Chapter 3:

From Human–Computer Interaction to Human–AI Collaboration: A New Paradigm for Intelligent Management Information Systems

Çağla Özen
İstanbul Topkapı University

doi: https://doi.org/10.66414/mls.978-1-0666009-1-5_3

Abstract

The rapid advancement of artificial intelligence (AI) is transforming the way individuals interact with digital technologies and Information Systems (IS), requiring a rethinking of some traditional assumptions underlying Human–Computer Interaction (HCI). In Management Information Systems (MIS), this transformation extends beyond the design of usable interfaces toward the development of intelligent systems that can actively support, augment, and collaborate with human users. This chapter examines the evolution from HCI to Human–AI Collaboration (HAC) and discusses its implications for the development of intelligent MIS. It first establishes the conceptual foundations of HCI, including human factors, user-centered design, usability, accessibility, and user experience (UX). It then examines the emergence of Human–AI Interaction (HAI) and the transition from computers as passive tools toward intelligent interaction partners. Building on this foundation, the chapter conceptualizes HAC through complementary human and AI capabilities, human oversight, AI-augmented decision-making, and increasingly autonomous AI systems. Particular attention is given to human-centered design, Generative AI, conversational and multimodal interfaces, intelligent UX, and the different roles humans may assume in AI-enabled environments, including interaction, evaluation, supervision, and, under appropriate conditions, collaboration with AI systems. The chapter further discusses ethical and organizational challenges, including algorithmic bias, privacy, transparency, accountability, automation bias, and human agency. It argues that the future of MIS will increasingly depend not only on technological intelligence but also on how effectively HAC is designed, governed, and integrated into organizational work.

Keywords: human–computer interaction, human–AI collaboration, management information systems, human-centered AI, generative AI

1. Introduction

The rapid development of digital technologies has fundamentally transformed the role of Information Systems (IS) within contemporary organizations. Management Information Systems (MIS) have traditionally been conceptualized as systems that collect, process, store, and deliver information to support managerial activities and organizational decision-making. However, the increasing integration of artificial intelligence (AI), machine learning, natural language processing (NLP), and other intelligent technologies is changing the nature of these systems. MIS are increasingly capable not only of providing information but also of interpreting data, generating insights, anticipating outcomes, supporting decisions, and interacting with users in increasingly adaptive ways. Consequently, the transformation of MIS is not merely a technological development; it also involves a transformation in how humans interact with, understand, control, and work alongside IS.

Human–Computer Interaction (HCI) provides an important theoretical and practical foundation for understanding this transformation. As an interdisciplinary field, HCI focuses on the design and evaluation of interactive technologies and on understanding how people use and experience such technologies (SIGCHI, n.d.). The evolution of HCI has historically followed changes in computing paradigms, from command-line interfaces and graphical user interfaces (GUI) to touch-based, mobile, ubiquitous, and multimodal interaction. The increasing intelligence of contemporary systems, however, introduces a qualitatively different interaction context. Rather than interacting solely with deterministic software through predefined interfaces, users increasingly interact with systems capable of inference, adaptation, recommendation, content generation, and autonomous action.

The emergence of Human–AI Interaction (HAI) illustrates this shift. AI-enabled systems introduce uncertainty, probabilistic outputs, changing system capabilities, and new forms of interaction that require users to understand not only what a system does but also when, why, and with what degree of confidence it should be relied upon. Amershi et al.

(2019) demonstrated the importance of explicitly considering these characteristics in the design of AI-infused interactive systems by proposing a set of general guidelines for HAI. Their work reflects an important transition within HCI: interaction design must increasingly account for systems that can make predictions, adapt their behavior, and produce outputs that may not always be deterministic or correct.

At the same time, the emergence of Human-Centered AI (HCAI) emphasizes that increasing system intelligence should not imply decreasing human control. Shneiderman (2020) argues for an approach in which high levels of automation can coexist with high levels of human control, while emphasizing human self-efficacy, responsibility, reliability, and trustworthy system design. This perspective is particularly relevant to MIS because organizational IS operate within decision-making structures in which accountability, human judgment, and organizational objectives remain important even when AI capabilities become increasingly sophisticated.

Recent research further indicates that HAI is developing into a broader research domain encompassing collaboration, competition, conflict, and symbiosis between humans and AI systems (Jiang et al., 2024). This development suggests that the relationship between humans and intelligent systems cannot be adequately understood solely through the traditional concept of interface interaction. The central question increasingly concerns how humans and AI can contribute complementary capabilities to shared tasks and decisions.

This transformation has direct implications for organizations and MIS. The implementation of AI in organizations involves organizational, technological, information-systems, and people-related dimensions, demonstrating that AI adoption cannot be understood exclusively as a technical implementation problem (Lee et al., 2023). Similarly, a systematic review of AI applications in MIS identifies intelligent process automation, predictive analytics, and NLP among the major areas of research, illustrating the expanding role of AI within management information environments (Stoykova & Shakev, 2023). These developments indicate

that intelligent MIS are increasingly becoming environments in which humans and AI jointly participate in information processing and organizational work.

This evolution raises a fundamental conceptual question: If IS are increasingly intelligent, adaptive, and capable of participating in decision-making, should humans still be conceptualized merely as users of IS? Recent IS research on Human–AI Collaboration (HAC) suggests that the answer requires a broader conceptualization of the relationship between humans and intelligent technologies. Seini et al. (2026), based on a systematic review of 137 IS studies, identify redefined human–machine relationships, effective interaction design, and organizational and societal implications as central themes in the emerging HAC literature.

Against this background, this chapter examines the transition from HCI to HAC and considers its implications for intelligent MIS. It argues that the evolution of MIS requires a broader understanding of the human role in intelligent information environments, where humans may interact with, evaluate, supervise, and, under appropriate conditions, collaborate with AI systems. The chapter therefore connects the theoretical foundations of HCI with HAI, HCAI, Generative AI, intelligent user experiences (UX), and organizational decision-making, while distinguishing HAC from other forms of HAI. It further examines the design, governance, and organizational implications of HAC and argues that the future of MIS will depend not only on technological intelligence but also on how effectively human–AI collaboration is designed, governed, and integrated into organizational work.

