

STRATEGIC MANAGEMENT OF LLM-BASED CHATBOTS: TRANSFORMING INTERNAL COLLABORATION AND DECISION-MAKING IN ORGANIZATIONS

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Abstract

The article develops a strategic management framework for LLM based chatbots that explains how these systems reshape internal collaboration and managerial decision making and the conditions that enable reliable use. The background is the shift from scripted chatbots to assistants that retrieve and synthesize organizational knowledge, sustain context aware dialogue, and support knowledge work. The methodology is an analysis of peer reviewed scientific literature retrieved from major academic platforms, using targeted keyword searches and selective inclusion of studies with organizational relevance. The data collecting process relied on database searches and screening of titles, abstracts, and full texts. Expected results indicate five practical roles for LLM based chatbots, namely Librarian, Analyst, Coordinator, Scribe, and Coach, which accelerate access to knowledge, bridge silos, improve coordination, and strengthen onboarding and meetings. Mapped to decision processes, these assistants support the intelligence, design, choice, and learning stages. The conclusions underline that value depends on human in the loop oversight, sound data management, simple usage protocols and training, and transparency through basic audit trails, while a small set of metrics can guide pilots and scaling.

Keywords: LLM based chatbots, Strategic management, Internal collaboration, Decision making, Artificial intelligence in management.

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1. INTRODUCTION

Organizations increasingly integrate artificial intelligence (AI) into everyday work as digital assistants shape collaboration and knowledge use. Management research frames these assistants as socio technical systems that create opportunities for productivity and collective intelligence while raising issues of opacity, bias, and trust that require deliberate governance (Maedche et al. 2019). A multilevel view shows that outcomes depend on individual, team, and organizational factors, which explains why results vary across contexts (Bankins et al. 2024).

Classic chatbots in customer service and frequently asked questions followed scripts and retrieval logic. They improved responsiveness but struggled with context, nuance, and sustained dialogue, which

constrained strategic impact inside firms (Adamopoulou and Moussiades 2020). Large language model chatbots (LLM) represent a shift from these scripted or retrieval based systems. Trained on massive text corpora, they generate adaptive, human like responses rather than fixed outputs. This distinction makes them suitable not only for handling queries but also for synthesizing knowledge, brainstorming ideas, and supporting decision processes (Adamopoulou and Moussiades 2020; Ramaul et al. 2024).

Recent progress confirms these new possibilities. Evidence with knowledge workers identifies both creation affordances opportunities to create or enhance content, automate tasks, and augment knowledge and conversational affordances opportunities to sustain contextual dialogue, improve accessibility, and integrate into human workflows. These affordances shorten time to information, support collaboration, and ease handovers across roles (Ramaul et al. 2024). Reviews document broad organizational uses together with the need for policies, audits, and risk controls for privacy and reliability (Ayinde et al. 2023). Early empirical work links incorporation of ChatGPT to performance through operational and market agility, moderated by the depth of use and the firm ethical identity (Talaie Khoei et al. 2024). Studies of teams also show that collaboration with an AI teammate can reduce decision asymmetries when knowledge is centralized and well integrated (Zercher et al. 2025).

This paper develops a conceptual framework for the strategic management of LLM based chatbots that explains how they transform internal collaboration and decision making, and specifies governance conditions for reliable use.

The contribution is to connect capabilities and affordances of LLM based chatbots to collaboration and decision process mechanisms, to propose practical roles and metrics for managers, and to align these practices with responsible AI governance that covers structural, relational, and procedural controls across the life cycle (Papagiannidis et al. 2025).

2. LITERATURE REVIEW

2.1 AI and chatbots in management

Artificial intelligence has progressed from narrow task automation to digital assistants that contribute to knowledge work. Management research positions such assistants as socio technical systems, emphasizing the interaction between user, task, and technology, and highlighting both opportunities such as productivity and cooperation and risks such as transparency, bias, and trust that require purposeful governance (Maedche et al. 2019). A multilevel perspective further explains how AI outcomes vary across contexts, pointing to individual attitudes, team processes, and organizational factors as key contingencies (Bankins et al. 2024).

