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A Comprehensive Review of Human-AI Collaboration From Decision Support to Co-Creation

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مراجعة شاملة للتعاون بين الإنسان والذكاء الاصطناعي من دعم القرار إلى الإبداع المشترك

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ABSTRACT

Human-AI collaboration (HAIC) is rapidly transforming how we make decisions, use our creativity, and tackle problems in fields like engineering, design, healthcare, and education. This review looks at methods for HAIC, the kinds of interactions they employ, and how we assess their effectiveness. We begin by examining the various forms of cooperation, such as AI supporting decision-making, humans working together on creative projects, and systems that divide control based on the situation, outlining the differences between each and the situations in which they function best. Then we examine how to develop intuitive interfaces, incorporating tools that utilize visuals, natural language and multiple communication methods. A great deal of the review is concerned with how we assess these systems, not only their technical performance but also their usability, fairness, transparency, and level of trust. We also highlight the shortcomings of the current approaches and offer potential directions for the future, such as more intelligent adaptive interfaces, real-time explainability, and human-centered methodologies. In order to develop AI that complements and enhances human skills rather than replaces them, this survey attempts to link the most recent technological developments with what users truly care about.

Keywords: Collaboration; Artificial Intelligence; HAIC; AI; human-AI; Interactive AI; co-creative systems; Decision support; interaction; Trust in AI; Collaborative interfaces.

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INTRODUCTION

Modern artificial intelligence (AI) is thought to be a useful tool for enhancing human abilities and cognitive processes. In the end, AI seeks to establish a partnership or collaboration between humans and technology to tackle issues and find solutions that neither can successfully handle on its own. Numerous industries, including healthcare [1], software engineering [2], education [3], and the creative arts [4], have seen drastic changes as a result of this partnership.

Developing AI systems which can actually work collaboratively with humans remains a tough challenge despite the many achievements that are actually impressive. Indeed, users are often faced with many challenges that include trying to comprehend the processes that AI adopts, developing a trust rapport with AI, and communicating with it appropriately, whereas evaluation methodologies that are traditional often appear incompetent in accommodating an important aspect that relates to cooperative efforts, such as shared intentions and interpretability. Challenges such as this remain critical for overcoming to ensure that AI enhances human decision-making and productivity.

To facilitate effective collaboration, it is necessary that the users comprehend and trust the AI involved in this guidance and that the AI can adapt itself according to the limitations, choices, and intentions of the human. As a consequence, there has been the creation of a host of models that support collaboration like decision support systems [5], co-creation systems [6] and hybrid approaches [7]. All of the models have different design criterias and test methods.

Recently, technology developments in Multimedia AI and large language models, such as OpenAI's GPT-4, AlphaCode, and Med-PaLM from Google, have escalated human AI interaction. AI models have become more than simple assistive tools; they can have conversations, arrive at solutions to problems, offer alternatives, and provide instant feedback [8, 9].

However, there are some challenges, especially with regards to interface design, trust, and evaluation criteria. Conventional usability analysis methods do not attest to collaboration quality very well, thus resulting in novel methods being proposed based on transparency, fairness, reliability, and user satisfaction [10] [11] [12].

The aims of this research include achieving such goals as:

1. Model analysis & categorization for human AI partnering.

2. Identifying designs of user interface and interaction encouraging simplicity and teamwork.

3. Stating current issues and providing solutions for human adaptive AI systems.

Figure 1 illustrates the three most important pillars of this paper: Models, Interfaces, and Evaluation Metrics, and how these interact to facilitate human and AI system cooperation in different application domains. The article will bring order to the latest research conducted on these aspects in an attempt to summarize achievements and future directions.

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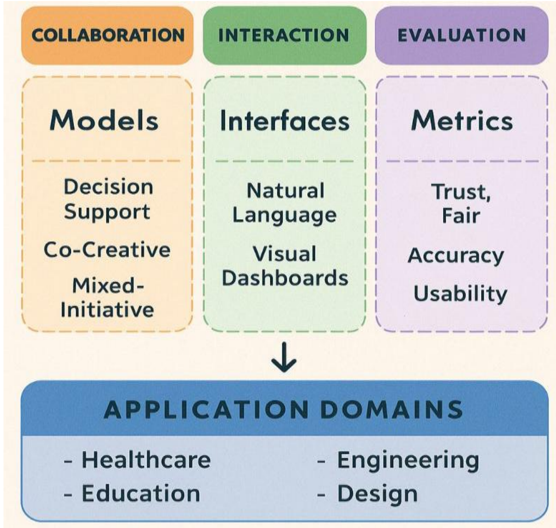

Figure 1: Core Components of Human-AI Collaboration

This review pulls together the latest research on human-AI collaboration by organizing it into three main areas: (1) models that explain how collaboration happens, (2) interface and interaction designs that make teaming effective, and (3) ways to measure both system performance and human outcomes. We also highlight what's been achieved so far, current challenges, and exciting paths for future work.

