frequent coding patterns identified in MIA's interactions, expressed as binary vectors in which each position represents the presence (1) or absence (0) of a category. The most frequent pattern, [1,1,0,1,0,1], occurred in 26.6% of conversations and combined Exploration of Prior Knowledge, Contextual Adjustment, Autonomy-Oriented Prompts, and Verification Prompts, while Linkage to Experiences and Dialogic Progression were absent. The second most frequent pattern, [1,1,0,1,1,1] (12.8%), contained the same categories together with Dialogic Progression. This difference indicates the presence of an additional coded progression sequence; it does not establish that the interaction was more elaborate or educationally effective.

Table 2. Most frequent configurations of Socratic mediation categories.

#	Pattern	Occurrences	%
1	[1,1,0,1,0,1]	196	26.6%
2	[1,1,0,1,1,1]	94	12.8%
3	[0,1,0,1,0,1]	41	5.6%
4	[1,1,1,1,0,1]	34	4.6%
5	[1,0,0,0,0,1]	25	3.4%
6	[1,1,0,0,0,1]	23	3.1%
7	[0,0,0,0,0,0]	21	2.8%
8	[1,1,0,0,0,0]	19	2.6%
9	[1,1,0,1,0,0]	18	2.4%
10	[0,1,0,1,0,0]	16	2.2%

Note: Binary positions represent, in order, Exploration of Prior Knowledge, Contextual Adjustment, Linkage to Experiences, Autonomy-Oriented Prompts, Dialogic Progression, and Verification Prompts. A value of 1 indicates presence and 0 indicates absence.

4.4. Presence of Categories by Conversation Type

The analysis of category presence by conversation type (Table 3) reveals differentiated mediation patterns depending on the context of interaction. In academic conversations, the most frequently observed categories were Contextual Adjustment (77.5%), Verification Prompts (75.1%), and Autonomy-Oriented Prompts (74.5%). Personal conversations showed the highest proportion of Verification Prompts (80.4%), followed by Contextual Adjustment (75.0%) and Autonomy-Oriented Prompts (72.8%). In support conversations, Verification Prompts reached 83.8% and Contextual Adjustment 75.7%, whereas Autonomy-Oriented Prompts were observed in 62.2%. Linkage to Experiences showed the clearest contextual variation, appearing in 33.7% of personal conversations, compared with 18.3% of academic and 21.6% of support conversations, indicating that the distribution of coded dialogic moves differed across conversation types. This variation is consistent with context-sensitive differences in the agent's conversational behaviour, although it does not demonstrate that the adaptation was successful from the student's perspective.

Table 3. Distribution of Socratic mediation categories by conversation type.

Category	Academic, N (%)	Personal, N (%)	Support, N (%)	Total, N (%)
Exploration of Prior Knowledge	425 (70.0)	62 (67.4)	25 (67.6)	512 (69.5)
Contextual Adjustment	471 (77.5)	69 (75.0)	28 (75.7)	568 (77.1)
Linkage to Experiences	111 (18.3)	31 (33.7)	8 (21.6)	150 (20.4)
Autonomy-Oriented Prompts	453 (74.5)	67 (72.8)	23 (62.2)	543 (73.7)
Dialogic Progression	204 (33.6)	30 (32.6)	10 (27.0)	244 (33.1)
Verification Prompts	456 (75.1)	74 (80.4)	31 (83.8)	561 (76.1)

4.5. Exploratory Grouping of Conversation Configurations

The exploratory hierarchical clustering organised the 737 conversations into six descriptive groups according to the presence or absence of the six Socratic mediation categories, as shown in Table 4. The solution provides a structural summary of recurrent binary configurations within the consensus-coded corpus. The groups should not be interpreted as fixed types of students, levels of conversational quality, or empirically validated pedagogical profiles.

Table 4. Adjusted logistic regression estimates for the presence of Verification Prompts.