The initial chatbots were mostly rule based or retrieval based and worked well for narrow tasks such as FAQs or customer support. They improved responsiveness but were unable to maintain context, recognize subtlety, or sustain ongoing dialogue. Early reviews document their architectures, development environments, and typical limitations in empathy and contextual understanding (Adamopoulou and Moussiades 2020). These features explain why traditional bots seldom provided strategic leverage within companies beyond operational efficiencies.

The most recent shift to large language model chatbots introduces generative and dialogic capabilities better suited for knowledge work. Qualitative studies among knowledge workers identify creation affordances such as generation and enrichment of content, knowledge augmentation, and automation, and conversational affordances such as context sensitivity, interactive access, and human AI workflow synergy. Together, these affordances reduce time to information, enhance collaboration, and smooth handovers across roles (Ramaul et al. 2024). At the same time, organizational reviews stress the need for policies, audits, and governance measures to address privacy, reliability, and ethical issues in integrating LLM chatbots into business processes (Ayinde et al. 2023).

Overall, the field has evolved from scripted support agents dealing with routine questions to LLM driven systems with abilities to synthesize knowledge and provide collaborative support. This evolution raises managerial concerns regarding how to deploy, govern, and evaluate LLM chatbots so that their novel features yield organizational value, issues that the following sections address by examining their connections with collaboration and decision making processes (Maedche et al. 2019; Bankins et al. 2024).

2.2 Collaboration and decision-making with LLM chatbots

Human AI collaboration is best conceived as complementarity: machines enhance information processing and humans contribute context and values, so collaboration outcomes depend on the fit between tools, users, and routines (Jarrahi 2018; Maedche et al. 2019). Within this view, knowledge sharing is central. Evidence shows that AI alone does not sustain performance gains unless it is paired with knowledge sharing practices and enabling routines; this AI-KS complementarity is associated with higher organizational performance and more effective handovers of know how (Olan et al. 2022). In teams, human AI collaboration is promising but coordination intensive. Reviews of AI teaming indicate that unclear roles and poorly managed expectations can erode trust and communication, which calls for explicit role design and ongoing calibration of how teams use AI (Schmutz et al. 2024).

Experimental work in managerial settings finds that managers welcome machine input when humans retain a clear majority of control: acceptance rises to around a 70 percent human and 30 percent machine mix, with little added benefit beyond that point, and with heterogeneous preferences across manager groups (Haesevoets et al. 2021). For decision making, LLM chatbots can assist the intelligence, design,

and choice stages by filtering information, laying out options and criteria, and structuring trade-offs for review. At the firm level, links to outcomes appear to flow through agility: integrating generative assistants into processes is associated with improvements in operational and market agility when adoption is embedded and aligned with organizational identity (Wang et al. 2022; Talaei Khoei et al. 2024).

Overall, current evidence supports viewing LLM chatbots as collaborative aids that speed knowledge flows and help structure decisions, provided organizations invest in role definition, user training, and governance routines that ensure reliability and accountability (Ayinde et al. 2023; Papagiannidis et al. 2025).

While reviews of chatbot technology describe both capabilities and limitations of earlier systems (Adamopoulou and Moussiades 2020; Gatzoufa and Saprikis 2022), and recent empirical studies demonstrate that generative models can enhance organizational agility and performance when adopted strategically (Wang et al. 2022; Talaei-Khoei et al. 2024), current research still treats these issues in a fragmented way. What remains missing is an integrated framework that consolidates these insights by specifying the strategic roles LLM chatbots can play, the mechanisms through which they shape collaboration, their contributions across decision-making stages, and the governance practices needed to ensure reliable and responsible use. Developing such a framework is essential to move beyond descriptive accounts and isolated findings toward a systematic understanding of how LLM chatbots can be managed as internal collaborators in organizations.

