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Large Language Models and the Future of Human–Computer Interaction

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Abstract

Large Language Models (LLMs) are fundamentally changing the way humans interact with computers by enabling natural-language communication, contextual reasoning, multimodal interaction, personalised assistance, and increasingly autonomous task execution. Traditional human–computer interaction (HCI) has largely depended on graphical user interfaces, menus, commands, and structured input mechanisms. LLMs introduce a more conversational interaction paradigm in which users can communicate with computing systems through ordinary language and receive context-sensitive responses. This study examines the emerging role of LLMs in the future of HCI, focusing on conversational interfaces, adaptive systems, multimodal interaction, personalised computing, accessibility, intelligent agents, collaborative knowledge work, and human-AI cooperation. A qualitative and conceptual research methodology is adopted to examine the opportunities and challenges associated with LLM-enabled interaction. The analysis indicates that LLMs can reduce interaction barriers, improve accessibility, support natural-language programming, assist knowledge workers, and enable interfaces that dynamically adapt to user needs. At the same time, hallucinations, privacy concerns, algorithmic bias, explainability, over-reliance, interaction ambiguity, and the changing role of traditional interface design present significant challenges. The study proposes a human-centred LLM-HCI framework based on contextual understanding, multimodal interaction, user control, transparency, verification, and continuous feedback. The study concludes that the future of HCI is unlikely to be defined by the disappearance of graphical interfaces, but by the emergence of hybrid interaction environments in which natural language, visual interfaces, voice, gestures, and intelligent agents operate together.

Keywords: Large Language Models, Human–Computer Interaction, Artificial Intelligence, Conversational AI, Intelligent Interfaces, Multimodal Interaction, Human-AI Collaboration, Natural Language Processing, Generative AI, Intelligent Agents.

1. Introduction

Human–Computer Interaction (HCI) has continuously evolved alongside advances in computing technology.

Early computer systems required specialised technical commands.
Later, graphical user interfaces introduced:

- Windows.
- Icons.
- Menus.
- Buttons.
- Pointers.
- Touch interfaces.

These innovations made computing accessible to a much broader population.
The emergence of Large Language Models introduces another major transition.
Instead of learning how a computer interface works, users can increasingly describe what they want in natural language.
For example, rather than navigating several menus to complete a task, a user may simply communicate the desired outcome to an AI system.
This represents a shift from:

Interface-Centred Computing
towards:

Intent-Centred Computing
The computer increasingly attempts to understand the user's goal rather than requiring the user to understand the computer's underlying interaction structure.

2. Concept of Large Language Models

Large Language Models are AI systems trained on extensive collections of text and other forms of data to learn statistical and semantic patterns in language.
Modern LLMs can perform tasks including:

- Text generation.
- Question answering.
- Summarisation.
- Translation.
- Classification.
- Coding assistance.
- Information extraction.
- Reasoning-oriented tasks.
- Conversational interaction.

The development of transformer-based architectures significantly accelerated progress in language modelling.

Transformer architectures allow models to analyse relationships between different parts of an input sequence, enabling more effective contextual language processing.

3. Human–Computer Interaction

HCI concerns the design and use of computer technologies and the interaction between people and computational systems.

Traditional HCI focuses on:

- Usability.
- Accessibility.
- Interface design.
- User experience.
- Interaction efficiency.
- Cognitive load.

LLMs expand HCI because the computer can increasingly interpret natural-language intent.

The interaction becomes less dependent on fixed commands and more dependent on conversational context.

4. Research Objectives

This study aims to:

1. Examine the transformation of HCI through LLMs.
2. Analyse conversational interfaces enabled by LLM technology.
3. Examine multimodal human-AI interaction.
4. Evaluate the role of LLMs in personalised computing.
5. Identify opportunities for accessibility and inclusive interaction.
6. Analyse challenges involving trust, privacy, bias, and reliability.
7. Develop a conceptual framework for future LLM-based HCI.
8. Examine the future relationship between humans and intelligent computing systems.

5. Research Methodology

The study adopts a qualitative and conceptual research methodology.

The analysis draws on secondary literature relating to:

- Human–Computer Interaction.
- Natural Language Processing.
- Generative Artificial Intelligence.
- Large Language Models.
- Conversational interfaces.
- Human-AI collaboration.
- Multimodal interaction.
- Intelligent agents.

The study evaluates LLM-based HCI across six dimensions:
1. Naturalness.
2. Adaptability.
3. Personalisation.
4. Accessibility.
5. User control.
6. Trustworthiness.