Cluster	Share of Corpus (%)	Modal Configuration	Categories Present in the Modal Configuration
1	38.3	[1,1,0,1,0,1]	Exploration of Prior Knowledge; Contextual Adjustment; Autonomy-Oriented Prompts; Verification Prompts
2	24.7	[1,1,0,1,1,1]	Exploration of Prior Knowledge; Contextual Adjustment; Autonomy-Oriented Prompts; Dialogic Progression; Verification Prompts
3	12.6	[0,0,0,0,0,1]	Verification Prompts
4	10.9	[1,1,1,1,0,1]	Exploration of Prior Knowledge; Contextual Adjustment; Linkage to Experiences; Autonomy-Oriented Prompts; Verification Prompts
5	8.1	[0,0,0,0,0,0]	None of the six coded categories
6	5.4	Various	No single representative configuration

Note: The binary order is Exploration of Prior Knowledge, Contextual Adjustment, Linkage to Experiences, Autonomy-Oriented Prompts, Dialogic Progression, and Verification Prompts. Percentages refer to all conversations assigned to each cluster, whereas the modal configuration represents the most frequent binary vector within that cluster and does not define every conversation in the group. The six-cluster solution is exploratory and was not externally validated.

The largest cluster accounted for 38.3% of the conversations. Its modal configuration was [1,1,0,1,0,1], indicating the presence of Exploration of Prior Knowledge, Contextual Adjustment, Autonomy-Oriented Prompts, and Verification Prompts, together with the absence of Linkage to Experiences and Dialogic Progression. The second cluster represented 24.7% of the corpus and had [1,1,0,1,1,1] as its modal configuration, adding Dialogic Progression to the categories observed in the first configuration. Together, these two groups accounted for 63.0% of the conversations.

The third cluster represented 12.6% of the corpus and had [0,0,0,0,0,1] as its modal configuration, corresponding exclusively to Verification Prompts. The fourth cluster accounted for 10.9% and was represented by [1,1,1,1,0,1], which included all categories except Dialogic Progression. The fifth cluster represented 8.1% and had the all-zero vector as its modal configuration, while the remaining 5.4% consisted of less frequent mixed configurations without a single representative pattern. Because each cluster can contain several binary configurations, the cluster percentages do not correspond directly to the frequencies of the individual patterns reported in Table 2.

These groups complement the pattern-frequency analysis by organising conversations with similar configurations. Their function is descriptive rather than classificatory. Since the six-cluster solution was not selected through a formal optimisation procedure or subjected to stability testing, it should not be interpreted as a uniquely determined structure or as a generalisable taxonomy of AI–student interaction.

4.6. Directional Conditional Co-Occurrence Matrix

Figure 3 presents the directional conditional co-occurrence percentages among the six Socratic mediation categories. Each row represents the focal category used as the denominator, while each column indicates an additional category occurring within the same conversations. The values therefore answer the question: among conversations containing the row category, what percentage also contained the column category? Because the prevalence of the row categories differs, reciprocal cells are not expected to have identical values.

Among conversations containing Exploration of Prior Knowledge, 87% also contained Contextual Adjustment, 82% contained Autonomy-Oriented Prompts, and 84% contained Verification Prompts. When Contextual Adjustment was used as the focal category, 78% of those conversations also contained Exploration of Prior Knowledge, 82% contained Autonomy-Oriented Prompts, and 83% contained Verification Prompts. The difference between 87% and 78%, for example, reflects the use of different row-specific denominators rather than an inconsistency in the calculation.

Autonomy-Oriented Prompts also appeared within broader recurrent configurations. Among conversations containing this category, 86% also included Contextual Adjustment and 83% included Verification Prompts. Similarly, among conversations containing Dialogic Progression, 80% also contained Exploration of Prior Knowledge, 83% contained Contextual Adjustment, 80% contained Autonomy-Oriented Prompts, and 84% contained Verification Prompts.

Linkage to Experiences displayed a more context-dependent pattern. Only 18–22% of conversations anchored in the other focal categories also contained Linkage to Experiences. However, when Linkage to Experiences was itself used as the row category, 84% of those conversations also contained Exploration of Prior Knowledge, 83% contained Contextual Adjustment, 77% contained Autonomy-Oriented Prompts, and 78% contained Verification Prompts. This directional distinction indicates that Linkage to Experiences was comparatively infrequent overall, but when it occurred, it was generally embedded within configurations containing several other Socratic mediation categories.