TABLE 1. COMPARISON OF CLASSIC AND LLM CHATBOTS IN ORGANIZATIONS

Dimension	Classic chatbots	LLM chatbots
Core capability	Scripted or retrieval-based responses, following pre-set rules and matching fixed intents. Suitable for repetitive and predictable tasks.	Generative and adaptive responses, trained on large corpora. Able to create novel outputs and maintain human-like conversation beyond scripted flows.
Context handling	Can handle only short queries with limited memory. Dialogue often breaks when context shifts or inputs are ambiguous.	Retains longer conversational context and adapts responses. Better at managing nuanced, multi-turn exchanges within organizational workflows.
Knowledge use	Relies on static FAQs and manually curated scripts. Updates require developer input and lag behind organizational changes.	Synthesizes information dynamically and drafts content on-the-fly. Can connect to internal databases or documents to enrich knowledge work.
Typical use	Deployed mainly in customer service and FAQ handling to reduce call center load. Focuses on operational efficiency.	Applied to internal collaboration, knowledge sharing, decision support, brainstorming, and documentation. Extends impact beyond front-line operations.
Collaboration support	Provides only basic routing, reminders, or escalation prompts. Limited value for cross-team collaboration.	Acts as a bridge between functions by providing faster knowledge access, smoother handovers, meeting summaries, and onboarding guidance.
Decision support	Minimal input into decisions, restricted to predefined options or rule-based advice.	Contributes to all stages of decision-making (intelligence, design, choice, learning). Helps filter information, generate scenarios, highlight trade-offs, and record lessons.
Value dependencies	Success depends mainly on good flow design and clear escalation paths.	Requires role clarity, AI literacy training, and governance routines to deliver sustainable

	Strategic value remains low.	value. Dependent on organizational adoption and knowledge-sharing practices.
Main risks	Prone to brittleness: unexpected inputs cause breakdowns. Narrow use scope prevents wider adoption.	Risks include hallucinations, privacy breaches, and over-reliance. Trust calibration is needed to prevent blind acceptance of outputs.
Governance focus	Monitoring conversation flows, handling escalation, and measuring response time are sufficient.	Stronger safeguards needed: human-in-the-loop oversight, access controls, audit trails, explainability, and evaluation metrics for safety and reliability.
Organizational impact	Improves responsiveness and efficiency in handling routine queries but rarely affects strategic decision-making.	Potential to transform knowledge flows and decision quality, increase agility, and support strategic collaboration across the enterprise.
Evaluation metrics	Commonly measured by resolution time, escalation rates, and customer satisfaction scores.	Assessed by accuracy, usefulness, decision quality, trust, compliance, and agility-related outcomes.

Source: Author's research

3. CONCEPTUAL FRAMEWORK

This framework integrates recent findings to explain how LLM based chatbots reshape internal collaboration and managerial decision making. It specifies strategic roles for the chatbot, the collaboration mechanisms they enable, their contributions across decision stages (Intelligence, Design, Choice, Learning), and the governance conditions that make these effects reliable and responsible (Maedche et al. 2019; Bankins et al. 2024)."

LLM assistants can take on five complementary roles. As Librarian, the chatbot retrieves and synthesizes internal knowledge so employees obtain contextually relevant answers rather than keyword hits, which accelerates access to organizational memory (Lee et al. 2024). As Analyst, it generates alternatives, scenarios, and risk lists that widen the option set for managers and improve draft quality in knowledge tasks (Ramaul et al. 2024; Noy and Zhang 2023). As Coordinator, it supports handovers, reminders, and workflow communication that keep multi person processes aligned (Gomez et al. 2024). As Scribe, it documents meetings, decisions, and rationales to create searchable records that support transparency and learning (Lee et al. 2024). As Coach, it provides onboarding tips, templates, and prompting guidance that raise the performance of less experienced staff and standardize good practice (Noy and Zhang 2023; Ramaul et al. 2024).

