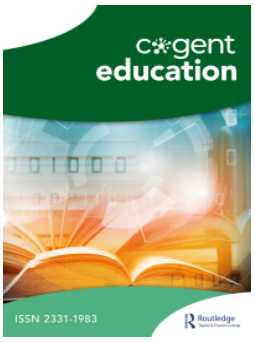

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Empathy and epistemic beliefs empower critical, culturally responsive ChatGPT integration in learning English academic writing

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ABSTRACT

Empathy is increasingly recognized as central to human-centred engagement with generative AI, yet its epistemic pathways remain under examined. This study explored how empathy and Internet Epistemic Beliefs (IEBs) shape undergraduates' perceptions of ChatGPT in English academic writing across Malaysian and Indonesian contexts. Employing a sequential explanatory mixed-methods design, we surveyed 239 English majors, modelled relationships using PLS-SEM, and conducted four in-depth interviews. Empathy significantly predicted positive perceptions of ChatGPT ($\beta = .61$) and influenced IEBs ($\beta = .68$); however, IEBs mediated this relationship only among Indonesian EFL students, reflecting culturally embedded critical-literacy orientations. Gender analysis revealed a stronger empathy–IEB link among males. Thematic insights identified strategic prompting, synthetic empathy, and shifting institutional norms as mechanisms guiding AI engagement. Findings suggest that empathy, while essential, must be paired with critical epistemic beliefs to support ethical, reflective AI use. This study informs empathy-based digital literacy programs and culturally responsive AI integration in higher education writing contexts.

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Introduction

The integration of artificial intelligence (AI) into higher education has reshaped academic practices, particularly in writing. Tools like ChatGPT are increasingly used to generate ideas, restructure content, and refine language for academic tasks. Their capacity to provide immediate feedback and simulate structured writing processes positions them as significant aids in student learning (Chan & Tsi, 2024; Roman-Acosta, 2024; Williams, 2024). These tools enable learners to focus on higher-order aspects of writing by offloading mechanical demands. However, while cognitive benefits are evident, the emotional dimension of writing—particularly the ability to craft empathetically resonant narratives—remains underexplored (Guan et al., 2024; Rubin et al., 2024).

The rise of "empathetic AI," exemplified by generative models like ChatGPT, promises to address this issue by generating contextually appropriate, emotionally nuanced responses (Divya et al., 2024; Kundu & Bej, 2024; Sethi & Jain, 2024). Drawing on frameworks such as the Mutual Theory of Mind (Doherty, 2008), AI systems emulate empathy through natural language (Wang et al., 2021), prompting students to interact with them as social agents. Yet, it remains unclear how students' empathy influences their interaction with and perception of these tools, especially when AI-generated texts often lack the human warmth that characterizes impactful writing. Empathy, as an epistemic asset, shapes how individuals

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interpret and evaluate knowledge (Betzler & Keller, 2021), but students' varying empathic dispositions may lead to contrasting AI engagement—ranging from critical evaluation to uncritical acceptance (Mitsopoulou & Giovazolias, 2015). Equally important are students' internet-specific epistemic beliefs (IEBs), which influence how critically they evaluate AI-generated content. Students with sophisticated IEBs scrutinize AI texts and question reliability, whereas those with naïve IEBs may accept outputs uncritically (BrÅten et al., 2005; Konnemann et al., 2018). It is plausible that IEBs mediate the empathy–AI perception relationship, where empathetic students with critical beliefs use ChatGPT to enhance human communication, while others may treat it as a shortcut.

Previous studies mainly focused on ChatGPT's pedagogical benefits, such as writing improvement (Chan & Hu, 2023; Katsantonis & Katsantonis, 2024), and ethical concerns like plagiarism (Alkaissi & McFarlane, 2023; Chetwynd, 2024). Few have linked empathy to evaluative strategies in AI use, leaving a gap in understanding how emotional and epistemic traits interact in shaping students' perceptions. This gap is critical since digital tools are not neutral; their use is shaped by users' cognitive–affective predispositions and sociocultural contexts (Eisenberg & Fabes, 1991; Kudrnáč et al., 2024; Reicher, 2010). This study clarifies how empathy and IEBs intertwine in shaping students' perceptions of ChatGPT in English academic writing. Guided by the Computers Are Social Actors (CASA) paradigm (Gambino et al., 2020; Reeves & Naas, 1996), it argues that highly empathetic students may anthropomorphize ChatGPT, perceiving it as emotionally supportive, though cultural factors likely mediate this response. Cross-national differences between Indonesia and Malaysia, with their distinct educational norms and AI adoption rates (Arista et al., 2023; Zhai & Wibowo, 2022), warrant such exploration. Additionally, gender differences in empathy are well-established (Baez et al., 2017; Christov-Moore et al., 2014), yet their impact on AI perception remains unclear (Bouzar et al., 2024; Iddrisu et al., 2025). To address these gaps, this study examines: (1) the influence of empathy on IEBs and perceptions of ChatGPT; (2) the mediating role of IEBs; and (3) differences across national and gender groups. By integrating emotional and epistemic constructs within a human–AI interaction framework, it contributes to empathy-sensitive AI literacy programs and culturally responsive academic writing practices.

Literature review

Empathy as an epistemic and affective construct in AI-mediated academic settings

Over the past decade, research on empathy has expanded from its psychological roots to interdisciplinary applications, including artificial intelligence (AI), digital literacy, and educational technology. This expansion has been driven by a growing recognition of empathy's role in promoting prosocial behavior, ethical reasoning, and effective communication in both human-human and human-computer interactions (Inzlicht et al., 2024; Lockwood et al., 2014; Pelau et al., 2021). Within academic settings, especially English writing practices, empathy is gaining traction as a critical factor influencing how students construct emotionally resonant texts, interpret others' ideas, and interact with intelligent technologies (Guan et al., 2024; Sethi & Jain, 2024; Shaffer et al., 2019). In parallel, AI systems such as ChatGPT are being designed to simulate empathic responses, prompting new questions about how human empathy interacts with machine-generated content (Inzlicht et al., 2024).