THE MOST RELATED WORKS

The study of human–AI collaboration has grown rapidly in recent years, with researchers examining how AI systems can better support human decision-making, trust, and shared control. Recent studies have proposed updated design principles for human-AI interaction, introducing 18 validated guidelines tested across real AI-enabled applications. Their evaluations with design practitioners highlight both the effectiveness of these guidelines and the remaining gaps that guide future research in human-AI collaboration [13].Ribeiro et al. [14] introduced the LIME framework, demonstrating how local explanations can help people understand and trust AI outputs, by learning an interpretable model locally around the prediction. They also present a method to explain models by presenting representative individual predictions and their explanations in a non-redundant way, framing the task as a submodular optimization problem. Researchers [15] presented Explanatory Debugging, an approach in which the system explains to users how it made each of its predictions, and the user then explains any necessary corrections back to the learning system. Amershi et al. [16] had examined the traditional applied machine-learning workflow, in which practitioners manage the full modeling pipeline, including data collection, feature selection, preprocessing, model representation and algorithm choice, parameter tuning, and model evaluation. Hoffman et al. [17] discussed specific methods for evaluating human–AI interaction and explainable AI (XAI) systems, including: the goodness of explanations, whether users are satisfied by explanations, how well users understand the AI systems, how curiosity motivates the search for explanations, whether users' trust and reliance on the AI are appropriate, and the last one how the human–XAI work system performs. De Visser et al. [18] contributed with a framework describing different levels of autonomy in AI–human teams, which is key to balancing control and delegation. Finally, Bommasani et al. [19] focused on the emergence of foundation models, large-scale systems like BERT and GPT that enable broad, adaptable capabilities across language, vision, and decision-making tasks. While they offer major opportunities, researchers emphasize their significant risks—such as bias, misuse, and unpredictable failures—calling for interdisciplinary work to address their sociotechnical impact. Xu et al. [20] reported the results of a behavioural experiment in which subjects were able to draw on the support of an ML-based decision support tool for text classification. Shneiderman [21] designed well- technologies that offer high levels of human control and high levels of computer automation can increase human performance, leading to wider adoption. Similarly, Lage *et al.* [22] optimized for interpretability by directly including humans in the optimization loop. Also they minimized the number of user studies by developing an algorithm to find models that are both predictive and interpretable.

Through these works, we observe continuous progress in improving collaboration models, calibrating trust, and evaluating systems, while also drawing attention to the difficulties of transferring these ideas to practical applications in the real world.

Table 1. Summary of Related Works.

Ref.	Authors & Year	Focus Area	Contribution
[13]	Amershi et al., 2019	Human–AI interaction design	18 guidelines for designing effective and trustworthy interactions.
[14]	Ribeiro et al., 2016	Explainability	Introduced LIME for local model explanations, improving transparency.
[15]	Kulesza et al., 2015	Interactive debugging	Showed how explanatory debugging helps users refine models.
[16]	Amershi et al., 2014	Interactive ML	Highlighted the role of humans in training and steering AI systems.
[17]	Hoffman et al., 2018	Evaluation metrics	Proposed metrics for explainable AI focusing on trust and usability.
[18]	De Visser et al., 2018	Human–AI teaming	Presented a framework for levels of autonomy in AI–human collaboration.
[19]	Bommasani et al., 2021	Foundation models	Examined risks and opportunities of foundation models for collaboration.
[20]	Xu et al., 2020	Medical AI & transparency	Studied how transparency affects trust and adoption in healthcare AI.
[21]	Shneiderman, 2020	Human-centered AI	Proposed a framework prioritizing responsibility, reliability, and empowerment.
[22]	Lage et al., 2018	Integrating human judgments into model interpretability	Introduces an interpretability prior based on human feedback, enabling models to learn explanations that align better with human intuition without sacrificing accuracy.

BACKGROUND AND MOTIVATION

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The vision of humans and intelligent machines working together has long been part of computing history, dating back to early conceptual frameworks such as Licklider's "man-computer symbiosis" in 1960 [23]. However, only in the last decade—thanks to significant advancements in artificial intelligence, especially in natural language processing, reinforcement learning, and deep learning—has effective human-AI collaboration become practically viable.