2. Foundations of Human–Computer Interaction

2.1. Concept and Scope of Human–Computer Interaction

HCI examines how people interact with computational systems and how these systems can be designed to support human goals, capabilities, and activities. Its development has drawn on computer science,

psychology, cognitive science, design, and ergonomics. The field therefore extends beyond interface appearance to consider how system characteristics influence human performance, understanding, behavior, and experience (Carroll, 2014).

Early HCI research focused on the relationship between human capabilities and system operation. Card et al. (1983) examined interaction through models of human information processing and task performance, while Norman and Draper (1986) emphasized user-centered approaches to system design. These foundations established a principle that remains relevant to intelligent IS: system design should account for the characteristics of the people who use it rather than treating interaction as a purely technical problem.

The scope of HCI subsequently expanded toward usability, UX, accessibility, context, and human-centered design. Interaction became understood as part of a broader relationship between people, technology, tasks, and environments. This perspective is particularly relevant to MIS because IS operate within organizational settings rather than as isolated technological artifacts.

2.2. Evolution of Human–Computer Interaction

The evolution of HCI reflects successive changes in how people communicate with computational systems. Early computing environments required users to formulate commands according to relatively rigid syntactic rules. GUIs introduced visual representations, menus, windows, icons, and pointing devices, shifting interaction from command recall toward recognition and direct manipulation. As the Web, mobile computing, touch interfaces, ubiquitous computing, and multimodal technologies developed, interaction moved beyond the conventional desktop and became increasingly embedded in everyday activities and organizational processes.

This evolution also changed the criteria for successful interaction. Functional correctness alone was no longer sufficient. Users expected systems to be understandable, efficient, consistent, responsive, and

supportive of their goals. Usability engineering emerged in response to these expectations, providing systematic approaches to usability evaluation and design (Nielsen, 1994). Bevan (2001) similarly showed how HCI and usability standards expanded beyond interface characteristics to include context of use, development processes, and organizational capabilities.

For MIS, this evolution is significant because IS are embedded in work practices, decision processes, communication structures, and organizational routines. Interaction quality can therefore affect not only individual task performance but also how effectively an IS supports organizational objectives.

2.3. Human Factors, Cognition, and Interaction

Human factors provide an important foundation for understanding why some interactions are easier, safer, or more effective than others. Users have limited attention, working memory, and information-processing capacity, and these constraints influence how information should be presented and how tasks should be structured. HCI consequently considers perception, attention, memory, learning, problem solving, and decision-making.

Mental models are particularly important because users form expectations about how systems work. When system behavior corresponds with these expectations, interaction becomes easier to understand and predict. Poorly designed systems can create mismatches between expectations and actual behavior, increasing errors and cognitive effort. Feedback, consistency, visibility, and clear system status help users understand what has occurred and what actions remain possible.

These principles remain relevant as systems become more intelligent. AI introduces additional cognitive demands because users may need to interpret outputs whose behavior is less predictable than that of conventional software. Understanding human cognition therefore remains important for designing interactions that allow users to interpret, question, and appropriately respond to system behavior.

2.4. User-Centered Design and User Experience

User-centered design shifted system development from designing technology first and expecting users to adapt toward involving users and their needs throughout the design process. Norman and Draper (1986) emphasized designing around users and their activities, while later approaches placed greater emphasis on iterative evaluation and context of use.

UX extends the discussion beyond whether a system can be used successfully. Hassenzahl and Tractinsky (2006) describe UX as encompassing users' perceptions and responses arising from interaction with a system, including pragmatic and experiential qualities. An MIS may therefore be technically functional and usable while still producing a poor experience if it creates unnecessary effort, uncertainty, frustration, or a lack of confidence.

This distinction becomes increasingly important as IS take on more active roles. When systems provide recommendations, generate content, or adapt to users, the experience depends not only on interface characteristics but also on how system behavior is perceived and interpreted.

2.5. Usability, Accessibility, and Inclusive Design

Usability remains a fundamental HCI concept. Nielsen (1994) associates usability with characteristics such as learnability, efficiency, memorability, error management, and satisfaction. ISO 9241-11 (International Organization for Standardization [ISO], 2018) similarly defines usability in relation to the extent to which specified users can achieve specified goals with effectiveness, efficiency, and satisfaction within a specified context of use.

Accessibility extends these concerns to people with different abilities, technologies, and interaction requirements. Inclusive design recognizes that users differ in physical, sensory, cognitive, cultural, and

contextual characteristics. Designing for accessibility therefore contributes to the broader goal of making systems usable across diverse conditions.

For intelligent MIS, these principles provide an important foundation but do not fully resolve the emerging interaction problem. Traditional HCI has primarily focused on designing and evaluating interactions between people and computer systems, with particular attention to usability, user needs, interaction design, and effective system use. AI-enabled systems can interpret intentions, generate content, provide recommendations, adapt to interaction histories, and increasingly perform actions. Interaction consequently becomes more adaptive, dynamic, and reciprocal.

The central question therefore shifts from how interfaces should respond to human commands toward how interaction should be designed when the computational system can interpret, generate, recommend, and increasingly act. This transition provides the conceptual basis for HAI, while also creating a further question: when does interaction with an AI system become HAC within organizational work?

3. From Human–Computer Interaction to Human–AI Interaction

3.1. From Predictable Interfaces to Intelligent Interaction

The transition from HCI to HAI is not simply a change in interface technology. It reflects a change in the system with which people interact. Traditional HCI has primarily focused on the design and evaluation of interactions between people and computer systems, including the relationship between user actions, system processes, and outputs. AI-enabled systems introduce a different interaction context because they can interpret intent, infer patterns, generate content, adapt their behavior, and produce outputs whose exact form may not always be anticipated in advance.