Collaboration mechanisms. These roles activate four mechanisms inside teams. First, faster access to knowledge reduces time to information and lowers the need for ad hoc expert queries when the chatbot surfaces relevant evidence on demand (Lee et al. 2024; Freire et al. 2024). Second, bridging silos occurs when the chatbot aggregates and translates information across functions, making dispersed know how usable in context (Olan et al. 2022). Third, smoother handovers and coordination follow from shared

summaries, action lists, and nudges that maintain a common picture of work in progress (Gomez et al. 2024). Fourth, improved onboarding and meeting efficiency arise when routine drafting and note taking are automated and newcomers can ask clarifying questions without slowing the group (Ramaul et al. 2024; Lee et al. 2024). These benefits depend on alignment between tool capabilities, user skills, and local routines, consistent with a socio technical view of assistants in organizations (Maedche et al. 2019; Bankins et al. 2024).

LLM chatbots provide structured support for decision making, with contributions that align to Simon's stages at multiple points. In intelligence, the Librarian scans sources, filters noise, and summarizes relevant facts so managers start from a shared evidence base (Lee et al. 2024). In design, the Analyst proposes alternatives and articulates evaluation criteria, which expands the space of solutions and makes trade offs explicit (Ramaul et al. 2024). In choice, structured comparisons, risk highlights, and well scoped explanations improve understanding and compliance when people retain control over the final decision (Westphal et al. 2023). In learning, the Scribe captures decisions and outcomes to support later review and reuse, closing the feedback loop (Lee et al. 2024). At the organizational level, these contributions are associated with agility improvements when adoption is embedded in workflows and aligned with identity and values (Wang et al. 2022; Talaei Khoei et al. 2024).

Governance conditions. Realizing value while managing risk requires clear guardrails. Human in the loop control increases trust, understanding, and adherence to recommendations when users can adjust or override system outputs (Westphal et al. 2023; Haesevoets et al. 2021). Data access and quality management addresses confidentiality, provenance, and factual reliability, including decisions about open versus closed models and fine tuning on internal data (Lee et al. 2024; Jobin et al. 2019). Usage protocols and training define appropriate tasks, set escalation and verification steps, and build AI literacy and prompting skills so users understand capabilities and limits (Zhang et al. 2021; Papagiannidis et al. 2025). Transparency, audit trails, and monitoring support accountability and reduce the risks of opacity by logging interactions, checking for bias and error, and tailoring explanations to cognitive load and user ability (Bauer et al. 2023; Westphal et al. 2023). Governance should also include evaluation and metrics for accuracy, safety, usefulness, and robustness, drawing on emerging LLM evaluation guidance to operationalize measurement in practice (Chang et al. 2024).

Moderators and boundary conditions. Effects vary with task type and complexity, relative human and AI expertise, data sensitivity and regulation, organizational culture and acceptance, and depth of adoption. Meta analytic evidence shows human and AI combinations tend to excel in generative tasks but may not always outperform the best individual agent in structured decision tasks, which underscores the importance of role clarity and fit to task (Vaccaro et al. 2024). Acceptance is higher when humans retain a clear majority of

control and when roles and expectations are explicit inside teams (Haesevoets et al. 2021; Schmutz et al. 2024). Implementation conditions such as leadership support, change management, and staged infusion rather than one off pilots further shape outcomes (Zhang et al. 2021; Wang et al. 2022).

TABLE 2. STRATEGIC ROLES OF LLM CHATBOTS IN COLLABORATION AND DECISION-MAKING

Role	Collaboration Mechanism	Decision Stage (Simon)	Primary Beneficiaries	Example Metrics	Governance Controls	Risks & Limits
Librarian	Knowledge retrieval and synthesis	Intelligence	Managers, analysts, cross-functional teams	Time to information, relevance/accuracy of sources	Data quality checks, access permissions	Outdated data, biased sources
Analyst	Option generation and scenario analysis	Design	Strategy teams, risk managers, executives	Number/diversity of alternatives, risk coverage	Human-in-the-loop validation, scenario vetting	Hallucinated outputs, unverified assumptions
Coordinator	Workflow reminders, handovers, scheduling	Choice (support)	Project teams, HR, operations units	Decision cycle time, coordination efficiency	Usage protocols, role clarity, scheduling standards	Overdependence, missed accountability
Scribe	Meeting notes, documenting rationale	Learning	Teams, compliance officers, auditors	Completeness of records, retrieval/reuse rate	Audit trails, transparency logs	Information overload, privacy risks
Coach	Onboarding, prompting guidance, templates	Across all stages	New employees, training managers, knowledge workers	Training uptake, prompt effectiveness, error reduction	Training guidelines, responsible use policies	Over-reliance, neglect of critical thinking