The cooperation of one or more humans with AI systems is referred to as human-AI collaboration. Human-AI collaboration suggests that AI systems collaborate with humans as partners or teammates to solve problems, as opposed to the past scenario where AI systems were primarily automating repetitive human tasks. Consider, for example a decision support system (CDSS) collaborating with a physician to identify the cancer stage [24] as well as software engineering, where AI assists developers using tools such, as GitHub Copilot [25].

Multiple key insights act as the motivation, for creating collaborative AI systems:

• **synergy:** People are superior in understanding, moral judgment and imagination whereas AI systems are superior, in processing speed, storage capacity and identifying patterns. This combination can enhance both the quality and speed of decision-making [26].

• **Trust deficits and user-friendliness:** Black-box AI models frequently underperform in settings because of limited transparency. Human-AI teamwork aims to bring interpretability and a feedback loop to bridge these shortcomings [27].

• **Task complexity**: For example, diagnosis in medical domains and in-car tasks has reached such a level of complexity that neither humans in isolation nor computers in isolation can operate effectively. Such a task can be usefully shared in a cooperative system [28].

• **Collaborative learning and adaptation capabilities:** Startups working on interactive machine learning aim at creating learning algorithms using a continuous interaction process with users, which on the other hand have also received prominence in adaptive systems regarding optimizing AI behavior in line with human workflow capabilities [29].

Further, research in massive infrastructure models such as GPT-4, Claude, and Gemini has allowed a new technology class to arise with capabilities for a dialogue system, solving issues, and creative problem-solving, in other words, a tool and a collaborator interface [30]. However, this raises challenges in designing appropriate interfaces, managing role distribution, and establishing clear standards for evaluating collaboration effectiveness.

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The following sections build on this motivation by analyzing different models of collaboration, interaction mechanisms, and evaluation strategies that define the current landscape of human-AI collaboration research.

MODELS OF HUMAN-AI COLLABORATION

Frameworks of AI partnership illustrate the ways humans and AI technologies engage, allocate control and split cognitive along, with operational responsibilities. These frameworks vary regarding efficiency, proactiveness, interaction approach and degree of independence influenced by the task, context and design of the system. In this part we examine the categories of collaboration frameworks: decision support systems, co-creative systems and mixed-initiative systems. We also explore recent developments in adaptive learning architectures and human-in-the-loop learning. Figure 2 illustrates the three main models of human–AI collaboration, highlighting how control, initiative, and interaction are distributed between humans and AI systems.

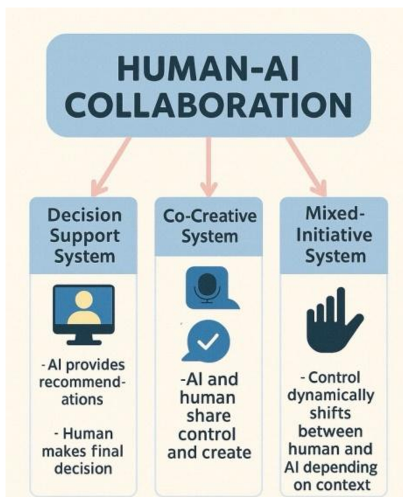

Figure 2: Models of Human-AI Collaboration

In decision support systems, artificial intelligence is used as a tool to assist decision-makers in analyzing data, providing recommendations, or predicting outcomes, while the final decision remains under human control. These systems are widely used in healthcare, finance, and risk assessment. For example, in medical diagnosis, systems like the AI-powered clinical decision support system "Watson for Oncology" provide doctors with ranked treatment recommendations based on clinical guidelines and the patient's history [31Systems like "Babylon Health" provide AI-assisted triage systems that support healthcare professionals through suggesting diagnoses and treatment options [32]. In general, decision support systems raise the important issue of trust calibration; that is, how to ensure users do not rely too much or too little on the AI suggestions given to them [33].

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Collaborative creativity systems collaborate with the AI as a creative partner in real time, working together to create various works, including texts, music, designs, and software. These systems share ideas, explore, and develop jointly, offering flexible and shared control. Perhaps the most well-known is Magenta Studio, a Google project running deep learning algorithms to assist musicians in the creation of melodies and rhythms in a collaborative manner. In the visual arts, there are tools like GANPaint Studio, where one can edit images in collaboration with the algorithms provided by the GAN. Then there are the collaborative writing tools like Sudowrite and AI Dungeon.

Collaborative initiative systems allow both humans and artificial intelligence to actively contribute to a process and lead it in a collaborative process. In collaborative initiative systems, both human participants and artificial intelligence share control. In other words, they can join in or leave a process depending on the situation.

