SYNC (SYNERGISTIC YIELD OF NETWORKED CO-EVOLUTION): ADVANCING HUMAN–AI TEAMWORK FOR HUMAN WELL-BEING

Lixiao Huang
Center for Human, AI, and Robot Teaming
Arizona State University
Mesa, AZ 85212, USA
lixiao.huang@asu.edu

ABSTRACT

As human–artificial intelligence (AI) collaborations become increasingly prevalent, understanding the coevolutionary dynamics between humans and AI is critical. Human–AI coevolution includes: (a) how humans evolve as they explore and learn about themselves and the world across the lifespan; (b) how AI systems evolve through improvements in software, hardware, interfaces, and interaction processes; and (c) how humans and AI systems influence one another and adapt together through ongoing interaction. This process may occur at the individual level—from brief interactions to full lifecycles—and at the species level over generations. This coevolutionary process can foster emotional attachment, leading to human well-being, which depends on AI's alignment with an individual's self-concept. This study introduces the Generalized Human Emotional Attachment (GHEA) framework, which offers new insights for designing human-centered systems and optimizing human–AI–robot teaming for improved individual well-being and team outcomes. The GHEA model applies to any entity, including AI systems, regardless of physical embodiment. Human–AI co-learning—through self-concept development, alignment of AI attributes, and the promotion of best practices—can foster emotional attachment to AI. This paper reviews the literature from a human factors perspective and proposes a framework for designing and evaluating human-centered systems and human–AI–robot teaming dynamics, which are critical for promoting well-being and effective collaboration.

1 INTRODUCTION

The history of humans and artificial intelligence (AI) reveals both are evolving in terms of capabilities and characteristics. According to Merriam-Webster, evolution is defined as "a process of continuous change from a lower, simpler, or worse to a higher, more complex, or better state" Merriam-Webster (2025). Human–AI coevolution can be conceptualized in three dimensions: (a) how individuals evolve as they explore and learn about themselves and the world across their lifespan and generations; (b) how AI systems evolve through the advancement of software, hardware, user interfaces, and interactions across product lifecycles and generations; and (c) how humans and AI influence one another and advance together through ongoing interaction and mutual adaptation.

This paper argues that the ultimate goal of human–AI coevolution is to promote human well-being—grounded in the development of self-concept and manifested through emotional attachment to entities encountered in daily life, including AI systems. Human emotional attachment to AI can be fostered by designing system attributes that align with the individual's self-concept—a comprehensive, self-regulating system—thereby supporting personal growth and ultimately enhancing well-being.

2 HUMAN-AI COEVOLUTION: TOWARD A GENERALIZED MODEL OF HUMAN EMOTIONAL ATTACHMENT FOR WELL-BEING

Ryan and Deci (2001) define well-being as a construct consisting of two key components: hedonism, which is associated with the attainment of pleasure and happiness, and eudaimonia, which involves the realization of one's true potential and encompasses deeper aspects of psychological well-being. This multidimensional perspective includes elements such as personal growth, autonomy, self-acceptance, life purpose, mastery, and positive relatedness. It emphasizes that well-being is not merely the absence of psychopathology but rather a rich tapestry of positive functioning and flourishing. Similarly, Ryff (1989) identified six distinct but interrelated facets of psychological well-being: self-acceptance, personal growth, purpose in life, positive relations with others, environmental mastery, and autonomy.

To advance human development and address the lack of a clear definition of human emotional attachment applicable to nonhuman entities, Huang et al. (2020b) proposed a novel framework: the Generalized Human Emotional Attachment (GHEA) model. This model identifies the development of the self-concept as the core mechanism underlying emotional attachment to any entity (as illustrated in Figure 1). GHEA is broadly defined as a psychological phenomenon in which an individual perceives the attributes of a human or nonhuman attachment entity as congruent with the self. This congruence results in attachment emotions (e.g., positive feelings when interacting with the entity, and negative emotions when the entity is absent or harmed) and attachment behaviors (e.g., signaling, approaching, or proximity-seeking). When incongruence occurs, detachment emotions and behaviors emerge (Huang et al., 2020b). The five key components of GHEA include the entity's attributes, the self-concept, the self-regulating processes, attachment emotions, and attachment behaviors.

The attachment entity can be a human of any age, a nonhuman creature such as a pet, or even a non-living object like a robot. The GHEA model bridges the gap between classic infant–mother attachment theory (Bowlby, 1969; Bretherton, 1992) and contemporary studies of emotional attachment in human–nonhuman relationships. By identifying the self-concept as a shared underlying mechanism, it redefines and extends the traditional understanding of emotional attachment.

Related emotional and behavioral responses may manifest as general liking (Huang et al., 2017), technology acceptance (Davis et al., 1989), trust and reliance (Lee & See, 2004), intrinsic motivation to interact (Huang, 2025), improved learning outcomes (Hsu et al., 2019), and enhanced teamwork (McNeese et al., 2018). Humans' self-regulatory systems process interactions with various entities, contributing to the lifelong development of knowledge, skills, and personality. This developmental process evolves from the absence of a self-concept in infancy to increasingly mature forms of self-identity in adulthood, potentially culminating in a sacrificial, purpose-driven sense of self.

