

From General to Personal: A Review of the Human-AI Interaction Frameworks through the Lens of Cognitive Styles

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ABSTRACT

Human-Computer Interaction (HCI) has rapidly evolved into Human-AI Interaction (HAI) in recent years, transforming the emphasis from standardised, general design to personalised frameworks. This article reviewed the evolution of interaction design frameworks through the lens of cognitive styles. The paper first outlines the limitations of general design frameworks, such as GOMS and KLM. These frameworks emphasise efficiency and predictability, but ignore individual differences. It then explores the rise of recommender systems, which introduce personalised interactions in the phase of behaviour. This review highlights the recent advancements in Large Language Models (LLMs) and multimodal AI systems. These systems can provide real-time responses, explainability, and customised responses tailored to users' cognitive styles. By organising the existing literature, this article ensures the key advantages, gaps, and challenges of integrating cognitive style into HAI frameworks. Future research should focus on further developing cross-field methodologies that combine cognitive psychology and AI-driven personalisation, and then create an HAI system with adaptability, explainability, and trustworthiness.

KEYWORDS

Human computer interaction; Human-AI interaction; Cognitive style; Personalized system; Large language models

1 Introduction

1.1 Research background and motivation

In recent years, the rapid development of artificial intelligence (AI) technologies has benefited research and applications across various domains, thereby making them more convenient and efficient. Human-Computer Interaction (HCI), a mature field of multidisciplinary intersection with decades of development, has recently given rise to a new research branch: Human-AI Interaction (HAI). HAI is driven by the rapid advancement and profound impact of AI, the rise of it signifies a shift in the focus of interaction "Human Computer" paradigms to encompass "human-AI systems". As a result, HAI has aroused extensive academic attention and commercial application.

1.2 Why cognitive style and personalization matter

Since HCI became a popular topic, most discussions have focused on its standardization and general interaction interface design that works for "all users". However, there has been less emphasis on classifying user types or considering the differences in cognitive style. However, with the deeper research on HAI, people started to realize the features of AI, which is the ability to provide different and personalized responses based on users' characteristics. To enhance the user experience, the design of HCI began to shift from a general to a personalized approach.

As the pattern of perception, memory, thinking, and solving problems, users' cognitive style has crucial theoretical and practical significance in the field of HCI and HAI^[1]. The existing research has shown that users' interaction method, efficiency, and satisfaction when interacting with AI system are directly influenced by their cognitive styles^[2]. User's experience and interaction outcomes can be greatly enhanced if the system accommodates different cognitive styles^[2].

Moreover, as the frontier research topic of HCI, the existence of HAI has driven several related research and applications. At present, HAI has deeply applied in many different fields such as healthcare, autonomous driving, customer service, education, intelligence recommendations, etc^[3]. HAI is a field with a very broad prospect and worth exploring, as it has potential to improve the intelligence and user experience of the system, and reduced users' cognitive load when they face the complex software and question^[4]. Nevertheless, the existing HAI system still mainly adopts universal design, and is less focused on the individual differences between users, especially on the personalized requirements in cognitive style aspects. This situation limited the usage experience and the practical application effect of the AI system to a certain extent. Therefore, research on how cognitive styles influence the personalized design paradigms and evolution of HAI holds significant research value and implications for promoting both theoretical innovation and practice application in the field.

1.3 Research aims

Although some studies have addressed the application of cognitive style in HAI, the review and discussion of how design frameworks have evolved remain limited. This study aims to review the evolution of HAI from a general approach

to a more personalized one, with a particular focus on how different cognitive styles influence the development of design frameworks. Additionally, this will summarize the commonalities, limitations, and future directions of existing literature.

2 Searching methodology

This chapter will briefly describe the strategy to collect and manage literature. To be more specific, it will contain the discussion of keywords and searching strategy, the criteria of including or excluding, and the introduction for literature management application.