This strategy has been highly effective in many areas, like autonomous vehicles, military strategy, and smart education. For example, “Kewalis” is a new-style mixed initiative system using LLMs to help leaders of civil society design targeted and meaningful questions in surveys, interviews, and discussion guides [36]. Current collaborative dialogue systems rely on sophisticated methods of handling neural dialog processes to guide dialog, make sure the responses of the AI system meet user intentions, and track dialog contexts [37].

There has been a recent trend in designing Human-in-the-Loop (HITL) interaction systems and collaborative adaptive systems, where users adapt to the patterns of sophisticated AI, and the sophisticated AI learns as well based on the feedback obtained from the users. Models that consist of similitude and dissimilitude are basic in fields that entail adaptive learning systems, for instance, AI-mediated programming systems.

Allowing users to correct errors, review results, and rate the responses from the AI helps greatly in making the system smarter and more enjoyable to use. However, studies also show that the way this feedback is collected is important, as a poorly designed process can reduce user trust or make the AI appear less accurate [38].

SUMMARY AND CHALLENGES

To clarify the distinctions among the major models of human–AI collaboration, the table below summarizes the respective roles of humans and AI, their modes of control sharing, and typical application domains. **Table 2** presents a concise comparison of decision support systems, co-creation systems, and mixed-initiative systems.

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Table 2. Comparison of Human-AI Collaboration Models

Model	Initiative	Human Role	AI Role	Examples
Decision Support	Human-dominant	Decision-maker	Advisor / recommender	Watson, Babylon
Co-Creative	Shared	Collaborator	Collaborator	Magenta, GANPaint
Mixed-Initiative	Context-driven	Co-controller	Co-controller	CALO, smart assistants
Human-in-the-Loop	Adaptive feedback	Trainer, corrector	Learner, personalizer	Teachably, PROSE

INTERFACE AND INTERACTION DESIGN

Human-AI collaboration is greatly dependent on interface design. Human-computer interfaces influence how people interpret, believe in, and interact with AI because they function as an intermediary between people and intelligent systems. While standard human-computer interfaces focus on awareness, control, transparency, and one-way communication, human-AI interfaces require awareness, control, transparency, and two-way communication.

KEY DESIGN PRINCIPLES

Best practices for collaborative interfaces have been formed by a number of human-computer interaction (HCI) studies. Amershi et al. [39] proposed many rules for connecting between human and AI to control user expectations, support meaningful feedback, and align with users' goals. Some of the fundamental ideas are:

- **Explain ability**: Communicating how and why the AI makes certain predictions.
- **Controllability**: enabling users to modify AI actions when is needed.
- **Error Management**: Ensuring that system errors are easily identifiable and enabling users to correct them or recover their costs.
- **Adaptation:** Continuous adaptation by learning from user behavior to improve the quality of interaction and personalization over time.

The necessity of system-to-user communication of system goals and status was also highlighted in a study by Pilotti et al. [40]. This study provides a basis that can be effectively used in building and adjusting trust.

MODALITIES OF INTERACTION

Artificial intelligence technology has over the years remained a core base pillar in multimodal interaction, used for the sensing of user intentions, actions, and emotional expressions. In this respect, it is apparent that the role of artificial intelligence has remained crucial toward enabling the use of technology towards making the interacting process with computer systems easier and more seamless through the multimodal approach. For instance, the best interface for a user can depend on the situation. In a medical setup or a scientific presentation, a graphical interface works perfectly. In education or composition, the natural language interface is more effective.

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Before examining the types of user interfaces, it is beneficial to examine a general overview of how information is communicated between humans and computers. Below is a general overview of how a human and artificial intelligence work together from Figure 3.

From this overview, it can be noted how a human inputs information such as writing or speaking, and how this information is then processed by artificial intelligence and how it produces an output. An example of this output could be in the form of hearing or seeing feedback, or seeing graphics and highlights.

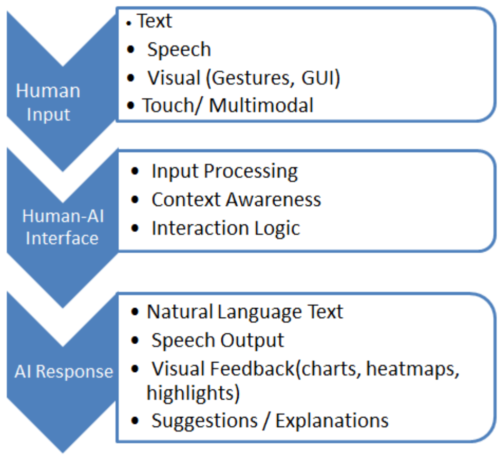

Figure 3: Modalities of Interaction in Human-AI Collaboration

There are many different ways that a user can interact with artificial intelligence, and the best one often depends on the task at hand, as illustrated in Figure 3. One of the most common is by using natural language-written or spoken input, as if the user were having a conversation with the system. When the information being conveyed is best understood in a graphical format-such as data analysis or space exploration-the AI system utilizes graphs, maps, and other visual tools for clearer communication. Nowadays, we also see systems that integrate more than one type of input and output, including voice, touch, and visual, in order to create an experience both richer and more flexible.

