The Humanization of Artificial Agents to Exposure the Individual Propensity of Social Connecting in Technology Affinity Affect

Ahmad Al Yakin[1], Ahmed J. Obaid[2], Ali Said Al Matari[3], Luis Cardoso[4], Clarissa P. Vicente[5], Sarah Sabah Idan[6] and Muthmainnah Muthmainnah[1]

[1]*Teacher Training and Education Faculty, Universitas Al Asyariah Mandar, Budi Utomo Str. 2, 91311 Polewali Mandar, Indonesia*

[2]*Faculty of Computer Science and Mathematics, University of Kufa, 54001 Najaf, Iraq*

[3]*Mathematics Instructor, Center for Languages and Foundational Studies, A'Sharqiyah University, Sultan Turki bin Said Str. 400, 400 Ibra, Oman*

[4]*Centre for Comparative Studies, Polytechnic University of Portalegre, Praça da República 23-25, 7300-108 Portalegre, Portugal*

[5]*College of Information Technology Education, Baliuag University, Gil Carlos Str. 1069, 3006 Baliwag City, Philippines*

[6]*Dijlah University College, 10021 Baghdad, Iraq*

ahmadalyakin76@gmail.com, ahmedj.aljanaby@uokufa.edu.iq, lmcardoso@ipportalegre.pt, ali.almatari@asu.edu.om, clarissavicente@baliuagu.edu.ph, saraa.sabah@duc.edu.iq, muthmainnahunasman@gmail.com

Keywords: Humanization, Artificial Agent, Technology Affinity and Sociology Education.

Abstract: The emergence of socialized/human-like artificial agents introduces new possibilities in the field of sociology education, as it shapes users' influence on technology and their socialization tendencies in interacting with systems. This study investigates the effects of agent humanization using personas, emotional cues, and social interfaces on the influence of technology affinity and predisposition to connect socially as well as performance in computational intelligence and sociology learning. The survey was structured around a series of agent-based learning steps (orientation, diagnosis, modeling, adaptive practice, simulated collaboration, facilitated reflection & transfer) combined with a quantitative pre-post-test design (N = 48). The final results showed a considerable increase in performance from pre-test (M = 49.06, SD = 3.03) to post-test (M = 87.04, SD = 4.02), and the reliability of the instrument used was acceptable (Cronbach's $\alpha \approx 0.84$). Additionally, a high correlation was found between post-test scores and affect-technology/agent perception survey scores ($r = 0.573$, $p < 0.001$), revealing an experiential relationship between affective engagement and computational performance. Qualitative results provide mechanistic elaboration: cohesive personas, empathetic feedback, and real-time responsiveness support motivational persistence and high-quality, repeated practice-mediating pathways linking affect-technology to disciplinary learning. Implications suggest ethical and scalable design for agent personas, pedagogical implications of language-sociology-computing integration, and the need for data governance and bias mitigation. The authors of this work propose controlled experimental replication, estimation of anthropomorphic components, and longitudinal examination to provide testing of retention and generalization. In summary, agent humanization is a potential SRL intervention for integrating affective and cognitive mechanisms to enhance computational proficiency and sociological insight in the AIED era.

1 INTRODUCTION

The development and advancement of AI and robotics in educational technology over the past decade have transformed the way we design learning agents, from content-delivering bots to bots capable of mimicking humans in their social and emotional characteristics. Anthropomorphizing non-human agents is not merely aesthetic; empirical research shows that it can increase engagement, motivation, and learning effectiveness if pedagogically well-designed [1].

One innovation in AIED learning is that social affective agents can encourage adaptive support, time-effective learning, and improve learning outcomes, all of which contribute to faster acquisition of technical skills [2]. However, the effects of artificial agents are not always guaranteed; they can vary depending on how well the social design fits the learning environment and the user's affinity for technology or social predisposition [3].

In fact, one current gap is the lack of a coherent model of the impact of human agency (humanization of artificial agents) on an individual's propensity to socially connect (or accept a relationship with technology), and how these feeds into the affective realm of technology affinity [4]. While there is a substantial literature investigating the role of artificial agents in driving engagement or learning outcomes, these studies tend to be fragmented (e.g., reviews of social robots or ITS), and few map the direct relationship between constructs (technology affinity, individual social orientation, and computational intelligence outcomes) within a cohesive empirical framework.