6. From Graphical Interfaces to Conversational Interfaces

Graphical user interfaces require users to select predefined functions.
For example:
Open Application → Select Menu → Choose Function → Enter Data → Submit
An LLM-based interface can potentially simplify this process:

User Intent → Natural-Language Request → AI Interpretation → Action
This does not mean graphical interfaces will disappear.
Instead, future systems may combine:

Text + Voice + Visual Interface + Gesture + AI Agent

7. Conversational HCI

Conversational interfaces allow users to interact with computers using dialogue.
Users can:
- Ask questions.
- Clarify requirements.
- Correct previous instructions.
- Refine outputs.
- Request explanations.

The conversational context can make interactions more flexible than conventional command-based systems.

8. Context-Aware Interaction

One of the most significant capabilities of LLM-based systems is contextual interaction.
An intelligent system can potentially consider:
- Previous conversation.
- Current task.
- User preferences.
- Available documents.
- Application state.
- Environmental information.

For example, a user might say:
"Make this shorter."
A context-aware system can infer that "this" refers to the text currently being edited.
This reduces the need for explicit instructions.

9. Personalised Computing

Future computers may increasingly adapt to individual users.
An AI assistant could potentially learn:

- Preferred writing style.
- Common workflows.
- Frequently used applications.
- Preferred information formats.
- Repetitive tasks.

Personalisation could reduce cognitive effort.
However, personalisation introduces important privacy questions.
Users should have meaningful control over what information the system retains and uses.

10. Multimodal Interaction

Future LLM-based HCI will increasingly involve multiple modalities.
Users may communicate through:

- Text.
- Speech.
- Images.
- Video.
- Screenshots.
- Gestures.
- Documents.

The system can combine these inputs.
For example, a user might upload an image of a machine, ask a question verbally, and receive a text-and-visual explanation.
This creates a multimodal interaction model:

See + Hear + Speak + Type + Act

11. Voice-Based Interaction

Voice interfaces have existed for years, but LLMs can significantly expand their capabilities.
Traditional voice assistants often depend on predefined commands.
LLM-powered voice systems can potentially handle more open-ended dialogue.
This can improve accessibility for users who have difficulty interacting with conventional keyboards or touchscreens.

12. Natural-Language Programming

LLMs are also changing interaction with software development.
Users can describe programming goals in natural language.
For example:
Human: "Create a database query that identifies duplicate customer records."
AI: Generates an appropriate SQL query.
This creates a new interaction layer between humans and software.
Programming becomes increasingly conversational.
However, generated code still requires verification because language models can produce incorrect or insecure implementations.

13. Intelligent Software Agents

LLMs are increasingly being integrated into agentic systems.
An intelligent agent may:

1. Understand a goal.
2. Break the goal into tasks.
3. Use tools.
4. Analyse results.
5. Modify its approach.
6. Produce an outcome.

This changes HCI from simple interaction toward delegation.
The user may increasingly communicate desired outcomes rather than individual commands.

14. Human-AI Collaboration

LLMs can function as collaborative partners rather than simple information-retrieval systems.
Potential applications include:

- Writing.
- Research.
- Programming.
- Design.
- Education.
- Business analysis.
- Decision support.

The human provides:

- Goals.
- Context.
- Judgement.
- Evaluation.

The AI provides:

- Information processing.
- Drafting.
- Pattern identification.
- Alternative suggestions.

15. Accessibility

LLM-based HCI could significantly improve accessibility.

Potential applications include:

- Automatic text simplification.
- Speech-based interaction.
- Real-time translation.
- Screen interpretation.
- Conversational navigation.
- Assistive writing.

People who experience difficulties with traditional interfaces may benefit from natural-language interaction.

16. Education and Learning

LLMs can transform educational HCI.

Students may interact with educational systems through dialogue.

Instead of simply displaying information, systems can:

- Explain concepts.
- Ask questions.
- Adjust difficulty.
- Provide examples.
- Identify misunderstandings.
- Offer personalised practice.

The interface becomes adaptive rather than static.

17. Healthcare Interaction

LLMs may also support healthcare-related interfaces.

Potential applications include:

- Patient information systems.
- Administrative assistance.
- Medical documentation.
- Patient education.
- Clinical information retrieval.

However, healthcare applications require strict safeguards because errors can have serious consequences.

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LLMs should therefore support, rather than independently replace, qualified healthcare professionals in high-stakes decisions.

18. Business and Knowledge Work

Knowledge workers spend considerable time processing information.
LLMs can support:

- Document analysis.
- Report generation.
- Meeting summarisation.
- Data interpretation.
- Email drafting.
- Research assistance.

This can transform enterprise HCI from application-by-application interaction toward a unified intelligent assistant.

19. Table

1. LLM Applications in HCI

HCI Area	LLM Application	Potential Benefit
Communication	Conversational assistants	Natural interaction
Accessibility	Voice/text assistance	Inclusion
Education	AI tutors	Personalisation
Programming	Code generation	Productivity
Healthcare	Information assistance	Accessibility
Business	Document analysis	Efficiency
Research	Knowledge assistance	Faster information processing
Design	Natural-language creation	Creativity
Customer Service	Conversational agents	Responsiveness
Software	AI agents	Task automation

20. Adaptive User Interfaces

Future interfaces may dynamically change according to:

- User expertise.
- Current task.
- Device.

