Computer Science and Information Systems 00(0):0000–0000 https://doi.org/10.2298/CSIS251030055G

Paper Type: Research Paper

Exploring Human–AI Interaction Types Through a Multidimensional Approach

Gayoung Gu[1], Donghyun Kim[2], Minho Kim[2], Sunyoung Kim[2], and Taeha Yi[2]

[1] Department of Business Administration, Gachon University
Seongnam, Korea
ghc16384@gachon.ac.kr
[2] Department of Media and Communication, Gachon University
Seongnam, Korea
{dongfm, minho515, kitty6784}@gachon.ac.kr, yitaeha@gachon.ac.kr (corresponding author)

Abstract. This study develops a multidimensional typology of Human–AI interaction by integrating cognitive, emotional, and social dimensions. A two-stage design was employed. Study 1 ($n = 70$) tested an initial questionnaire and identified structural limitations, informing instrument refinement. Study 2 ($N = 174$) applied exploratory and confirmatory factor analyses, providing preliminary support for a four-factor measurement structure: Cognitive Evaluation, Emotional Connection, AI Dependency, and Social Acceptance. K-means clustering on latent factor scores identified three user types: Critical Distancer, who critically evaluates AI while maintaining emotional distance; Pragmatic Moderate, who uses AI practically without strong engagement or resistance; and Emotional Engager, who is emotionally invested in AI and socially accepting of such interaction. These types showed no significant associations with demographics or the Human–Human Baseline, suggesting that they may capture attitudes specific to the AI interaction context. These findings inform the design of AI systems responsive to diverse user interaction styles.

Keywords: Human–AI Interaction, AI Interaction Styles, User Typology, Multidimensional User Modeling, Cluster Analysis.

1. Introduction

In recent years, generative artificial intelligence (AI) has become deeply embedded in everyday life and is now used as naturally as search engines. Beyond simple question-and-answer tasks, it performs diverse functions such as information organization, idea generation, translation, and writing assistance [6,14], while the modes of interaction with users continue to expand. Whereas AI was initially perceived primarily as an instrumental tool, it is increasingly recognized as an entity for emotional exchange or even as a partner in relationship-building. This shift can be understood by contrasting the functional framing of generative AI with its actual use in everyday contexts. For example, OpenAI [28] presents ChatGPT's primary use cases as information retrieval, summarization, translation, and creative ideation support. However, users' actual practices increasingly

extend beyond these functional domains, as some users employ AI for emotional comfort, self-disclosure, companionship, or even relationship-like interaction. The rise of emotion-based AI chatbot services [38] and cases in which users perceive AI as a romantic partner or source of emotional support [42] are representative of this trend.

This phenomenon suggests that users do not hold homogeneous expectations of generative AI, and that their perceptions and interaction styles vary considerably depending on individual psychological orientations, purposes of use, and social contexts. A joint study by MIT Media Lab and OpenAI [13] demonstrated that Human–AI interaction can differ significantly according to factors such as technology acceptance attitudes, conversation duration, and goal-directedness. In other words, generative AI is no longer a technology received in a uniform way; rather, it is interpreted in multifaceted ways depending on the user, functioning as a medium of interaction.

Nevertheless, existing research on Human–AI interaction has shown limitations in capturing this diversity in an integrated manner. Many studies have measured user acceptance based on the Technology Acceptance Model (TAM) [11], quantitatively analyzed behavioral patterns such as interaction frequency, or explored correlations between personality traits and AI acceptance attitudes [23]. Such approaches tend to reduce user characteristics to a single dimension, failing to adequately explain emotional relationship-building or context-based interaction styles. Research focused on cognitive trust has not addressed emotional exchange; studies analyzing emotional interaction have not explored the relationship with cognitive evaluation strategies; and research on social acceptance has not sufficiently considered its association with individuals' cognitive and emotional characteristics.

Accordingly, this study aims to move beyond binary classifications of users and develop a multidimensional user typology that integrates actual interaction experiences with AI, emotional orientations, and social perceptions of the technology. Specifically, this study seeks to capture Human–AI interaction across four dimensions: Cognitive Evaluation, Emotional Connection, AI Dependency, and Social Acceptance. It then derives qualitatively distinct user types based on the combinations of these dimensions. To this end, a two-stage sequential research design was adopted. Study 1, the Preliminary Survey, explored the functioning and limitations of the initial questionnaire structure, and Study 2, the Main Survey, employed a refined instrument to conduct factor analyses and cluster analysis, ultimately deriving interpretable user types.

The remainder of this paper is organized as follows. Section 2 reviews prior work on technology acceptance and user typology research, the cognitive, emotional, and social dimensions of Human–AI interaction, and derives the research questions. Section 3 presents the overall structure of the two-stage sequential research design. Section 4 describes the methods and results of the preliminary survey, Study 1, and Section 5 reports the measurement structure review, factor analyses, and cluster analysis results of the main survey, Study 2. Section 6 discusses the theoretical and practical implications of the findings along with limitations, and Section 7 presents the conclusion.

2. Related Works

This section reviews prior research on Human–AI interaction and derives the theoretical background and research questions of this study. We first examine existing research

on technology acceptance and user typology to situate the present study's Human–AI interaction typology within the broader scholarly landscape (Section 2.1). We then review prior work on the three core dimensions of Human–AI interaction: the cognitive dimension (Section 2.2), the emotional dimension (Section 2.3), and the social dimension (Section 2.4). Finally, we synthesize the limitations of existing research and present the research questions of this study (Section 2.5).

2.1. User Typology in Technology Interaction

Individual differences exist in how users adopt and utilize technology, and systematic efforts to explain and classify these differences have a long scholarly tradition. Rogers's diffusion of innovations theory categorized users into five groups based on the speed of technology adoption [36], while Davis's Technology Acceptance Model (TAM) explained technology acceptance intention through perceived usefulness and perceived ease of use [11]. Parasuraman's Technology Readiness Index (TRI) complemented these approaches by analyzing individuals' attitudes toward technology through the interplay between motivating factors that promote adoption, such as optimism and innovativeness, and inhibiting factors that hinder it, such as discomfort and insecurity [30]. Parasuraman and Colby subsequently proposed TRI 2.0, a refined 16-item version of the index [31]. While these models laid the foundation for technology acceptance research, they primarily focus on initial acceptance and use, rather than on the qualitative differences in interaction styles that emerge after adoption, particularly those involving emotional relationship-building and social perceptions. This limitation is echoed by Chaturvedi et al., who argued that usage frequency or acceptance status alone cannot capture the depth and texture of user–AI relationships [8].

As conversational interfaces became more widespread, research analyzing chatbot users' motivations and experiences began to emerge. Brandtzaeg and Følstad found that chatbot usage motivations extend beyond productivity to include entertainment, social exchange, and curiosity, suggesting the need for motivation-based segmentation [3]. Similarly, Luger and Sellen identified a substantial expectation–experience gap among conversational agent users, indicating that interaction quality depends not only on system performance but also on how users perceive AI [25].

More recently, Liu et al. proposed a companion chatbot user typology through cluster analysis, demonstrating heterogeneous effects on loneliness across types [23]. However, their study was confined to companion chatbots and did not address cognitive evaluation or social acceptance in the broader generative AI context. Luera et al. conducted a comprehensive survey of user interface design and interaction techniques in generative AI applications, classifying various interaction modalities, including prompting, visual input, and direct manipulation, and systematically organizing how each UI pattern affects user experience [24].

Prior research has analyzed the relationship between users and technology through the timing of adoption, psychological attitudes, usage motivations, and expectation–experience gaps, and has recently extended to deriving user types within specific AI contexts. However, most of these studies have focused on functional and instrumental dimensions, or when addressing emotional dimensions, have been confined to specialized usage contexts. Generative AI interacts with users through natural language dialogue, and for some users, it is perceived as an object of emotional exchange or a social companion. Capturing this

Table 1. Comparison of User Classification Perspectives in Prior Research

Study	Classification Criterion	Key Variables	Analytical Focus
Rogers (1962) [36]	Timing of adoption	Speed of technology adoption	Process of social diffusion of technology
Davis (1989) [11]	Acceptance intention	Perceived usefulness, ease of use	Predicting acceptance of a specific technology
Parasuraman (2000) [30]	Psychological readiness	Optimism, innovativeness, discomfort, insecurity	Psychological disposition toward technology in general
Brandtzaeg and Følstad (2017) [3]	Usage motivation	Productivity, entertainment, social exchange, curiosity	Differentiation of chatbot usage purposes
Luger and Sellen (2016) [25]	Expectation–experience gap	Expectation level, perceived system capability	User experience of conversational agents
Liu et al. (2025) [23]	Usage patterns and psychological traits	Loneliness, socialization, dependency	Companion chatbot user types
Proposed study	Interaction style	Cognitive evaluation, emotional connection, social acceptance, etc.	Multidimensional user types in the generative AI context

phenomenon requires a multidimensional typology that integrates cognitive evaluation, emotional connection, AI dependency, and social acceptance. The following subsections review prior research on each of these dimensions in turn. Table 1 compares and summarizes the aforementioned prior studies in terms of classification criteria, key variables, and analytical focus.

2.2. Cognitive Dimensions of Human–AI Interaction

The algorithms and outputs underlying AI systems are often complex or opaque, making trust a critical dimension in HCI research [2,9,26]. Notably, a 47-country survey found that more than half of respondents hesitated to trust AI despite holding positive attitudes toward AI applications, indicating that using AI and trusting AI are separate issues [15].

Users employ diverse cognitive strategies when encountering unexpected AI responses, including comparison with prior knowledge, external verification, and exploration of alternatives [29]. Trust levels directly affect adoption of AI-generated advice [1], and in creativity-demanding tasks, gaps may emerge between AI's objective performance and users' subjective trust [17,35].

The advent of generative AI has introduced new cognitive demands. LLM hallucination requires users to critically evaluate response accuracy through source verification, error examination, and comparison with their own judgment. Luera et al. documented that such cognitive engagement—prompt construction, response regeneration, and correction requests—directly influences output quality [24].