2.1 Keywords and searching strategy

To answer the question of how cognitive style changes the design of HAI, this article will apply the narrative literature review method. The search focused on three main topics: HAI, cognitive style, and their combination and co-evolution. The incipient searching direction is to gather topic-related information and learn existing findings and definitions; hence, the method focuses on searching for single or multiple keywords, including but not limited to “Human-Computer Interaction or HCI”, “Human-AI Interaction or HAI”, “Cognitive Style”, and “Personalized Design”. The search keywords will be updated by combining these research fields to gain significant cross-field research. Combined search keywords “the evolution from HCI to HAI” and “Cognitive Style and HAI” became the target field at next stage.

Furthermore, the choice of target databases is directly related to the scope and authority of the literature review, which plays a significant role in this article. Different databases have their own characteristics and rules for embodying articles. In this review, databases named “Web of Science” and “Scopus” are used during the literature search, and both databases contain cross-field and high-quality journals. Additionally, Google Scholar is another valuable search engine for locating academic articles, supporting basic and advanced keyword searches. Compared with databases, Google Scholar provides a broader range of searching, which can supplement the parts of articles that are not included in databases, such as conference and preprint articles.

2.2 Including/excluding criteria

The criteria of including/excluding literature need to be carefully designed to screen the literature with high quality, it can not only provide a filter list, but also specified the research direction and edge of this review. This chapter will introduce multiple criteria that have been used during the literature searching.

2.2.1 Including criteria

- (1) The literature is directly connected to the research topic/core of the topic, with an important insight into theory, method, or empirical research.
- (2) The literature should be peer-reviewed journal articles, academic monographs, or reports from official organizations. Moreover, preprints are also valuable since this study aims for an emerging research field.
- (3) The primary focus is on the literature published in the past 10 years to ensure this article showcases the latest research trends.
- (4) The written language should be English to ensure the internationality of the article.
- (5) The article should have clear and detailed research content on the core concept (Human-AI Interaction, cognitive style, personalized, etc.).
- (6) Literature that does not directly meet the criteria can be selectively included if it provides inspiration or contains a valuable methodology.

2.2.2 Excluding criteria

- (1) Although the literature has the same terminology or keywords, it is in a different field.
- (2) The literature lacks academic review, such as a meeting abstract, a business report, or an unverified blog.
- (3) Outdated and lacking updated literature, unless it has historical value.
- (4) The literature other than English will not be considered.
- (5) The study where core concepts have been generalized will not be considered.

2.3 Management tool

Literature management is a significant step for a review article because it usually contains and cites a large amount of literature. The selected literature can be managed and cited properly by applying Zotero^[5], a professional literature reading and management tool. In Zotero, the selected literature can be classified by different dimensions. In addition, because most literature that can be searched online will be downloaded in PDF format, Zotero provides a complete PDF reading system, which allows users to translate, make notes, and highlight important content easily.

3 Result

3.1 HCI and HAI

3.1.1 The universal design of HCI

Accessibility is a key element in HCI; traditionally, it was understood as a support technology for disabled people that developed after the requirement appeared. Nevertheless, this idea no longer supports the requirement, in which the design needs to be updated into a universal design that ensures functions are well-designed during the early stage of development ^[6]. Universal design is a meaningful topic; it aims to transfer the idea from “the good design needs to be based on user” to “the design that satisfy the requirement from all potential users” ^[7]. The universal design of HCI is to actively and systematically apply methods, principles, and tools to develop technology products and services that can be accessed by all individuals ^[7]. In other words, universal design does not develop special functions on existing products; instead, it should consider individuals’ requirements and usage conditions as broadly as possible.