- Context.
- Cognitive load.

A beginner might receive detailed guidance.
An expert might receive a compact interface.
The same software could therefore provide different interaction experiences for different users.

21. LLMs and Cognitive Load

Traditional interfaces require users to remember where functions are located.
Conversational interfaces can reduce this burden.
Instead of remembering:
"Which menu contains this function?"
the user can state:
"Show me the monthly sales trend."
The system attempts to determine how to satisfy the request.
This could reduce interaction complexity.
However, conversational interaction can also create cognitive challenges when responses are overly long, ambiguous, or inconsistent.

22. Trust and Transparency

Trust is critical for effective human-AI interaction.
Users should understand:

- What the AI knows.
- What it does not know.
- Where information came from.
- Whether an action was executed.
- How confident the system is.

AI systems should distinguish between:

Information Retrieval

And

Generated Inference

This distinction can help users evaluate outputs appropriately.

23. Hallucination and Reliability

One of the major limitations of LLM-based HCI is hallucination.
An LLM can produce a plausible-sounding response that is factually incorrect.

This creates a significant HCI problem because users may interpret fluent communication as evidence of accuracy.

Future interfaces should therefore provide:

- Source verification.
- Confidence indicators where appropriate.
- Citation mechanisms.
- Fact-checking tools.
- Human review for high-risk applications.

24. Privacy

LLM-based interfaces may process highly personal information.

Potentially sensitive information may include:

- Personal conversations.
- Documents.
- Work information.
- Voice data.
- Images.
- Behavioural patterns.

Privacy-preserving architectures and clear data policies are therefore essential.

Users should understand what information is collected and how it is used.

25. Algorithmic Bias

LLMs learn patterns from large datasets.

If training data contain biases, model outputs may reproduce or amplify them.

Bias can affect:

- Recommendations.
- Language generation.
- Hiring support.
- Educational systems.
- Search.
- Decision support.

Future HCI systems should incorporate continuous evaluation for fairness and unintended discriminatory outcomes.

26. Human Control

An important principle for future HCI is meaningful human control.

Users should be able to:

- Correct AI outputs.
- Reject recommendations.

- Undo actions.
- Inspect important decisions.
- Change system behaviour.
- Disable automation.

This becomes particularly important as LLMs move from conversational systems toward autonomous agents.

27. Case Study: LLM-Based Workplace Assistant

Consider a knowledge worker who needs to prepare a weekly management report.

A conventional workflow might involve:

Email → Spreadsheet → Database → Documents → Presentation → Report

An LLM-based assistant could potentially provide a unified interface.

The user might request:

"Prepare this week's management report using the latest sales spreadsheet and meeting notes."

The system could:

1. Retrieve authorised data.
2. Analyse the information.
3. Identify trends.
4. Draft the report.
5. Highlight uncertainties.
6. Ask for clarification where necessary.
7. Allow the user to approve the final version.

The critical point is that the human remains responsible for reviewing the final output.

28. Table

2. Illustrative Evaluation of Future LLM-HCI Capabilities

Capability	Potential Impact (%)
Natural-Language Interaction	97
Personalisation	93
Accessibility	92
Productivity Support	95
Multimodal Interaction	94
Knowledge Retrieval	96

Capability	Potential Impact (%)
Task Automation	91
User Adaptation	90
Collaborative Work	94
Interface Simplification	93

Note: These values are illustrative conceptual indicators for comparative discussion and are not empirical measurements from a specific user study.

29. Proposed LLM-HCI Framework

A future human-centred LLM interface can be represented as:

User Intent
↓
Natural-Language / Multimodal Input
↓
Context Interpretation
↓
LLM Reasoning and Planning
↓
Tool / Application Integration
↓
Generated Response or Action
↓
Verification
↓
User Feedback
↓
System Adaptation

The feedback loop is essential.
Users should remain capable of correcting the system and influencing subsequent behaviour.

30. Future HCI Paradigm

The evolution of HCI can be conceptualised as:

First Generation
Command-Based Interaction
Second Generation
Graphical Interaction
Third Generation
Touch and Mobile Interaction
Fourth Generation
Conversational and Multimodal Interaction
Emerging Fifth Generation
Agentic and Intent-Based Interaction
In the fifth generation, the user may communicate a goal while the AI determines the sequence of actions required to accomplish it.

31. Challenges for Interface Designers

LLMs require designers to rethink traditional HCI principles.
Designers must consider:

- Prompt ambiguity.
- Conversation flow.
- Error recovery.
- AI uncertainty.
- User expectations.
- Model limitations.
- Automation boundaries.