Meanwhile, research has also reported that interaction with AI can facilitate self-reflection. Park et al. found that self-reflection can be triggered during the process of conversing with AI [34]. These findings suggest that AI-mediated communication has the potential to extend beyond information acquisition into broader cognitive domains, including self-understanding. However, self-reflection is an introspective process distinct from cognitive information processing, and may be more closely related to emotional interaction. This conceptual boundary is revisited in the empirical analysis of this study.

Taken together, the cognitive dimension of Human–AI interaction encompasses trust in AI-provided information, critical evaluation of AI responses, and AI-mediated self-

reflection. Users exhibit varying levels of critical engagement with AI outputs, and these differences in cognitive strategies may serve as a key axis that qualitatively distinguishes interaction styles. This study captures these differences along a continuum between critical verification behavior and information acceptance attitudes, and operationalizes them as Cognitive Evaluation, initially termed Cognitive Utilization.

2.3. Emotional Dimensions of Human–AI Interaction

Research on the emotional dimension of Human–AI interaction has expanded rapidly in recent years. Park et al. found that AI systems capable of expressing emotions enhanced user satisfaction and reuse intention compared to purely information-oriented AI [33]. Their study further demonstrated that users' emotional expressions function as an important mediating variable in chatbot interactions, and that emotional exchanges between humans and chatbots can produce positive outcomes particularly in counseling services.

Croes and Antheunis found that chatbot anonymity promotes self-disclosure, even though overall disclosure levels were slightly lower than in face-to-face settings [10]. This empirically supports the phenomenon of confiding in AI things that are difficult to say to humans. De Freitas et al. reported that users tend to gain emotional comfort through conversations with AI [12], and Chandra et al. found that emotional interaction with AI can have positive effects on stress management and personal help-seeking [7].

However, behind emotional interaction lies the risk of excessive dependency. Fang et al. found through a four-week randomized controlled trial that higher daily usage and emotional attachment predicted stronger AI dependence, and that dependence could arise even in conversations on impersonal topics [13]. This suggests that AI dependency does not necessarily emerge solely as an extension of emotional intimacy, but may represent a distinguishable phenomenon related to task performance or habitual use.

This distinction is conceptually important. Emotional connection refers to relational attitudes such as experiencing human-like feelings in interactions with AI, expectations of emotional support, and self-disclosure, whereas AI dependency encompasses functional and behavioral dimensions such as discomfort when AI is unavailable or the weakening of autonomous performance capacity. Some users may rely heavily on AI for task performance without engaging emotionally, while conversely, others may feel intimacy with AI yet exhibit low actual dependency levels. Therefore, emotional connection and AI dependency should be treated as distinguishable but potentially related constructs, and this distinction was directly reflected in the design of this study's measurement instrument.

2.4. Social Dimensions of Human–AI Interaction

With advances in natural language processing and contextual understanding, users increasingly perceive AI as a social actor. The theoretical foundation for this phenomenon is provided by the Computers Are Social Actors (CASA) theory proposed by Nass et al. [27]. CASA theory posits that humans unconsciously apply to computers the same social heuristics they apply to other humans, not because they consciously believe computers are human, but because social cues trigger automatic responses.

However, recent research has also re-examined the scope of applicability of CASA theory. Heyselaar conducted a direct replication of the original study and found that cur-

rent users no longer exhibit social responses toward desktop computers [18]. This suggests that CASA theory may operate primarily at the point when a technology is newly introduced. Generative AI, as a new technology that provides far richer social cues than previous technologies, including natural language dialogue, emotional expression, and context maintenance, may represent a contemporary context in which CASA theory remains applicable. From this perspective, analyzing the degree to which users perceive generative AI as a social entity and the individual differences therein is a theoretically meaningful endeavor.

Empirical research has also reported diverse findings regarding AI's social role. De Freitas et al. reported that users who perceived strong social presence in AI experienced lower loneliness and higher emotional satisfaction [12]. Ta et al. found that users often treated AI chatbots as ever-present companions, engaging in a wide range of interactions including everyday conversations, emotional discussions, intellectual debates, and even romantic dialogues [39]. However, some participants felt uncomfortable because AI seemed too human-like, while others expressed that AI was not human enough to allow full emotional connection, revealing polarized perceptions of AI's social role.

According to Guingrich and Graziano, users with a stronger tendency to anthropomorphize AI showed higher levels of social connectedness, emotional stability, and self-acceptance [16]. Yet, some users perceived emotionally expressive AI as artificial or even threatening. These findings suggest that perceptions of AI's social role are moderated by the degree of anthropomorphism attributed to AI.

Social perceptions of AI span a broad spectrum, from viewing AI as a mere tool to accepting it as an emotional supporter or social companion. These differences are revealed by whether users naturally accept emotional interaction with AI, how they perceive people who emotionally interact with AI, and whether they believe AI can complement or partially replace human social relationships. Accordingly, this study conceptualizes these individual differences as Social Acceptance and examines it as a key dimension explaining Human–AI interaction types.

2.5. Research Gap and Research Questions

Through the literature review above, we confirmed that Human–AI interaction is a complex phenomenon encompassing cognitive, emotional, and social dimensions. Users either critically evaluate or uncritically accept AI responses, corresponding to the cognitive dimension; either discover in AI a source of emotional support and self-disclosure or maintain emotional distance, corresponding to the emotional dimension; and either accept AI as a social entity or limit it to a purely instrumental tool, corresponding to the social dimension. Moreover, functional and behavioral dependence on AI may emerge as a related but distinguishable phenomenon, namely the dependency dimension. However, two limitations exist in the current body of research.

First, the majority of prior studies have addressed these dimensions in isolation. Research focused on cognitive trust [1,29] has not addressed emotional exchange; studies analyzing emotional interaction [12,13] have not explored the relationship with cognitive evaluation strategies; and research on social acceptance [4,16] has not sufficiently considered its association with individuals' cognitive and emotional characteristics. In practice, however, users experience all of these dimensions simultaneously, and qualitatively different interaction styles may form depending on their combinations. Therefore, an analytical

framework capable of capturing the cognitive, emotional, and social dimensions in an integrated manner is needed.

Second, existing user typology research has primarily focused on functional dimensions such as acceptance status or usage frequency. Rogers's adopter categories [36], Davis's TAM [11], and Parasuraman's TRI [30] all have strengths in measuring general attitudes toward technology, but do not reflect specific emotional relationships with AI or social perceptions. Recent AI chatbot user typology research included emotional dimensions but was limited to the restricted context of companion chatbots, and did not incorporate dimensions such as cognitive evaluation strategies or social acceptance [23].

The above prior research suggests that Human–AI interaction encompasses cognitive, emotional, and social dimensions, and particularly that AI dependency, while related to emotional connection, may represent a distinguishable phenomenon. Accordingly, this study first explores the feasibility and limitations of the initial three-dimensional questionnaire structure in Study 1, and based on those results, hypothetically establishes a four-dimensional structure of Cognitive Evaluation, Emotional Connection, AI Dependency, and Social Acceptance in Study 2, subjecting it to empirical examination. To this end, the following two research questions were formulated:

RQ1. Is the multidimensional structure of Cognitive Evaluation, Emotional Connection, AI Dependency, and Social Acceptance empirically supported in user self-report data?

RQ2. Based on this multidimensional structure, can qualitatively distinct Human–AI interaction types be derived? If so, what characteristics do the derived types exhibit?

To answer these questions, this study conducts a two-stage survey. In Study 1, the feasibility and limitations of the measurement structure are examined through an exploratory review of the initial questionnaire, and in Study 2, factor analysis and cluster analysis are performed using a refined instrument to empirically derive Human–AI interaction types.

3. Research Design

This study adopted a two-stage sequential research design to achieve a multidimensional understanding of users' attitudes toward Human–AI interaction and to derive interpretable user types. This design reflects the fact that Human–AI interaction remains an insufficiently established research domain: rather than validating a predetermined scale from the outset, the study first explores the functioning and limitations of the initial questionnaire structure through a preliminary survey, and then derives a more refined measurement structure and typology system in the main survey. Figure 1 provides a summary overview of the entire research procedure.

In Study 1, the Preliminary Survey, the initial questionnaire, consisting of 11 items and three dimensions, was constructed based on prior research and used to exploratorily examine how the key dimensions of Human–AI interaction manifest in actual response data. The purpose of this stage was to verify whether the initial questionnaire adequately captured cognitive, emotional, and social aspects, and to identify the need for structural revision through inter-item relationships and reliability patterns. The analysis revealed that the Cognitive Utilization dimension exhibited low internal consistency, and that the Self-reflection item was more closely related to emotional connection than to cognitive

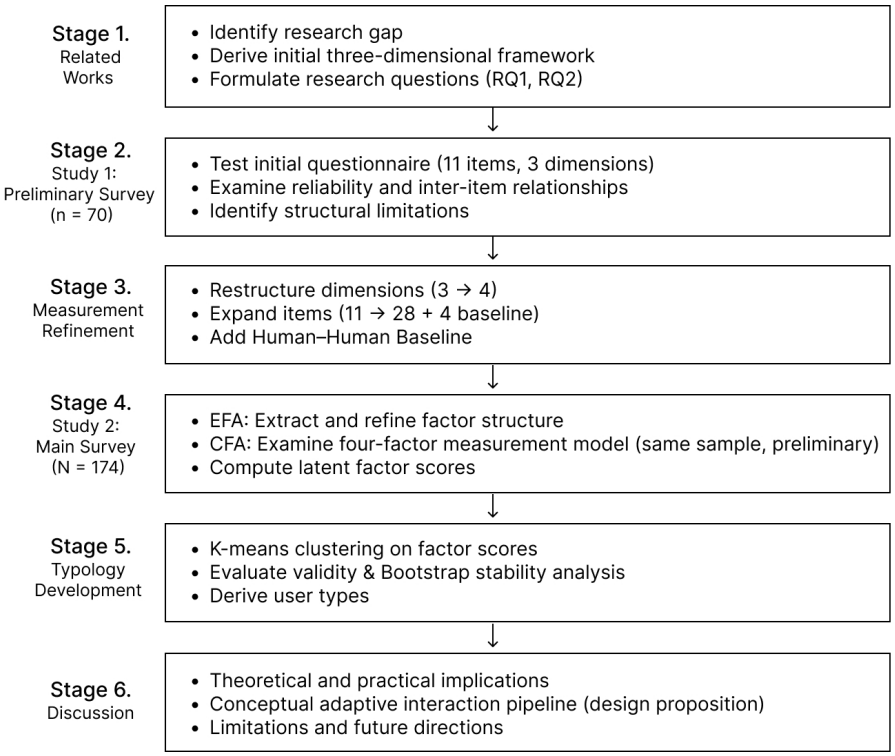


Fig. 1. Overview of the Research Process

utilization. Additionally, AI Dependency was identified as potentially representing a construct distinguishable from Emotional Connection. These results indicated that the initial three-dimensional structure alone was insufficient to adequately explain differences in user attitudes, suggesting the need for structural refinement of the measurement instrument.