Empathy is commonly defined as the capacity to recognize and respond to the emotional states of others and is traditionally divided into two interrelated components: cognitive empathy (understanding another's perspective) and affective empathy (sharing another's emotional state) (Cuff et al., 2016; Jolliffe & Farrington, 2006). While cognitive empathy entails analytical reasoning and inferential thinking, affective empathy involves emotional resonance. Research suggests these dimensions are not isolated but coactivate in complex decision-making and social interaction (Betzler & Keller, 2021). Within educational contexts, both forms of empathy are linked to collaborative learning, critical thinking, and inclusive communication (Emaliana et al., 2025; Kudrnáč et al., 2024; Li, 2018). Merging with language learning, empathy becomes essential as it allows the adaptation of a new language identity that is sensitive to social and cultural nuances (Guiora et al., 1972)

Emerging studies posit that empathy is not merely a dispositional trait but also an epistemic resource that shapes how individuals engage with knowledge (Fricker, 2007; Smith, 2001). For instance, according to Betzler and Keller (2021) empathetic learners are more likely to seek diverse perspectives, verify digital sources, and adjust communication to meet others' needs. This aligns with findings that high-empathy individuals are less prone to misinformation and are more reflective in their online information behavior (Melchers et al., 2015). However, despite this growing body of research, empathy is still underexplored in relation to AI-assisted learning, especially in the context of English academic writing where emotional nuance and communicative clarity are essential. While some scholars have emphasized empathy's role in fostering inclusive and student-centered AI pedagogies (Maxwell, 2017; Sun & Li, 2024), others argue that empathy toward AI itself, especially when anthropomorphized, may blur the lines between human-machine boundaries (Deshpande et al., 2023).

Notably, the literature offers contrasting views on whether simulated empathy in AI tools like ChatGPT promotes genuine emotional engagement or undermines users' interpersonal sensitivity. While some studies assert that AI can support emotional well-being through personalized and compassionate responses (Rehman et al., 2024; Welivita & Pu, 2024), others warn against over-identification with AI agents, suggesting such interactions may reduce the user's real-life empathy (Inzlicht et al., 2024). These debates highlight the need to examine not just how AI simulates empathy, but how users' own empathy shapes their interpretation and use of AI tools, an area that remains largely unexplored.

Internet epistemic beliefs and critical engagement with AI tools

Internet epistemic beliefs (IEBs) which are beliefs about the nature, justification, and source of knowledge accessed via the internet, have become an increasingly prominent area of research as digital tools mediate knowledge acquisition and communication (BrÅten et al., 2005; Hofer & Pintrich, 1997). IEBs are particularly relevant in the context of AI writing tools, which generate persuasive yet occasionally inaccurate or biased content (Chetwynd, 2024; Alkaissi & McFarlane, 2023. Sophisticated IEBs encourage users to verify, cross-reference, and reflect on digital outputs; naïve IEBs, by contrast, may result in passive acceptance of AI-generated information (Ulyshen et al., 2015; Meniado et al., 2024).

IEBs typically encompass two dimensions: general internet epistemic beliefs (e.g. the belief that knowledge from the internet is credible) and internet-specific justification for knowing (e.g. the need to corroborate online information with other sources) (BrÅten et al., 2005; Puspitasari et al., 2025). Research demonstrates that learners with higher IEBs are more likely to critically evaluate AI-generated content, such as ChatGPT's output, for relevance, accuracy, and coherence (Konnemann et al., 2018). These users employ metacognitive strategies, such as source triangulation and fact-checking, when engaging with digital information, making IEBs a crucial construct in digital literacy education (Greene et al., 2010).

Despite the theoretical relevance of IEBs to AI perception, the literature presents some inconsistencies. For example, while several studies link sophisticated epistemic beliefs with increased criticality toward digital content (Puspitasari et al., 2025; Ulyshen et al., 2015), others find minimal predictive power of IEBs in real-time decision-making tasks, particularly in emotionally charged or time-constrained environments (Emaliana et al. 2025; Mason et al., 2010). Moreover, many studies do not account for individual differences such as empathy, which may interact with IEBs to influence behavior. As empathy facilitates the understanding of others' perspectives and awareness of the social consequences of misinformation (Betzler & Keller, 2021), it could play a moderating role in how epistemic beliefs are enacted.

These findings point to a significant gap: while IEBs are increasingly studied in relation to information evaluation and source credibility, little attention has been paid to how affective traits like empathy might shape or moderate these beliefs, particularly in interactions with AI systems. Furthermore, few studies have examined how these constructs co-influence students' perceptions of AI tools in educational contexts, creating a need for integrative models that consider both emotional and cognitive factors.

Human-AI perception: the role of empathy and socio-cultural moderators

Perceptions of AI are shaped by a constellation of variables including utility, trustworthiness, ethical alignment, and anthropomorphic characteristics (Pelau et al., 2021; Waytz & Gray, 2018). The *Computers Are Social Actors* (CASA) paradigm suggests that users apply social scripts to human-computer interactions when digital systems simulate human-like behaviors (Gambino et al., 2020; Reeves & Naas, 1996). This includes empathy-oriented responses such as comforting language, perspective-taking, or emotion recognition, which may lead users to anthropomorphize AI and perceive it as socially competent or emotionally present.

Empirical studies have shown that individuals with high trait empathy are more likely to attribute emotional intelligence to AI tools, interpret their responses positively, and use them for emotionally resonant writing (Tsumura & Yamada, 2023; Welivita & Pu, 2024). This phenomenon has been observed not only in affective computing but also in educational settings where empathetic learners report greater trust and engagement with intelligent tutoring systems (Rossi & Fedeli, 2015; Sethi & Jain, 2024). However, a contrasting view posits that empathic users might also be more critical of the superficiality of machine-generated empathy and less inclined to form genuine relational bonds with AI agents (Shen et al., 2024). These competing interpretations underscore the complexity of AI perception as shaped by empathy.

Additionally, cross-cultural and gender factors may further moderate this relationship. Studies reveal that cultural backgrounds affect how users interpret and interact with AI. For instance, Malaysian and Indonesian English learners, despite geographic proximity, differ in digital literacy exposure, language use, and AI adoption norms, which may impact how empathy translates into perceptions of AI (Arista et al., 2023; Zulfikar, 2019). Similarly, while females generally report higher empathy levels (Baez et al., 2017; Eisenberg & Lennon, 1983), evidence on gender differences in AI perception is mixed with some studies report greater acceptance among males (Cachero et al., 2025), while others find no significant gender-based variance in the use of writing tools like ChatGPT (Bouzar et al., 2024).

These findings emphasize the necessity of accounting for socio-demographic moderators when investigating the interplay between empathy, epistemic beliefs, and AI perception. Most studies consider these variables in isolation rather than exploring their combined influence. Moreover, there is limited qualitative inquiry into how students actually negotiate emotional and cognitive responses during AI use. Without such insights, we risk overgeneralizing the effects of empathy or underestimating the nuanced ways learners engage with technology.

The literature underscores the conceptual importance of empathy and IEBs in shaping student interactions with AI tools in academic contexts. Empathy has been linked to enhanced information scrutiny, prosocial communication, and favorable AI perceptions, while IEBs determine the degree to which learners critically assess digital content. However, few studies have examined how these constructs interact, especially in relation to AI systems that simulate human affect.

Despite growing interest in empathetic AI, there remains a lack of empirical evidence linking users' emotional traits to their critical engagement with AI outputs. Moreover, the influence of sociocultural variables such as nationality and gender on these dynamics has not been systematically investigated. Therefore, this study responds to these gaps by examining how empathy predicts students' IEBs and perceptions of ChatGPT, whether IEBs mediate this relationship, and how these associations differ across Indonesian and Malaysian university students and between male and female English learners.