This distinction is particularly important when AI is embedded in MIS. A conventional IS may present a predefined report or execute a query according to established rules. An AI-enabled system may instead summarize information, identify relevant patterns, formulate recommendations, or generate a response to a natural-language request. The user is consequently no longer interacting only with a predefined set of functions. The user is interacting with a system that interprets the request and determines how to respond within the boundaries of its model, available information, and operational context.

Amershi et al. (2019) identify these characteristics as central challenges for HAI design. Their guidelines emphasize that AI systems introduce issues related to imperfect performance, uncertainty, system behavior over time, and the need for users to understand and control AI-supported functionality. Interaction design therefore needs to accommodate not only successful system behavior but also uncertainty, failure, correction, and changes in system performance.

3.2. From System Response to Adaptive Interaction

The shift toward intelligent interaction also changes the role of feedback. In conventional interfaces, feedback primarily communicates the result of an action. With AI-enabled systems, feedback can become part of an ongoing interpretive process. Users may need to understand why a recommendation was produced, whether an output is reliable, how an error occurred, and what can be done to correct or refine the result.

Interaction can consequently become iterative and adaptive. A user may provide an initial instruction, inspect the AI-generated response, revise the instruction, add contextual information, reject part of the output, and continue the exchange until the result becomes useful. Rather than following a simple input–processing–output sequence, the interaction develops through repeated cycles of interpretation, evaluation, correction, and adaptation.

Raees et al. (2024) argue that HAI research needs to move beyond approaches focused primarily on explaining AI decisions or allowing users to contest them. Their analysis points toward more interactive forms of AI in which users have greater agency and can influence how systems behave. This is particularly relevant to MIS because organizational users often possess contextual knowledge that may not be available to the system. Effective HAI therefore requires mechanisms through which users can provide context, correct assumptions, and shape subsequent system responses.

3.3. The Changing Role of the User

As AI becomes more capable of interpreting and generating information, the conventional concept of the user becomes increasingly limited. In traditional HCI, the user is generally understood as the person who operates a technological system to accomplish a task. In HAI, the user may also evaluate AI outputs, provide feedback, correct errors, formulate instructions, supervise system behavior, and decide whether an AI recommendation should be accepted or rejected.

This does not make the human passive. In many situations, greater system intelligence increases the importance of human judgment. Users need to understand the capabilities and limitations of the system and retain meaningful control over how its outputs are used. Human agency therefore becomes a central design concern. A system that performs more functions but leaves users unable to understand, challenge, or redirect its behavior may increase automation without necessarily improving the quality of interaction.

Jiang et al. (2024) show that contemporary HAI research encompasses several forms of human–AI relationships, including collaboration, competition, conflict, and symbiosis. HAI therefore does not imply collaboration by definition. The nature of the relationship depends on the task, the distribution of capabilities, the degree of system autonomy, and the consequences of errors. This distinction becomes particularly important in MIS, where the objective is often not simply to

automate an activity but to improve how information, judgment, and technological capabilities are combined in organizational work.

3.4. Toward Human–AI Interaction in MIS

The significance of the transition from HCI to HAI for MIS lies in the changing role of the IS itself. When systems can interpret requests, generate analyses, recommend actions, and adapt to interaction, the interface becomes more than a mechanism for accessing information. It becomes a setting in which information is interpreted, evaluated, negotiated, and potentially transformed into organizational action.

This development creates a conceptual bridge between interaction and collaboration. HAI concerns how humans and intelligent systems interact and influence one another, whereas collaboration concerns the coordination of their contributions within a shared organizational task or decision. This distinction provides the conceptual foundation for examining the conditions under which HAI develops into HAC in MIS.

4. From Human–AI Interaction to Human–AI Collaboration

4.1. From Interaction to Collaboration

HAI does not necessarily imply HAC. An AI system may respond to requests, generate information, or provide recommendations without becoming a collaborator in a meaningful organizational sense. Collaboration involves coordinating human and AI capabilities around an organizational task or decision (Wang et al., 2026).

The distinction is better understood through the nature of the work than through the sophistication of the technology. When an employee asks an AI system to summarize a document and uses the result without further interaction, the relationship remains largely tool-oriented. A different relationship emerges when the employee evaluates the summary, provides organizational context, questions an interpretation, requests revisions, and combines the result with professional judgment. The AI contribution is

then integrated into a broader task rather than simply consumed as an output.

For MIS, this distinction matters because adding an AI capability to an existing IS does not by itself create collaboration. The distribution of responsibilities, coordination of contributions, and decision authority determine whether an AI-supported activity constitutes collaboration.

4.2. Complementary Capabilities and Task Allocation

The rationale for HAC lies in combining capabilities that are difficult to reproduce within a single actor. AI systems can process large volumes of information rapidly, identify patterns, generate alternatives, and perform repetitive analytical activities. Humans contribute contextual knowledge, professional experience, social understanding, ethical reasoning, and organizational judgment.

The value of this combination depends on the task. A manager may understand institutional constraints while an AI system can compare historical cases, identify patterns, and generate alternative scenarios. Collaboration becomes valuable when these contributions are coordinated rather than when one simply replaces the other.

Hao et al. (2024) found that Generative AI can reduce cognitive burden and support decision-making in situations involving information overload, while also identifying risks associated with over-reliance. Effective collaboration therefore does not require maximizing AI involvement. Responsibility should be distributed according to task characteristics and the relative strengths and limitations of human and AI contributions.

Shneiderman (2020) similarly emphasizes combining automation with meaningful human control. Automation transfers execution to a system; augmentation extends human capabilities; collaboration coordinates human and AI contributions around a task. These arrangements may coexist within the same MIS workflow. A system may

automate data preparation, augment managerial analysis, and require human judgment at the decision stage.