3.1.2 The rise and characteristics of HAI

Xu ^[8] claimed a systematic conceptual framework named “Human-Centered Artificial Intelligence” (HCAI), and this framework mainly discussed that during the development of AI, humans and ethics are two aspects that require consideration in addition to technology. Besides, HAI is the product that emerged under the guidance of HCAI and widely affects the current society. As long as the design or application involves the interaction between humans and AI, such as smartphones or intelligent decision-making systems, they all belong to the scope of HAI ^[9]. Specifically, HAI is a cross-field research that studies the cooperation between human users and AI systems in real-world situations ^[10]. HAI takes HCAI as a core idea, focusing on how to design an AI system that can understand and adapt to users, explain their own behavior, and maintain the trust of humans and ethical standards, which enables the AI system to enhance and improve humans’ ability instead of replacing them ^[10]. As a result, people start to pay more attention to AI systems. A study showed that the work efficiency can be improved when a human and an AI system work as a group instead of individually ^[11]. Compared with HCI, the adaptability and learning of HAI show significant differences. With the support of AI, the system can analyze users’ behavior, so that it has the potential to adapt to different tasks and environments ^[3].

3.2 Concept and classification of cognitive style

In cognitive psychology, cognitive style refers to individuals’ thinking habits; in other words, it determines individuals’ patterns of solving problems, thinking, perceiving, and memorizing ^[1]. An individual’s cognitive style has relatively stable characteristics; most people will be stable during an extended period, but it also has certain plasticity ^[12]. Furthermore, the individual differences in cognitive style are usually noticeable. Because the cognitive style is built on different social activities, concept acquisition, and culture, it will keep growing and developing throughout the life cycle; hence, most people have unique cognitive styles ^[13].

Riding and Cheema ^[14] researched different dimensions of cognitive style. They integrated several cognitive style studies, and classified them into two most basic dimensions: “Wholist-Analytic style” and “Verbaliser-Imager style”. Besides, these two dimensions are independent, which means that an individual can be “Wholist + Verbaliser” or “Wholist + Imager”. The description of the four types of cognitive styles will be listed below ^[14].

(1) Wholist: the individual who tends to recognise the information as a whole, prefers cooperation and studying as a group.

(2) Analytic: the individual who tends to break down and analyze information, prefers to work alone, and is good at structural tasks.

(3) Verbaliser: the individual tends to use words and languages to indicate and process information.

(4) Imager: the individual tends to use images and visual effects to indicate information.

Detailed relationship and combination between the dimension above can be found in table 1.

Table 1 Two-dimensional cognitive style framework table

	Verbaliser	Imager
	Wholist + Verbaliser:	Wholist + Imager:
Wholist	This style tends to use language to control the global structure; prefers to understand the abstract first; and is suited to understand the content through summaries, explanations, and narratives.	This style tends to perceive the whole through the image; it prefers to understand the abstract first; it is suitable to use images, tables, and diagrams to understand.
	Analytic + Verbaliser:	Analytic + Imager:
Analytic	This style proceeds through logical reasoning in language; prefers a step-by-step, structured learning approach; is suitable for understanding the content through textual explanations and logical deductions.	This style will gradually analyze details through graphical means; it prefers visual decomposition methods; and is suitable for using flowcharts and diagrams to explain step by step.

3.3 Personalized interaction

In HCI, personalisation refers to designing an interaction system that can support the user's special requirements^[15]. Moreover, the meaning of personalised is mainly presented in three aspects: (1) saving cognitive resources and making control easier. Personalised functions can reduce the time spent and mental load when the user searches and recognises information^[16]. (2) Enhanced the relevance of content and the user's satisfaction. Compared with a general interface, a personalised system can provide an interaction that fits users' background and habits better, significantly increasing the experience satisfaction^[15]. (3) Enhanced users' trust and loyalty. An appropriate personalised system contributes to building trust, enhancing the adhesiveness of users, and increasing users' loyalty to the system^[17].

3.4 The evolution of HAI framework: from general to personal

3.4.1 Stage of general interaction model

Early HCI and HAI research widely applied generalised interaction models. Due to the limitations of technology and data collection, the designer tended to use a uniform, standardised interface that could satisfy most users, to simplify the development and maintenance process. This type of design meets the requirements of high predictability, low cost, and easy to popularise.

Two classic interaction frameworks were introduced by Card, Moran, and Newell in 1983: Goals-Operators-Methods-Selection (GOMS) and its simplified form, Keystroke-Level Model (KLM)^[18]. GOMS divides a complete task into goals, operators, methods, and selections, then quantitatively predicts the execution time of the task. KLM further simplified this process; it only considers the standard operations, such as keystroke, pointing, or mental preparation, making it suitable for rapidly estimating task performance.