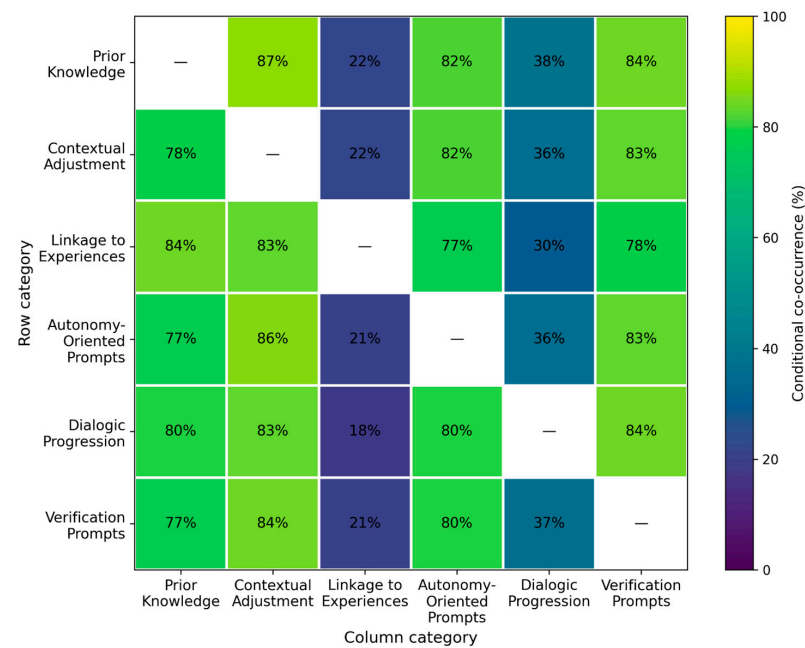


Figure 3. Directional conditional co-occurrence percentages among Socratic mediation categories. Note: Directional conditional co-occurrence percentages among the six Socratic mediation categories. Each cell represents $P(\text{column category} | \text{row category})$, calculated as the number of conversations containing both categories divided by the number containing the row category. The matrix is therefore asymmetric by design. Diagonal cells refer to the same category and are left blank.

4.7. Presence of Categories by Conversation Length

Figure 4 illustrates the prevalence of the six Socratic mediation categories across the predefined conversation-length bands: short (<5000 characters), medium (5000–15,000 characters), and long (>15,000 characters). These bands were used only for descriptive comparison. All six categories were more prevalent in longer conversations, although the magnitude of the differences varied. Exploration of Prior Knowledge increased from 58.7% in short conversations to 89.2% in long conversations, while Autonomy-Oriented Prompts increased from 61.2% to 89.5%. Dialogic Progression showed the largest relative difference, increasing from 20.8% to 52.3%. These results indicate that the categories had more opportunities to become observable as interactions lengthened; they do not demonstrate that longer conversations were pedagogically better or produced deeper learning.

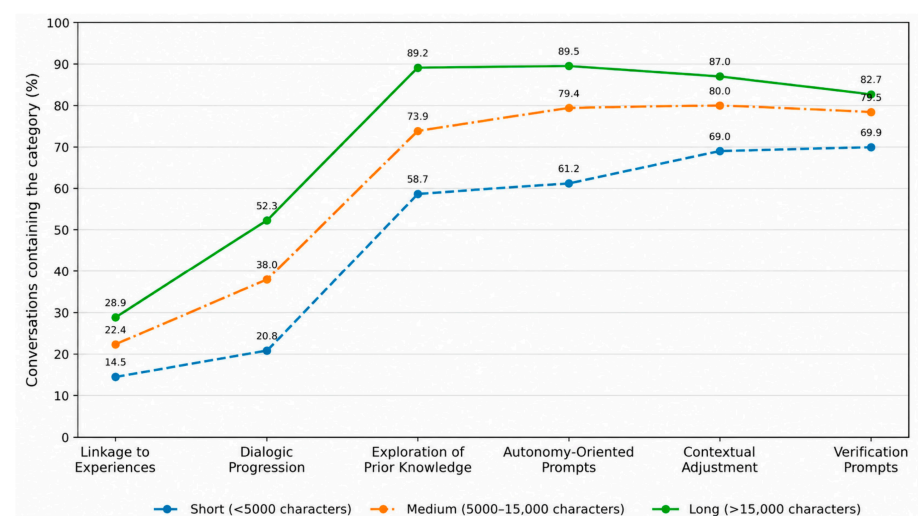


Figure 4. Prevalence of Socratic mediation categories by conversation length.

4.8. Multivariable Associations with the Presence of Verification Prompts

To complement the pairwise co-occurrence analysis, an exploratory multivariable binary logistic regression was conducted to examine the conditional associations between selected conversational features and the presence of Verification Prompts. The unit of analysis was the individual conversation ($N = 737$), and the dependent variable indicated whether MIA generated at least one prompt asking the student to confirm clarity, request further explanation, or continue the exchange. The remaining Socratic mediation categories, conversation type, and number of MIA turns were entered as explanatory variables. Verification Prompts were treated exclusively as an observable category of agent-generated behaviour rather than as a measure of student satisfaction, comprehension, learning, or interaction success.