Task allocation is consequently a central design issue. Activities should not be assigned to AI simply because the technology can perform them, and human involvement should be determined not only by the value it adds but also by task complexity, ambiguity, contextual requirements, consequences of error, AI reliability, accountability, and the need for appropriate human oversight. Decision authority should be aligned with these factors and with the potential consequences of the action.

4.3. Human Agency, Control, and Calibrated Reliance

Task allocation also determines how much control humans retain over AI-supported processes. In a human-in-the-loop arrangement, human judgment is incorporated directly into the process, such as when an AI recommendation requires approval. In a human-on-the-loop arrangement, the system operates with greater autonomy while humans monitor its behavior and intervene when necessary.

Human agency cannot be reduced to the existence of an override function. A control mechanism has limited value if users cannot recognize when intervention is necessary, lack sufficient information to evaluate an output, or lack authority to change the resulting action. Meaningful control requires practical capacity to understand, evaluate, and influence AI-supported outcomes.

Effective collaboration also requires calibrated reliance. Users should rely on AI when its capabilities are appropriate and question its outputs when uncertainty, limitations, or contextual factors warrant caution. AI systems may produce fluent and persuasive outputs even when information is incomplete or incorrect. Excessive reliance can therefore shift practical decision authority toward the system without a formal transfer of responsibility.

The opposite problem can occur when users reject potentially useful AI recommendations because of previous failures or limited understanding of system capabilities. The objective is not to maximize trust but to establish an appropriate relationship between system capability, user expectations, and human judgment.

4.4. AI Agents, Autonomy, and Emerging Forms of Collaboration

AI agents introduce a further change because AI systems can increasingly carry out sequences of actions rather than responding only to individual requests. An agent may interpret a goal, determine intermediate steps, retrieve information, use available tools, and execute defined actions with limited human intervention.

Greater autonomy increases the importance of delegation, authorization, monitoring, escalation, and accountability. An organization may allow an agent to gather information and prepare a recommendation while requiring human authorization before a financial, personnel, or customer-facing action is executed.

Seini et al. (2026) identify AI copilots and agentic AI as developments reshaping HAC. Increasing autonomy should not, however, be equated with collaboration. An autonomous system can simply automate a process. Collaboration exists when AI activity is connected to human contribution within an organizational task and when decision authority remains appropriate to the consequences of the action.

For the purposes of this chapter, HAC in MIS is understood as a structured work arrangement in which human and AI capabilities are deliberately coordinated to accomplish an organizational task or decision, with responsibilities and decision authority distributed according to task characteristics, system capabilities, and organizational context.

This perspective changes the central question for MIS. Instead of asking only whether AI can perform a particular task, organizations need to determine how that task should be structured when both human and

AI capabilities are available. The resulting IS becomes an intelligent work environment in which computational capabilities, human expertise, organizational context, and decision authority are deliberately brought together.

5. Human-Centered Design of Intelligent MIS

5.1. From Human-Centered Design to Human-Centered AI

The transition from HCI to HAC changes what needs to be considered during system design. User-centered design emphasizes users, their goals, tasks, and contexts throughout development. Human-centered design extends this perspective by considering people, their broader contexts, and the effects of technology across its lifecycle. ISO 9241-210 (ISO, 2019) places human needs, contexts of use, iterative development, and human involvement at the center of interactive system design.

When AI becomes an active component of an IS, the design problem becomes less predictable. Outputs may vary across situations, contain uncertainty, and change according to data, model behavior, or interaction history. HCAI provides a perspective for addressing these conditions. Shneiderman (2020) emphasizes meaningful automation, human control, reliability, and accountability.

HCAI should not be treated as another term for HAC. HCAI concerns principles for designing AI systems around human needs and capabilities, whereas HAC concerns how human and AI capabilities are coordinated within a task. For intelligent MIS, the challenge is to translate human-centered principles into systems that remain useful and understandable while accommodating AI uncertainty.

5.2. Designing for Human Agency, Transparency, and Uncertainty

Human control becomes particularly important when AI systems influence decisions or perform actions. An intelligent MIS should allow users to understand relevant system behavior, intervene when necessary, and determine whether an AI recommendation or action should be accepted. Amershi et al. (2019) emphasize communicating AI capabilities and limitations, providing appropriate feedback, and supporting users in correcting or overriding system behavior.

Transparency is valuable insofar as it enables users to understand, evaluate, and appropriately influence AI-supported outcomes. Transparency concerns the visibility of relevant system behavior, whereas explainability concerns users' ability to understand why a particular output or recommendation was produced. A manager evaluating an AI recommendation may not need a technical description of the model architecture. More useful information may concern the factors influencing the recommendation, the evidence considered, and relevant limitations. Raees et al. (2024) similarly emphasize user agency in Interactive AI, extending the discussion beyond explanation toward the user's ability to influence and contest AI behavior.

Meaningful agency also depends on the character of AI outputs. Unlike many conventional IS functions, AI outputs are not fully predetermined. They may vary across inputs and contexts and can contain uncertainty even when presented confidently. Human-centered design should therefore communicate relevant uncertainty and provide opportunities to question, compare, or revise system outputs. An override mechanism is insufficient if users cannot recognize when intervention is necessary or lack the information and authority required for evaluation.

5.3. Adaptive Interfaces and Organizational Context

AI can transform interfaces from relatively fixed structures into adaptive environments. Intelligent MIS may adjust information presentation, recommend actions, anticipate information needs, and personalize interaction according to user behavior or organizational context. Such capabilities can reduce the effort required to locate and interpret information.

Adaptation nevertheless creates a tension between responsiveness and predictability. If system behavior changes substantially without an understandable reason, users may find it difficult to develop reliable expectations. Personalization can create similar problems when recommendations are based on assumptions that users cannot inspect or modify. Human-centered design should therefore make important forms of adaptation visible and adjustable.