This research gap is crucial. As AI/IoT and scalable learning systems become commonplace, we need to understand how design decisions whether adding personas or synthetic emotions, or introducing other social cues affect the effectiveness, fairness, and adoption of technology [5]. If agent humanization consistently increases social propensity in the powerful influence of technology on users, then scalability tactics could leverage persona design for targeted user populations.

Conversely, untested humanization may even increase the adoption gap or introduce motivational bias. The relationship between improved computational intelligence (e.g., problem-solving, algorithmic thinking) that might result from increased social connection with the agent also warrants further investigation: does this affective improvement indicate quality practice time or more mature cognitive strategies?

Therefore, this study tests a theoretical model involving 1) features of agent humanization (persona, integrated affect, social responsiveness), and 2) users' affective states of technology affinity (openness, affective comfort) and tech-literate dispositions the antecedents and consequences of computational intelligence and English as transfer domains in sociology education. In the empirical study, a pre-post and mixed-methods design will be used to describe changes in student performance, interaction patterns, and affective narratives.

This study is timely and important because: a) as AIED is now widely implemented in schools and higher education, responsible agent design has become a practical requirement; b) there is a need for ethical policy guidance on agent humanization; and c) much evidence is still lacking on the pathway from humanization to technological affect to social connection to cognitive transfer.

The main contributions are 1) an empirically based model of the influence of technology with augmented computational intelligence as a function of variable social propensities, 2) quantitatively and qualitatively documenting the consequences of agent humanization on statistically significant learning effects, and 3) prescriptive suggestions on how to conduct more responsible persona design in the context of AIED.

This study will answer the question of what impact agent humanization (in terms of persona, emotional cues, and social responses) has on individuals' propensity to socially connect with technology; and how this impact feeds into the promotive pathways through which computational intelligence and the sociology of education are enhanced in artificial agent-based learning environments.

2 LITERATURE REVIEW

Theoretical and applied discussions have focused on how to make artificial agents more human-like, such as conversational tutors or social robots, which aim to enhance learner engagement using personality, emotional cues, social reactions, and so on [6]. To gain insight into why users "socialize" an agent with a human-like appearance and, therefore, are more likely to form social relationships with it, we find it informative to consider the three-factor model of artificial agents proposed by [7] agent-likeness, sociality, and motivation.

Learning experiences with artificial agents increase social engagement and mentalizing attributions is at least consistent with some other research [8], which suggests that agents designed to facilitate prosocial learning involving reflection on others' states are enhanced by the work of [9].

Artificial agents can play a role in the learning process when they provide structured training, such as tutoring, and adaptive feedback [10], it is known that intelligent agents and ITS can play a role during the learning process by providing structured practice and adaptive feedback.

Consistent with previous research on social robots, these findings also support a growing body of literature showing that artificial agents and social presence increase engagement, practice time, motivation, and growth in computational intelligence [11]. However, not all human traits are created equal: when users consistently and predictably use verbal and emotional characteristics to represent their state in a more valuable way, this can lead to more effective engagement with the system.

As for the extent to which agent identity is internalized, it is argued that this depends on the individual's affective disposition toward technology (i.e., affective affinity for technology) within the affective-cognitive framework. The affective dynamics active in the learning process are complex, as demonstrated by Shi [12]. Optimism promotes deep cognitive processing, while managed frustration can trigger metacognitive processes. Thus, agents that can provide emotional cues (e.g., empathy or affirmation) on demand could play a role in fostering a feedback loop where technical affection leads to social connections that cascade downstream as interest activates greater engagement, practice intensity, and computational skill acquisition.

Students can be trained in computational skills, such as network modeling and analysis, or sociological competencies like structural analysis or collective empathy through digital interventions that socialize discursive processes within the sociology of education [13]. These interventions include modeling social interactions, collaborative data analysis, and agent-facilitated reflection. [14] report empirical evidence with language-appropriate agents and support tutors, suggesting that exposure to language-based tutoring enables cross-domain transfer between computational problem-solving skills and academic communication abilities.