By integrating affective and epistemic constructs within a human-AI interaction framework, this study contributes to a more comprehensive understanding of digital writing practices. It also informs the development of empathy-aware AI pedagogies and culturally responsive digital literacy programs, aiming to enhance the ethical and effective use of AI in higher education.

Methods

Research design

This study employed a sequential explanatory mixed methods design as conceptualized by Ivankova et al. (2006). The primary rationale for choosing this design was to obtain a comprehensive understanding of the relationships between empathy, internet epistemic beliefs (IEBs), and students' perceptions of ChatGPT in academic writing practices. In line with Creswell's (2013) typology, the study began with a quantitative phase, which utilized a correlational explanatory design to examine hypothesized paths among the key variables. The quantitative findings were then followed by a qualitative phase to elaborate, contextualize, and interpret the statistical results through students' lived experiences and narrative accounts.

The quantitative phase served to assess the directional relationships among empathy, IEBs, and perceptions of ChatGPT using Partial Least Squares Structural Equation Modeling (PLS-SEM). The choice of PLS-SEM is based on its utility in analyzing complex models with latent constructs, especially in the field of education where predictive accuracy is often emphasized (Hair & Alamer, 2022). The subsequent qualitative phase involved semi-structured interviews with a selected sample to provide interpretive depth and explore variations in AI engagement across different empathy profiles. This approach is consistent with methodological guidelines for mixed methods research that seek not only to quantify relationships but also to understand the mechanisms behind those relationships (Riazi & Candlin, 2014). This study adopts a pragmatic philosophical stance, aligning with mixed-methods principles where quantitative and qualitative approaches are integrated to address research questions holistically. The pragmatic stance assumes that knowledge is both constructed and empirically verifiable, thus supporting the combination of PLS-SEM predictive modelling with inductive thematic exploration.

Research context and participants

Participants were undergraduate students majoring in English, all of whom were enrolled in academic writing courses during the time of data collection. This specific demographic was chosen because English academic writing represents a cognitively and emotionally demanding domain that intersects with both technological and communicative skills, making it a suitable context for investigating the interplay of empathy and AI perception.

The minimum sample size was determined using the Monte Carlo simulation method via G*Power (Wolf et al., 2013), assuming a power of 0.8 and a 5% significance level, requiring at least 200 participants to detect a moderate effect size (path coefficient $\geq$ .20). A total of 239 students participated in the quantitative phase, comprising 119 students from Malaysia and 120 from Indonesia. However, we acknowledge that the sample size, though sufficient for PLS-SEM modelling, may limit the robustness of cross-national comparisons, and findings should therefore be interpreted cautiously. Participants were purposefully sampled to capture variations in language background and gender. Of these, 179 identified as female and 60 as male, with age ranges primarily concentrated between 19 to 20 years old (57.32%). Linguistic profiles varied: 81 participants reported being bilingual, 109 trilingual, while others reported fluency in four or more languages. Indonesian participants predominantly spoke Indonesian, English, and their ethnic languages, while Malaysian participants commonly spoke Malay and English.Ethical clearance for the study was granted by the Health Research Ethics Committee, Faculty of Health Sciences, Brawijaya University through an official approval letter: No. 82/UN10.F17.10.4/TU/2025. All participants provided informed consent prior to data collection and were assured of the confidentiality and voluntary nature of their involvement. Participation was not incentivized, and students retained the right to withdraw at any point without penalty.

In the qualitative phase, four participants were interviewed: two males and two females. They were purposefully selected based on their survey scores to represent contrasting profiles—those with high empathy and positive perceptions of ChatGPT, and those with lower empathy and more skeptical perceptions. This maximum variation sampling strategy was implemented to capture the range of experiences and cognitive-affective orientations towards AI use in English writing. The selection process adhered to ethical standards, ensuring voluntary participation, transparency and confidentiality.

Instrumentation

Three validated self-report questionnaires were used in the quantitative phase to measure the constructs of interest: empathy, internet epistemic beliefs, and perceptions of ChatGPT use in English academic writing. Each instrument utilized a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), and underwent pilot testing to ensure reliability and contextual suitability for the Southeast Asian student population. The pilot study involved a sample from the target student population to assess the clarity, reliability, and validity of the instruments. Feedback from the pilot study informed item refinement, including the removal or rewording of low-performing items.

Empathy was measured using the Basic Empathy Scale (BES) developed by Jolliffe and Farrington (2006). The scale originally contains 20 items across two sub-dimensions: cognitive empathy and affective empathy. Following pilot testing, items with low validity were removed, resulting in a refined 17-item version with an acceptable Cronbach's alpha of 0.796, indicating strong internal consistency. Sample items include statements such as, "I can often understand how people are feeling even before they tell me," and reverse-coded items like, "My friend's emotions don't affect me much."

To assess Internet Epistemic Beliefs, the study adopted a 7-item scale developed by Puspitasari et al. (2025), grounded in the framework by BrÅten et al. (2005). This scale measures both general beliefs about the reliability of internet-based knowledge and justification beliefs, which capture students' tendencies to corroborate online information with other sources. A sample item from the general belief dimension is, "The internet can provide me with most of the knowledge about the topics I study at school" while an example from the justification dimension is, "Many different sources provide the correct answer to questions related to my course on the internet". The instrument showed good reliability in the pilot test.

Students' perceptions of ChatGPT were assessed using a scale adapted from Meniado et al. (2024). The instrument is divided into two dimensions: the perceived usefulness of ChatGPT in L2 writing and external factors influencing perception, such as pedagogical integration. Each dimension comprises 15 items. The reliability test in the pilot phase yielded Cronbach's alpha values of 0.941 for the usefulness dimension and 0.742 for the second factor, suggesting excellent and acceptable reliability, respectively.

For the qualitative phase, a semi-structured interview protocol was developed to probe students' subjective experiences with ChatGPT. The interview questions focused on how empathy influenced the students' usage and perception of the tool, and how they navigated its limitations and potentials in emotionally sensitive writing tasks. The questions were pilot-tested for clarity and revised accordingly to ensure alignment with participants' language proficiency and familiarity with the subject matter.

Data collection procedures

Quantitative data were collected through an online survey distributed via institutional channels, with informed consent obtained electronically. Participants were assured of anonymity and informed that their responses would be used solely for academic purposes. Data cleaning included removing incomplete responses and ensuring that participants met the inclusion criteria.

The qualitative interviews were primarily conducted offline, with one conducted online to accommodate participant's unavailability for an offline meeting. Each session lasted between 20 to 30 minutes and was audio-recorded with participant consent. Interviews were conducted in English, the medium of instruction in the participants' academic programs, but interviewers accommodated occasional code-switching to support comfort and clarity. Audio recordings were transcribed verbatim and checked for accuracy.