Organizational context adds another layer. Decisions are rarely determined by structured data alone. Policies, informal knowledge, professional responsibilities, organizational culture, stakeholder relationships, and situational factors can influence interpretation. An AI system operating primarily on available data may therefore produce technically plausible outputs that remain incomplete from a managerial perspective. Technical intelligence does not by itself produce organizational intelligence.

Intelligent MIS should provide ways for users to contribute contextual information that is not captured directly in the underlying data. Editable assumptions, contextual inputs, scenario comparison, feedback, and correction mechanisms can connect computational analysis with organizational knowledge. The objective is not simply to make the AI model more capable, but to make its outputs interpretable within actual organizational circumstances.

5.4. Designing Collaborative Intelligent Management Information Systems

These considerations shift design from the interface alone toward the relationship between people, AI capabilities, and organizational processes. Designers need to consider how AI behavior is communicated, how users contribute context, how outputs can be evaluated and corrected, and how intelligent functions fit within existing workflows. The quality of an intelligent MIS therefore depends on more than model performance or interface usability.

Taken together, these principles suggest that intelligent MIS should align AI capabilities with task characteristics, provide sufficient visibility into system behavior, communicate relevant uncertainty, accommodate organizational context, and allow users to evaluate and influence important outputs. Adaptation should remain understandable and adjustable rather than becoming an opaque feature of the system.

The broader task is to create an intelligent work environment in which computational capabilities, human expertise, organizational knowledge, and system behavior function together without making the human role merely symbolic. Intelligent MIS should support efficient interaction as well as informed evaluation, contextual interpretation, and responsible use of AI.

This design perspective provides a foundation for understanding Generative AI. As AI systems become capable of producing text, analyses, and other forms of content in response to natural-language instructions, the design challenge extends toward new forms of interaction and experience.

6. Generative AI and the Transformation of User Experience

6.1. From Information Retrieval to Generative Interaction

Generative AI changes interaction with IS by allowing users to request, transform, and produce information without relying entirely on predefined system functions. Conventional MIS interfaces organize access through menus, forms, queries, dashboards, and reports. Generative AI allows users to describe an information need in natural language and ask the system to interpret that need and produce a response.

The difference is more fundamental than replacing menus with conversational interfaces. In a conventional system, the path from request to result is largely determined by the interface and application logic. With Generative AI, users can describe an objective without necessarily knowing which technical function should accomplish it. The system interprets the request and determines an appropriate response. A manager might ask for changes in quarterly sales, request an explanation of significant deviations, and then ask for the findings to be prepared for a management meeting.

The key change is therefore not merely how users access system functions, but how users express goals when the system can interpret and operationalize those goals. Interaction becomes more open-ended. Summarization, comparison, classification, explanation, drafting, and synthesis can occur within the same exchange. Luera et al. (2024) identify conversational and iterative interaction as important characteristics of emerging Generative AI interfaces.

Greater flexibility also creates a problem of interpretation. A natural-language request can be incomplete or ambiguous, while a generated response may appear convincing even when the system has misunderstood the user's intention. Interfaces therefore need to support

clarification and correction. Amershi et al. (2019) emphasize helping users understand system capabilities, recover from errors, and appropriately guide AI behavior.

6.2. Prompting, Co-Creation, and the Changing Nature of User Experience

Generative AI changes what users do during an interaction. Instead of simply selecting functions, users formulate instructions, provide context, examine generated material, identify problems, and decide how the interaction should continue. Prompting therefore becomes part of the work involved in expressing and refining an information need.

A typical interaction may develop through several rounds. A user begins with a broad request, receives an output, recognizes that an organizational constraint is missing, provides additional context, and evaluates a revised result. Generative AI may reduce operational effort while creating new forms of interpretive and evaluative work.

This change is particularly visible in managerial and knowledge-intensive activities. A manager preparing an analysis of customer complaints might ask the system to identify recurring issues, specify a customer segment, distinguish operational problems from product-related complaints, and request implications for the following quarter. The usefulness of the interaction develops through the user's ability to recognize what is missing and direct the system toward a more relevant result.

Generative AI also allows users to participate directly in producing organizational artifacts. Reports, presentations, summaries, and scenarios can be developed through iterative exchanges. Research on Generative AI in UX and design has identified applications in ideation, prototyping, and evaluation while emphasizing human assessment and refinement (Luo, 2025; Muehlhaus & Steimle, 2024).

This creates a more complicated understanding of UX. A successful experience cannot be assessed only by how quickly a system produces an

output. Human decision makers need to determine whether that output is accurate, relevant, sufficiently complete, and appropriate for its intended use. A report generated within minutes may save production time while requiring substantial verification. Generative AI can therefore redistribute effort rather than simply eliminate it.

Co-creation emerges from this redistribution. Humans contribute objectives, contextual knowledge, preferences, evaluation, and judgment, while AI contributes generation, synthesis, variation, and rapid transformation of information. Co-creation should not automatically be equated with HAC. Collaboration requires coordinated contributions, an organizational task or objective, and an appropriate distribution of responsibilities.

6.3. From Frictionless User Experience to Collaborative Experience

Generative AI also challenges the assumption that reducing interaction friction is always desirable. Fewer steps and faster responses can improve an experience, but eliminating every interruption may also remove opportunities to inspect, question, or reconsider an AI-generated result.

This distinction is particularly important in intelligent MIS. An AI system may generate a financial analysis and incorporate it into a managerial report with almost no additional interaction. The process appears efficient, but the user may have little opportunity to examine assumptions, data limitations, or unusual findings. A review step can introduce additional interaction while improving decision quality. Malaguti et al. (2025) therefore argue for a more nuanced understanding of interaction friction in Generative AI environments.

Interaction friction should consequently be evaluated according to its function rather than minimized by default. Friction that supports verification, reflection, or accountability may contribute to better organizational outcomes. Generated content can be fluent and persuasive even when information is incomplete or incorrect. UX in Generative AI

environments must therefore support verification, correction, and calibrated reliance.