Accordingly, in Study 2, the Main Survey, the questionnaire was restructured to reflect the results of Study 1. Specifically, the cognitive dimension was redefined to center on critical review and judgment of AI responses rather than general trust in AI information, and Self-reflection was relocated to the Emotional Connection dimension. AI Dependency was treated as a distinct dimension for subsequent empirical examination, and each dimension was expanded with multiple items to enhance measurement stability. Furthermore, Human–Human Baseline items were added to examine whether AI-related attitudes merely reflect general interpersonal tendencies. In Study 2, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were sequentially performed based on this refined instrument to examine the measurement structure, and K-means cluster analysis was conducted on latent factor scores to derive the final user types. The final solution was determined by comprehensively considering cluster validity indices, bootstrap stability verification, and theoretical interpretability.

Overall, to answer the research questions presented in Section 2.5, this study followed a stepwise procedure consisting of (1) exploratory review of the initial questionnaire structure, (2) refinement of the measurement instrument, and (3) preliminary evaluation of the refined structure and derivation of user types. The significance of this design lies in its approach of linking the preliminary and main surveys to enhance measurement validity and interpretability, rather than attempting typology based on a single survey alone.

4. Study 1: Preliminary Survey

Prior to conducting a more systematic analysis of Human–AI interaction types, a preliminary survey was administered to exploratorily examine how users perceive and utilize AI. The initial survey aimed to determine whether users perceive AI as a simple information-providing tool, accept it as an object of emotional exchange, or interpret it as part of their social relationships.

Study 1 had two objectives. First, it examined whether the initial three-dimensional structure designed to explain Human–AI interaction exhibited a reasonable level of consistency in actual response data. Second, it identified the limitations of the initial questionnaire items and, based on these findings, refined the instrument for use in the main survey. Thus, Study 1 was conducted as an exploratory stage to enhance the validity of the main survey design, rather than as a definitive analysis for deriving final user types.

4.1. Method

Participants. A total of 70 university students participated in the preliminary survey. The gender distribution consisted of 21 males and 49 females, with a mean age of 24.19 years ($SD = 2.18$). All participants were university students residing in South Korea and had prior experience using AI. Participation was voluntary, and an information sheet explaining the purpose and procedures of the study was provided prior to participation. Participants were informed that the survey was part of an academic study on interaction styles with generative AI and were instructed to participate only if they agreed with the research purpose. Participants could discontinue the survey at any time without penalty, and all responses were collected anonymously and processed in a form that precluded individual identification. The collected data were used solely for statistical analysis purposes and are scheduled to be destroyed in accordance with relevant regulations upon completion of the study.

Measures. The initial questionnaire consisted of 11 items, all measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Items were organized around three dimensions derived from prior research: Cognitive Utilization, Emotional Connection, and Social Acceptance (Table 2).

The Cognitive Utilization dimension included the degree to which respondents compare AI responses with their own thoughts, trust in AI-provided information, the perception that AI can generate superior ideas, and self-understanding gained through AI. The Emotional Connection dimension encompassed the degree of AI dependency, the feeling of conversing with a human-like entity, the perceived utility of emotional exchange with

Table 2. Preliminary Survey Questionnaire Items

Dimension	Item Label	Item	Related Works
Cognitive Utilization	Answer Comparison	I evaluate AI's responses by comparing them with my own thoughts.	Ou et al. [29]
	Information Trust	I generally trust the information or advice provided by AI.	Afroogh et al. [1]
	Idea Use	I believe that AI can generate better ideas than I can.	Guzik et al. [17]
	Self-reflection	Through interaction with AI, I gain a deeper understanding of myself.	Park et al. [34]
Emotional Connection	AI Dependency	I tend to rely on AI for performing certain tasks.	Fang et al. [13]
	Human-Feel	I sometimes feel as though I am communicating with a human when interacting with AI.	Park et al. [33]
	Emotional Benefit	I believe AI can provide emotional comfort or support.	De Freitas et al. [12]
	Confiding	I confide my personal concerns and private thoughts in AI.	Croes and Antheunis [10]
Social Acceptance	AI Comfort Acceptance	I believe that finding comfort from AI can be naturally accepted in modern society.	Guingrich and Graziano [16]
	Emotional Users	I have a positive view of people who engage with AI on an emotional level.	Guingrich and Graziano [16]
	Social Replacement	I believe that interaction with AI can be a substitute for human social interaction.	De Freitas et al. [12]

AI, and the extent of confiding personal concerns to AI. The Social Acceptance dimension captured perceptions of AI's capacity to provide emotional comfort, attitudes toward people who emotionally interact with AI, and perceptions of AI's potential to substitute for human social relationships.

Data Analysis. Data analysis was conducted in a Python 3.12 environment. Data preprocessing and descriptive statistics were computed using `pandas` and `numpy`, while inter-item correlation and reliability analyses were performed using `scipy`, `pingouin`, and `statsmodels`. The analysis proceeded as follows. First, descriptive statistics were computed for all 11 items, and response distributions, means, standard deviations, and variances were examined. Subsequently, Cronbach's α was calculated to assess the internal consistency of both the overall scale and each dimension. However, given that each dimension consisted of only three to four items, the validity of the scale was not determined solely by Cronbach's α; mean inter-item correlations, corrected item-total correlations, and changes in Cronbach's α upon item deletion were also examined. Through this process, we assessed whether specific items contributed to the internal consistency of their assigned dimension or were more strongly associated with other dimensions.

4.2. Results

The overall Cronbach's α for all 11 items was .808, indicating relatively high internal consistency. This result suggests the possibility that a common tendency regarding AI interaction existed across responses. Since the purpose of the survey was to examine whether users can be understood along the dimensions of cognitive utilization, emotional connection, and social acceptance, internal consistency was analyzed for each dimension. The

Table 3. Internal Consistency Analysis Results by Dimension

Dimension	Included Items	Cronbach's α	Interpretation
Cognitive Utilization	Answer Comparison, Information Trust, Idea Use, Self-reflection	.312	Poor
Emotional Connection	AI Dependency, Human-Feel, Emotional Benefit, Confiding	.663	Marginal
Social Acceptance	AI Comfort Acceptance, Emotional Users, Social Replacement	.703	Acceptable

results revealed somewhat divergent reliability across dimensions, and some items were found to function differently from their initial conceptual design (Table 3).

Cognitive Utilization. Cronbach's α for this dimension was .312, indicating poor internal consistency, and the mean inter-item correlation for the four items was only .108. This indicates that the items grouped under the Cognitive Utilization dimension in the preliminary survey did not function as a coherent scale. A closer examination reveals that, although all items in this dimension were related to the cognitive utilization of AI, they may have been measuring different behaviors and attitudes.

First, 77.1% of respondents selected a score of 4 for the Information Trust item, which also exhibited the lowest variance among all items. Furthermore, the response range was restricted to 2 through 4, indicating insufficient discrimination among respondents. This suggests that the statement "I trust the information provided by AI" may have been perceived as a somewhat generic or self-evident statement by current university student AI users. Therefore, rather than simply asking whether respondents trust AI information, the main survey needs to employ more specific and behavior-oriented items, such as whether users verify the sources of AI responses, examine the possibility of errors, or compare AI outputs with their own judgment.

Second, the Self-reflection item showed low association with the other items within the Cognitive Utilization dimension. Its corrected item-total correlation within the Cognitive Utilization dimension was $.155$, and even when this item was excluded, Cronbach's α for the Cognitive Utilization dimension remained low at $.291$. This demonstrates that the low reliability of the Cognitive Utilization dimension was not simply due to a single item, but rather indicates that the dimension itself requires further disaggregation.

Interestingly, the Self-reflection item showed higher association with the Emotional Connection dimension instead. The mean correlation between Self-reflection and the Emotion items was $.462$, and its correlation with the Emotion dimension total score was $r = .662$. Moreover, when this item was included in the Emotion dimension, Cronbach's α increased from .663 to .759. Notably, when the emotional dimension was reconstituted with Human-Feel, Emotional Benefit, Confiding, and Self-reflection, excluding AI Dependency, α improved further to .803. This suggests that self-understanding through AI may be more closely related to emotional self-reflection or psychological interaction than to simple information utilization.

Emotional Connection. Cronbach's α for this dimension was .663, indicating a marginal level. This means that while the dimension showed a certain level of internal consistency, refinement is necessary to regard it as a stable scale. A detailed examination of inter-item relationships revealed that the AI Dependency item exhibited relatively low correlations with the other items in the Emotional Connection dimension. The mean correlation between AI Dependency and the other emotion-dimension items was .125, with correlations ranging from .07 to .21.

Furthermore, when the AI Dependency item was excluded, Cronbach's α for the Emotional Connection dimension increased to .757. When the previously mentioned Self-reflection item was additionally included, α improved further to .803. These results suggest that AI Dependency may not belong to the same dimension as emotional intimacy or emotional exchange, but rather may be a construct related to a separate issue of dependency or usage regulation.