TRUST AND TRANSPARENCY

Trust is believed to be a key component in teamwork. The user interfaces should aid users in comprehending the degrees of trust in AI, reasoning paths, and the limitations of AI reasoning. Visualization-based approaches have widely demonstrated a positive effect on increasing the trusting perception of users and the efficiency of the AI system itself [41].

On the other hand, excessive information may confuse the user; therefore, a degree of adaptive transparency may be necessary in the system. This is where the system will adapt the information given based on the level of expertise of the user.

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PERSONALIZATION AND USER MODELING

Advanced collaborative environments require user modeling, where the design of the user interface is adapted according to the past experience, preferences, and intellectual patterns of the users. More recently, an intelligent tutoring system was put together by Shamkar and his colleagues in the field of education, and the system is called “Ravel and Riley.” It holds conversations that are very much interactive in nature between the students and the tutor, and this is done through the use of the large language model, similar to the way teachers converse with the students.

However, the goal of finding an equilibrium between personalization and consistency is not easily accomplished because the availability of adaptive interfaces increases complexity [44].

CONCLUSION

The collaboration made possible between Humans and AI allows for both independent work. In this review, cooperation frameworks beginning with a choice-support role to a human and other forms involving dynamic shared control have been highlighted. In addition to this, design requirements for interfaces featuring both language and image have been covered for effective cooperation. The evaluation of systems like this entails more than the necessary technology requirements with important consideration for aspects like user trust levels, transparency, and human-AI collaboration quality. The success in human-AI collaboration will depend on finding a delicate balance between technology development and human needs. Human-AI collaboration will enable the design of true human collaboration tools. We will test this in real-world settings.

Conflict of Interests.

There are non-conflicts of interest.

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مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية

الخلاصة

يُحدث التعاون بين الإنسان والذكاء الاصطناعي تحولًا سريعًا في كيفية اتخاذنا للقرارات، واستخدامنا لخيالنا، وحل المشكلات في مجالات عديدة، تشمل التصميم والهندسة والرعاية الصحية والتعليم .تستعرض هذه الدراسة أساليب التعاون المختلفة بين الإنسان والذكاء الاصطناعي، وأنواع التفاعلات التي يستخدمونها، وكيفية تقييم فعاليتها .نبدأ بتحليل الأشكال الأساسية للتعاون، مثل مساعدة الذكاء الاصطناعي في اتخاذ القرارات، والتعاون مع البشر في الإبداع، والأنظمة التي تتشارك التحكم بناءً على الموقف، مع وصف ما يميز كل شكل منها، وفي أي سياق يكون أكثر فعالية .بعد ذلك، نستكشف كيفية إنشاء واجهات موثوقة وسهلة الاستخدام، بما في ذلك الأدوات التي تستخدم العناصر المرئية واللغة الطبيعية وقنوات الاتصال المختلفة .يركز جزء كبير من هذه الدراسة على كيفية تقييم هذه الأنظمة، ليس فقط من حيث أدائها التقني، بل أيضًا من حيث سهولة استخدامها، وعدالتها، وشفافيتها، ومستوى الثقة بها .كما نسلط الضوء على أوجه القصور في المناهج الحالية، ونقدم توجهات مستقبلية محتملة، مثل واجهات تكيفية أكثر ذكاءً، وقدرة على التفسير في الوقت الفعلي، ومنهجيات تركز على الإنسان .من أجل تطوير الذكاء الاصطناعي الذي يكمل ويعزز المهارات البشرية بدلاً من استبدالها، تحاول هذه الدراسة الاستقصائية ربط أحدث التطورات التكنولوجية بما يهتم به المستخدمون حقًا.

الكلمات المفتاحية: التعاون بين الإنسان والذكاء الاصطناعي؛ أنظمة الذكاء الاصطناعي التفاعلية؛ الأنظمة الإبداعية المشتركة؛ دعم اتخاذ القرار ؛ التفاعل ذو المبادرات المختلطة؛ الثقة في الذكاء الاصطناعي؛ واجهات التعاون.