Despite initial recruitment challenges such as non-responsiveness and reluctance to be recorded, replacement participants were identified through the same stratification criteria. Participants were informed of their right to withdraw at any stage of the process, and pseudonyms were used to protect their identities in the transcripts and analysis.

Data analysis

Quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a reflective measurement model. PLS-SEM was selected for its robustness in handling models with complex path structures and its suitability for predictive, exploratory research in social sciences (Hair & Sarstedt, 2019). The software applied included SmartPLS and supplementary regression testing using standard statistical packages.

To evaluate the measurement model, construct reliability was assessed through Cronbach's alpha, with values above 0.7 considered acceptable. Indicator reliability was examined through loading coefficients (>0.70), and convergent validity was confirmed through Average Variance Extracted (AVE > 0.50). The model also included linearity testing using the Ramsey RESET test, where non-significant p-values indicated that the specified linear relationships were statistically valid. For the inner model, coefficients of determination (R^2) values were used to assess the explanatory power of empathy and IEBs on students' perceptions. Multigroup Analysis (PLS-MGA) was employed to examine structural differences across national (Indonesia vs. Malaysia) and gender (male vs. female) subgroups. Significant t-values and p-values (<0.05) determined whether path coefficients differed significantly across groups.

Qualitative data were analyzed using thematic analysis, following Braun and Clarke's (2006) six-phase framework. Initial codes were developed inductively, allowing themes to emerge naturally from participants' narratives. Two independent coders generated the initial codes after repeated readings of the transcripts. Codes were compared and consolidated into categories based on conceptual similarity, and intercoder reliability was established using Cohen's Kappa ($\kappa = 0.61$), indicating substantial agreement (Cohen, 1960). Themes were then developed through iterative discussion, with codes grouped into higher-order patterns that best represented recurring ideas. Discrepancies were resolved through consensus discussions. This process ensured that the thematic outcomes accurately reflected participants' lived experiences. The integration of quantitative and qualitative findings followed an explanatory merging strategy, wherein statistical trends were contextualized with narrative accounts from the interviews. This analytical approach enabled a richer interpretation of the relationships among constructs, highlighting not only what patterns exist but why and how they manifest within specific sociocultural and academic contexts.

Results

This section reports the empirical findings from the sequential explanatory design, beginning with the quantitative survey ($N = 239$) and proceeding to the thematic interpretation of four confirmatory interviews. Sub-sections follow the logical progression recommended for Partial Least Squares Structural Equation Modelling (PLS-SEM) studies while adhering to best-practice reporting standards.

Participant profile

The final sample comprised 120 Indonesian and 119 Malaysian undergraduates enrolled in academic-writing courses. Females constituted 74.9% ($n = 179$) and males 25.1% ($n = 60$). Most participants were aged 19–23 years (97%), and 65% identified as tri- or multilingual (mean number of spoken languages = 3.07). Indonesian students predominantly reported three working languages (Bahasa Indonesia, English, and an ethnic language), whereas Malaysian students most often operated bilingually (Malay–English). The participant demographic profile is depicted in Table 1.

The achieved sample exceeds the minimum of 100–150 cases required for stable PLS-SEM estimates and aligns with Kline's (2005) power recommendations for medium-complexity path models.

Descriptive statistics and normality

Table 2 informs that mean construct scores were moderately high—Empathy: $M = 3.73$, $SD = 0.49$; Internet Epistemic Beliefs (IEB): $M = 3.92$, $SD = 0.65$; Perception of ChatGPT: $M = 3.73$, $SD = 0.55$. Females reported marginally higher empathy ($M = 3.80$) than males ($M = 3.53$). Absolute skewness and kurtosis values were all < 1.0, satisfying univariate normality assumptions for descriptive interpretation.

Measurement-model evaluation

Cronbach's α values met or exceeded the .70 threshold (Empathy = .75; IEB = .88; Perception = .90), indicating satisfactory internal consistency. Convergent validity was confirmed as Average Variance Extracted (AVE) ranged from .795 to .884—well above the .50 criterion (see Table 3). Besides, as depicted in Table 4, all retained indicator loadings exceeded .70, evidencing indicator reliability. Collectively, these metrics support the adequacy of the reflective measurement model (Hair & Sarstedt, 2019).

Table 1. Participant demographic profile (N = 239).

Variable	n	%
Country		
Indonesia	120	50.2
Malaysia	119	49.8
Gender		
Female	179	74.9
Male	60	25.1
Age (years)		
19–20	137	57.32
21–23	97	40.59
24–27	5	2.09
Language Profile		
Bilingual	81	33.5
Trilingual	109	45.6
≥4 languages	49	20.9

Table 2. Descriptive statistics and normality indices for core constructs.

Variable	Mean	Standard deviation
Empathy	3.73	0.49
Internet Epistemic Beliefs	3.92	0.65
Perception of ChatGPT	3.73	0.55

Table 3. Explained variance (R^2).

	R^2 value				
Latent variable	Main	Indonesia	Malaysia	Female	Male
Empathy → IEB	0.382	0.981	0.469	0.323	0.549
Empathy → IEB → Perception	0.825	0.909	0.726	0.799	0.896

Table 4. Construct reliability and convergent validity.

Latent variable	Cronbach alpha	AVE value
Empathy	0.749	0.795
IEB	0.882	0.809
Perception	0.896	0.884

All Cronbach $\alpha > 0.70$ and AVE > 0.50 satisfy recommended thresholds.

Structural-Model results

Linearity diagnostics. Ramsey RESET statistics upheld linearity for Empathy → Perception ($F = 0.38$, $p = .685$) but signalled misspecification for Empathy → IEB and IEB → Perception (both $p < .001$). These latter paths may involve curvilinear dynamics warranting exploration in future models (See Table 5).

Explained variance (R^2). As shown in Table 6, for the full sample, Empathy accounted for 38.2% of variance in IEB, and the Empathy + IEB block explained 82.5% of variance in ChatGPT Perception. R^2 values were notably higher in Indonesian (Perception = .909) and male (Perception = .896) sub-samples, indicating stronger prediction accuracy within these strata.

Direct and indirect effects. Bootstrapped path estimates (5,000 resamples) are summarised in Table 5. Empathy positively predicted IEB ($\beta = .618$, $t = 12.1$) and Perception ($\beta = .889$, $t = 25.6$), supporting H1 and H3. The IEB → Perception pathway was non-significant ($\beta = .031$, $p = .373$), failing to confirm the full-sample mediation posited in H2.