Despite GOMS and KLM having advantages in accessibility evaluation, they assume that all users take the same operations, and no mistakes happen, which ignores users' individual differences, learning curve, and cognitive style differences. Besides, it is difficult to apply to non-expert and rookie users; hence, these models are hard to support personalised interaction.

3.4.2 Introduction of differential interaction

With the development of the internet and data collection technologies, researchers noticed significant differences in behaviors and preferences between users. Hence, the focus of the HCI system gradually transformed to individual differences instead of a general system for all users. The rise of user modeling and recommendation systems promoted research on diverse responses of different users to the interactive interface.

The representative framework for this stage is the Recommender System, which was widely applied during the 2000s, and it is designed to handle the problem of information overload caused by the explosive growth of information on the Internet^[19]. This system will aggregate and match the recommendations from different users, then push the appropriate content to the people who need it^[20]. The system uses filter technology such as content-based, collaborative, and hybrid filtering to aggregate users' preferences and provide personalized service^[19].

Although the difference between users' preferences is considered, most personalized systems are still behavior-driven recommendations, and have not combined the system with deeper psychological features, such as cognitive style, which leaves room for improvement in personalized interaction experience.

3.4.3 Cognitive style adaptation between LLM and multi-modal interaction

In recent years, the Large Language Model (LLM) and multi-modal AI systems have developed rapidly, which makes interaction more intelligent. Thanks to the high performance of LLM, it provides a suitable interaction experience in real time by dynamically collecting users' feedback and cognitive characteristics. The system can recognize and generate personalized responses, then combine them with multi-modal input, such as sending text, speaking a message, and pictures, to adapt to individual differences accurately^[21]. The studies indicate that the personalized interface supported by LLM can achieve an active response, be highly explainable, and provide a reply that matches the user's cognitive style^[22-23].

Despite the LLM having stronger adaptation ability, people are worried about their privacy since AI knows more and more about users. In this case, a chain of rules that aims to handle the AI-related problem, such as user privacy, controllability, and ethics, should be carefully considered.

4 Discussion and conclusion

This research revealed the transfer process from general design to personalised design by reviewing the evolution process from HCI to HAI. During the early stage, researchers relied more on general frameworks with high predictability and efficiency, such as GOMS and KLM. Although these frameworks have advantages in usability assessment, they

overlook individual differences between users, which makes it challenging to meet the needs of new users or those with different cognitive styles. With the appearance of recommender systems and differential interaction, personalisation gradually becomes a significant characteristic of system design. Nonetheless, the personalisation in this stage focused more on user behaviour-driven recommendations and has not been fully integrated with the deeper psychological characteristics. For the past few years, the LLM and multimodal AI have developed rapidly, pushing personalised interaction into a new era. LLM can not only collect feedback dynamically from users and generate corresponding responses, but also exhibit great explainability and initiative, which provides new opportunities for the application of cognitive style in the HAI framework. However, the current researches still have limitations: (1) Over-reliance on behavioural data, the psychological differences such as cognitive style have not been fully modelled yet; (2) The balance between personalisation and privacy protections, controllability and ethics is not entirely solved yet.

5 Future work

As a result, future research should further explore the combination of cognitive style and LLM-driven interaction mechanisms from a cross-field perspective, building a personalised framework with higher adaptability and explainability under the premise of privacy and trust.