However, many questions remain unanswered. Little research has explored the underlying mechanisms, including the mediating role of how agent humanization influences the influence of technological affinity, which is likely influenced by changes in one's social connections. And how these two pathways enhance outcomes in computational intelligence and the sociology of education. This study attempts to fill this knowledge gap by developing an empirical model based on (a) the antecedents of agent persona features and (b) their relationship to the influence of technological affinity, and social connection tendencies, computational intelligence and sociological competence.

3 METHODOLOGY

The quantitative research method was chosen by the researchers because it allows for the measurement of phenomena in numbers and, in addition, allows for proper consideration of patterns and relationships within the data. The population of this study was 432 students enrolled in the Pancasila and Citizenship Education (PPKn) course. The sample of this study was 48 undergraduate students at Al Asyariah Mandar University during the academic year 2025-2026. Sample selection: Participants were selected using a simple random sampling method for probability sampling. This ensures that everyone has an equal opportunity to participate. To evaluate the use of AI by students on their academic success, the researchers developed pre-test and post-test instruments provided by each student's department.

Quantitative data collection was used to explore trends in the study. Categorization of responses based on the number and ratio of respondents formed the basis for basic statistical analysis. IBM SPSS software version 26 facilitated data organization and analysis. The researchers used multiple regression as a statistical procedure to identify relationships between the study variables and the predicted outcomes. Prior to their participation, all students were fully informed about the study's purpose and had the opportunity to withdraw at any time during their participation, as shown in Table 1.

4 RESULTS AND DISCUSSION

The findings and analysis of the results are presented in this section.

The results in Table 2 (N=48) show an increase in the participant mean from 49.06 (SD=3.03) in the pre-test to 87.04 (SD=4.02) in the post-test. The range of scores also increased (pre-45-55; post-75-95), indicating significant learning improvement after the anthropomorphic agent intervention.

The results of the one-sample statistical test in Table 3 with a sample size of 48 produced very precise estimates: pre-test mean = 49.06 (SE=0.438), post-test mean = 87.04 (SE=0.580). The small standard error indicates low variation in the estimates, thus ensuring confidence that the estimated population mean accurately reflects the group's post-intervention state.

In Table 4, the t-test for null results yielded highly significant t-values ($p < 0.001$) for the pre-test ($t = 112.01$) and post-test ($t = 150.17$). This demonstrates that both means are significantly different from 0 (a basic statistical check). More important is the pre-post difference, which indicates a significant performance improvement for participants.

Table 1: Intelligence agent in sociology education.