The same principle applies to co-creation. An AI system can generate alternatives, revise a document, or propose interpretations, but human decision makers retain responsibility for evaluating which contributions are appropriate within their role and decision context. The relationship becomes more clearly collaborative when AI contributions and human judgment are connected within an organizational task and the responsibilities of each participant are understood.

This transformation represents a movement from navigation-centered UX toward interaction-centered and increasingly collaboration-oriented UX. Conventional MIS interfaces emphasize navigation and retrieval, whereas Generative AI introduces instruction, generation, evaluation, and refinement as central components of the experience. When these activities become embedded in organizational tasks, UX becomes part of a broader Human–AI collaborative experience.

Generative AI therefore represents more than a change from graphical interfaces to conversational ones. Users are no longer only navigating information structures; they are interacting with systems that can interpret requests and produce new content. For MIS, the central UX question becomes how effectively an intelligent system supports the movement between human intention, AI generation, critical evaluation, and organizational action.

7. Human–AI Collaboration in Management Information Systems

7.1. Human–AI Collaboration in Managerial Decision-Making

MIS have traditionally supported managerial decision-making by collecting, processing, organizing, and presenting information. AI extends this role by contributing directly to analysis, prediction, recommendation,

and scenario generation. An AI-enabled MIS can identify patterns, compare alternatives, summarize large information sets, and formulate possible courses of action. The manager is consequently no longer limited to selecting information from predefined reports; decision-making can involve an exchange between managerial judgment and computational analysis.

The value of this arrangement as HAC depends on whether human and AI contributions are coordinated within a shared organizational decision process, with responsibilities and decision authority appropriately distributed. Hao et al. (2024) show that Generative AI can reduce cognitive burden and support decision-making in situations involving information overload, while also identifying risks associated with excessive reliance on AI-generated outputs. The relevant question is therefore not whether AI should make decisions instead of managers, but under what conditions its analytical capabilities can be coordinated with managerial judgment within a shared decision process.

Decision authority remains important. AI may analyze data, estimate outcomes, simulate alternatives, or generate recommendations without having authority over the final decision. Human decision makers can introduce contextual knowledge, question assumptions, reject recommendations, and authorize consequential actions. The appropriate balance depends on the task, system reliability, uncertainty, and consequences of error.

7.2. Human–AI Collaboration in Knowledge Work and Organizational Processes

HAC can also emerge in knowledge-intensive activities such as reporting, document analysis, forecasting, information synthesis, communication, and organizational analytics when human and AI contributions are coordinated within a shared organizational task. The important change is not simply that individual tasks become faster. The sequence and distribution of work can change when AI performs selected activities within a larger organizational process.

A knowledge worker may define a problem, use AI to identify relevant information, examine alternative interpretations, provide organizational context, and integrate validated results into a final report. Such a process constitutes HAC when these contributions are deliberately coordinated around a shared organizational objective and responsibilities and decision authority are appropriately distributed. Different stages of the same process can therefore involve different levels of human and AI participation. Seini et al. (2026) identify AI copilots and increasingly agentic systems as developments reshaping the relationship between AI and organizational work.

An AI capability that performs well in isolation may have limited value if it does not fit the activities surrounding it. Information dependencies, approval requirements, escalation procedures, monitoring, and responsibility for reviewing outputs all influence how AI should be incorporated. The integration of AI should therefore be evaluated at the workflow level, since the organizational effects of an AI capability depend on how its outputs enter subsequent human and system activities.

Not every form of AI-supported work constitutes HAC. Collaboration emerges when these contributions are coordinated within a shared organizational task and responsibilities are appropriately distributed. Employees may supervise outputs, provide contextual information, correct system assumptions, determine when further analysis is needed, and integrate AI-generated material with organizational knowledge. AI may perform information-intensive activities, generate alternatives, monitor patterns, or initiate defined process steps. The distribution can vary across different stages of the same workflow.

This development broadens the role of MIS. Decision-support systems, business intelligence platforms, knowledge-management systems, enterprise workflows, and organizational analytics can increasingly become environments in which human and AI capabilities are coordinated. The relevant question is therefore not only how employees interact with an AI feature, but how AI participation changes the structure of organizational work.

7.3. Organizational Value, Performance, and the Limits of Collaboration

The organizational value of HAC should not be assessed solely through the amount of work performed by AI or the time saved through automation. AI capability does not automatically translate into organizational value. More meaningful measures include decision quality, knowledge quality, responsiveness, productivity, innovation, service quality, and the effective use of managerial expertise.

AI can redistribute work rather than simply eliminate it. A system may accelerate information processing while increasing the verification required from employees. A Generative AI system may produce a report within minutes while requiring substantial effort to check its assumptions, calculations, and contextual relevance. Productivity gains should therefore be evaluated across the complete human–AI workflow rather than at the level of an individual AI-assisted task.

The appropriate degree of AI participation also depends on task characteristics. Routine and information-intensive activities may benefit substantially from AI assistance, whereas tasks involving ambiguous objectives, sensitive relationships, ethical judgments, or significant consequences may require stronger human involvement. Task structure, uncertainty, contextual dependence, system reliability, and the consequences of error should influence decisions about delegation and oversight.

HAC in MIS should therefore be understood as an organizational design problem rather than an objective of maximizing AI adoption. The aim is to determine where AI capabilities can improve organizational work and where human expertise, judgment, and authority need to remain central. Intelligent MIS can create greater value when AI analysis and generation are connected to human context and evaluation, organizational workflows, and accountable decision-making.

Combining human and AI capabilities also creates new questions concerning accountability, oversight, fairness, and the governance of AI-

supported organizational action. These questions become increasingly important as AI systems move from analytical support toward more autonomous participation in organizational processes, providing the basis for the ethical and governance challenges examined in the following section.

8. Ethical Challenges and Future Directions of Human–AI Collaboration

8.1. Ethical Challenges of Human–AI Collaboration

The increasing integration of AI into organizational decision-making and work processes creates ethical challenges that cannot be addressed through technical performance alone. When AI systems influence recommendations, generate organizational knowledge, or perform actions, questions arise concerning fairness, privacy, transparency, accountability, and human control. These concerns become more significant as AI moves from providing information toward participating directly in decisions and organizational processes.