References

- [1] M. Kozhevnikov, 'Cognitive styles in the context of modern psychology: Toward an integrated framework of cognitive style', *Psychol. Bull.*, vol. 133, no. 3, pp. 464–481, May 2007.
- [2] Y. Shin, K. Ranjan, M. C. Kowalski, and J. Yoon, 'Toward personalized AI-powered recommender systems to support users' daily music choice experiences', *Int. J. Hum.-Comput. Stud.*, vol. 203, p. 103574, Sept. 2025.
- [3] C. Zhao, 'Human-AI Interaction Design Standards', 2025.
- [4] M. Virvou, 'The Emerging Era of Human-AI Interaction: Keynote Address', in 2022 13th International Conference on Information, Intelligence, Systems & Applications (IISA), July 2022, pp. 1–10.
- [5] 'Zotero', Zotero. [Online]. Available: <https://www.zotero.org/>
- [6] D. Akoumianakis and C. Stephanidis, 'Universal Design in HCI: A critical review of current research and practice'.
- [7] C. Stephanidis, D. Akoumianakis, and A. Savidis, 'Universal Design in Human-Computer Interaction'.
- [8] W. Xu, 'Toward human-centered AI: a perspective from human-computer interaction', *Interactions*, vol. 26, no. 4, pp. 42–46, June 2019.
- [9] W. Xu, L. Ge, and Z. Gao, 'Human-AI interaction An emerging interdisciplinary domain for enabling human-centered AI', Oct. 2021.
- [10] Interaction Design Foundation, 'What is Human-AI Interaction (HAX)?', What is Human-AI Interaction (HAX)? Accessed: Aug. 06, 2025. [Online]. Available: <https://www.interaction-design.org/literature/topics/human-ai-interaction>.
- [11] G. Bansal, B. Nushi, E. Kamar, D. S. Weld, W. S. Lasecki, and E. Horvitz, 'Updates in Human-AI Teams: Understanding and Addressing the Performance/Compatibility Tradeoff', *Proc. AAAI Conf. Artif. Intell.*, vol. 33, no. 01, pp. 2429–2437, July 2019.
- [12] R. C. A. Bendall, A. Galpin, L. P. Marrow, and S. Cassidy, 'Cognitive Style: Time to Experiment', *Front. Psychol.*, vol. 7, Nov. 2016.
- [13] M. Kozhevnikov, C. Evans, and S. M. Kosslyn, 'Cognitive Style as Environmentally Sensitive Individual Differences in Cognition: A Modern Synthesis and Applications in Education, Business, and Management'.
- [14] R. Riding and I. Cheema, 'Cognitive Styles—an overview and integration', *Educ. Psychol.*, vol. 11, no. 3–4, pp. 193–215, Jan. 1991.
- [15] T. Neumayr and M. Augstein, 'A Systematic Review of Personalized Collaborative Systems', *Front. Comput. Sci.*, vol. 2, p. 562679, Nov. 2020.
- [16] M. Zanker, L. Rook, and D. Jannach, 'Measuring the impact of online personalisation: Past, present and future', *Int. J. Hum.-Comput. Stud.*, vol. 131, pp. 160–168, Nov. 2019.
- [17] K. Hardcastle, L. Vorster, and D. M. Brown, 'Understanding Customer Responses to AI-Driven Personalized Journeys: Impacts on the Customer Experience', *J. Advert.*, vol. 54, no. 2, pp. 176–195, Mar. 2025.
- [18] S. K. Card, T. P. Moran, and A. Newell, *The psychology of human-computer interaction*, Repr. Mahwah, NJ: Erlbaum, 1983.
- [19] F. O. Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, 'Recommendation systems: Principles, methods and evaluation', *Egypt. Inform. J.*, vol. 16, no. 3, pp. 261–273, Nov. 2015.
- [20] P. Resnick and H. R. Varian, 'Recommender systems'.
- [21] R. Mendoza et al., 'Adaptive Self-Supervised Learning Strategies for Dynamic On-Device LLM Personalization', Sept. 25, 2024, arXiv: arXiv: 2409.16973.
- [22] J. Chen et al., 'When Large Language Models Meet Personalization: Perspectives of Challenges and Opportunities', *World Wide Web*, vol. 27, no. 4, p. 42, July 2024.
- [23] X. Li, R. Zhou, Z. C. Lipton, and L. Leqi, 'Personalized Language Modeling from Personalized Human Feedback', Dec. 09, 2024, arXiv: arXiv: 2402.05133.