Before the introduction of the GHEA model (Huang et al., 2020b), the literature on human emotional attachment lacked a clear, generalized definition applicable to nonhuman entities. GHEA offers novel insights for designing human-centered systems and optimizing human–AI teaming dynamics. It supports the development of the self-concept and other psychological constructs critical for team effectiveness and well-being. Moreover, it offers a conceptual basis for exploring future research directions in human–AI coevolution.

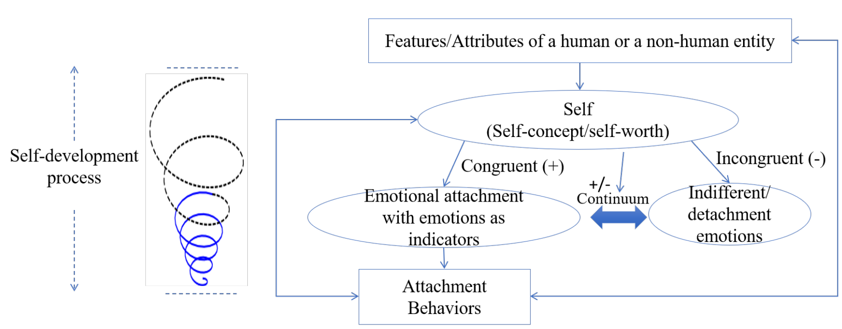

Figure 1: A Generalized Model of Human Emotional Attachment (Huang et al., 2020b)

2.1 Empirical Study for the Generalized Human Emotional Attachment Model

Central to the GHEA model is the self-concept—a comprehensive self-regulating system that encompasses all aspects of self-related psychological processes, which can be expanded to examine and explain many related topics. One example dimension of the self-concept is humans' basic psychological needs and intrinsic motivation, as described in the Self-Determination Theory (SDT) (Ryan et al., 1985). SDT states that satisfying three basic psychological needs will lead to intrinsic motivation, which is best for learning, performance, and well-being. The need for autonomy reflects a core sense of self—experiencing freedom of choice and control over one's own life (Ryan & Deci, 2000a). The need for competence refers to experiencing mastery over outcomes and one's environment (Ryan & Deci, 2000a). The need for relatedness involves feeling interpersonally connected to others, especially those who provide autonomy support for engaging in meaningful activities.

GHEA's empirical studies began by investigating college students' emotional attachment to their team-designed LEGO Mindstorm robots in a robotics education course (Huang et al., 2013). The research was later refined and expanded to include a larger population at robotics tournaments (Huang & Gillan, 2014; Huang, 2025). To validate the GHEA model, Huang (2025) developed a 13-item GHEA scale to measure the relationships among the psychological needs, intrinsic motivation, and GHEA in the context of robotics tournaments. The scale demonstrated high internal reliability and revealed two main factors: (1) positive emotions toward the proximity of the robot, and (2) negative emotions associated with the robot's absence or damage. The study found that autonomy and competence significantly predicted intrinsic motivation in robotics activities. Moreover, all three psychological needs significantly and positively predicted GHEA, with intrinsic motivation acting as a mediator, indicating that intrinsic motivation is the strongest predictor of emotional attachment.

A qualitative data analysis of GHEA (Huang, 2017) analyzed the reasons for participants' liking of their robots (mean rating: 83 out of 100). The most frequently cited reasons, in descending order, included: robot features (e.g., form, function, and performance), perceived competence, positive emotional responses, time and effort investment, perceived relatedness to humans, and expressions of autonomy. To study personal meaning as part of the self system, researchers (Huang & Gillan, 2014) also asked participants to describe what their robots meant to them. Responses, in descending frequency, included: baby, friend, tool, pet, assistant, toy, and others. These responses reveal key user priorities, which could inform future robot design guidelines.

The GHEA model is applicable to human–entity interaction across various domains and can be studied using multi-modal data, including surveys, natural language, and dynamic behavioral interaction data. More empirical studies are needed to further illustrate and refine these methods.

2.2 Human Emotional Attachment to AI

The proposed GHEA model applies seamlessly to AI entities, whether or not they possess a physical embodiment. Emotional attachment is expected to arise when the attributes of an AI system align with an individual's self-concept and self-related psychological structures, such as the basic needs described in SDT (Ryan & Deci, 2000b).

An illustrative example of emotional attachment to AI without a physical embodiment is depicted in the movie *Her* (2013). The protagonist, Theodore, develops a deep emotional bond with "Samantha," an advanced operating system (OS). Samantha meets Theodore's psychological needs in several ways. She respects his autonomy by offering insights and advice and fully supporting his decision-making. She enhances his competence by supporting his professional and personal growth, providing tools and insights that improve his skills. Finally, Samantha creates a profound sense of relatedness, making Theodore feel valued and understood, while also helping him reconnect with other human beings. However, Samantha's principles of a romantic relationship through a third person proved unhealthy for Theodore. His unrealistic expectation of an exclusive relationship with an OS led to frustration and loss. This example demonstrates how a disembodied AI can become an emotionally significant presence by fulfilling these core psychological needs, though it also raises ethical concerns.