Algorithmic bias remains a central concern. AI systems can reproduce or amplify patterns contained in training data, organizational records, or existing decision processes. In MIS, this may affect recruitment, customer evaluation, resource allocation, risk assessment, or managerial recommendations. Human involvement does not automatically eliminate such problems. If users routinely accept AI recommendations without examining their assumptions, existing biases may become less visible while continuing to influence outcomes.

Privacy presents another challenge. Intelligent MIS can process large volumes of organizational and individual data, while Generative AI and agentic systems may require access to multiple information sources to perform increasingly complex tasks. Integrating information across systems can create substantial value, but it also increases the consequences

of inappropriate access, secondary use, or disclosure. HAC therefore requires clear boundaries concerning what information AI systems can access, how that information can be processed, and under what conditions outputs can be shared.

Accountability becomes particularly difficult when an organizational outcome results from a combination of AI recommendations, human judgment, organizational rules, and automated actions. HAC can consequently create forms of distributed responsibility in which no single technological or human action fully explains the final outcome. Responsibility must nevertheless remain connected to identifiable organizational roles, decision authority, and governance mechanisms. Transparency and explainability can support this process, but an explanation alone does not create accountability. A human may receive an explanation without having sufficient authority to reject an AI recommendation, or may formally retain responsibility without having enough information to evaluate the output.

Human agency is therefore a central ethical requirement. The important question is not whether a human remains somewhere in the process, but whether that person retains meaningful capacity to influence consequential outcomes. Automation bias and over-reliance can gradually shift practical decision authority toward AI even when formal responsibility remains with a human. Governance mechanisms such as approval requirements, access controls, monitoring, audit trails, escalation procedures, and clearly assigned responsibility are therefore necessary components of intelligent MIS.

8.2. Future Directions: Toward Governed Human–AI Systems

Future forms of HAC are likely to involve increasingly adaptive and autonomous systems, although greater autonomy should not be understood as inherently constituting a more advanced form of collaboration. AI agents may move beyond generating recommendations toward planning and executing sequences of actions across organizational

systems. Their operation can increasingly follow a cycle of planning, acting, observing results, and revising subsequent actions. Such capabilities could substantially expand the role of intelligent MIS, particularly in information-intensive and repetitive processes. Greater autonomy, however, also makes the boundaries of delegation, monitoring, escalation, and accountability more consequential.

The central issue is therefore not autonomous AI alone but governed autonomy. Future intelligent MIS will need to establish conditions under which autonomous action remains observable, controllable, and accountable. The appropriate degree of human oversight may vary according to task characteristics, system reliability, potential consequences, and organizational risk. A low-risk routine activity may permit extensive delegation, whereas a consequential managerial decision may require direct human involvement and explicit authorization.

AI literacy will also become an organizational capability. Effective collaboration requires more than knowing how to formulate prompts. Managers and employees need to understand AI capabilities and limitations, evaluate generated outputs, recognize uncertainty, identify inappropriate automation, and determine when human intervention is required. Organizational AI literacy should therefore encompass judgment and critical evaluation as well as operational skills.

8.3. From Human–Computer Interaction to Governed Human–AI Collaboration

The progression examined throughout this chapter represents more than a sequence of technological developments. HCI established the importance of designing systems around human capabilities, goals, usability, and experience. HAI extended this perspective to systems that can interpret, generate, adapt, and increasingly act. HAC goes a step further by asking how human and AI capabilities should be combined within shared tasks and organizational processes.

From this perspective, the future of MIS is not simply a matter of increasing system intelligence or autonomy. Intelligent systems need to be designed around human agency, organizational context, complementary capabilities, appropriate task allocation, and accountable governance. The central design question consequently shifts from what AI can do to what AI should do, when humans should intervene, and how responsibility should be maintained when both contribute to organizational decisions and actions.

The evolution from HCI to HAC therefore reflects a fundamental transformation in the relationship between humans, intelligent systems, and organizational work. The future of MIS will depend not simply on more intelligent automation, but on governed forms of HAC in which AI capabilities are combined with human judgment, organizational knowledge, meaningful human control, and accountable decision-making.

9. Conclusion

This chapter contributes to the understanding of intelligent Management MIS by distinguishing HCI, HAI (HAI), and HAC as related but distinct concepts. Its central argument is that the integration of AI into organizational systems does not automatically establish collaboration. Rather, HAC emerges when human and AI capabilities are deliberately coordinated within a shared organizational task or decision, with responsibilities and decision authority appropriately allocated. The central issue is therefore no longer limited to how people use IS, but also concerns how different forms of HAI can be structured and, where appropriate, developed into effective HAC within organizational tasks and decision processes.

For MIS, this distinction shifts attention from AI capability alone toward the design of human–AI relationships within organizational contexts. Effective systems must account for uncertainty, contextual knowledge, human judgment, and the capacity to evaluate and influence AI-supported outcomes. Human agency and meaningful control are therefore not separate design considerations but essential conditions for

ensuring that intelligent systems support rather than undermine organizational decision-making.

The chapter also highlights the implications of intelligent technologies for MIS design and UX. As AI systems generate content, provide recommendations, and adapt to user input, system quality depends not only on usability but also on the interpretability, reliability, and appropriate use of AI outputs. Designing effective intelligent MIS consequently requires attention to how users evaluate system responses, provide contextual information, and integrate AI-generated results into their work.

At the organizational level, HAC offers a framework for examining how human expertise and AI capabilities can be combined in managerial decision-making, knowledge work, and business processes. Its organizational value depends on the fit between task requirements and the capabilities of each contributor, as well as on workflow integration, system reliability, and the allocation of responsibilities. The relevant objective is not to maximize automation, but to organize human and AI contributions in ways that improve task performance while preserving appropriate decision authority.