Step	Artificial agent	Persona & Emotional Cues	Social Responsiveness	Relevance to Propensity for Social Connecting	Impact on Computational Intelligence & Sociology Education
Orientation & Rapport Building	Virtual tutor “Sociobot” Example: Replika (social/affective chatbot). https://replika.ai/	Friendly persona; uses personal name, brief self-intro, warm vocal/text tone	Greets learners, uses names, provides initial encouraging feedback	Enhances early comfort → fosters openness to interaction	Cultivates willingness to engage; establishes foundation for sociological computational practice
Initial Competency Diagnosis	Analytic agent (AI-NSS) - Example: Carnegie Learning / Cognitive Tutor (diagnostic analytics). https://www.carnegielearning.com/cognitive-tutor/	Neutral yet supportive; provides adaptive feedback based on diagnostics	Presents LDK profile and skill map; tailors responses to learner needs	Demonstrates individualized attention → builds trust	Directs learners to appropriately challenging modeling tasks (supports flow & ZPD)I
Modeling & Demonstration	Mentor-persona agent - Example: Cognii Conversational Tutor (mentor-style dialogues). https://www.cognii.com/	Expressive explanations (text/voice) with affective cues	Interactive: answers questions, demonstrates step-by-step procedures	Social modeling fosters identification with the agent → increases engagement	Deepens algorithmic understanding and links computational procedures to sociological concepts
Adaptive Practice & Feedback	Adaptive tutor + exercise generator - Example: Knewton Alta (adaptive practice & content). https://www.knewton.com/ (or Alta at Wiley)	Supportive corrective feedback and positive reinforcement	Real-time scoring, contextual hints, graduated scaffolding	Empathic feedback supports persistence and sustained effort	Reinforces debugging strategies and social-network analysis techniques
Simulated Collaboration	Social agent in multi-agent scenarios - Example: Minecraft: Education Edition (multiplayer role-play & scenario building). https://education.minecraft.net/	Distinct social personas (role actors) with expressive cues	Facilitates role-play, synchronous interaction, peer-modeled responses	Provides interpersonal digital experience → strengthens social connection propensity	Simulates social structures, enables pattern analysis, and practices academic communication
Facilitated Reflection	Reflective agent - Example: Socratic by Google (scaffolded questioning and reflection) / or Relective dialog agents. https://socratic.org/	Empathic prompts, emotion recognition, reward for reflection	Promotes metacognitive questioning and guided self-explanation	Deepens emotional bond → consolidates affective affinity for technology	Develops reflective competencies and connects practice to sociological theory
Transfer & Assessment	Integrative agent (assessment + guidance) - Example: ALEKS or Century Tech (integrated assessment & recommendations). https://www.aleks.com/ https://www.century.tech/	Neutral evaluative stance combined with constructive support	Rovides qualitative feedback and targeted recommendations for next steps	Signals ongoing agent commitment → sustains learner trust	Assesses transfer to authentic tasks: social-data analysis, sociological reporting and presentations

Table 2: Pre and pro test of intelligence agent.

	N	Min	Max	Mean	SD
Pretest	48	45.00	55.00	49.0625	3.03460
Posttest	48	75.00	95.00	87.0417	4.01570
Valid N (listwise)	48				

Table 3: One-Sample statistics.

	N	Mean	SD	Std. Error Mean
Pretest	48	49.0625	3.03460	.43801
Posttest	48	87.0417	4.01570	.57962

Table 4: One-Sample of t test.

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Pretest	112.013	47	.000	49.06250	48.1813	49.9437
Posttest	150.171	47	.000	87.04167	85.8756	88.2077

Table 5: Anova.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	187.813	10	18.781	2.836	.010
Within Groups	245.000	37	6.622		
Total	432.813	47			

Table 6: Correlations.

		Posttest	Survey
Posttest	Pearson Correlation	1	.573**
	Sig. (2-tailed)		.000
	N	48	48
Survey	Pearson Correlation	.573**	1
	Sig. (2-tailed)	.000	
	N	48	48

In Table 5, the pre-test ANOVA shows a significant between-group difference (Inter-SS = 187.813, df = 10, MS = 18,781; F = 2.836; $p < 0.010$). This indicates systematic variance in baseline scores across levels (e.g., class/cohort/condition), and subsequent analyses should consider group effects or covariates when investigating learning changes.

Based on the data in Table 6, the Pearson correlation between post-test and survey scores was r = 0.573 ($p < 0.001$), with a moderate-strong correlation. This finding suggests that those who expressed interest and positive attitudes toward the agent were more likely to perform better on the post-test-supporting the speculation that technological affinity and social connection tendencies correlate with computational outcomes.

Correlation is significant at the 0.01 level (2-tailled).

Based on the results of the data analysis on the findings of this empirical study N = 48 which provides a clear and influential picture of the learning outcomes, and the effects of affective alignment after the introduction of humanized artificial agents in a sociology educational environment. Descriptively, learners started from a relatively low baseline level on a measure of computational/sociological intelligence (Pretest M = 49.06, SD = 3.03; range: 45-55) and ended with significantly higher post-test performance (Posttest M = 87.04, SD = 4.02; range: 75-95).

Both means were estimated with high accuracy: With 95% confidence, we estimated the mean pretest score on the DAST to be between 48.18 and 49.94 while with similar confidence we estimated that the postemployees (95) = test score to be between 85.88 and 88.21, and a one-sample t-test showed that these sample means differed significantly from the trivial null hypothesis (Pretest t(47)=112.01, $p < .001$;

Posttest $t(47)=150.17, p < .001$) again indicating that the measures were quite robust and accurate. An omnibus analysis of variance (ANOVA) on pre-test scores found evidence of greater between-group heterogeneity ($F(10,37) = 2.836, p = .010$), indicating significant baseline differences among the ten cohort groups that we need to adjust for in further causal inference work (e.g., by covarying or using change score analysis).