Multi-group analysis (MGA)

Nationality as moderator. SEM-PLS MGA detected significant path-coefficient differences between Indonesian and Malaysian cohorts on all three structural paths ($\Delta\beta$ $p < .05$). As depicted in Figure 1, for Indonesians, Empathy almost perfectly predicted IEB ($\beta = .99$), which in turn strongly predicted Perception ($\beta = -.89$); the direct Empathy → Perception link disappeared ($\beta = -.01$), indicating full mediation. Conversely, As shown in Figure 2, Malaysians displayed significant Empathy → IEB ($\beta = .69$) and

Table 5. Linearity assumption test (Ramsey RESET).

Regression path	F-statistic	*p*-value	Decision
Empathy → IEB	20.821	4.733×10^{-9}	Non-linear
Empathy → Perception	0.3795	0.6846	Linear
IEB → Perception	113.39	$<2.2 \times 10^{-16}$	Non-linear

Table 6. Full-sample path coefficients and hypothesis tests.

Path	β	*t*	*p*	Hypothesis
Empathy → IEB	0.618	12.1	<.001	H1 Supported
Empathy → Perception	0.889	25.6	<.001	H3 Supported
IEB → Perception	0.031	0.893	.373	H2 Not Supported

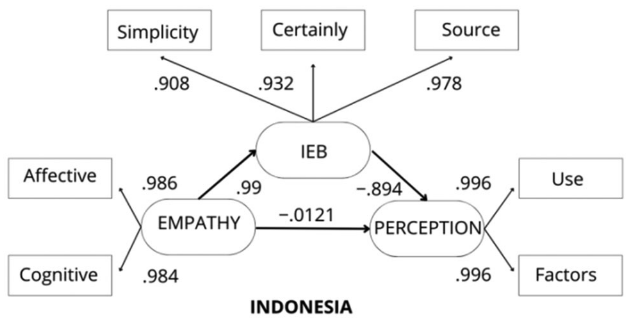

Figure 1. PLS-SEM path model of Indonesian sample with significant paths highlighted.

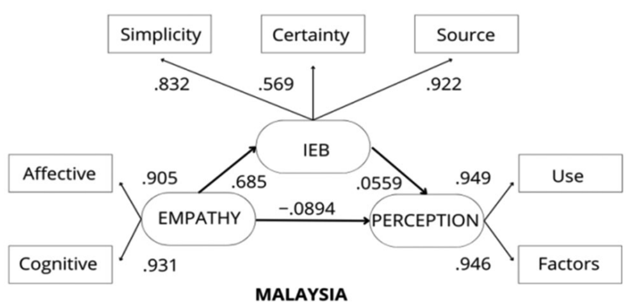

Figure 2. PLS-SEM path model of Malaysian sample with significant paths highlighted.
caption: "Multi-group PLS-SEM results for Indonesian and Malaysian samples".

Empathy → Perception ($\beta = -.09$) effects, but a trivial IEB → Perception coefficient; thus mediation was not observed. Besides that, Table 7 effect-size differences across Indonesian and Malaysian participants.

These findings uphold H4 and corroborate literature suggesting that reflective pedagogies in Indonesia heighten the salience of epistemic vigilance.

Gender as moderator

Only the Empathy → IEB path differed by gender ($\Delta\beta = .17$, $p = .008$), being stronger for males ($\beta = .74$) than females ($\beta = .57$) (See Figures 3 and 4 in details). Other paths were invariant, partially supporting H5 and aligning with mixed evidence on gendered AI perceptions. In addition, Table 8 mentions effect-size differences across genders.

Qualitative findings. In the study, several main themes highlighted how students perceive ChatGPT in the context of their English academic writing and how empathy relationships towards humans affect their views on this AI tool. Of the four participants selected for interviews, both participant A (female) and participant C (male) indicated high scores in empathy in the self-response survey while participant B (female) and participant D (male) scored lower. There are five emerging themes from the participants' responses. Elaborations of each theme are presented and direct quotes are also included to elucidate the themes.

Table 7. Effect-size differences across nationality.

Parameter	Indonesia β	Malaysia β	$\Delta\beta$	SE	t	p
Empathy → IEB	0.990	0.685	0.305	0.420	7.27	<.001
Empathy → Perception	−0.012	−0.089	0.923	0.228	4.05	<.001
IEB → Perception	−0.894	0.056	1.055	0.234	4.50	<.001

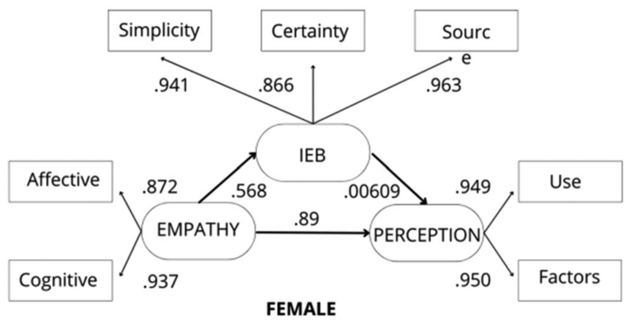

Figure 3. PLS-SEM female path coefficients.

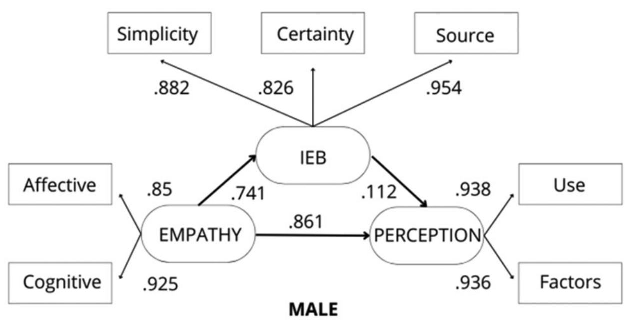

Figure 4. PLS-SEM male path model coefficients.

Table 8. Effect-size differences across genders.

Parameter	Female β	Male β	$\Delta\beta$	SE	t	p
Empathy → IEB	0.568	0.741	0.173	0.071	2.44	.008
Empathy → Perception	0.029	0.861	0.029	0.056	0.52	.301
IEB → Perception	0.105	0.112	0.105	0.073	1.44	.076

1. Adaptive Use of ChatGPT

All participants confirmed that they always make some changes with ChatGPT response for their English writing including idea generation and expansion to full-text drafting, proofreading, vocabulary refinement, and even search of previous studies. Students with high scores on empathy items in the questionnaire demonstrate adaptive strategies like rewording outputs, comparing AI results, and refining prompts to suit academic tone.

> Sometimes I feel like when the ChatGPT gives the response to me, it does not suit my criteria that I want. So, I kept on asking it to reconstruct, redo it until I got the best result. But sometimes I go to Gemini, Google to get another AI response to compare which one has the best response. (Participant A)

On one hand, students who exhibit lower empathy tend to limit their use of ChatGPT. They often perceive AI writing as unnatural or difficult to personalize, which reduces their willingness to depend on it.

