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Beauty or the Borg: Agentic artificial intelligence organizational socialization in synergistic Hybrid Transformative Dynamic Flows

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ABSTRACT

This article introduces a framework for optimizing managerial decisions through a process/flow thinking approach, incorporating the impact of AI-human socialization in a tourism organizational context. It reflects the transformative nature of hybrid interactions shaped by human-AI socialization process. Despite AI's expansion across industries, research on its social integration in tourism remains limited. This study critically reviews sociotechnical systems theory and applies a continuous socio-technological transformation approach to tourism organizations. The proposed framework conceptualizes decision-making in a human-agentic AI hybrid system via implementation of Intelligent Choice Architectures, emphasizing teamwork, trust-building, and legitimacy. An example case on pricing optimization illustrates the framework's applicability, demonstrating how AI can enhance decision-making in tourism, while streamlining allocation of resources across the human-AI hybrid system.

1. Introduction

The rapid diffusion of AI technologies across industries has transformed service co-creation, production, and decision-making processes (Rajesh et al., 2022; Yang et al., 2024). Despite AI's increasing presence, its social aspects in tourism remain underexplored. Philosophical and sociological conceptualizations of AI's role in human socialization are broad yet underutilized in tourism research (Lindgren & Holmström, 2020). While there are concerns about AI reducing human interaction in tourism, it also holds potential for sustainability and innovation (Majid et al., 2023). A deeper understanding of AI's socialization role is crucial as tourism organizations undergo rapid digital transformation (McDonald & Pearson, 2019; Schintler & McNeely, 2022).

AI is not an additive feature of the Industry 4.0 era; it disrupts traditional human values and decision-making structures. Tussyadiah (2020, p. 2) describes AI as "a system that thinks humanly, acts humanly, thinks rationally, or acts rationally". To achieve this human-like behavior, AI agents require six core capabilities: natural language processing, knowledge representation, automated reasoning, machine learning, computer vision, and robotics (Alter, 2024). As AI advances in competence and integration, its impact on daily life and work continues to expand, transforming human-AI interactions. Understanding human-AI hybridization requires new theoretical frameworks that incorporate business ecosystems, governance, and organizational transformations (Makarius, Mukherjee, Fox, & Fox, 2020; Shibasaki et al., 2020, pp. 67–83). Lindgren and Holmström (2020) argue that AI's role in decision-making should be viewed beyond discrete tasks—emphasizing AI's evolving social and cognitive interactions within complex infrastructures. Sociotechnical Systems Theory (STS, henceforth) highlights human-technology interdependence in organizations, yet AI's ability to engage in discourse, negotiation, and socialization differentiates it from past technological shifts. Consequently, new theoretical models are needed to examine AI's integration into contemporary decision-making.

Previous research has focused on AI agents as decision-support tools in tourism, finance, retail, and healthcare (Bock et al., 2020). However, actor-centric frameworks such as Actor-Network Theory (ANT) are increasingly viewed as less effective than process-based approaches (Baygi et al., 2021). Alternative perspectives, including Social Practice Theory (Mercuur et al., 2020) and the Viable Systems Approach (Casares, 2018), incorporate AI's social role into hybrid decision-making. Yet, further exploration is required to understand the

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transformative nature of AI-human collaboration in dynamic, service-oriented ecosystems (Baygi et al., 2021).

The tourism industry, as a complex open system, involves multiple stakeholders influenced by public and private interests, evolving business models, and emerging technologies (Huang et al., 2023). AI integration in tourism directly impacts service co-creation, consumer experiences, and organizational efficiency (Stylos et al., 2021). However, AI's adoption introduces business, ethical, and social challenges that require a balance between innovation, management needs, and societal well-being (Ozmen Garibay et al., 2023). Transformative AI applications must align with human values and real-time hybrid activity to enhance service design.

New theoretical development in decision-making is needed to integrate human values and AI agency in the tourism industry (Kim et al., 2024). This paper responds to Tussyadiah's (2020) call for conceptualizing AI's role in organizational decision-making, particularly from an organizational viewpoint. Tourism organizations and AI co-shape hybrid meta-tourism environments, influencing dynamic human-AI partnerships in decision processes. This study builds on the assertion that users form social interactions with technologies (Gretzel, 2011), and it incorporates the latest AI advancements within a hybrid socio-digital context. Building on this, our study incorporates contemporary AI advancements to examine human-AI hybrid decision-making in tourism.

This paper critically advances STS Theory (Trist, 1981, 2013) by incorporating human-AI socialization in tourism organizations. STS traditionally focuses on human-technology interactions, asserting that organizational performance improves when social and technical systems are integrated (Sony & Naik, 2020). However, organizational change efforts often fail due to an overemphasis on technology without considering human-AI interdependence. Using the Continuous Socio-Technological Transformation approach (Baygi et al., 2021), this study examines hybrid human-AI interactions (Cimini et al., 2020), identifies beneficial and limiting STS elements, and proposes an advanced decision-making framework—the Hybrid Transformative Dynamic Flows framework—that integrates AI-driven socialization in tourism organizations.