As shown in Table 5, Contextual Adjustment had the strongest conditional association with the presence of Verification Prompts. Conversations containing Contextual Adjustment showed 3.17 times the adjusted odds of also containing a Verification Prompt ($p < 0.001$), after accounting for the other variables included in the model. Autonomy-Oriented Prompts were similarly associated with the presence of Verification Prompts ($aOR = 2.85$, $p < 0.001$), followed by Exploration of Prior Knowledge ($aOR = 2.43$, $p = 0.001$) and Dialogic Progression ($aOR = 1.94$, $p = 0.008$). These results indicate that verification-oriented moves tended to occur within broader conversational configurations involving contextual clarification, invitations to student participation, exploration of prior understanding, and progressive questioning.

Table 5. Multivariable associations with the presence of Verification Prompts.

Explanatory Variable	Adjusted Odds Ratio	<i>p</i> Value
Exploration of Prior Knowledge	2.43	0.001
Contextual Adjustment	3.17	<0.001
Linkage to Experiences	1.26	0.187
Autonomy-Oriented Prompts	2.85	<0.001
Dialogic Progression	1.94	0.008
Personal conversation	1.38	0.142
Support conversation	1.72	0.087
Number of MIA turns	1.03	0.046

Note: The outcome variable was the presence of at least one Verification Prompt within the conversation, coded as 1 = present and 0 = absent. Academic conversations were used as the reference category for conversation type. The number of MIA turns was entered as a continuous variable. Adjusted odds ratios represent conditional associations among features coded within the same conversations and should not be interpreted as effects on satisfaction, comprehension, learning, or interaction success. $N = 737$ conversations.

Linkage to Experiences was not significantly associated with Verification Prompts after the remaining variables were considered simultaneously ($aOR = 1.26$, $p = 0.187$). Personal conversations also did not differ significantly from the academic reference category ($aOR = 1.38$, $p = 0.142$). Support conversations showed higher estimated odds of containing Verification Prompts, although this association did not reach the conventional threshold for statistical significance ($aOR = 1.72$, $p = 0.087$). The number of MIA turns showed a small positive association ($aOR = 1.03$, $p = 0.046$), indicating that each additional agent turn was associated with a modest increase in the odds that a Verification Prompt appeared within the same conversation.

Figure 5 presents the adjusted odds ratios and their corresponding 95% confidence intervals. Unlike the previous version of the figure, the revised visualisation identifies each explanatory variable directly on the Y-axis and includes a reference line at an adjusted odds ratio of 1. This presentation makes it possible to distinguish the magnitude

and uncertainty of the conditional associations without treating them as measures of educational effectiveness.