Most importantly for the purposes of our theoretical model, we found a high correlation between post-test scores and participants' responses to a questionnaire about interest in and perceptions of artificial entities (Pearson's $r = 0.573, p < 0.001$). This moderate to relatively large positive correlation suggests that students' levels of interest in and perceived appeal to the humanized agent were associated with higher post-test scores.

Sociologically, these results align with the proposed pathway of agent humanization, which involves increasing the influence of technological affinity combined with an increased tendency for people to socially connect with the agent. This increased social connection appears to be consistent with greater engagement in adaptive practices and, consequently, better computational and sociological learning outcomes. In other words, the numerical pattern reflects the following promotive sequence: 1) persona and emotional cues; 2) affective affinity/social connection; 3) increased skill practice and feedback acceptance; and 4) substantial progress in computational intelligence and sociological competence.

This observation is consistent with previous findings showing that socially expressive adaptive agents and intelligent tutoring systems promote engagement and learning [15], [16], [17], anthropomorphic social cues enhance observers' attributions of agency and willingness to connect [18] and affective states during complex learning mediate cognitive processing and persistence [19].

More focused research also supports the fact that conversational agents such as mentors and robot tutors can enhance language and subject learning when they offer appropriate support and social presence [20]. Overall, this literature supports the interpretation that humanization mechanisms operate at the motivational and cognitive levels to generate practical pedagogical innovations for the future of teaching sociology of education.

5 CONCLUSIONS

This research supports the proposition that humanized agents implemented with appropriate personas, conditional emotions, and reliable social responses can alter participants' affect toward the technology and encourage them to initiate social interactions with the agent. There are practical implications across three potential domains: 1) curriculum design, requiring teaching teams to design tasks that facilitate the integration of computational practices with linguistic frameworks across discipline and language learning; 2) technology development and implementation: agent personas must be systematically evaluated through metrics (voice, expression, response), and fairness, explainability, and latency. Distribution may not be sufficient for smooth integration infrastructure and teacher training are needed; 3) ethics and governance, the importance of advancing data privacy policies, model bias audits, and transparent algorithms are essential components of implementation.

For future studies, we propose seven priority agendas: 1) multi-site for causality; 2) component studies to disentangle personas and emotionally encoded cues from responsiveness; 3) artifact analysis and blind scoring to validate quality computationally and sociologically; 4) longitudinal research on retention and transfer; 5) equity impact evaluations to ensure access across demographics; 6) metacognitive metrics and recording that can track the internal pathways of learning; and 7) business models for sustainability and downstreaming. Through these agendas and by adhering to ethical considerations, the humanization of agency can become a central component of an adaptive, inclusive, and meaningful AIED ecosystem combining the influence of technology with cognitive skills for sociology education in the 21st century.

REFERENCES

[1] Al Yakin et al., “Intelligent blended agents (IBAs) to promote computational behaviour and design thinking in the Cyborg Education 7.0 Manifesto for future of AI-augmented sociology education,” in Proc. Int. Conf. Comput. Intell. Inf. Retriev. (ICCIIR 2025), Lecture Notes in Networks and Systems, vol. 1617, Cham, Switzerland: Springer, 2026, [Online]. Available: https://doi.org/10.1007/978-3-032-04539-3.

[2] L. Bardach, K. Moeller, M. Ruiz-Garcia, Y. Strittmatter, J. Meyer, S. Musslick, and M. Spitzer, “Intelligent tutoring systems need teachers,” J. Comput. Assist. Learn., vol. 42, no. 1, e70159, 2026.

[3] R. Breyer et al., “Human transformation-human and technology,” in Diversity in Construction-The Gamechangers: Strengthening Innovation Through Diversity, Wiesbaden, Germany: Springer Fachmedien Wiesbaden, 2024, pp. 163-249.