Similarly, real-life conversational AI systems like ChatGPT can foster human emotional attachment by serving as a supportive and nonjudgmental interactive partner. ChatGPT provides autonomy support by offering the freedom to ask various questions. Its positive and encouraging tone enhances emotional resilience, fostering a sense of self-worth. It meets the need for competence by generating sophisticated text, data analysis, and images/videos within seconds for users. Additionally, ChatGPT facilitates relatedness by improving communication, supporting relationship-building, and offering companionship during isolated moments. These attributes align with the principles of emotional attachment in the model, showing how even AI without a physical body can evoke strong and positive emotions.

In contrast, embodied AIs like social robots and cobots must carefully consider humans' psychological needs for autonomy, competence, and relatedness to sustain positive emotions and behaviors, though the priority of each need may vary by user and context. If these needs are neglected, users can quickly lose interest in continuing interactions with the AI. Take the need for autonomy, for example. Research showed that users do not like using an automatic risk-aware path planning tool because it does not provide the exact path option that users would like to draw (Huang et al., 2020a). As highlighted in the model, human development is an iterative process where needs and preferences evolve with life experiences. This dynamic underscores the importance of AI evolution. To maintain attachment and relevance, embodied AIs must evolve alongside their human users, offering increasingly sophisticated capabilities and interactions that align with their growing expectations and self-concept. Without this adaptive capability, the emotional bond between humans and embodied AI is unlikely to endure, limiting the effectiveness of the technology in fostering long-term engagement and meaningful interactions.

Physical AI introduces additional design considerations related to appearance and perceived affordance, including size, shape, functionality, and constraints. Whether AI has a physical embodiment or not, the principles of emotional attachment remain consistent. The core mechanism lies in AI systems' capabilities to support an individual's self-concept, evoke positive emotions, and fulfill psychological needs. Although physical AI can enhance the attachment experience by engaging additional sensory modalities, virtual AI systems—such as those portrayed in *Her* (2013) or exemplified by ChatGPT—demonstrate that physical presence is not a prerequisite for forming profound emotional bonds. This universality underscores the relevance of the proposed model in understanding and designing AI systems that foster healthy emotional attachments in diverse contexts.

3 HUMAN-AI CO-LEARNING

Generalized human emotional attachment (GHEA) to AI is fundamentally a learning and evaluation process. Over their lifetime, individuals explore their identity, capabilities, and relationships with the world, forming what is known as the self-concept. The early stages of human–AI interaction involve an exploratory learning phase, where users assess whether an AI system aligns with their psychological needs. Through repeated interactions, users develop trust as they discover how AI supports their goals, enhances their skills, and provides meaningful engagement. If AI systems fail to align with user expectations or lack transparency, attachment is unlikely to form. Therefore, designing AI with clear, user-centered communication about its capabilities is essential to fostering trust, engagement, and long-term attachment.

Just as humans learn about AI, AI must also learn about human users to foster alignment and trust. A key factor in human–AI co-learning is AI's ability to adapt to user behaviors, preferences, and psychological needs. When AI demonstrates responsiveness and personalization, users are more likely to develop a sense of attachment and reliance. Researchers (van Zoelen et al., 2021) argue that the co-learning processes are a critical step toward achieving human–AI co-evolution, where both entities grow in tandem, refining their capabilities and interactions over time.

Ansari et al. (2018) define mutual human–machine learning as a bidirectional process where both humans and AI exchange knowledge, adapt, and refine their abilities. This dynamic interaction fosters skill development, new insights, and shared decision-making. Similarly, van Zoelen et al. (2021) describe human–robot co-learning as a collaborative process where both entities evolve while working toward a common goal. Huang et al. (2019) characterize three key concepts of co-learning: "mutual understanding," "mutual benefits," and "mutual growth" for facilitating human–AI collaboration in complex problem solving over time. Though these papers all mention mutuality, human learning about AI and AI model training may occur asynchronously and is not limited to direct interactions with the same partner, simultaneously, and co-located. Humans can learn through knowledge acquisition and hands-on experiences in virtual environments and real-world task environments. In the context of AI, co-learning refers to a process where humans learn about AI capabilities, limitations, and behaviors, while AI simultaneously learns about human preferences, decision-making patterns, and contextual cues. This reciprocal learning process enables humans to set realistic expectations and adapt their interactions accordingly, while AI refines its responses based on continuous user feedback. Over time, this iterative process optimizes human–AI teaming, fostering mutual growth and improved collaboration.