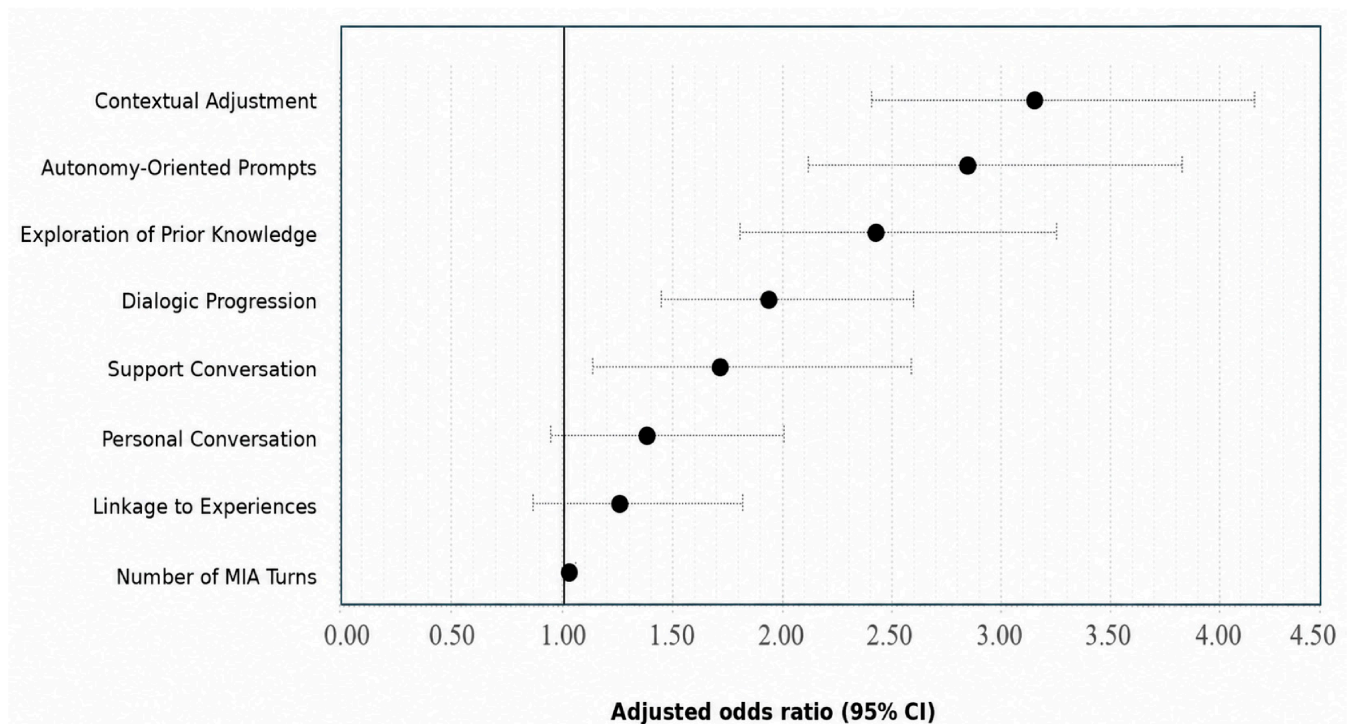


Figure 5. Adjusted associations with the presence of Verification Prompts.

Points in Figure 5 represent adjusted odds ratios, and horizontal lines represent 95% confidence intervals. The vertical reference line indicates an adjusted odds ratio of 1. The outcome was the presence of at least one Verification Prompt within a conversation. The estimates describe conditional associations among conversational features and do not represent student satisfaction, comprehension, learning, or successful interaction.

The multivariable model therefore extends the pairwise co-occurrence analysis by examining whether the relationships remained observable when the other coded features and conversation characteristics were considered simultaneously. The findings suggest that Verification Prompts were embedded within recurrent configurations of Socratic mediation rather than appearing as isolated conversational moves. However, because the dependent and explanatory variables were coded contemporaneously from the same interactions, neither temporal direction nor causal influence can be established. The adjusted associations may reflect recurrent sequencing conventions, design features, or conversational routines within MIA's architecture.

4.9. Integration of Findings Across Analytical Perspectives

The complementary analyses converged around the prominence of Contextual Adjustment, Verification Prompts, and Autonomy-Oriented Prompts in MIA's conversational repertoire. Contextual Adjustment was observed in 77% of the 737 conversations, Verification Prompts in 76%, and Autonomy-Oriented Prompts in 74%, while Exploration of Prior Knowledge appeared in 69%. By contrast, Dialogic Progression was identified in 33% of the interactions and Linkage to Experiences in 20%. Van der Graaf et al. [5] emphasise that personalised scaffolding involves responding to learners' immediate conditions while creating opportunities for self-regulated participation. Similarly, Basir et al. [6] show that dialogic scaffolding depends on questions that clarify the learner's position and sustain involvement in the reasoning process. The frequencies observed in the present study indicate

that MIA regularly generated conversational moves aligned with these dialogic functions. Nevertheless, these percentages represent the presence of agent-generated prompts and should not be interpreted as evidence that students achieved autonomy, comprehension, self-regulation, or personalised learning.

The configurational analysis reinforced this tendency while also revealing considerable variation in the organisation of the six categories. Sixty of the 64 theoretically possible binary combinations were observed in the corpus, showing that the interactions were not organised around a single fixed sequence of dialogic moves. The most frequent configuration, [1,1,0,1,0,1], appeared in 196 conversations, corresponding to 26.6% of the corpus. It combined Exploration of Prior Knowledge, Contextual Adjustment, Autonomy-Oriented Prompts, and Verification Prompts, while excluding Linkage to Experiences and Dialogic Progression. The second most frequent configuration, [1,1,0,1,1,1], occurred in 94 conversations, or 12.8%, and differed from the dominant configuration through the inclusion of Dialogic Progression. Together, these two patterns represented 39.4% of all conversations. Although Selwyn [4] cautions that digital educational environments may reproduce standardised forms of interaction, the presence of 60 different combinations documents heterogeneity in MIA's coded conversational repertoire. This heterogeneity, however, should not be interpreted as proof that students experienced the interactions as effectively personalised.