Traditionally, tourism research assumes humans as sole decision-makers, with technology playing a supportive role (Ibrahim et al., 2024; Roodbari & Olya, 2024). This study challenges that notion, proposing an integrated human-AI ecosystem where decision-making is dynamic, socially interactive, and continuously evolving (Baygi et al., 2021). The proposed framework conceptualizes tourism decision-making as a hybrid, process-driven model where AI is not just a tool but an active social agent influencing organizational socialization, managerial decision-making, and service co-creation. In particular, this study's main objectives are threefold: first, to conceptualize hybrid human-AI decision-making from a mutual socialization perspective in tourism organizations; second, to critically assess and update STS theory, incorporating AI-driven intelligence into organizational decision-making; and third, to propose a framework that optimizes managerial decision-making through process-oriented, AI-human socialization dynamics.

2. Background

2.1. AI agents and human-AI teaming

Effective managerial decision-making has traditionally been a human-driven process, with computational tools offering support. However, advances in deep learning and artificial neural networks have significantly enhanced AI's learning capabilities and autonomy, improving decision-making efficiency and effectiveness (Sarker, 2021; Shrestha et al., 2021). From Large Language Models (LLMs) to Generative AI, robotics, and Agentic AI, modern AI technologies aim to replicate human intelligence (Yang et al., 2024). For example, LLMs like ChatGPT demonstrate decision-making and problem-solving abilities, aligning with moral judgments and simulating human reasoning (Binz & Schulz, 2023; Dillon et al., 2023). Meanwhile, robotic AI advancements focus on sensors, actuators, and embodied intelligence, illustrating varied technological trajectories across AI domains (Sarker et al., 2024).

Among AI innovations, Agentic AI stands out for its autonomy, goal-orientation, decision-making, proactivity, and adaptability (Shapiro et al., 2023). These systems integrate machine learning, real-time processing, and adaptive algorithms to address complex problems (Chawla et al., 2024). Their engagement with the world has been intensified, thus continuously improving their causal reasoning abilities (Binz & Schulz, 2023). Applications span industrial robotics, autonomous vehicles, avatars, and smart home systems. Unlike other AI types, Agentic AI mimics cognitive functions and dynamically learns through recurring adaptation cycles (Dutta & Kannan Poyil, 2024; Felin & Holweg, 2024). By leveraging real-time data, AI agents enhance decision-making across industries, dynamically adjusting responses and mitigating bias (Chen et al., 2024). They work complementarily with humans, optimizing efficiency and problem-solving in manufacturing, healthcare, retail, and customer service.

Agentic AI operates independently or in multi-agent environments, collaborating with both humans and AI systems to optimize organizational objectives (Nechesov et al., 2025). These systems assist internal and external stakeholders, offering strategic decision support while ensuring human oversight (Abedin et al., 2022). Rather than replacing humans, Agentic AI enhances human-AI teaming, supporting context-driven, ethical, and adaptive decision-making (Pan et al., 2024). Human-AI collaboration in sociotechnical systems is evolving toward integrated partnerships, exemplified by centaur models and cybernetic organisms (Thiele, 2021). Effective human-AI teaming requires goal alignment, trust, and seamless communication to optimize collaboration (Endsley, 2023; Schelble et al., 2022). The co-evolution of AI and human decision-makers fosters mutual adaptation and collective growth, cultivating synergistic digital ecosystems (Chaffer, Goldston, & A I, 2024). As AI integration expands, human-AI teaming will become increasingly prevalent across industrial and service sectors, shaping the future of hybrid meta-societies (Chaffer, Goldston, & A I, 2024).

Fig. 1 illustrates an example of human–Agentic AI interaction within the tourism context, highlighting how humans can collaborate with one or more AI-powered agents from an organizational perspective. The figure presents various possible configurations of human–AI teaming. Solid arrow lines represent the contributions of human agents, while dashed arrow lines indicate alternative pathways for integrating AI

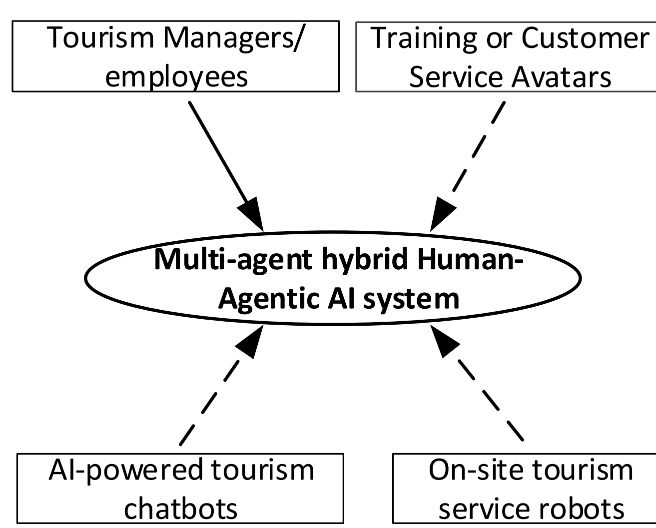

Fig. 1. An example of multi-agent hybrid human-Agentic AI system for a tourism organization. (Source: Developed by authors).

agents, ultimately forming multi-agent hybrid systems that blend human and Agentic AI capabilities.