> Let's say I need the *hasil akhir*, the final product, then it wouldn't be a good one. … like sometimes the words may sound robotic, so maybe I change that part. If I were to adjust, then the whole sentence would be discarded and I just use my brain. (Participant B)

2. Emotional Expectation and Peer Support

Female students tend to perceive how ChatGPT response sounds emotional for them while male students, both higher and lower empathy felt none of the responses sounded emotional unless they prompted for it. All participants shared that they can understand others' feeling of frustration with ChatGPT.

> I feel frustrated too, because sometimes ChatGPT does not always get our [idea right], does not get things right. So, when my friends get frustrated, I feel, [like I] wanted to give [them] another solution. (Participant A-Female)

Interestingly, students with lower empathy scores stated that even though they share similar frustration towards ChatGPT, it does not affect their own perception.

> I have a friend who is frustrated with ChatGPT. But I also wonder why do they [get] frustrated?…. If my friend is frustrated with ChatGPT, maybe it's just his fault. Because maybe it's the prompt or something. Because in my opinion, from the beginning I used it until now, if the prompt is correct, the results will definitely be satisfying. (Participant D)

3. Frustration with Limits of ChatGPT

While the tool was generally appreciated, students expressed recurrent challenges and frustration. These were mostly tied to misalignment of responses with task expectations, lack of natural flow, or vague interpretation of prompts. Interestingly, there were differing insights on how they deal with the cause of their frustration. Male participants shared they feel frustrated only in some situations and it is not a big deal for them, tend to persevere through iterative prompting and show greater understanding of prompt refinement.

> Sometimes, yes. But it's because my prompts lack clarity… So, I need to give the structure that is in it, like mentioning the activity name, the aim of the activity, and the time allotment, I need to give the details on that. So, that is the thing that I need to be specific about. (Participant C)

Higher empathy students shared they felt frustrated that the ChatGPT response did not meet their expectation when requesting emotional terms.

> When I told it [ChatGPT] to generate my script in a fun way, in a very clear way, sometimes [ChatGPT] doesn't really understand what is fun. … I feel frustrated with ChatGPT. (Participant A)

4. Shifting Norms of ChatGPT Use

Social influences to students' attitudes toward AI use were identified in all participant responses. Initially, students reported strict discouragement of AI tools, which later evolved into conditional acceptance

> At first, my teachers don't let us use AI. [They are] very strict about us using it. But slowly, we all know about ChatGPT and everyone keeps using it. So, our teacher slowly let us use it. ….They just [say], *You can use it for general ideas, but don't copy [from it]*. (Participant A).

> Before I got to know how to use it [chatGPT] correctly, they [lecturers] actually suggested [to us] using AI, but not specifically ChatGPT. So, they suggest using AI, but in a modern way. So, in a way that is not like full AI. (Participant C)

5. Empathy via AI

Students with higher empathy used ChatGPT to compose emotionally sensitive messages they needed to send to friends or peers. They relied on the tool to frame their feelings clearly and respectfully, particularly when it comes to how to phrase things empathetically. This usage of ChatGPT reflects a desire for linguistic support in expressing concern, comfort, or understanding to peers. This suggests a functional use of AI to address social or linguistic anxiety, where students want to ensure their messages are received in a kind and caring tone.

> I always come to ChatGPT to write an apology letter because … I'm scared of hurting other people's feelings. So, I always come to ChatGPT [and ask],"How do I apologize to this person? I did this, I did that". So, it will give me suggestions on what I [need to] do. Sometimes I ask ChatGPT to write a sentence that will, you know, umm, will melt that person's heart. But sometimes, the sentence that ChatGPT gave [me], *oh, I don't think of that, oh, that's so sweet of it*. (Participant A)

Interestingly, female participants with lower scores in the empathy items also reported that ChatGPT's responses felt emotionally comforting, particularly when it uses empathetic language like "I understand how you feel." While they recognized that this was not genuine human empathy, the tone still provided reassurance.

> I do a kind of rant where I say, *I don't understand this. It's a bit overwhelming for me*. And then the responses [from ChatGPT] would be, *oh, it's okay to not be… We can start slow*. That's the response of ChatGPT. … I can sense that the wording in ChatGPT is empathizing with me. (Participant B)

On one hand, a male student with lower score of empathy shared that ChatGPT' responses lack authenticity of real life interaction;

> So if you want to apply it [ChatGPT responses] in real life, in my opinion, it's a bit less real life [inauthentic]. Because in my opinion; we already have empathy, so why would we ask ChatGPT? (Participant D)

Inductive thematic analysis yielded four overarching themes, as seen in Table 9 explaining how empathy shapes students' AI engagement in their English academic writing:

1. Strategic Prompting and Post-editing

> High-empathy participants iteratively refined prompts and cross-checked external sources before accepting ChatGPT output, mirroring sophisticated IEB protocols.

2. Perceived "Synthetic Empathy"

> Participants described the ChatGPT language as "comforting" and "reassuring," echoing claims that generative AI can mimic empathic cues (Inzlicht et al., 2024).

3. Emotionally-Targeted Communication

> ChatGPT was leveraged to craft apologies, consolations, or motivational notes that participants felt incapable of composing unaided.

4. Shifting Institutional Norms

> Lecturers moved from prohibitive to conditional endorsement of AI, framing ChatGPT as a supplementary "writing buddy."

Table 9. Thematic table of qualitative codes.

Theme	Description	Sample quote
Adaptive Use	Strategic and emotional tailoring of ChatGPT output	"I ask it to reconstruct until I get the best result." (Participant
Emotional Expectations	Emotional validation appreciated from ChatGPT responses	"I understand how you feel"
Frustration with Limits	AI perceived as lacking nuance or contextuality	"It would sound robotic to me."
Shifting Norms	From institutional resistance to pragmatic acceptance	"Our teacher slowly let us to use it."
Empathy via AI	Using AI to communicate difficult emotions	"I always come to ChatGPT to write an apology letter."

caption: "Interplay of empathy and epistemic vigilance in AI-assisted writing"

Table 10. Summary of hypotheses testing across analytic tiers.

Hypothesis	Full sample	Indonesia	Malaysia	Gender difference
H1 Empathy → IEB	Supported	Supported	Supported	Stronger in males
H2 Mediation via IEB	Not supported	Full mediation	Not supported	Not supported
H3 Empathy → Perception	Supported	Not significant	Supported	Invariant
H4 Nationality Moderation	✓ (all three paths differ)	–	–	–
H5 Gender Moderation	Partial (Empathy → IEB only)	–	–	$\Delta\beta$ sig. for Empathy → IEB

Symbol "✓" denotes significant moderation; dashes indicate "not applicable."

Interview data converged with survey results indicating that empathetic students perceived greater utility in ChatGPT when they could verify and emotionally refine its output. By contrast, low-empathy participants either accepted responses uncritically or dismissed AI empathy as "inauthentic."