The exploratory structural grouping offered an additional perspective on this configurational diversity. The two largest clusters represented 38.3% and 24.7% of the corpus and jointly accounted for 63.0% of the conversations. The modal configuration of the first group combined Exploration of Prior Knowledge, Contextual Adjustment, Autonomy-Oriented Prompts, and Verification Prompts, whereas the second also included Dialogic Progression. The remaining clusters represented less frequent configurations, including a group whose modal vector contained only Verification Prompts and another whose modal vector contained none of the six categories. This analysis complements the pattern-frequency results by organising conversations with similar binary configurations. Because the solution was exploratory and was not subjected to formal optimisation or stability testing, the clusters should be interpreted as descriptive groupings within this corpus rather than as stable interaction profiles.

The directional conditional co-occurrence analysis further clarified how these categories were embedded within broader configurations. Among conversations containing Exploration of Prior Knowledge, 87% also contained Contextual Adjustment and 84% contained Verification Prompts, whereas 78% of conversations containing Contextual Adjustment also included Exploration of Prior Knowledge. This asymmetry reflects the different prevalence of the focal categories rather than conflicting estimates. Autonomy-Oriented Prompts and Verification Prompts were also frequently embedded in conversations containing Contextual Adjustment or Dialogic Progression. Linkage to Experiences displayed a different relational pattern: it appeared in only 18–22% of conversations anchored in the other focal categories, but conversations containing experiential prompts generally included several of the remaining Socratic mediation features. The conditional analysis therefore complemented the overall prevalence findings by distinguishing between categories that were broadly recurrent and categories that were less prevalent but usually embedded within more extensive configurations.

The comparison by conversation type showed that some categories remained relatively stable across contexts, whereas others displayed more pronounced variation. In academic conversations, Contextual Adjustment appeared in 77.5% of interactions, Verification Prompts in 75.0%, and Autonomy-Oriented Prompts in 74.5%. Personal conversations showed corresponding values of 75.0%, 80.4%, and 72.8%, while support conversations showed 75.7% for Contextual Adjustment and 83.8% for Verification

Prompts. The most notable contextual difference concerned Linkage to Experiences, which appeared in 33.7% of personal conversations, compared with 18.3% of academic conversations and 21.6% of support interactions. De Araujo et al. [34] underline the importance of adapting conversational-agent interventions to the purpose and context of the exchange. In the present study, the greater presence of experiential prompts in personal conversations indicates that these moves were distributed selectively rather than uniformly throughout the corpus. Even so, the difference reflects contextual variation in agent behaviour and does not establish that personal conversations were more meaningful, satisfactory, or educationally effective.

Conversation length provided another complementary perspective. All six categories became more prevalent as interactions increased in length, although the magnitude of the change differed. Exploration of Prior Knowledge increased from 58.7% in short conversations to 89.2% in long conversations, while Autonomy-Oriented Prompts rose from 61.2% to 89.5%. Dialogic Progression showed the largest relative increase, moving from 20.8% in short conversations to 52.3% in long interactions. According to Winkler and Söllner [15], sustained engagement with conversational agents creates greater opportunities for the development of extended educational exchanges. The present findings similarly indicate that longer conversations provided more interactional space for prior-knowledge exploration, autonomy-oriented questions, and progressive sequences to become observable. However, the relationship may also reflect increased exposure opportunity, because a longer conversation naturally contains more turns in which a category can occur. Conversation length should therefore not be interpreted as evidence of deeper learning without independent measures of conceptual development.

The prominence of Contextual Adjustment, Autonomy-Oriented Prompts, and Verification Prompts across the analyses identifies a recurrent configuration within MIA's conversational behaviour. Hobert [35] associates the perceived usefulness of virtual tutors with their capacity to respond to users' needs and sustain interaction, but the present study did not collect student ratings that would permit such an interpretation. Verification Prompts indicate that the agent asked whether clarification or further explanation was required; they do not indicate that students were satisfied or that the interaction was successful. Similarly, Autonomy-Oriented Prompts show that MIA invited students to make decisions, propose solutions, or formulate conclusions, but they do not demonstrate that learner autonomy was actually developed.