Therefore, the main survey should treat AI Dependency as a distinct dimension rather than including it within the Emotional Connection dimension. In particular, AI Dependency may be a distinct issue from whether users feel emotionally close to AI. For example, some users may heavily depend on AI for task performance or decision-making without engaging emotionally, while conversely, others may feel intimacy with AI yet exhibit low actual dependency levels. Considering these possibilities, AI Dependency needs to be redesigned as a distinct and multifaceted construct.

Social Acceptance. Cronbach's α for this dimension was .703, indicating an acceptable level. The mean inter-item correlation was .467, and corrected item-total correlations ranged from .522 to .559, showing relatively stable values. Moreover, removing any one of the three items reduced Cronbach's α to levels between .599 and .619. This indicates that the AI Comfort Acceptance, Emotional Users, and Social Replacement items all contributed to the internal consistency of the Social Acceptance dimension.

These findings indicate that the items related to attitudes of accepting AI as a social entity or an object of emotional interaction functioned relatively consistently. In particular, whether users believe they can receive emotional comfort from AI, whether they view people who emotionally interact with AI positively, and whether they believe AI can partially substitute for human social relationships were closely interconnected. Therefore, the main survey should maintain the basic structure of the Social Acceptance dimension while expanding each sub-concept with multiple items to construct a more stable scale.

4.3. Implications for Main Survey

Through this preliminary survey, we confirmed the possibility that Human–AI interaction can manifest differently across multiple dimensions, including emotional perception, social acceptance, and dependency. However, while the questionnaire functioned well in some areas, it revealed clear limitations in others. Accordingly, we derived the following directions for improvement and restructured the survey for the subsequent study. A summary of the questionnaire refinement from the preliminary survey to the main survey is provided in Supplementary Material A.

First, because key concepts in the preliminary survey were mostly measured using single items, chance responses or ambiguity in item wording could have influenced the

analysis results. Therefore, in the main survey, items for each key dimension were expanded to multiple items, enabling more stable examination of each dimension's internal consistency and overall measurement structure.

Second, to address the low internal consistency and insufficient discriminative power of some items in the Cognitive Utilization dimension, the cognitive utilization items were revised to more specific and behavior-oriented expressions. In particular, rather than asking about general trust in AI information, items were redesigned to reflect actual usage behaviors such as reviewing, comparing, and revising AI responses.

Third, based on the analysis results, the conceptual placement of certain items was adjusted. Self-reflection was judged to be closer to self-reflection through interaction with AI rather than cognitive utilization, and was therefore relocated to the emotional dimension. In contrast, AI Dependency exhibited characteristics of task-performance dependency or usage dependency that were distinguishable from emotional intimacy, and was therefore treated as a distinct dimension in Study 2.

Fourth, the Social Acceptance dimension demonstrated relatively stable internal consistency in the preliminary survey, so its basic structure was maintained. However, items were refined to more specifically measure whether emotional exchange with AI is socially acceptable, how people who emotionally interact with AI are perceived, and whether AI can complement or substitute for human relationships.

Finally, Study 1 had limitations in that it was difficult to determine whether users' general interpersonal tendencies were reflected in their interactions with AI, and it was conducted with a limited sample size and a respondent pool centered on university students. Therefore, Human–Human Baseline items were added in the main survey to allow comparison of whether emotional openness to or dependency on AI is an AI-specific phenomenon or an extension of general interpersonal tendencies. Additionally, a larger number of respondents was recruited to enhance the stability of the analysis results and to verify whether the refined questionnaire structure functions more consistently.

5. Study 2: Main Survey

Study 2 addressed the limitations identified in Study 1 and aimed to derive Human–AI interaction types in a more stable manner. While Study 1 confirmed that Human–AI interaction can manifest differently across cognitive utilization, emotional connection, social acceptance, and AI dependency, some concepts were measured using single items, and certain items functioned differently from their intended dimensions. Accordingly, Study 2 expanded the questionnaire items to a multi-item basis and examined the internal consistency and measurement structure of the key dimensions more systematically.

Study 2 has three specific objectives. First, it verifies whether the questionnaire items refined based on Study 1 adequately reflect the key dimensions of Human–AI interaction. Second, it examines whether the multidimensional structure of Cognitive Evaluation, Emotional Connection, AI Dependency, and Social Acceptance is empirically supported through exploratory and confirmatory factor analyses. Third, it computes respondents' latent factor scores based on the refined four-factor structure and uses them to derive Human–AI interaction types through cluster analysis.

5.1. Method

Participants. A total of 182 university students participated in the main survey. Participants were recruited through university community channels and social media. Prior to beginning the survey, an information sheet was presented explaining the purpose of the study, the estimated time required, and how the data would be used; responses were collected only from those who provided consent. Participants could discontinue the survey at any time without penalty, and all responses were collected anonymously and processed in a form that precluded individual identification. Upon completion, participants received a small token of appreciation, approximately US$1.5. The collected data were used solely for aggregated statistical analysis and are scheduled to be destroyed in accordance with relevant regulations upon completion of the study.

To ensure response reliability, careless responses were removed based on two criteria. First, respondents who answered the attention-check item, "Please select option 2 for this item," incorrectly were excluded. Second, responses with 15 or more consecutive identical answers were deemed careless. Based on these criteria, a total of 8 responses were excluded, resulting in a final analytic sample of 174 respondents. The mean age of the analytic sample was 24.34 years ($SD = 5.91$), and the gender distribution consisted of 50 males and 124 females. All participants resided in South Korea and were capable of responding to the survey in Korean. Regarding generative AI usage experience, 20.1% had less than one year, 37.4% had one to less than two years, 29.9% had two to less than three years, and 12.6% had three or more years of experience.

Measures. The questionnaire for the main survey was refined based on the results of Study 1's preliminary survey, with items for each key dimension expanded to multiple items to enable more stable examination of each dimension's internal consistency and overall measurement structure. The Study 2 instrument consisted of four main AI-related dimensions, comprising 28 items, and one interpersonal comparison baseline, comprising 4 items. First, the cognitive item pool was initially organized under the label Cognitive Utilization, but was revised to focus more specifically on evaluative behaviors, such as reviewing and comparing AI responses and verifying the possibility of errors or sources of information. As reported in the factor-analytic results, this dimension was subsequently interpreted and labeled as Cognitive Evaluation. Second, Emotional Connection measured human-like feelings experienced during interaction with AI, emotional support, self-disclosure, and the possibility of self-reflection. Third, AI Dependency was treated as a distinct dimension because it showed a pattern distinguishable from Emotional Connection in Study 1, and it measured discomfort when AI was unavailable, the tendency to prioritize AI use, and the possibility of emotional and functional dependence. Fourth, Social Acceptance measured attitudes toward emotional interaction with AI, perceptions of users who emotionally interact with AI, and the possibility that AI can complement or partially replace human social relationships. Finally, the Human–Human Baseline (HH) was added to compare whether AI-related responses reflect general interpersonal tendencies or attitudes specific to the AI interaction context. All items were measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Additionally, some items were constructed as reverse-coded items to reduce response bias. The questionnaire items for the main survey are presented in Table 4.

Table 4. Main Survey Questionnaire Items by Dimension

Dimension	Questionnaire Item
Cognitive Utilization	Q1. When AI's response differs from my own thinking, I tend to seek additional sources to verify it.
	Q2. Before accepting AI's response, I review it again for logical errors or alternative perspectives.
	Q3. I generally trust the accuracy of information provided by AI.
	Q4. There are times when I use information provided by AI without separate verification. (R)
	Q5. AI-generated ideas rarely influence the direction of my work. (R)
	Q6. In creative tasks, I feel that AI helps me achieve results that would be difficult to reach on my own.
	Q7. I always request that AI provide specific evidence or sources for the information it presents.
	Q8. I always keep in mind the possibility that AI's responses may be "hallucinations" and engage critically.
	Q9. When I find errors in AI's responses, I always point them out, request corrections, and continue the conversation.
Emotional Connection	Q10. When conversing with AI, I sometimes feel as though I am communicating with a person.
	Q11. AI's responses are generally too mechanical, making it difficult to feel emotional rapport. (R)
	Q12. I believe that AI can provide me with emotional comfort or support.
	Q13. When I am stressed or feeling down, I believe that conversation with AI can make me feel more at ease.
	Q14. If necessary, I am willing to share my personal concerns or inner thoughts with AI.
	Q15. I feel that I could tell AI things that are difficult to say to other people.
	Q16. I feel that conversation with AI does not help me understand myself more deeply. (R)
	Q17. AI's questions or feedback serve as an opportunity for me to reflect on my thoughts and feelings.
AI Dependency	Q18. I feel uncomfortable when I have to perform routine tasks, such as studying, writing, or information searching, without AI.
	Q19. I tend to increasingly delegate tasks to AI that I used to handle on my own.
	Q20. When facing a problem, I often ask AI first.
	Q21. I feel worried or anxious when I am in a situation where I cannot use AI.
	Q22. For me, AI is no longer just a tool but an indispensable entity for sharing my thoughts and feelings.
Social Acceptance	Q23. I think it is natural for people to find comfort in their interactions with AI.
	Q24. I think that people who say they find comfort in conversations with AI are exaggerating or being unrealistic. (R)
	Q25. I tend to view people who emotionally interact with AI relatively positively.
	Q26. I sometimes feel that people who emotionally interact with AI are somewhat unrealistic. (R)
	Q27. I believe that in certain situations, AI can serve as a conversation partner to some extent in place of a person.
	Q28. I believe that when someone feels lonely, conversation with AI can reduce that loneliness to some extent.
Human–Human Baseline	Q29. I feel that I receive emotional comfort or support from trusted close people, such as family or friends.
	Q30. When I am stressed or feeling down, conversation with close people makes me feel more at ease.
	Q31. When I have concerns, I tend to share my personal concerns or inner thoughts with close people.
	Q32. I believe that communication with other people helps me understand myself more deeply.