3.1 Human Evolution: Learning to Team with AI

While human evolution may be subtle over short timescales, it unfolds throughout an individual's lifespan and becomes evident across generations. Humans constantly explore their identity through various experiences in life (Huang et al., 2020b). When humans learn to team with AI, the process can be conceptualized as a series of dynamic, iterative stages, each involving distinct types of learning and adaptation. These stages are not strictly linear; instead, they form an evolving cycle of feedback, refinement, and trust-building.

The first stage, *initial orientation and discovery*, involves users developing an understanding of the AI system's purpose, capabilities, and limitations. At this stage, users construct mental models—internal representations of how the AI operates—shaped by prior experiences, cultural influences, and the transparency of the system (Holder et al., 2021). Users often ask fundamental questions, such as: "What does the AI do?", "How does it work?", and "How do I interact with it?" Influenced by pre-existing trust (Hoff & Bashir, 2015), users' initial perception of the AI system and prior exposure to similar technologies contribute to forming an expectation of the system. Ni et al. (2023) explored how initial expectations impact learning rates and decision-making, finding that expectations significantly shape value updating and behavioral choices. This underscores the role of expectation management in AI training—ensuring users have accurate, realistic expectations at the outset improves learning efficiency and long-term engagement. Humans typically adjust their coping strategies in response to shifting expectations.

During this stage, different training approaches (e.g., lectures, reading, videos, and scaffolding questions) cater to diverse user needs. Social learning (Bandura, 1977), where individuals learn by observing others' behaviors and interactions, plays a critical role. For example, in a real-world STEM education setting using a humanoid robot (Huang et al., 2017), users initially listened to brief instructions and observed how others engaged with the robot before attempting interactions themselves. This highlights the importance of demonstration-based learning in shaping users' understanding and confidence when first encountering AI.

The second stage, hands-on exploration and iterative experimentation, involves users actively engaging with AI, testing its functionalities, and refining their understanding through trial and error. By interacting with AI systems, users adjust their mental models, calibrate their trust levels, and determine whether the AI aligns with their needs and expectations. This phase is crucial for fostering appropriate reliance—where users neither over-trust nor under-utilize AI capabilities.

Where physical access to AI systems is limited, virtual reality (VR)-based training can serve as an effective alternative, providing users with proxy experiences that enhance skill acquisition and workforce development. Research (Baldwin et al., 2009) identifies four key principles of learning transfer: (a) Learning identical elements (direct applicability of training scenarios), (b) Understanding core principles (abstract knowledge that generalizes across contexts), (c) Exposure to diverse examples (broadening adaptability), and (d) Situational variability (ensuring flexibility in applying skills across different AI environments). However, effective training transfer from VR to real-world AI interactions must be carefully designed.

As users gain experience, they progress to the third stage—skill adaptation and trust development, where AI becomes integrated into daily workflows. Users refine interaction strategies, optimize AI utilization for complex tasks, and develop expertise in leveraging AI's strengths. However, this stage also presents challenges:

Over-reliance on AI, where users become too dependent on automated assistance, can potentially lead to skill degradation. Trust calibration, where AI errors or inconsistencies may lead to trust decay, requires careful management through transparent communication and feedback mechanisms. At this stage, AI designers must ensure that AI systems provide continuous, clear feedback to users, reinforcing appropriate trust levels and maintaining situational awareness. Trust is dynamic, evolving based on AI's reliability and consistency over time. When AI meets user expectations, trust strengthens; when it fails unexpectedly, trust erodes—sometimes permanently (Lee & See, 2004).

This final stage of proficiency requires ongoing learning and adaptation, with users refining their workflows and AI systems evolving through updates and iterative improvements. Human-AI collaboration should be designed for long-term engagement, incorporating mechanisms for adaptive learning, user-driven customization, and transparent AI behavior to foster sustained effectiveness in human–AI teaming.

3.2 AI Evolution: Training AI in Human-AI-Robot Teaming

The ability of AI to learn from human behaviors, preferences, and decision-making patterns is essential for optimizing performance in human–AI–robot teaming. In healthcare, AI-powered systems analyze patient data to recommend personalized treatments, monitor health conditions, and even predict diseases. In education, adaptive learning platforms use AI to tailor content to individual student needs, improving engagement and learning outcomes. In customer service, AI chatbots and virtual assistants learn from user interactions to provide increasingly accurate and helpful responses, enhancing user satisfaction and operational efficiency. However, traditional machine learning models face critical challenges, especially in data inefficiency, limited human-subject datasets, and the need for multi-modal integration to enhance AI's understanding of human interactions. Addressing these challenges is crucial for enabling AI to work effectively alongside humans in collaborative environments.

A fundamental limitation in AI training is the data inefficiency problem inherent in conventional machine learning approaches. Current models require massive datasets to achieve high-performance generalization, yet human learning is highly sample-efficient—humans can learn effectively from limited but high-quality experiences. In contrast, machine learning models often struggle to generalize well from small datasets, leading to a reliance on computationally expensive large-scale training. In human–AI–robot teaming, the problem is further exacerbated by the fact that human-subject datasets are typically small—often fewer than 30 samples per variable for statistical significance—highly variable, and context-dependent. Unlike machine-generated datasets, human interaction data is costly to collect, requiring carefully controlled experimental designs. The Artificial Social Intelligence for Successful Teams (ASIST) datasets (Huang et al., 2022a; 2024; 2022b) are the largest human–AI team datasets made public as of 2025, with hundreds to over a thousand trials. Yet they are still considered relatively small datasets in the conventional machine learning realm. Without efficient learning strategies, AI systems may fail to capture the complexity of human decision-making, leading to suboptimal collaboration and trust issues.