These implications make governance integral to intelligent MIS. Organizations need arrangements that address bias, privacy, accountability, and oversight while ensuring that individuals responsible for consequential decisions have sufficient information and authority to evaluate AI-supported outcomes. As AI systems become more autonomous, governance must also clarify the boundaries of delegation, the conditions for human intervention, and the assignment of responsibility for resulting actions.

The chapter's central contribution is to position HAC not as an inevitable endpoint of technological development, but as an organizational arrangement that must be deliberately designed and governed. This perspective provides a basis for future MIS research examining how task characteristics, human expertise, system capabilities, and governance mechanisms shape the outcomes of AI-supported work. Ultimately, the

contribution of intelligent MIS will depend not simply on advances in AI, but on how effectively organizations align technological capabilities with human judgment, organizational objectives, and accountable decision-making.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, ChatGPT (OpenAI) was utilized for language editing, academic writing refinement, and the revision of the chapter in response to editorial feedback. The author retains full responsibility for the content of the chapter.

Conflict of Interest: The author declares that there is no conflict of interest.

Funding: The author declares that this chapter received no financial support from any institution, project, or funding body.

Third-Party Materials and Permissions: No third-party figures, tables, images, or other materials requiring permission were used in this chapter. The author confirms that no third-party materials requiring permission have been reproduced or adapted in the chapter.

References

Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for human-AI interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1-13).

Association for Computing Machinery. https://doi.org/10.1145/3290605.3300233

Bevan, N. (2001). International standards for HCI and usability. *International Journal of Human-Computer Studies, 55*(4), 533-552. https://doi.org/10.1006/ijhc.2001.0483

Card, S. K., Moran, T. P., & Newell, A. (1983). *The psychology of human-computer interaction*. Lawrence Erlbaum Associates.

Carroll, J. M. (2014). Human computer interaction - brief intro. In M. Soegaard & R. F. Dam (Eds.), *The encyclopedia of human-computer interaction* (2nd ed.). Interaction Design Foundation. https://ixdf.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/human-computer-interaction-brief-intro

Hao, X., Demir, E., & Eyers, D. (2024). Exploring collaborative decision-making: A quasi-experimental study of human and generative AI interaction. *Technology in Society, 78*, 102662. https://doi.org/10.1016/j.techsoc.2024.102662

Hassenzahl, M., & Tractinsky, N. (2006). User experience – a research agenda. *Behaviour & Information Technology, 25*(2), 91-97. https://doi.org/10.1080/01449290500330331

International Organization for Standardization. (2018). *Ergonomics of human-system interaction—Part 11: Usability: Definitions and concepts (ISO 9241-11:2018).* https://www.iso.org/standard/63500.html

International Organization for Standardization. (2019). *Ergonomics of human-system interaction—Part 210: Human-centred design for interactive systems (ISO 9241-210:2019).* https://www.iso.org/standard/77520.html

Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management, 8*(4), 100078. https://doi.org/10.1016/j.dim.2024.100078

Lee, M. C. M., Scheepers, H., Lui, A. K. H., & Ngai, E. W. T. (2023). The implementation of artificial intelligence in organizations: A systematic literature review. *Information & Management, 60*(5), 103816. https://doi.org/10.1016/j.im.2023.103816

Luera, R., Rossi, R. A., Siu, A. F., Dernoncourt, F., Yu, T., Kim, S., Zhang, R., Chen, X., Salehy, H., Zhao, J., Basu, S., Mathur, P., & Lipka, N. (2024). *Survey of user interface design and interaction techniques in generative AI applications*. arXiv. https://doi.org/10.48550/arXiv.2410.22370

Luo, Y. (2025). Designing with AI: A systematic literature review on the use, development, and perception of AI-enabled UX design tools. *Advances in Human-Computer Interaction, 2025*(1), 3869207. https://doi.org/10.1155/AHCI/3869207

Malaguti, P., Karran, A. J., Le, D., Mortin, H., Coursaris, C. K., Sénécal, S., & Léger, P.-M. (2025). Investigating interaction friction in generative AI: Improving user experience and decision-making. *SIGHCI 2024 Proceedings*, 26. https://aisel.aisnet.org/sighci2024/26/

Muehlhaus, M., & Steimle, J. (2024). *Interaction design with generative AI: An empirical study of emerging strategies across the four phases of design*. arXiv. https://doi.org/10.48550/arXiv.2411.02662

Nielsen, J. (1994). *Usability engineering*. Morgan Kaufmann.

Norman, D. A., & Draper, S. W. (Eds.). (1986). *User centered system design: New perspectives on human-computer interaction*. Lawrence Erlbaum Associates.

Raees, M., Meijerink, I., Lykourentzou, I., Khan, V.-J., & Papangelis, K. (2024). From explainable to interactive AI: A literature review on current trends in human-AI interaction. *International Journal of Human-Computer Studies, 189*, 103301. https://doi.org/10.1016/j.ijhcs.2024.103301

Seini, A. B., Adam, I. O., & Preko, M. (2026). Human-AI collaboration in information systems research: A systematic literature review and future research directions. *Human-Intelligent Systems Integration*. https://doi.org/10.1007/s42454-026-00100-7

Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human-Computer Interaction, 36*(6), 495-504. https://doi.org/10.1080/10447318.2020.1741118

SIGCHI. (n.d.). *ACM Special Interest Group on Computer-Human Interaction*. https://sigchi.org/

Stoykova, S., & Shakev, N. (2023). Artificial intelligence for management information systems: Opportunities, challenges, and future directions. *Algorithms, 16*(8), 357. https://doi.org/10.3390/a16080357

Wang, Y., Ni, Q., Wei, T., Xu, H., Liu, L., & He, L. (2026). How AI-assisted decision-making paradigms and explainability shape human-AI collaboration. *Sustainability, 18*(7), 3516. https://doi.org/10.3390/su18073516