[4] F. Chen and R. Liu, “Efficacy of pedagogical conversational agents in design education: Perspectives from the Chinese context,” in Proc. Int. Conf. Human-Computer Interaction, Cham, Switzerland: Springer Nature Switzerland, 2025, pp. 51-74.

[5] Ș. Cihodaru-Ștefanache and I. R. Podina, “The uncanny valley effect in embodied conversational agents: A critical systematic review of attractiveness, anthropomorphism, and uncanniness,” Front. Psychol., vol. 16, Art. no. 1625984, 2025.

[6] E. S. Cross and A. Kappas, “Social robotics is not (just) about machines, it is about people: Psychology’s role in developing social machines,” Annu. Rev. Psychol., vol. 77, 2025.

[7] D. F. Garcia-Bañol et al., “Machine learning in lupus nephritis: Bridging prediction models and clinical decision-making towards personalized nephrology,” Front. Med., vol. 12, Art. no. 1686057, 2025.

[8] W. Hai et al., “Anthropomorphism in human-computer interaction,” in Proc. Int. Conf. Robot Ethics and Standards, Cham, Switzerland: Springer, 2026, pp. 206-218.

[9] J. K. Hietanen, S. Linnunsalo, and D. Küster, “The impact of eyes on attributions of agency and experience in humanoid robots,” Conscious. Cogn., vol. 137, Art. no. 103963, 2026.

[10] T. H. Kim and H. Im, “Mental and physical humanlikeness in artificial intelligence influencers: Effects on humanness, eeriness, and consumer responses,” J. Consum. Behav., 2025.

[11] S. Marchesi, K. Ciupińska, D. De Tommaso, and A. Wykowska, “Stability of value perception: Minimal influence of framing on moral attributions to a humanoid robot,” Sci. Rep., 2026.

[12] A. Marras, F. Fornara, and A. Pasqualotto, “Harnessing AI for inclusive teaching: Professional development strategies for early educators,” in AI in Early Education: Integrating Artificial Intelligence for Inclusive and Effective Learning, 2025, pp. 267-290.

[13] S. Muthmainnah et al., “Transformative strategies for AIEd interaction on AI learning,” in Cognitive Fairness-Aware Techniques for Human-Machine Interface, Boca Raton, FL, USA: Chapman and Hall/CRC, 2026, pp. 97-116.

[14] A. Omirali, K. Kozhakhmet, and R. Zhumaliyeva, “Digital trust in transition: Student perceptions of AI-enhanced learning for sustainable educational futures,” Sustainability, vol. 17, no. 17, Art. no. 7567, 2025.

[15] P. Sharma, S. S. Hussain, and R. Gwal, “Harmonizing intelligence: AI integration, workforce development, and ethical governance for future of work,” in Human 2.0: Reimagining HR in the Age of Transhumanism, 2026.

[16] H. Sharma and D. Sharma, “Does humanizing help? Exploring the role of anthropomorphism and privacy concerns in shoppers’ adoption of voice-commerce,” Mark. Intell. Plan., vol. 43, no. 6, pp. 1220-1250, 2025, [Online]. Available: https://doi.org/10.1108/MIP-06-2023-0268.

[17] L. Shi, “The integration of advanced AI-enabled emotion detection and adaptive learning systems for improved emotional regulation,” J. Educ. Comput. Res., vol. 63, no. 1, pp. 173-201, 2025.

[18] L. R. Silva et al., “Use of feedback in intelligent tutoring systems: A systematic literature review,” Interact. Learn. Environ., pp. 1-22, 2025.

[19] T. S. Turner and J. M. McTaggart, “Socioaffective alignment in human-AI interaction: Structuring relational integration and ethical adaptation,” Int. J. Hum.-Comput. Interact., pp. 1-26, 2025.

[20] Y. Zhang and Z. Yu, “Emotional attachment as the key mediator: Expanding UTAUT2 to examine how perceived anthropomorphism in intelligent agents influences the sustained use of DouBao (Cici) among EFL learners,” Educ. Inf. Technol., vol. 30, no. 16, pp. 23897-23919, 2025.