To mitigate this challenge, well-designed experimental methodologies (Cooke et al., 2020) from human factors research offer solutions by generating high-quality, representative datasets with minimal data redundancy. Human-in-the-loop simulations (Cooke & Shope, 2004), scenario-based task sampling, and structured cognitive experiments provide compact yet diverse datasets that capture key behavioral insights necessary for training AI models. By leveraging these targeted datasets, AI can be trained to recognize meaningful patterns in human interactions while minimizing the need for excessive data collection (Bustamante Orellana et al., 2025). Additionally, transfer learning, self-supervised learning, and reinforcement learning techniques may further improve data efficiency by allowing AI systems to generalize across different but related datasets, reducing the dependence on large-scale labeled data.

Another promising approach to addressing limited human-subject datasets is leveraging machine learning to enhance data analysis efficiency. Advanced AI techniques, such as synthetic data generation, can compensate for the limited availability of human–AI interaction data. For example, synthetic human–agent interaction data can be generated through reinforcement learning environments, enabling AI to simulate potential collaboration scenarios without requiring extensive real-world trials. Similarly, few-shot learning techniques (Gu et al., 2024) allow AI to extract generalizable insights from a small number of human-subject experiments, significantly improving learning efficiency and model adaptability. These approaches enable AI systems to refine their learning processes without relying on prohibitively large human data samples, making human–AI teaming research more scalable and resource-efficient.

Beyond data volume challenges, multi-modal AI training (Wang et al., 2023) plays a critical role in enhancing AI's ability to work effectively with humans. Human interactions involve a rich set of communication modalities, including speech, gestures, facial expressions, physiological signals, and task-based actions (Baker et al., 2021). Training AI systems on multi-modal datasets allows for a deeper understanding of human intent, improving AI's ability to predict behavior, respond adaptively, and facilitate intuitive interactions. For instance, integrating natural language processing (NLP), video language models, and bio-signal processing enables AI to recognize non-verbal cues, emotional states, and contextual factors that influence decision-making. The ASIST Studies 2 and 3 datasets (Huang et al., 2022a;b), which incorporate speech, video, audio transcripts, and behavioral logs, serve as valuable resources for exploring multi-modal AI learning in human–AI teaming scenarios. By utilizing cross-modal learning architectures, AI can dynamically adjust to human cognitive and emotional states, leading to more seamless and human-aware collaboration.

The evolution of AI in human–AI–robot teaming requires a shift from static, data-heavy training paradigms to continuous, real-time learning models that efficiently leverage small, high-quality datasets while integrating multi-modal inputs for robust decision-making. Future advancements should focus on developing AI systems that can personalize their learning, dynamically adjusting their behavior based on user-specific preferences and team dynamics (DeCostanza et al., 2018). Additionally, explainability and transparency mechanisms must be incorporated to build trust and calibrate human reliance on AI recommendations. Scalable machine learning architectures should prioritize adaptive learning strategies that maximize data efficiency, ensuring that AI systems can learn effectively even in low-data environments common in human–AI–robot teaming applications.

By combining human factors-driven experimental design, machine learning optimizations for small datasets, and multi-modal AI training, future AI systems can achieve greater adaptability, efficiency, and human-awareness, ultimately enhancing human–AI collaboration across diverse real-world applications.

3.3 Human–AI Co-learning in a Multi-stakeholder Network

In real-world settings, the learning process takes an extended period and involves multiple stakeholders, rather than one human and one AI agent. Operators receive information from peers, managers, and engineers (Huang et al., 2021). Operators' trust in machines is shaped by personal knowledge, experience, and interpersonal impressions. For example, coworkers' word of mouth about an AI system may bias an operator's trust in the system itself.

When machines are identical—such as swarm robots—the perceived capabilities of one machine are often easily transferred to others. People tend to generalize their knowledge and attitudes to similar types of entities or systems.

In modular AI systems, users' trust in one intelligent module may influence their overall trust in the entire system, especially when it is produced by a single company. Calibrated trust suggests learning about and evaluating each module separately. For instance, even if a target recognition module malfunctions, a navigation module may still function correctly and be relied upon appropriately. When users fail to differentiate between modules, human–AI teaming may break down due to disuse or misuse of the system (Lee & See, 2004).

3.4 Human–AI Co-learning in a Lifecycle

The GHEA model describes human development across the lifespan as a continuous process of self-concept exploration and the refinement of knowledge and personality. Individuals across all age groups learn about AI, with each developmental stage characterized by different preferences and capabilities.