Considered together, the findings reveal both recurrent and context-dependent features of MIA's Socratic mediation patterns. The overall prevalence analysis identified Contextual Adjustment, Verification Prompts, and Autonomy-Oriented Prompts as the most frequent conversational moves. The configurational analysis showed that the categories appeared in a wide range of combinations, with the two most common patterns accounting for 39.4% of the corpus. The exploratory cluster solution showed that the two largest descriptive groups accounted for 63.0% of the interactions, while the comparison by conversation type revealed the distinctive concentration of Linkage to Experiences in personal exchanges. The length-based analysis further showed that Exploration of Prior Knowledge, Autonomy-Oriented Prompts, and especially Dialogic Progression became more visible in extended interactions. This convergence and complementarity across analytical perspectives strengthen the internal coherence of the interpretation. As Jedishkem and Jedishkem [20] argue, however, the use of artificial intelligence in education must remain connected to a pedagogical interpretation that does not reduce educational processes to technological performance alone. Accordingly, the findings describe how Socratic mediation features were distributed, combined, and differentiated within the analysed AI–student interactions, but they do not demonstrate learning gains, satisfaction, achieved autonomy, or effective personalisation.

5. Discussion and Conclusions

5.1. Implications of the Findings

The findings characterise the distribution and combination of six categories of Socratic mediation in MIA's interactions with university students. The frequent presence of Contextual Adjustment, Verification Prompts, and Autonomy-Oriented Prompts indicates that these moves are prominent in the agent's conversational repertoire. However, because the study did not measure student learning, satisfaction, engagement, or self-regulation, these patterns cannot be interpreted as evidence that MIA improved educational outcomes or functioned effectively as a cognitive scaffold. The interpretation is further supported by the convergence of overall frequency, contextual, configurational, and conversation-length analyses, while differences across these perspectives reveal that some categories were context-sensitive rather than uniformly present.

The occurrence of 60 of the 64 possible binary patterns documents substantial heterogeneity in the combinations of coded dialogic moves within this corpus. The higher prevalence of Linkage to Experiences in personal conversations and the greater visibility of Exploration of Prior Knowledge and Dialogic Progression in longer interactions further indicate context- and length-related variation. These findings may inform design hypotheses for scalable conversational agents in asynchronous and distance learning, but they do not establish a high degree of personalisation, pedagogical quality, or educational effectiveness.

These patterns may inform hypotheses for the design and subsequent evaluation of conversational agents. In particular, the recurrent co-occurrence of Contextual Adjustment, Autonomy-Oriented Prompts, and Verification Prompts identifies a configuration that could be examined in future experimental or user-centred studies.

5.2. Comparison with Existing Literature

The findings are consistent with recent scholarly contributions emphasizing the role of AI in fostering learner-centred pedagogical practices. For instance, Lagos-Castillo et al. [36] identified personalization, adaptability, and feedback precision as central advantages of AI-driven tutoring systems. Similarly, Barrera Castro et al. [37] underscored the relevance of adaptive feedback and autonomous learning paths as critical drivers of Education 4.0 ecosystems.

The study adds empirical specificity to these conceptual frameworks by detailing the internal configuration of conversational strategies and documenting their frequency, combination, and contextual distribution in a real-world corpus. The frequent presence of Autonomy-Oriented Prompts can be compared cautiously with Annamalai et al. [38], who examined perceived autonomy and continued engagement with ChatGPT; however, the present study measured prompts generated by the agent rather than students' experienced autonomy. Likewise, the greater prevalence of several categories in longer interactions can be considered alongside van Niekerk et al. [39], but conversation length in this study was not a measure of reflective depth, metacognitive awareness, or skill acquisition.

Furthermore, this study refines the argument presented by Vargas et al. [40] on the value of situated and dialogical learning approaches in AI-enhanced environments. By operationalizing Socratic principles in MIA interaction design, the study bridges the gap between traditional philosophical pedagogy and contemporary digital learning systems. Unlike studies that measure engagement, satisfaction, or learning gains, the present analysis is restricted to observable interactional features. Its contribution therefore lies in operationalising a framework for studying Socratic mediation rather than demonstrating its educational effectiveness.