Integration of quantitative and qualitative evidence

Triangulation highlights empathy as the principal driver of favourable ChatGPT perceptions. Quantitatively, its direct effect on Perception remained robust across contexts except where mediation via IEB emerged (Indonesia). Qualitatively, empathy informed deliberate strategies (prompting, fact-checking) and the interpretive lens through which AI feedback was anthropomorphised. The partial mediation pattern corroborates theorising that empathic concern motivates epistemic vigilance only in cultural milieus emphasising reflective learning.

Importantly, IEB functioned as a context-sensitive conduit, implying that empathy alone is insufficient for critical AI adoption unless paired with sophisticated beliefs about online knowledge vetting. Gender differences, though modest, suggest that emotional traits and epistemic processing interact differently across sexes, echoing neuroscientific evidence of divergent empathic circuitry. The summary of the hypotheses testing across analytic tiers is depicted in Table 10 below.

Discussion

This study sets out to unravel how empathy and Internet-specific epistemic beliefs (IEB) jointly shape English major undergraduates' perceptions of ChatGPT as an academic-writing partner and to probe whether these relations vary by national and gender lines. By integrating variance-based structural modelling with thematic interviewing, we generated a multidimensional account of the affective–epistemic nexus underlying AI adoption. The present section interprets the quantitative and qualitative results in turn, situates them within extant literature, and outlines the theoretical, pedagogical, and methodological implications that follow, while acknowledging key limitations.

Empathy as a central predictor of AI perception

Across the full sample, empathy emerged as the most potent determinant of favourable attitudes towards ChatGPT ($\beta = 0.61$; Table 5). This finding corroborates Computers-as-Social-Actors theory, which posits that users project interpersonal scripts onto autonomous systems when they detect social cues (Nass & Moon, 2000). Highly empathic students may be more attuned to such cues—lexical politeness, apology markers, or expressions of concern—leading them to attribute greater communicative value to the tool. Qualitative evidence reinforces this interpretation: high-empathy participants explicitly praised the "comforting" and "reassuring" tone of ChatGPT replies (Table 8, Theme 2), whereas low-empathy peers dismissed the same output as "robotic" or "inauthentic".

Empathy's direct influence also accords with social–cognitive frameworks of technology acceptance. Recent work shows that empathic concern predicts prosocial technology use, including help-seeking and peer feedback in online learning environments (Coyne et al., 2018). This study extends prior findings by showing that empathy influences not only AI adoption but also shapes subjective quality judgments in academic writing tasks, reinforcing the need to consider affective dispositions in AI-integrated writing pedagogy.

Conditional mediation by internet epistemic beliefs

Contrary to the hypothesised full-sample mediation, IEB did not significantly transmit the empathy effect on perception in the pooled model ($\beta = 0.031$, $p = .37$). This null finding suggests that empathic dispositions alone were sufficient to explain most of the variance in acceptance, rendering IEB statistically redundant once empathy entered the equation. Yet multi-group analysis painted a more nuanced picture: in the EFL Indonesian subgroup, empathy almost perfectly predicted IEB ($\beta = 0.99$), and IEB, in turn, exerted a strong negative weight on perception ($\beta = -0.89$), eliminating the direct path from empathy to perception (Table 7; Figure 1).

The full mediation observed in Indonesia aligns with culturally rooted pedagogical practices that emphasise reflective reading and source triangulation (Apsari, 2018; Inaayah & Fithriani, 2024). Thus, empathetic students trained in critical literacy may channel their interpersonal sensitivity into epistemic vigilance, reducing naïve enthusiasm for ChatGPT outputs. In contrast, Malaysian students, who are more exposed to experiential and debate-oriented writing approaches (Mat et al., 2024; Nurakhir et al., 2020), exhibited parallel direct-effect patterns, implying that empathy and IEB function as independent drivers in that context. These cross-national contrasts underscore the context-sensitivity of epistemic beliefs, lending support to the argument that the structure and function of IEB vary across learning ecologies (Bråten et al., 2019). This culturally sensitive finding highlights the need for differentiated AI-literacy interventions tailored to local educational norms.

Gendered dynamics in the empathy–IEB link

Although most structural paths were gender-invariant, males exhibited a significantly stronger empathy $\rightarrow$ IEB slope than females ($\Delta\beta = 0.17$; Table 7). This aligns with neuroscientific evidence indicating that men may rely more on cognitive perspective-taking (associated with dorsolateral prefrontal activation) when processing social cues, whereas women often employ affective sharing mechanisms (anterior insula activity) (Christov-Moore et al., 2014). Empathic men in our sample may have converted their concern for others into deliberate information-evaluation routines, whereas empathic women relied on more holistic impressions of usefulness without additional scrutiny, attenuating the empathy–IEB correlation. Consequently, male students in this study appeared to translate empathic concern into analytic checking routines, whereas female students were guided more by holistic impressions of usefulness.

Practically, this gendered pattern suggests that AI-literacy interventions should be sensitive to differential cognitive routes. For male students, scaffolds that consolidate analytic checking strategies (e.g. fact-verification checklists) could leverage their tendency to translate empathy into epistemic vigilance. For female students, design features that foreground relational authenticity such as tone-adjustment sliders or transparency about training data, may resonate more strongly.

Integrative insights from qualitative themes

Thematic analysis illuminated three mechanisms through which empathy and IEB converge. First, strategic prompting and post-editing (Theme 1) revealed that empathic-and-critical students iteratively refined their queries to elicit emotionally resonant yet factually precise text, a behaviour consonant with the high R^2 values reported for Indonesian perception (0.909). Second, the notion of synthetic empathy (Theme 2) reflected students' tendency to anthropomorphise generative AI, echoing findings that perceived warmth predicts trust in conversational agents (Go & Sundar, 2019). Third, shifting institutional norms (Theme 4) highlighted that lecturer signals substantially modulate student attitudes, dovetailing with technology-adoption models that stress subjective norms (Venkatesh, 2015). Understanding this is also consistent with the notion that instructors' emotional support was perceived meaningfully contributes to the greater students' empathy within the context of English learning (Liu et al., 2025; Liu, Shen, Shen, et al., 2025). In Indonesian and Malaysian contexts, since English is the primary medium of academic and technological discourse, lecturers' support or rejection of tools like ChatGPT can shape not only students' perceptions of AI but also their willingness to engage with English-language content. For many English learners, AI-assisted writing tools can serve as aids which further reinforces the role of institutional cues in shaping confidence and usage patterns in multilingual environments. By triangulating both survey and interview data, we confirm that statistical relations are enacted through concrete English classroom practices: empathic dispositions lead English learners to invest greater effort in prompt engineering, to cross-validate content, and to calibrate emotional tone; actions that ultimately drive acceptance or rejection of AI output. Collectively, these insights reinforce the CASA paradigm, illustrating how empathetic dispositions shape not only attitudes but also concrete interactional strategies, such as prompt engineering and tone calibration.