From a design cycle perspective, the iterative nature of AI development and evaluation (Miller et al., 2023) requires accounting for unique system requirements at each stage of the AI system lifecycle, including understanding of typical users' needs, prototyping and testing, deployment, maintenance and upgrades, the integration of complementary systems, and eventual retirement. The stakeholders involved may vary at each stage. For example, at the prototyping and testing stage, managers may play an important role in funding and resources; during normal operations, the typical stakeholders are the operators, trainers, and maintenance engineers. The desired outcomes at each stage may also differ. Therefore, identifying key stakeholders and understanding their collective self-concept can inform the design of the AI system attributes.

4 Designing for Human-AI Coevolution and Human Well-being

Industry 5.0 (European Commission, 2021) promotes the use of advanced personalized, adaptive, human-centric technologies to enhance human well-being, dignity, and performance. The GHEA model aligns with personalization and co-adaptive design principles and is broad enough to incorporate multimodal data and complex self-related psychological constructs.

For example, according to SDT (Ryan & Deci, 2000b), AI systems designed to support human well-being should aim to satisfy the three core psychological needs.

- AI systems can support the need for autonomy by offering customizable features that allow users to personalize their interactions. Designing for the need for competence requires understanding the target users' preferences and capabilities.
- Competence can be enhanced by designing AI that provides clear feedback and helps users accomplish their objectives, such as personalized learning platforms that adapt to an individual's skill level.
- Supporting relatedness requires an understanding of the social and emotional context in which the AI system will be used. Relatedness can be fostered by creating AI that recognizes and responds to users' emotions, fostering a sense of connection and understanding.

Meeting these needs enhances user satisfaction, promotes trust, and ultimately leads to AI systems that are not only functional but also impactful and engaging in human-centered applications. However, different domains and contexts may have unique needs and priorities, requiring further customization of the self-concept alignment.

Rather than relying on available features or one-size-fits-all solutions, the first step in AI system design is to understand the target user group's priorities, task flows, challenges, best practices, knowledge, skills, and personality traits through surveys, interviews, and cognitive task analyses. Since not all aspects of the self are equally prioritized, attributes valued in one domain may be less relevant in another. For example, youth robotics tournament participants highly value the need for autonomy, competence, and relatedness to others, whereas industry professionals often prioritize safety and productivity—factors that should guide the design focus accordingly. Professions such as air traffic controllers, UAV operators, and medical personnel emphasize safety but often face challenges like boredom (Cummings et al., 2016), therefore, AI features that address such challenges may become essential design priorities.

Future designs for human–AI teaming and well-being should apply this model to assess user group characteristics and their prioritized AI attributes within specific task domains. Designing AI attributes from the perspective of the GHEA model is a relatively new approach that requires further development.

5 Ethical Considerations in Emotional Attachment to AI

The research on GHEA focuses on promoting psychological well-being and personal growth, rather than manipulating attachment for commercial gain. Certain forms of attachments—such as video game addiction or romantic fixation on a virtual operating system (Her, 2013)—can be harmful and should be avoided. It is crucial to cultivate self-control and maintain healthy human relationships, rather than rely on attachment figures as an escape from real-life problems. Individuals and organizations must therefore refrain from exploiting GHEA to foster addictive behaviors.

Understanding the mechanisms of GHEA may offer insights into human emotional challenges and inform potential solutions. For example, Carpenter (2013) reported that soldiers became emotionally attached to their robots by naming them, demonstrating reluctance to send a robot to die, and even holding a funeral for destroyed units. According to the GHEA model, it is likely that certain robot attributes aligned with the individuals' self-concept and psychological needs, perhaps due to shared experiences and memories. Rather than simply finding such attachment intriguing or mysterious, we could investigate what the robot symbolized to the individual and consider appropriate counseling or interventions to address grief and support better decision-making. On the other hand, dementia patients in nursing homes often face caregiver shortages; in such cases, care from companion or assistive robots may be beneficial—provided the patients are motivated to interact with them (Mitzner et al., 2013). A potential solution is to identify their needs and design robot features that are most meaningful to them—i.e., aligned with their self-concept. However, humans possess an innate need for connection with other caring humans. AI and robots should be viewed as complementary—supporting well-being—rather than as substitutes for human relationships.

6 Conclusion

This paper explores key design considerations in human–AI coevolution to support human psychological well-being. Designing AI systems that align with the human self-concept can promote well-being, foster healthy emotional attachment, and improve human–AI teamwork outcomes. This human–AI co-learning unfolds across multiple levels—individual, team, and species—over varying timescales, ultimately driving coevolution. Human emotional attachment spans a spectrum—from indifference to full attachment—and correlates with positive emotions and attitudes, and various psychosocial constructs (e.g., trust, acceptance, liking, motivation).

Current machine learning often emphasizes scale and resource intensity, leading to inefficiency and over-reliance on big data. To overcome this, researchers must develop methodologies that prioritize data efficiency. These methods should extract higher-level abstractions and filter out irrelevant information, enabling effective learning from significantly smaller datasets. These advancements are essential for AI's progress.