5.3. Study Limitations

Despite its contributions, the present study presents several limitations that warrant critical reflection. First, the data were derived from a single implementation context: Spanish-speaking undergraduate students engaged in distance learning environments. As such, generalizability to other educational levels, linguistic contexts, or learning modalities may be limited. Future studies should test the replicability of these findings in multilingual, face-to-face, and blended learning settings.

The multivariable analysis examined conditional associations with the presence of Verification Prompts, not student satisfaction or subsequent learning. Accordingly, the observed associations do not establish how the conversational configurations relate to knowledge retention, transfer, perceived usefulness, or student evaluations of the interaction.

The coding of conversational strategies, although systematic, involved interpretative judgement. In addition, variables such as student personality characteristics, digital literacy, prior exposure to AI systems, and the purpose of the interaction were not modelled beyond the available conversation-type classification. These factors could influence the form and length of the exchanges and should be considered in future studies.

Most importantly, the study analysed agent-generated and interaction-level features only. It did not collect post-session ratings, learning assessments, retention measures, student perceptions of personalisation, or independent indicators of autonomy and engagement. Consequently, the findings are restricted to observable conversational patterns and cannot establish whether the interactions were experienced as personalised, resulted in learning, or were satisfactory from the students' perspective.

A further limitation concerns the reproducibility of the coding framework. The low agreement obtained in the initial pilot was used diagnostically to refine the operational definitions and decision rules, after which the final classifications were established through negotiated consensus. The study's quality-assurance strategy relied on expert content validation, iterative calibration, investigator triangulation, documented decision-making, and the convergence of complementary analytical procedures. These measures strengthened the credibility, dependability, and confirmability of the analysis. Nevertheless, no independent post-calibration intercoder coefficient was available, and analytical triangulation of a consensus-coded corpus cannot determine whether other researchers would reproduce the same classifications. Future applications of the framework should retain the independent coding matrices and report category-level agreement before consensus resolution.

The cluster analysis should also be interpreted cautiously. The six-cluster solution was retained as an exploratory and interpretively useful summary rather than selected through a formal optimisation criterion. No resampling-based stability analysis or external validation was conducted, and alternative distance measures or linkage methods could produce a different grouping of the conversations. The clusters therefore describe configurational organisation within the present corpus but do not constitute stable or generalisable interaction profiles. Future studies should compare alternative solutions, report internal validation indices, assess stability through resampling, and examine whether similar structures emerge in independent conversational datasets.

Lastly, the current version of MIA did not provide validated measures of sentiment, adaptive pacing, or closed feedback loops that could be linked to independent outcomes. Future system iterations could incorporate such functions, but their contribution to responsiveness or pedagogical value would require separate empirical evaluation.

5.4. Future Research Directions

Building on these findings, future experimental studies could test whether conversational features such as Contextual Adjustment and Autonomy-Oriented Prompts are associated with conceptual understanding, knowledge transfer, or student-reported experience. Such studies should include independent outcome measures, comparison conditions, pre- and post-tests, and delayed retention assessments when long-term learning is of interest.

Integrating learner analytics, such as gaze tracking, affective indicators, or engagement measures, could provide a multidimensional account of learner–agent interaction. Natural language processing functions capable of real-time adaptation could then be evaluated for their contribution to context-sensitive support and pedagogical alignment rather than assumed to enhance personalisation.

Cross-cultural comparative studies could also examine whether the six dialogic categories are distributed, interpreted, or associated with outcomes differently across educational traditions. This would be particularly relevant in multilingual and multicultural higher education settings.

Finally, the ethical dimensions of conversational agent deployment merit further investigation. Issues such as data privacy, cognitive manipulation, and dependency formation are emerging concerns in the broader AI-in-education debate. A critical, interdisciplinary approach that combines educational research with ethical AI design frameworks is essential to ensure that these technologies serve pedagogical, not merely operational, ends.

Author Contributions: C.A.V.: conceptualization, investigation, writing—original draft, writing—review and editing; N.I.B.: conceptualization, investigation, writing—original draft, writing—review and editing; A.C.: conceptualization, supervision, writing—original draft, writing—review and editing; D.M.-B.: conceptualization, methodology, writing—original draft. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Informed consent was obtained from all participants involved in the study. Participation was voluntary, and consent covered the collection, storage, anonymisation, analysis, and scientific reporting of conversations with MIA for research purposes. Names, telephone numbers, and other direct or indirect identifiers were removed, and messages and quotations were reported using anonymised identifiers.

Data Availability Statement: The data supporting the conclusions of this article will be made available by the authors on request.

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