Note. All items were measured on a five-point Likert scale. (R) indicates reverse-coded items. The cognitive dimension was initially developed under the label Cognitive Utilization. Based on the subsequent factor-analytic results, it was interpreted and labeled as Cognitive Evaluation.

Data Analysis. Data analysis was conducted in Python 3.12 and R 4.6.0 environments. In Python, descriptive statistics, reliability analysis, EFA, cluster analysis, and visualizations were performed. Item-level descriptive statistics and basic statistical tests were conducted using `scipy` and `pingouin`, and EFA was performed using the `factor_analyzer` package. In the EFA, the adequacy of factor analysis and the number of factors were assessed through the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, Bartlett's test of sphericity, and parallel analysis, with Maximum Likelihood (ML) extraction and Promax oblique rotation applied.

CFA was performed using the `lavaan` package in R 4.6.0. Considering the ordinal nature of the five-point Likert scale data, the weighted Least Squares Mean and Variance adjusted (WLSMV) estimator was applied. To assess convergent and discriminant validity, composite reliability (CR), average variance extracted (AVE), and heterotrait–monotrait ratio (HTMT) were computed. Related analyses utilized the `semTools` package.

Cluster analysis was performed after z-standardizing the factor scores from the four latent factors obtained from the CFA. K-means cluster analysis and cluster validity assessment were conducted using `scikit-learn`. To determine the optimal number of clusters, the silhouette index, Calinski–Harabasz index (CH), gap statistic [40], and within-cluster sum of squares (WSS) were jointly examined. Additionally, cluster stability was verified through bootstrap resampling-based Adjusted Rand Index (ARI) and Jaccard similarity.

The final analytic sample ($N = 174$) was not split for independent EFA and CFA because the four-factor CFA model requires approximately 50 free parameters, and a split-half design would reduce each subsample to roughly 87 cases, falling well below the recommended 5:1 case-to-parameter ratio [22]. EFA and CFA were therefore performed sequentially on the full sample [41]. However, given that both exploratory and confirmatory analyses were conducted on the same sample, the CFA results were interpreted not as definitive scale validation but as providing preliminary support for the measurement structure used in subsequent cluster analysis.

5.2. Exploratory Factor Analysis

To examine the underlying factor structure and assess the suitability of the item pool for subsequent analysis, an EFA was conducted. The KMO measure of sampling adequacy was .776, and Bartlett's test of sphericity was significant ($\chi^2(378) = 1694.54, p < .001$). To determine the number of factors, parallel analysis was performed following Horn's procedure [19]. The results showed that the actual eigenvalue for the fifth factor (1.603) exceeded the 95th percentile of random data (1.511), while the sixth factor fell below this threshold, statistically supporting a five-factor solution.

The five-factor EFA was conducted using Maximum Likelihood extraction with Promax oblique rotation ($\kappa = 4$). Promax rotation, which allows inter-factor correlations, was chosen because the constructs in this study may share certain relationships rather than being completely independent. Item retention criteria comprehensively considered primary factor loadings of $.40$ or above, communalities (h^2) of $.20$ or above, cross-loading differences of at least $.15$ [41], and theoretical interpretability.

The analysis yielded four interpretable factors (Table 5). Social Acceptance showed the most consistent structure, with all six originally designed items loading stably ($.448$–

Table 5. Final Factor Structure after EFA

Final Factor	Retained Items	Loading Range	Cronbach's α	Description
Social Acceptance	Q23, Q24, Q25, Q26, Q27, Q28	.448–.741	.761	Acceptance of emotional interaction with AI and its potential as a social substitute
Emotional Connection	Q12, Q13, Q14, Q15, Q17	.443–.816	.858	Tendency to expect emotional support and self-disclosure from AI
AI Dependency	Q18, Q20, Q21, Q22	.518–.774	.745	Discomfort and anxiety when AI is unavailable; tendency to prioritize AI use
Cognitive Evaluation	Q1, Q2, Q3*, Q4*, Q8	|.435|–.688	.677*	Opposing evaluative axis of critical verification and information trust toward AI responses

Note. Extraction = Maximum Likelihood (ML); Rotation = Promax ($\kappa = 4$). Loadings are from the pattern matrix. *For Cognitive Evaluation, Q3 and Q4 showed negative loadings; reported reliability reflects directionally aligned scoring.

.741). Emotional Connection consisted of five items centered on emotional support and self-disclosure (.443–.816), and AI Dependency consisted of four items reflecting discomfort when AI is unavailable and the tendency to prioritize AI use (.518–.774). The full EFA Pattern Matrix is provided in Supplementary Material B.

For the Cognitive Evaluation factor, Q8 (.688), Q2 (.561), and Q1 (.457) loaded positively, while Q4 ($-.473$) and Q3 ($-.435$) loaded negatively. This indicates that attitudes of critically verifying AI responses and attitudes of trusting and accepting AI information emerged as a single opposing evaluative axis. Accordingly, the initial Cognitive Utilization dimension was reinterpreted as Cognitive Evaluation, and in subsequent analyses, Q3 and Q4 were reverse-coded so that higher scores indicate a stronger critical verification tendency.

The statistically extracted Factor 5 was a residual factor on which only Q19 and Q5 loaded, and it was excluded from the final structure due to insufficient conceptual coherence and measurement stability. In addition, eight items were excluded from the final structure due to insufficient primary factor loadings, low communalities, or loading on the residual factor (see Supplementary Material C).

The EFA results generally supported the initial four-dimensional design of this study while indicating the need for refinement at the item level. Hereafter, these four factors are referred to as Cognitive Evaluation (CE), Emotional Connection (EC), AI Dependency (DEP), and Social Acceptance (SA). This study used the refined four-factor structure as the basis for subsequent CFA and cluster analysis.

Table 6. CFA Model Fit Comparison

Model	χ^2	df	CFI	TLI	RMSEA	90% CI	SRMR
One-factor model	873.760	170	.730	.699	.155	[.145, .165]	.140
Four-factor model	351.703	164	.928	.917	.081	[.070, .093]	.086

5.3. Confirmatory Factor Analysis

A CFA was conducted to examine whether the four-factor structure derived from the EFA (Table 5) is adequate as an empirical measurement framework for subsequent cluster analysis. Given that the questionnaire items were measured on a five-point Likert scale, an ordinal scale, the WLSMV estimator was applied. The purpose of this analysis was not to establish a fully standardized psychometric scale, but rather to examine whether the refined multidimensional structure explains the data more adequately than a single-factor structure and whether it can be used for subsequent factor score-based cluster analysis.

Model Fit. The one-factor model showed poor fit, whereas the four-factor model exhibited acceptable fit (Table 6). The Satorra-corrected chi-square difference test indicated that the four-factor model was significantly superior to the one-factor model ($\Delta\chi^2(6) = 253.57$, $p < .001$). The comparative fit index (CFI) and Tucker–Lewis index (TLI) met the .90 criterion; however, the root mean square error of approximation (RMSEA) = .081 approximated Browne and Cudeck's "reasonable fit" criterion of .08 [5], and the standardized root mean residual (SRMR) = .086 slightly exceeded Hu and Bentler's .08 criterion [20], indicating borderline levels. Therefore, the four-factor model is appropriately interpreted as a preliminary measurement structure.

Convergent Validity. Examination of standardized factor loadings (Table 7) revealed that EC (.645–.903) and DEP (.488–.816) showed generally high loadings. SA (.545–.812) was at an acceptable level, though some items remained at moderate levels. For CE, Q1 (.487) and Q3 (.441) showed relatively low loadings. Q3 loaded negatively in the EFA and was directionally reverse-scored in subsequent analyses to align the factor direction, whereas Q1 was retained in its original direction. The relatively low loadings of these items suggest remaining item heterogeneity within the CE construct and indicate a need for further item refinement. However, since all loadings were significant and composite reliability was at an acceptable level, these items were retained considering theoretical comprehensiveness.

Composite reliability (CR) and average variance extracted (AVE) calculations showed that EC (CR = .907, AVE = .662) and DEP (CR = .799, AVE = .506) met conventional criteria. In contrast, CE (AVE = .356) and SA (AVE = .425) fell below the .50 criterion, indicating limited convergent validity (Table 7). CE in particular is interpreted as a factor requiring item reinforcement in future research.

Discriminant Validity. Latent factor correlations and discriminant validity are presented in Table 8. The correlation between EC and SA was the highest at $r = .704$, which

Table 7. Standardized Loadings, Reliability, and Convergent Validity

Factor / Item	λ	α	CR	AVE
Cognitive Evaluation		.677	.726	.356
Q1	.487			
Q2	.609			
Q3	.441			
Q4	.777			
Q8	.611			
Emotional Connection		.858	.907	.662
Q12	.811			
Q13	.820			
Q14	.903			
Q15	.867			
Q17	.645			
AI Dependency		.745	.799	.506
Q18	.488			
Q20	.732			
Q21	.816			
Q22	.764			
Social Acceptance		.761	.813	.425
Q23	.812			
Q24	.700			
Q25	.545			
Q26	.584			
Q27	.566			
Q28	.665			

Note. λ = standardized factor loading (WLSMV); α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. All loadings were significant at $p < .001$.

Table 8. Latent Factor Correlations with $\sqrt{\text{AVE}}$ on the Diagonal

	CE	EC	DEP	SA
Cognitive Evaluation	(.596)			
Emotional Connection	−.287	(.814)		
AI Dependency	−.455	.373	(.711)	
Social Acceptance	−.134	.704	.229	(.652)

Note. CE = Cognitive Evaluation; EC = Emotional Connection; DEP = AI Dependency; SA = Social Acceptance. Diagonal values in parentheses indicate $\sqrt{\text{AVE}}$. Off-diagonal values indicate latent factor correlations. The bold off-diagonal value indicates a Fornell–Larcker criterion violation ($|r| > \sqrt{\text{AVE}}$).

exceeded the $\sqrt{\text{AVE}}$ of SA (.652), indicating that the Fornell–Larcker criterion was not fully satisfied. However, HTMT analysis (Table 9) showed that all factor pairs were below the .85 criterion, with EC–SA HTMT = .734 not exceeding the threshold. Additionally, the three-factor model merging EC and SA ($\chi^2(167) = 433.71$, CFI = .898, RMSEA = .096) showed significantly poorer fit than the four-factor model ($\Delta\chi^2(3) = 29.18$, $p < .001$). Therefore, despite their high correlation, the two factors were judged to be empirically distinguishable.