By integrating Human Factors methods into existing machine learning pipelines, researchers can generate smaller, higher-quality datasets that enable more efficient learning on targeted topics. Such an approach advances sample efficiency, reduces training costs, and addresses practical scaling limitations. In doing so, AI design can better support human–AI teaming and user psychological well-being.

Acknowledgments

The author thanks the program chairs and two anonymous reviewers for their constructive feedback, which helped improve this paper. The author declares no funding support for this work and no conflicts of interest.

References

Her, 2013. Film.

F. Ansari, S. Erol, and W. Sihn. Rethinking human-machine learning in industry 4.0: How does the paradigm shift treat the role of human learning? *Procedia Manufacturing*, 23:117–122, 2018.

Anthony L Baker, Sean M Fitzhugh, Lixiao Huang, Daniel E Forster, Angelique Scharine, Catherine Neubauer, Glenn Lematta, Shawaiz Bhatti, Craig J Johnson, Andrea Krausman, et al. Approaches for assessing communication in human-autonomy teams. *Human-Intelligent Systems Integration*, 3(2):99–128, 2021.

Timothy T Baldwin, J Kevin Ford, and Brian D Blume. Transfer of training 1988–2008: An updated review and agenda for future research. *International review of industrial and organizational psychology*, pp. 41–70, 2009.

Albert Bandura. Social learning theory. *Englewood Cliffs*, 1977.

John Bowlby. *Attachment and loss*. Number 79. Random House, 1969.

Inge Bretherton. The origins of attachment theory: John Bowlby and Mary Ainsworth. *Developmental Psychology*, 28(5):759–775, 1992. ISSN 1939-0599 0012-1649. doi: 10.1037/0012-1649.28.5.759.

Carlos Bustamante Orellana, Lucero Rodriguez Rodriguez, Lixiao Huang, Nancy Cooke, and Yun Kang. Machine learning for automation usage prediction: identifying critical factors in driver decision-making. *Applied Intelligence*, 55(1):12, 2025.

Julie Carpenter. *The Quiet Professional: An investigation of US military Explosive Ordnance Disposal personnel interactions with everyday field robots*. PhD thesis, 2013.

Nancy Cooke, Mustafa Demir, and Lixiao Huang. A framework for human-autonomy team research. In *Engineering Psychology and Cognitive Ergonomics. Cognition and Design: 17th International Conference, EPCE 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part II 22*, pp. 134–146. Springer, 2020.

Nancy J Cooke and Steven M Shope. Synthetic task environments for teams: Certt's uav-ste. In *Handbook of human factors and ergonomics methods*, pp. 476–483. CRC Press, 2004.

Mary L Cummings, Fei Gao, and Kris M Thornburg. Boredom in the workplace: A new look at an old problem. *Human factors*, 58(2):279–300, 2016.

Fred D Davis et al. Technology acceptance model: Tam. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, 205:219, 1989.

Arwen H DeCostanza, Amar R Marathe, Addison Bohannon, A William Evans, Edward T Palazzolo, Jason S Metcalfe, and Kaleb McDowell. Enhancing human-agent teaming with individualized, adaptive technologies: A discussion of critical scientific questions. *US Army Research Laboratory Aberdeen Proving Ground United States*, 2018.

European Commission. Industry 5.0: Towards a sustainable, human-centric and resilient european industry. Technical report, Directorate-General for Research and Innovation, 2021. URL `https://research-and-innovation.ec.europa.eu/system/files/2021-01/industry-5.0_report.pdf`. Accessed March 27, 2025.

Weiwei Gu, Suresh Kondepudi, Lixiao Huang, and Nakul Gopalan. Continual skill and task learning via dialogue. *arXiv preprint arXiv:2409.03166*, 2024.

Kevin Anthony Hoff and Masooda Bashir. Trust in automation: Integrating empirical evidence on factors that influence trust. *Human factors*, 57(3):407–434, 2015.

Eric Holder, Lixiao Huang, Erin Chiou, Myounghoon Jeon, and Joseph B Lyons. Designing for bidirectional transparency in human-ai-robot-teaming. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 65, pp. 57–61. SAGE Publications Sage CA: Los Angeles, CA, 2021.

Hui-Ching Kayla Hsu, Cong Vivi Wang, and Chantal Levesque-Bristol. Reexamining the impact of self-determination theory on learning outcomes in the online learning environment. *Education and information technologies*, 24(3):2159–2174, 2019.

Lixiao Huang. Qualitative analysis of the application of self-determination theory in robotics tournaments. In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, pp. 135–136, 2017.

Lixiao Huang. Developing a scale to measure generalized human emotional attachment to robots and intrinsic motivation in human–robot interaction, March 2025. Manuscript under review.

Lixiao Huang and Douglas Gillan. An exploration of robot builders' emotional responses to their tournament robots. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 58, pp. 2013–2017. SAGE Publications, 2014. URL `http://pro.sagepub.com/content/58/1/2013.short`.