Source: Author's research

These roles are not mutually exclusive, a single AI assistant can embody several roles depending on the context. Together, they illustrate the versatile ways an LLM chatbot can add strategic value inside organizations, beyond the basic Q&A or task automation of earlier-generation bots.

4. DATA AND METHODOLOGY

This article is based on an analysis of peer-reviewed scientific literature that examines the role of large language model (LLM) chatbots in organizations. Data were collected from leading academic databases and publisher platforms, including Elsevier ScienceDirect, Springer Nature/SpringerLink, Wiley Online Library, SAGE Journals, Emerald Insight, ACM Digital Library, Taylor & Francis Online, Frontiers, and MDPI. The reviewed studies were published between 2018 and 2025, a period that captures the transition from traditional chatbots to advanced LLM-based assistants. Search terms combined technological and managerial themes, such as “LLM chatbot,” “generative AI assistant,” “human–AI collaboration,” “decision making,” “knowledge sharing,” “governance,” and “evaluation.”

The inclusion criteria required that the studies were peer-reviewed and provided clear organizational implications for collaboration, decision-making, or governance. Non-peer-reviewed sources, opinion pieces, and purely technical benchmarking studies without management relevance were excluded. This analysis offers a comprehensive overview of recent research trends and provides the foundation for examining how LLM chatbots can be strategically managed to transform collaboration and decision processes in organizations.

5. CONCLUSIONS

LLM based chatbots are becoming reliable partners in everyday management work. When used with clear goals, they speed up access to knowledge, connect information across teams, support coordination, and keep a record of decisions. Framed against the decision process, they help managers gather evidence, design alternatives, choose with clearer trade-offs, and learn from outcomes. The core message is simple: these tools lift the quality and pace of collaboration and decisions when leaders treat them as part of the organization's system, not as a bolt on gadget.

The value is human centered. Chatbots extend human judgment rather than replace it. People bring context, values, and accountability. The assistant brings reach, recall, and drafting power. Results are best when the division of roles is explicit and when people keep a clear majority of control for important choices. Good practice is to decide up front what the bot can suggest, what it can automate, and where human review is mandatory.

Conditions for success are practical and manageable. Data must be accurate and accessible to the assistant, with sensible guardrails for privacy and confidentiality. Teams need basic training in how to ask for help, how to check outputs, and how to capture decisions and rationales. Explanations should be short and useful, and decision control should remain with managers. Monitoring and simple audit trails protect trust and make it easy to fix problems early.

Managers can start small and scale with evidence. Pilot in a few processes where knowledge is scattered and cycle time matters. Assign clear roles such as Librarian, Analyst, Coordinator, Scribe, and Coach so everyone knows what to expect from the assistant. Track a handful of metrics that matter, such as time to information, decision cycle time, breadth of options considered, rework and error rates, and the share of decisions with documented rationale. Use these measures to refine prompts, workflows, and review points, then expand to adjacent teams once the playbook works.

There are limits and open questions. Not every task benefits equally, and the assistant can still make confident mistakes. Work that is sensitive or highly regulated needs tighter controls and more human

review. Future studies should test the framework across sectors and task types, examine how much explanation and how much decision control produce the best outcomes for different users, and follow implementations over time to see how productivity, quality, and trust evolve.

The direction is clear. With thoughtful roles, simple rules, and steady measurement, LLM based chatbots can help organizations work faster, decide better, and learn as they go, while keeping people in charge of what truly matters.

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