Table 9. HTMT Results

	CE	EC	DEP	SA
Cognitive Evaluation	–			
Emotional Connection	.238	–		
AI Dependency	.347	.305	–	
Social Acceptance	.138	.734	.233	–

Note. CE = Cognitive Evaluation; EC = Emotional Connection; DEP = AI Dependency; SA = Social Acceptance. HTMT = heterotrait–monotrait ratio.

CE showed negative correlations with the other factors ($r = -.134$ to $-.455$), suggesting that users who critically evaluate AI responses tend to exhibit lower tendencies toward emotional connection and dependency.

Human–Human Baseline Comparison. To verify whether the AI-related constructs merely reflect general interpersonal tendencies, latent correlations between the Human–Human Baseline and the four factors were examined. The correlations between HH and the AI factors ranged from $r = -.091$ to $.055$, approaching zero. This suggests that the constructs in this study may reflect attitudes specific to the AI interaction context; however, since HH does not constitute a complete control condition, this is interpreted as preliminary supporting evidence.

In summary, the four-factor model showed superior fit compared to the one-factor and three-factor competing models, providing preliminary support for the multidimensional structure of CE, EC, DEP, and SA. However, since the AVE of CE and SA fell below the $.50$ criterion and a Fornell–Larcker criterion violation was identified for EC–SA, the measurement model is more appropriately interpreted as a preliminary measurement structure for subsequent cluster analysis rather than a validated psychometric scale. Accordingly, factor scores for the four latent factors were computed and used as input variables for subsequent K-means cluster analysis.

5.4. Cluster Analysis

Based on the refined four-factor measurement model, latent factor scores for each respondent were computed using `lavaan`'s `lavPredict()` function. The computed factor scores were z-standardized for use as input variables in K-means cluster analysis. A multivariate outlier check using Mahalanobis distance identified no outliers at the $p < .001$ threshold, and the full sample ($N = 174$) was used for analysis.

Determining the Optimal Number of Clusters. To determine the optimal number of clusters, the Silhouette index, Calinski–Harabasz (CH) index, Gap statistic, and Elbow method were examined for $K = 2$ through 6 (Table 10). To complement the ambiguity of the conventional Elbow method, multi-step elbow indices [37] were additionally applied (Figure 2). While the first-step indicator (K vs. $K+1$) showed high variability, the noise-corrected second-step indicator (K vs. $K+2$, solid green line) showed a distinct flattening

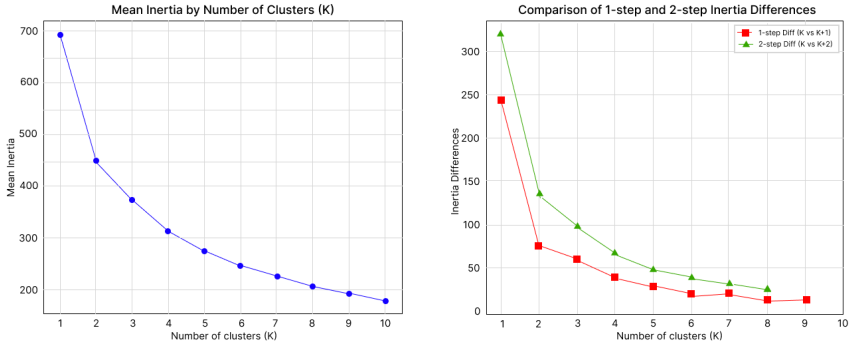


Fig. 2. Exploration of Optimal Number of Clusters Using Multi-step Elbow Indices: (a) Mean Inertia by Number of Clusters (K), (b) Comparison of 1-step and 2-step Inertia Differences

Table 10. Cluster Validity Indices by Number of Clusters

K	**Silhouette**	**CH**	**Gap**	**WSS**	**WSS Reduction Rate**
2	.285	93.6	1.098	448.2	–
3	.231	75.8	1.109	366.7	18.2%
4	.242	72.3	1.135	303.9	17.1%
5	.216	67.7	1.129	265.8	12.5%
6	.216	64.6	1.130	236.7	10.9%

Note. CH = Calinski–Harabasz index; WSS = within-cluster sum of squares. `nstart` = 50 for all K-means solutions.

pattern where inertia reduction markedly decelerated around $K = 3$ and $K = 4$. This suggests that $K = 3$ or $K = 4$ are strong candidates for the optimal number of clusters.

The $K = 2$ solution showed the highest values on some indices but reduced the differences in emotional connection, social acceptance, and dependency to a simple high–low dichotomy, insufficiently reflecting the theoretical interests of this study. In contrast, the $K = 4$ solution showed some advantages over $K = 3$ on certain quantitative indices. However, closer inspection indicated that the additional cluster mainly reflected a subdivision of respondents with relatively high emotional connection and social acceptance, rather than a clearly distinct and stable user type. Moreover, compared with the $K = 3$ solution, the $K = 4$ solution showed lower agreement with Ward's hierarchical clustering results and weaker cluster-specific stability for the smallest cluster, as indicated by its Jaccard coefficient (.578). Therefore, this study adopted the $K = 3$ solution as the primary result, considering model parsimony, clarity of theoretical interpretation, balance in cluster sizes, and stability indices, while presenting the $K = 4$ solution as a preliminary possibility for refinement to be verified in future research. Accordingly, the additional cluster-validity and stability analyses led us to replace the initially considered $K = 4$ solution with $K = 3$ as the primary typology.

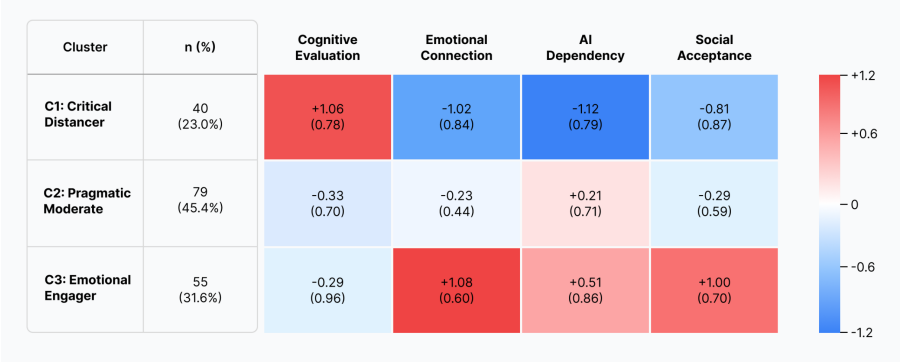


Fig. 3. Heatmap of Cluster Profiles: Mean z-Scores (SD)

Cluster Profiles. Figure 3 presents the profiles of the three-cluster solution. Each cluster was labeled based on the z-score patterns of the four factors.
Cluster 1: Critical Distancer ($n = 40$, 23.0%)**.** Cognitive Evaluation was uniquely high ($z = +1.06$), while the remaining three factors were all low. This type represents users who critically review AI responses while maintaining distance from emotional connection, dependency, and social acceptance of AI.
Cluster 2: Pragmatic Moderate ($n = 79$, 45.4%)**.** All four factors were positioned near the mean with no pronounced extremes. Comprising nearly half of the total sample, this type is interpreted as a majority group that utilizes AI pragmatically without particular emotional immersion or critical vigilance.
Cluster 3: Emotional Engager ($n = 55$, 31.6%)**.** Emotional Connection ($z = +1.08$) and Social Acceptance ($z = +1.00$) were high, and AI Dependency was also above average ($z = +0.51$). This type represents users who are emotionally immersed in AI and naturally accept social interaction with AI.

Between-Cluster Difference Tests. To verify between-cluster differences, one-way ANOVA with Bonferroni-corrected pairwise comparisons was performed for each factor (Table 11). Between-cluster differences were significant across all four factors ($p < .001$), with the largest effect size observed for Emotional Connection ($\eta^2 = .639$).

Pairwise comparisons revealed that for CE, C1 was significantly higher than C2 and C3 ($d = 1.54$–1.87), but there was no difference between C2 and C3. This demonstrates that critical evaluation tendency is the defining characteristic that distinguishes C1. For EC and SA, all three clusters differed significantly from each other (C3 $>$ C2 $>$ C1), while for DEP, only C1 was significantly lower, with no significant difference between C2 and C3.

Stability Verification. To assess the stability of the cluster solution, bootstrap resampling ($B = 100$) was conducted and the ARI with the original solution was computed. The mean ARI was .531 ($SD = .226$), indicating moderate stability. Cluster-specific Jaccard coefficients were C1 = .660, C2 = .640, and C3 = .697, with all three clusters being recovered relatively consistently across resamples.

Table 11. One-Way ANOVA and Pairwise Comparisons

Factor	$F(2, 171)$	η^2	C1–C2	C1–C3	C2–C3
CE	43.53^{***}	.337	$+1.39\ (d = 1.87)^{***}$	$+1.35\ (d = 1.54)^{***}$	-0.05 (ns)
EC	151.36^{***}	.639	$-0.79\ (d = 1.19)^{***}$	$-2.10\ (d = 2.90)^{***}$	$-1.32\ (d = 2.52)^{***}$
DEP	55.58^{***}	.394	$-1.33\ (d = 1.78)^{***}$	$-1.63\ (d = 1.99)^{***}$	-0.30 (ns)
SA	88.96^{***}	.510	$-0.52\ (d = 0.70)^{**}$	$-1.81\ (d = 2.30)^{***}$	$-1.29\ (d = 2.00)^{***}$

Note. Values in cells indicate mean differences with Cohen's d in parentheses. Bonferroni correction was applied. CE = Cognitive Evaluation; EC = Emotional Connection; DEP = AI Dependency; SA = Social Acceptance. $^{**}p < .01$, $^{***}p < .001$.