Accordingly, empathy emerged as a consistent and strong predictor of favorable perceptions, confirming that emotional traits significantly influence how students interpret AI-generated responses. This supports the Computers-as-Social-Actors (CASA) paradigm, which posits that users attribute social qualities to machines when perceiving social cues (Nass & Moon, 2000). Highly empathic students appeared more sensitive to ChatGPT's conversational tone and perceived it as reassuring and supportive, aligning with prior research that empathy activates positive technology appraisals (Coyne et al., 2018). Interestingly, IEBs only mediated the empathy–perception relationship among Indonesian students, suggesting that cultural-educational contexts emphasizing reflective learning foster deeper evaluative processing. Gender effects were modest, although males demonstrated a stronger empathy–IEB link, supporting neuroscientific claims that men rely more on cognitive perspective-taking in processing social cues (Christov-Moore et al., 2014). These findings collectively suggest that affective dispositions and epistemic reasoning interact differently depending on sociocultural norms and cognitive styles.

Theoretically, this study refines the CASA framework by showing that emotional traits alone do not fully account for AI acceptance; empathy's influence depends on epistemic beliefs, which are themselves shaped by cultural learning norms. This context-sensitive view adds to epistemic-belief theory by positioning empathy as a motivational antecedent for critical information evaluation. The finding that Indonesian students demonstrated full mediation via IEBs underscores the importance of integrating socio-pedagogical factors when modeling human–AI interaction in academic contexts. Additionally, the evidence of "synthetic empathy"—students interpreting AI-generated supportive language as emotionally meaningful—extends existing theories on anthropomorphism by showing that human emotional traits, rather than AI sophistication alone, drive these interpretations. By integrating affective and epistemic constructs, this study contributes to a socio-epistemic understanding of how students adopt generative AI in writing.

The practical implications are substantial for higher education. First, curriculum developers should embed empathy-sensitive AI literacy modules into English academic writing courses. Activities could include prompt engineering tasks where students critique both factual accuracy and emotional tone of AI-generated texts, fostering balanced cognitive and affective engagement. Peer-review exercises involving AI-assisted drafts may further strengthen critical reflection while promoting awareness of tone management. Empathy-building strategies, such as perspective-taking and collaborative editing, could be integrated into digital writing courses to help students maintain human-centered communication when using AI tools.

Second, AI designers should consider developing adjustable empathy features, such as tone sliders or explanatory feedback, to support students with high epistemic vigilance who may otherwise penalize AI for lacking transparency. These features could reconcile the tension observed among Indonesian students who valued critical evaluation but viewed ChatGPT as insufficiently trustworthy. For gender-responsive design, tools that provide clear source transparency may appeal to male students who convert empathy into analytic checking, whereas features emphasizing relational authenticity may resonate more with female users who rely on holistic impressions of usefulness. Finally, institutional policies should move toward conditional endorsement of AI, promoting its use as a supplementary writing partner rather than a replacement for human judgment. Lecturers' attitudes play a crucial role, as shifting institutional norms significantly influence students' acceptance and ethical use of AI in academic writing.

Confounding variables and limitations

This study acknowledges several potential confounding variables. Students' prior familiarity with AI tools may have influenced their ease of use and perceptions of ChatGPT, and instructor attitudes could have shaped students' reported acceptance, particularly in contexts where lecturers explicitly encouraged or discouraged AI use. Additionally, participants' varying levels of English proficiency and digital literacy might have moderated their ability to critically evaluate AI outputs.

The findings should also be interpreted cautiously due to limitations in sampling and design. The relatively small cross-national groups, drawn from single universities in Indonesia and Malaysia, restrict the generalizability of the results. The reliance on self-report measures may introduce social desirability bias, and the researchers' presence during qualitative interviews might have influenced participants' responses despite assurances of confidentiality. Furthermore, as a cross-sectional study, it cannot capture changes in empathy or IEB over time, warranting longitudinal or experimental follow-ups.

Conclusion

This study set out to examine how empathy and IEBs interact to shape students' perceptions of ChatGPT as an academic writing tool, with particular attention to national and gender differences. Employing a sequential explanatory mixed-methods design, the study integrated PLS-SEM modelling and thematic interviews to provide a nuanced understanding of the affective–epistemic nexus underpinning students' engagement with AI in English academic writing. Findings consistently highlighted empathy as the strongest predictor of favorable perceptions of ChatGPT, confirming its critical role in shaping how students interpret the tool's communicative and supportive qualities. Empathetic students tended to view ChatGPT as reassuring and helpful, aligning with the CASA paradigm, which posits that users attribute social agency to systems displaying human-like cues. However, empathy's influence was context-dependent: IEBs mediated the empathy–perception relationship only among Indonesian students, where reflective pedagogical traditions encourage critical literacy. By contrast, Malaysian students showed a direct empathy–perception link, suggesting that cultural and educational norms influence how emotional and epistemic dispositions coalesce in AI use. Gender effects were modest but notable, with males demonstrating a stronger empathy to IEB association, supporting evidence that men rely more on cognitive perspective-taking to evaluate AI outputs.

The study makes several theoretical and practical contributions. Theoretically, it refines the CASA framework by demonstrating that emotional traits alone do not fully account for AI acceptance; instead, epistemic beliefs moderate how empathy translates into evaluative behaviors, and this interaction is shaped by cultural learning norms. It also introduces the concept of **"**synthetic empathy**,"** showing that students often perceive AI-generated supportive language as emotionally meaningful, even when recognizing its artificiality. Pedagogically, the findings support empathy-aware AI literacy programs, integrating prompt engineering, tone evaluation, and collaborative editing into academic writing curricula. They also suggest culturally tailored approaches: reflective-learning contexts may benefit from fact-checking and source-verification tasks, while experiential-learning settings could emphasize relational authenticity in AI use.

Despite its contributions, the study has limitations. The sample, drawn from two universities, may restrict the generalizability of findings, and self-report measures introduce potential social desirability bias. Additionally, the cross-sectional design cannot track changes in empathy or IEB over time. Future research should employ longitudinal or experimental designs to examine how affective and epistemic dispositions evolve with sustained AI use. Broader cross-cultural comparisons, inclusion of diverse disciplines, and exploration of AI design features (e.g. adjustable empathy settings) are also recommended to deepen understanding of empathy-driven, culturally responsive AI adoption in higher education.

Authors contributions

Elyisa Kurniati – conceptualization, methodology, investigation, formal analysis, writing – original draft preparation, writing – review and editing, and validation; Ive Emaliana – conceptualization, methodology, supervision, writing – review and editing, project administration, and funding acquisition; Rafidah Sahar– conceptualization, formal analysis, validation, writing – review and editing, and visualization.

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article. However, some data are not publicly available because they contain information that could compromise the privacy of research participants.

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