An interface must communicate not only what the system can do, but also what it cannot reliably do.

32. Future Directions

32.1 Personal AI Agents

Users may increasingly have persistent AI assistants capable of managing multiple tasks.

32.2 Ambient Computing

Computing may become less visible as AI operates across devices and environments.

32.3 Multimodal Agents

Future systems will combine language, vision, speech, and action.

32.4 Brain-Computer Interfaces

Long-term HCI research may combine AI with emerging neural interfaces.

32.5 Emotion-Aware Interaction

Future systems may attempt to recognise emotional or behavioural signals, although this raises significant ethical and privacy concerns.

32.6 AI-Native Operating Systems

Future computing platforms may integrate AI as a fundamental interaction layer rather than as a separate application.

33. Ethical Recommendations

Future LLM-HCI systems should:

1. Maintain meaningful user control.
2. Clearly communicate AI involvement.
3. Protect personal information.
4. Provide mechanisms for correcting errors.
5. Evaluate algorithmic bias.
6. Support human verification.
7. Clearly distinguish generated content from verified information.
8. Provide appropriate transparency.
9. Avoid unnecessary automation of high-risk decisions.
10. Design for accessibility and inclusion.

34. Questionnaire

5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree

No.	Statement
1	LLMs can make computer interaction more natural.
2	Conversational interfaces can reduce the complexity of software interaction.
3	LLMs can improve accessibility for users with different needs.
4	Multimodal AI will become important to future HCI.
5	LLMs can improve workplace productivity.
6	Users should be able to verify important AI-generated information.
7	Privacy is a major concern for LLM-based interfaces.
8	Human control should remain central to AI-based interaction.
9	AI agents will increasingly perform multi-step tasks on behalf of users.
10	LLMs will fundamentally influence the future development of HCI.

35. Discussion

LLMs represent more than another interface technology.
They potentially change the relationship between humans and computers.
Traditional HCI largely requires humans to learn the structure of computer systems.
LLM-based HCI increasingly enables computers to interpret human goals.
This creates a shift from:

"How do I operate the system?"
to:
"What do I want the system to accomplish?"
However, this transition creates new problems.
Natural language is inherently ambiguous.
AI systems can misunderstand instructions.
LLMs can generate incorrect information.
Users may also develop excessive trust in fluent AI responses.
Consequently, future HCI design must combine conversational convenience with strong mechanisms for verification, transparency, correction, and control.
The most effective systems will therefore not simply make computers more conversational.
They will make computing more understandable, controllable, adaptive, and human-centred.

36. Conclusion

Large Language Models are transforming the foundations of Human–Computer Interaction.
Their ability to process natural language, maintain context, generate content, interpret multimodal information, and interact with external tools enables a new generation of intelligent interfaces.
LLM-based systems can support:

- Conversational interaction.
- Personalised computing.
- Accessibility.
- Education.
- Programming.
- Research.
- Business productivity.
- Intelligent agents.
- Multimodal interaction.

The future of HCI is therefore likely to move beyond conventional application-centric interaction toward intent-centric, conversational, multimodal, and agentic computing.
Nevertheless, technological capability must be balanced with responsible design.

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Privacy, reliability, bias, transparency, explainability, and human control will determine whether LLM-based interaction becomes genuinely beneficial.

The emerging paradigm can be summarised as:

Natural Language + Context + Multimodal AI + Human Control = Next-Generation Human–Computer Interaction

37. References

1. Vaswani, Ashish, et al. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30.
2. Brown, Tom B., et al. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901.
3. Devlin, Jacob, Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT, 4171–4186.
4. Ouyang, Long, et al. (2022). Training language models to follow instructions with human feedback. Advances in Neural Information Processing Systems, 35.
5. OpenAI. (2023). GPT-4 technical report. arXiv preprint arXiv:2303.08774.
6. Bommasani, Rishi, et al. (2021). On the opportunities and risks of foundation models. arXiv preprint arXiv:2108.07258.
7. Bender, Emily M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? Proceedings of FAccT, 610–623.
8. Amershi, Saleema, et al. (2019). Guidelines for human-AI interaction. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–13.
9. Shneiderman, Ben. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human–Computer Interaction, 36(6), 495–504.
10. Arrieta, Alejandro Barredo, et al. (2020). Explainable Artificial Intelligence: Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115.
11. Goodfellow, Ian, Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
12. LeCun, Yann, Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436–444.
13. Norman, Don. (2013). The Design of Everyday Things: Revised and Expanded. Basic Books.
14. Nielsen, Jakob. (1994). Usability Engineering. Morgan Kaufmann.
15. Clark, Herbert H.. (1996). Using Language. Cambridge University Press.