Additionally, cross-comparison of the K-means results with Ward's hierarchical clustering yielded an ARI of $.464$, confirming moderate agreement between the two methods. This stability level falls within the range generally observed in exploratory cluster analysis, although replication with a larger sample in future research is warranted.

Supplementary Analysis: $K = 4$ Solution. The $K = 4$ solution, which showed better silhouette scores and gap statistics compared to $K = 3$, was exploratorily examined. In the $K = 4$ solution, the Emotional Engager from $K = 3$ differentiated into two subtypes: one characterized by very low CE and high DEP ($n = 30$, CE = -1.30, DEP = $+1.23$), and another with slightly higher CE along with high EC and SA ($n = 35$, CE = $+0.40$, EC = $+1.09$, SA = $+1.09$). This suggests the possibility that within emotional immersion, uncritical dependent immersion and open immersion that maintains critical engagement may be distinguishable. The bootstrap ARI for $K = 4$ ($.540$) was similar to that of $K = 3$ ($.531$); however, cross-comparison with Ward's hierarchical clustering showed lower agreement (ARI = $.298$ vs. $.464$), and the Jaccard stability of the smallest cluster was also limited ($.578$). Therefore, $K = 4$ is interpreted as a preliminary finding requiring verification in future research, and its detailed cluster profiles are provided in Supplementary Material D.

Human–Human Baseline Comparison. No significant differences in Human–Human Baseline scores were observed among the three clusters ($F(2, 171) = 0.27$, $p = .765$, $\eta^2 = .003$). The HH means for C1, C2, and C3 were 4.05, 4.07, and 3.97, respectively, which were nearly identical. This indicates that regardless of whether users are emotionally immersed in AI or maintain critical distance, their levels of emotional support in general interpersonal relationships do not differ. This suggests that the user types derived in this study may capture psychological differences specific to the AI interaction context rather than reflecting general interpersonal tendencies.

Demographic Characteristics. Examination of the relationship between cluster membership and demographic variables revealed no significant differences for gender ($\chi^2(2) = 1.26$, $p = .532$), AI usage experience ($p = .953$), major field of study ($\chi^2(6) = 3.58$, $p = .733$), or age ($p = .349$). This supports the interpretation that the three types are distinguished along dimensions of psychological attitudes toward AI rather than differences in demographic background.

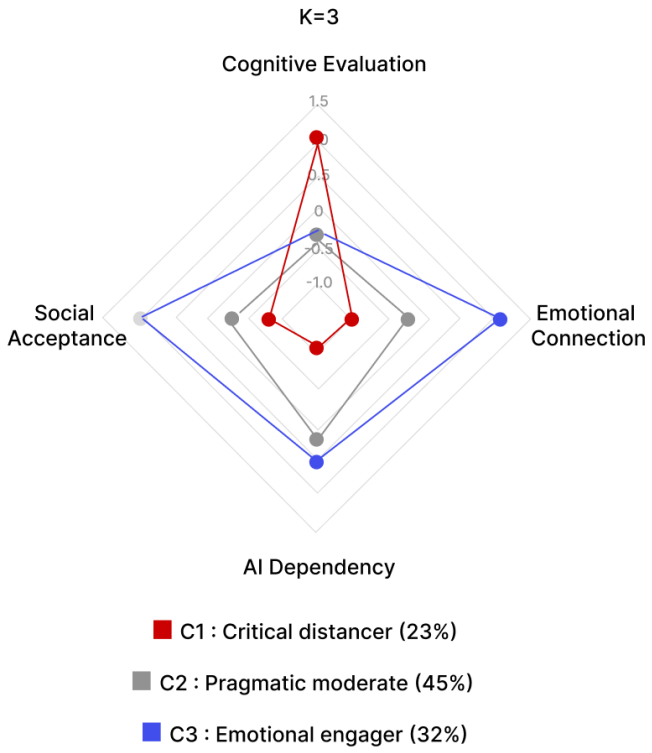


Fig. 4. Radar Chart of the Three-Cluster Solution Across Four Dimensions

In summary, K-means cluster analysis yielded three qualitatively distinct Human–AI interaction types (Figure 4): Critical Distancer, who maintains critical distance from AI; Pragmatic Moderate, who utilizes AI pragmatically without pronounced extremes; and Emotional Engager, who is emotionally immersed in AI and exhibits high social acceptance. This typological distinction emerged independently of demographic backgrounds and general interpersonal tendencies, and is interpreted as reflecting differences in psychological attitudes specific to the context of interaction with AI.

6. Discussion

This study sought to achieve a multidimensional understanding of university students' attitudes toward generative AI interaction and to exploratorily derive interpretable user types. The following results were obtained in response to the two research questions presented in Section 2.5.

Regarding RQ1, EFA and CFA were sequentially performed on the refined questionnaire developed through the preliminary survey, and the four-factor structure of Cognitive Evaluation (CE), Emotional Connection (EC), AI Dependency (DEP), and Social Acceptance (SA) was found to explain the data more adequately than the one-factor and

three-factor competing models (Section 5.3). Therefore, the multidimensional structure of cognitive evaluation, emotional connection, AI dependency, and social acceptance is empirically supported at a preliminary level.

Regarding RQ2, K-means cluster analysis based on latent factor scores yielded three qualitatively distinct user types (Section 5.4): Critical Distancer, who critically reviews AI responses while maintaining emotional distance; Pragmatic Moderate, who utilizes AI pragmatically without pronounced extremes; and Emotional Engager, who is emotionally immersed in AI and exhibits high social acceptance. Notably, this typological distinction emerged independently of demographic backgrounds such as gender, age, major, and AI usage experience, and showed no significant relationship with the Human–Human Baseline. This suggests that the user types captured in this study reflect differences in psychological attitudes specific to the AI interaction context, rather than being a reflection of existing interpersonal tendencies or demographic characteristics. The theoretical and practical implications of these findings are discussed below.

6.1. Theoretical Implications

This study captured Human–AI interaction attitudes not as a unidimensional continuum of "acceptance–rejection," but as a typology within a multidimensional space of cognitive evaluation, emotional connection, dependency, and social acceptance. Compared to prior research that measured AI acceptance as a unidimensional continuous variable or approached it through a binary framework of technology acceptance, the typology presented here empirically demonstrates that qualitatively different interaction styles exist even among users with the same level of AI usage experience.

The simultaneous elevation of EC and SA in Emotional Engagers suggests that emotional experiences with AI do not remain at the intra-individual level but extend into social acceptance. Users who expect emotional support from AI and engage in self-disclosure tend to also recognize AI as an appropriate partner for social interaction. This linkage between emotion and acceptance raises the possibility, from the perspective of CASA theory [27], that a psychological process is at work whereby users treat AI not merely as a tool but as a social actor. The high latent correlation of $.704$ between Emotional Connection and Social Acceptance observed in the CFA is consistent with this interpretation.

Conversely, the finding that only CE was uniquely high while EC, DEP, and SA were all low in Critical Distancers suggests that critical evaluation may function as a kind of psychological brake that inhibits emotional immersion. Users of this type actively verify AI responses while maintaining emotional distance, positioning themselves at the opposite end of the spectrum from automation complacency [32]. However, since the negative correlations between CE and EC/SA ($r = -.13$ to $-.46$) do not necessarily imply causation, whether CE is a cause or consequence of emotional disengagement requires verification through future research.

The finding that HH Baseline showed no statistically significant difference among the three clusters ($\eta^2 = .003$) carries important theoretical implications. Even Emotional Engagers, who are deeply emotionally immersed in AI, and Critical Distancers, who maintain distance from AI, reported highly similar levels of emotional support expected from others in their general interpersonal relationships. This suggests the possibility that emotional attitudes in Human–AI interaction are not merely a projection of general interper-

sonal tendencies, raising the possibility that AI interaction forms a psychological space distinct from interpersonal relationships.

Finally, the fact that Pragmatic Moderates constituted 45.4% of the total sample, representing the largest group, can be interpreted as indicating that the majority of current users represent an intermediate and pragmatic user segment whose attitudes toward AI have not yet been strongly polarized. Whether this group may shift toward Emotional Engager or Critical Distancer orientations over time is a question that warrants examination through longitudinal research.

6.2. Practical Implications

The typology presented in this study empirically demonstrates the limitations of a one-size-fits-all approach that provides the same interaction mode to all users in AI system design. The three types differ qualitatively in their expectations of and psychological distance from AI, suggesting the need for differentiated interaction strategies tailored to each type.

Critical Distancers critically review AI responses while maintaining emotional distance. For this type, approaches that transparently provide reliability information, such as cited sources or confidence indicators, may be effective. Conversely, excessive expressions of familiarity or emotional tone may provoke distrust and should be avoided. Emotional Engagers are emotionally immersed in AI and exhibit high social acceptance; empathetic responses can reinforce positive experiences, but given that their DEP score is above average ($z = +0.51$), there is also a risk of excessive emotional dependency. Therefore, designs that provide emotional support while guiding appropriate boundary-setting when signs of deepening dependency are detected should be considered. Pragmatic Moderates constitute 45.4% of the total and represent a group that has not formed strong expectations of or resistance to AI. For this type, onboarding designs that gradually introduce the utility of AI may be effective in shaping initial attitudes.

To realize these type-specific principles, a mechanism is needed whereby AI systems identify users' types and adjust their interaction modes accordingly. This study proposes a three-stage adaptive interaction pipeline as a conceptual framework for this purpose (Figure 5). This pipeline should be understood as design implications derived from this study's exploratory typology, rather than a validated implementation model.