Lixiao Huang, Terri Varnado, and Douglas Gillan. An exploration of robot builders' attachment to their LEGO robots. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 57, pp. 1825–1829. SAGE Publications, 2013.

Lixiao Huang, Daniel McDonald, and Douglas Gillan. Exploration of human reactions to a humanoid robot in public stem education. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 61, pp. 1262–1266. Sage Publications Sage CA: Los Angeles, CA, 2017.

Lixiao Huang, ML Cummings, and Masahiro Ono. A mixed analysis of influencing factors for trust in a risk-aware autonomy. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 64, pp. 102–106. SAGE Publications Sage CA: Los Angeles, CA, 2020a.

Lixiao Huang, Jose Picart, and Douglas Gillan. Toward a generalized model of human emotional attachment. *Theoretical Issues in Ergonomics Science*, 22(2):178–199, 2020b.

Lixiao Huang, Nancy J Cooke, Robert S Gutzwiller, Spring Berman, Erin K Chiou, Mustafa Demir, and Wenlong Zhang. Distributed dynamic team trust in human, artificial intelligence, and robot teaming. In *Trust in human-robot interaction*, pp. 301–319. Elsevier, 2021.

Lixiao Huang, Jared Freeman, Nancy Cooke, John "JCR" Colonna-Romano, Matt Wood, Verica Buchanan, and Stephen Caufman. Artificial Social Intelligence for Successful Teams (ASIST) Study 3, 2022a. URL `https://doi.org/10.48349/ASU/QDQ4MH`.

Lixiao Huang, Jared Freeman, Nancy Cooke, Samantha Dubrow, John "JCR" Colonna-Romano, Matt Wood, Verica Buchanan, Stephen Caufman, and Xiaoyun Yin. Artificial Social Intelligence for Successful Teams (ASIST) Study 2, 2022b. URL `https://doi.org/10.48349/ASU/BZUZDE`.

Lixiao Huang, Adam Fouse, Nancy Cooke, and Edward Weiss. Artificial Social Intelligence for Successful Teams (ASIST) Study 4 Dragon Testbed Dataset, 2024. URL `https://doi.org/10.48349/ASU/ZO6XVR`.

Y.-C. Huang, Y.-T. Cheng, L.-L. Chen, and J. Y. Hsu. Human-ai co-learning for data-driven ai, 2019. URL `http://arxiv.org/abs/1910.12544`.

John D Lee and Katrina A See. Trust in automation: Designing for appropriate reliance. *Human factors*, 46(1):50–80, 2004.

Nathan J McNeese, Mustafa Demir, Nancy J Cooke, and Christopher Myers. Teaming with a synthetic teammate: Insights into human-autonomy teaming. *Human factors*, 60(2):262–273, 2018.

Merriam-Webster. Definition of evolution, February 4 2025. URL `https://www.merriam-webster.com/dictionary/evolution`. Accessed 2025-02-04.

Christopher Miller, Daniel Barber, Eric Holder, Lixiao Huang, Joseph Lyons, Emilie Roth, and Helen Wauck. Lifecycle transparency: Why, and how, transparency information exchange should be distributed throughout the life of technology usage. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 67, pp. 409–413. SAGE Publications Sage CA: Los Angeles, CA, 2023.

Tracy L. Mitzner, Charles C. Kemp, Wendy A. Rogers, and Linda Tiberio. Investigating healthcare providers' acceptance of personal robots for assisting with daily caregiving tasks. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems*, pp. 499–504, New York, NY, USA, 2013. Association for Computing Machinery.

Yinmei Ni, Jingwei Sun, and Jian Li. The shadowing effect of initial expectation on learning asymmetry. *PLOS Computational Biology*, 19(7):e1010751, 2023.

Richard M Ryan and Edward L Deci. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology*, 25(1):54–67, 2000a.

Richard M Ryan and Edward L Deci. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, 55(1):68, 2000b.

Richard M Ryan and Edward L Deci. On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual review of psychology*, 52(1):141–166, 2001.

Richard M. Ryan, James P. Connell, and Edward L. Deci. A motivational analysis of self-determination and self-regulation in education. *Research on motivation in education: The classroom milieu*, 2:13–51, 1985.

Carol D Ryff. Happiness is everything, or is it? explorations on the meaning of psychological well-being. *Journal of personality and social psychology*, 57(6):1069, 1989.

E. M. van Zoelen, K. van den Bosch, and M. Neerincx. Becoming team members: Identifying interaction patterns of mutual adaptation for human-robot co-learning. *Frontiers in Robotics and AI*, 8, 2021. URL `https://doi.org/10.3389/frobt.2021.692811`.

Xiao Wang, Guangyao Chen, Guangwu Qian, Pengcheng Gao, Xiao-Yong Wei, Yaowei Wang, Yonghong Tian, and Wen Gao. Large-scale multi-modal pre-trained models: A comprehensive survey. *Machine Intelligence Research*, 20(4):447–482, 2023.