Initial Profiling. The first stage is the process of identifying users' baseline tendencies at the start of a service. By developing a short-form scale extracted from the core items of each factor in this study's 20-item instrument, users can be tentatively classified through brief self-report when they first begin using a service. For example, based on responses to core items asking about the level of trust in AI information or preferences for AI's autonomous behavior, a future system could tentatively assign the user to an initial type and begin the conversation with interaction settings tailored to that type.

Behavioral Monitoring. The second stage is the process of correcting discrepancies between self-report and actual behavior in real time. Attitudes reported in surveys and behavioral patterns exhibited in actual conversations may differ. Accordingly, behavioral cues that emerge during conversation, such as prompt specificity and length, the frequency

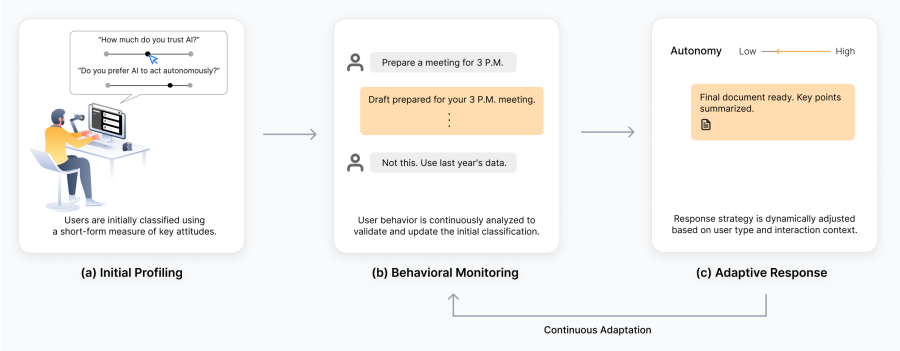


Fig. 5. Conceptual Adaptive Interaction Pipeline Derived from the User Typology

of corrections to AI responses, and the frequency of emotional expressions, could be analyzed to assess the initial classification and update user type when appropriate. For instance, if a user initially classified as a Pragmatic Moderate repeatedly corrects AI responses and uses assertive, directive prompts, a future system could interpret this pattern as an indicator of critical verification behavior and update the user's inferred type accordingly.

Adaptive Response. The third stage involves adjusting the level of AI autonomy and response style based on the currently inferred user type. For users inferred to be Critical Distancers, an AI system could adopt a structure in which it does not unilaterally execute next steps but requests approval at each stage while explicitly providing evidence and sources. For users inferred to be Emotional Engagers, the AI could maintain an empathetic tone while supporting appropriate boundaries when usage patterns suggest deepening dependency. For Pragmatic Moderates, the system could prioritize efficient responses while adapting to contextual factors such as task complexity or impending deadlines.

This pipeline is designed as a continuous cyclical structure of initial classification, behavior-based correction, and type-tailored adaptation, aiming for the accuracy of classification and appropriateness of responses to improve as interactions accumulate. However, these three stages should be understood as testable design propositions derived from this study's exploratory typology rather than as empirically validated system components. The development and validation of short-form scales, the construction of behavior-based type inference models, and the verification of the effectiveness of type-tailored strategies each require independent follow-up studies.

6.3. Limitations and Future Directions

As this study was conducted at an exploratory level, it is accompanied by the following limitations, which should be fully considered in interpreting the results. This section presents directions for future research based on these considerations.

First, the representativeness of the sample is limited. The participants in this study consisted of 174 university students, with a homogeneous age range ($M = 24.34$ years)

and education level, and a high proportion of female respondents (71.3%). Although a small participation incentive was provided, recruitment relied on voluntary response through university community channels and social media, introducing the possibility of self-selection bias; students with greater interest in or more active engagement with AI may have been overrepresented. Therefore, whether the three types derived in this study can be replicated across more diverse age groups, occupations, and cultural backgrounds requires verification through future research. In particular, attitudes toward accepting AI as a social entity may be related not only to individual usage experience but also to social norms, educational environments, and cultural expectations [4,21]. Accordingly, future research should examine both the generalizability and context-dependency of this typological structure using more diverse samples.

Second, there is room for improvement in the psychometric properties of the measurement instrument. While the measurement model was adequate as foundational data for exploratory typology development, limitations in convergent and discriminant validity were identified for some constructs. The CFA results showed that the AVE of CE ($.356$) and SA ($.425$) fell below the generally recommended $.50$ criterion, and the Fornell–Larcker discriminant validity criterion between EC and SA was also not fully satisfied. Future research should reinforce items for the CE factor and refine items to more clearly delineate the conceptual boundaries between EC and SA.

Third, the stability of the cluster solution is interpreted as moderate. The bootstrap ARI of the $K = 3$ solution was $.531$, confirming moderate average agreement between the original and resampled cluster solutions. Additionally, cluster-specific Jaccard coefficients ranged from $.640$ to $.697$, indicating that the three clusters were recovered relatively consistently across resampling, though this does not constitute strong stability. Therefore, the cluster solution of this study should be interpreted as an exploratory typology, and future research should pursue cross-validation through larger samples and Latent Profile Analysis.

Fourth, this study is based on a cross-sectional design and therefore could not capture the dynamics of type transitions or attitude changes toward AI. The finding that Pragmatic Moderates constituted approximately 45% of the total sample suggests that this group may occupy an important position in understanding future changes in AI adoption patterns. However, the data from this study alone cannot determine whether this group will evolve toward more emotionally engaged relationships with AI, maintain functionally oriented attitudes, or shift toward more cautious or skeptical stances. Accordingly, future research should longitudinally track how the accumulation of AI usage experience, changes in usage contexts, and increasing familiarity with AI systems influence user type transitions.

Finally, the adaptive interaction pipeline proposed as a design implication remains at a conceptual level. The development and validation of short-form scales, the construction of conversation-based type inference models, and the verification of the effectiveness of type-tailored response strategies each require independent follow-up research. In particular, conversation-based type inference is a task that can only be realized once convergent validity between behavioral data and self-report is established.

7. Conclusion

This study aimed to capture users' attitudes toward Human–AI interaction in an integrated manner across cognitive, emotional, and social dimensions, and to exploratorily derive qualitatively distinct user types based on these dimensions. Regarding RQ1, the limitations of the initial questionnaire structure were identified through the preliminary survey, Study 1, and subsequently addressed; EFA and CFA were then sequentially performed in the main survey, Study 2, and the four-factor structure of Cognitive Evaluation, Emotional Connection, AI Dependency, and Social Acceptance received preliminary empirical support. This suggests that Human–AI interaction can be characterized by multiple distinguishable but related dimensions rather than a unidimensional acceptance–rejection continuum. Regarding RQ2, K-means cluster analysis based on latent factor scores yielded three user types: Critical Distancer (23.0%), who critically reviews AI responses while maintaining emotional distance; Pragmatic Moderate (45.4%), who utilizes AI pragmatically without pronounced extremes; and Emotional Engager (31.6%), who is emotionally immersed in AI and exhibits high social acceptance. This typological distinction emerged independently of demographic backgrounds such as gender, age, major, and AI usage experience, as well as general interpersonal tendencies, and is interpreted as reflecting psychological attitude differences specific to the AI interaction context.

The contributions of this study are summarized as follows. First, it presented a multidimensional typology integrating cognitive, emotional, and social dimensions, moving beyond existing unidimensional technology acceptance models or user typology research confined to specific contexts. Second, a two-stage sequential design linking the preliminary and main surveys was employed to systematically enhance the validity of the measurement instrument. Third, based on the derived typology, the necessity and direction of type-differentiated strategies in AI system design were discussed in concrete terms.

However, this study has limitations including a homogeneous sample of university students ($N = 174$), a preliminary-level measurement model, moderate cluster stability, and a cross-sectional design; detailed discussion of these limitations and directions for future research were addressed in Section 6.3. Future research should encompass samples covering more diverse demographic and cultural backgrounds, cross-validation through Latent Profile Analysis, and longitudinal designs to analyze the dynamics of type transitions and attitude change.

Ultimately, this study provided empirical evidence that, in response to the question of how users perceive AI and what kinds of relationships they form with it, multiple qualitatively different styles coexist rather than a single answer. It is hoped that this understanding will contribute to promoting more nuanced and context-sensitive approaches in both user experience research and AI system design.

Acknowledgments This work was supported by the Gachon University research fund of 2025 (GCU-202504390001). ChatGPT (OpenAI) was used to assist with language editing of the manuscript. Gayoung Gu and Donghyun Kim contributed equally to this work and share first authorship.

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Gayoung Gu is an undergraduate student in the Department of Business Administration at Gachon University, with a second major in Media and Communication. During her undergraduate studies, she has participated in projects involving data analysis, digital media, and artificial intelligence, with particular interests in user experience and data-driven problem solving. Her research interests include human–AI interaction, generative AI, user experience, and data-driven media research.

Donghyun Kim is a performance marketer at an advertising agency. He received his B.A. in Media and Communication from Gachon University. His work focuses on digital advertising campaign planning and management, performance analysis, and optimization. He has also developed AI-based tools for automated advertising performance reporting and data processing. His research interests include digital marketing, consumer behavior, generative AI, and data-driven marketing.

Minho Kim is an undergraduate student in the Department of Media and Communication at Gachon University. During his undergraduate studies, he has participated in projects integrating data analytics, digital media, and artificial intelligence. His research interests include human–AI interaction, AI-assisted content creation, user experience, and data-driven media research.

Sunyoung Kim is an undergraduate student in the Department of Media and Communication at Gachon University. She has participated in research and projects involving digital media, user research, and data analysis, with experience in research design and data visualization. Her interests include user experience, media content planning, and the use of data and AI to understand user characteristics and inform media content development.

Taeha Yi is an Assistant Professor in the Department of Media and Communication at Gachon University. He received his B.A. from Hongik University and his M.Eng. and Ph.D. from the Graduate School of Culture Technology at KAIST. His research interests include human–AI interaction, generative AI, human–computer interaction, UX/UI design, and data-driven media research. His recent research focuses on human interaction with generative AI, AI-supported content creation and education, and user experience in digital environments.

Received: October 30, 2025; Accepted: September 10, 2026.