In the tourism sector, hybrid human-Agentic AI collaboration can be implemented in various forms and applications, to enhance both front- and back-office tourism service operations. Such collaborations can lead to significant improvements including real-time information delivery, personalized services, dynamic pricing schemes for optimal revenue management, enhanced financial risk management contributing to greater resilience and overall Improvements in customer service quality.

Nevertheless, the development of multi-agent hybrid human-AI systems requires careful consideration and integration of several key processes within the tourism service blueprint. These include the integration of Agentic AI with existing human resource systems and service platforms, training both humans and AI agents to operate as a team; integration of robust data monitoring, collection, and analysis systems; and implementing ethical guidelines that ensure the roles and organizational positioning of both human and AI agents are respected.

Despite the promise of these transformative systems, several challenges remain—both for organizational structures and customer-facing service delivery. These challenges often stem from limitations in harmonizing human–AI collaboration. For instance, service roles and collaboration styles between humans and AI agents must be clearly defined to ensure service effectiveness. Limited resources may also constrain implementation, particularly in relation to organizational size and structure (e.g., multinational corporations versus SMEs). Moreover, variability and biases in decision-making—stemming from both human judgment and AI algorithms—can impact the reliability, validity, and speed of operational decisions. The model proposed in this paper seeks to address several of these limitations and challenges, offering a structured approach to more effective and ethical human–Agentic AI teaming in tourism services.

2.2. Systems thinking, sociotechnical systems, and transformative dynamic processes

STS are configurations of interacting sub-systems between humans and technological structures (tangible or intangible) and are influenced by environmental factors (Bednar & Welch, 2020). Their design and evolution enhance work experiences, productivity, and organizational effectiveness by integrating technical and social components during technological and structural transformations (Davis et al., 2014). These systems foster peer-to-peer collaboration and share awareness, prioritizing bottom-up decision-making over rigid hierarchical control (Trist, 1981). Advancements in sociotechnical systems theory conceptualize subsystems as networked structures that evolve dynamically. As open systems, STS continuously interact with external environments and evolve dynamically, adapting to maintain dynamic equilibrium and self-correcting errors amid change (Trist, 2013). Information exchange across system boundaries is essential for sustaining resilience and adaptability.

In service industries, sociotechnical complexity is particularly high, requiring optimized integration of human and AI-driven components. Recent technological leaps have outpaced organizational redesign efforts, prompting renewed interest in sociotechnical models for modern management (Melville et al., 2023; Pasmore et al., 2019). In contemporary service organizations, processes are fluid, emergent, and shaped by dynamic, contingent interactions (French & Shim, 2024). As Industry 4.0 advances, AI-assisted workflows play an increasingly transformative role, necessitating new frameworks to guide AI-integrated organizational processes. However, relevant theoretical and managerial applications are still evolving.

2.3. Artificial intelligence in service decision-making: trust, collaboration, and the unique challenges of tourism

AI is transforming decision-making in service industries, enhancing efficiency, personalization, and human-AI collaboration. This study first considered how various theories, including Actor-Network Theory (ANT), Social Practice Theory (SPT), and STS theory may provide key foundations for contextualizing AI's integration into decision-making. ANT views AI as an active agent, shaping and being shaped by human and organizational interactions. SPT highlights AI's role in routine-based decision-making, influencing service dynamics. STS theory, in contrast, emphasizes AI's co-evolution with organizational structures, portraying it as an adaptive, transformative agent rather than a passive tool; thus, STS theory appears to be particularly suitable for hybrid service contexts (Blaurock et al., 2024). AI's role is fluid, shifting based on automation levels, human oversight, and operational complexity.

AI adoption varies across service sectors, each with distinct decision-making needs and trust dynamics. In banking and healthcare, AI minimizes human intervention to enhance efficiency and risk reduction. However, in tourism, AI is more than a tool—it co-creates experiences, making human-AI interaction more complex and emotionally driven (Azer & Alexander, 2024). Unlike transactional industries, tourism services depend on personalization, adaptability, and emotional intelligence (Koponen et al., 2023). AI applications such as virtual concierges, chatbots, and predictive analytics must mimic human intuition and sociability, balancing automation with authentic customer interaction (Blaurock et al., 2024).

Depending on the type of service contexts, trust in AI may differ accordingly. In banking and healthcare, it is built on accuracy, security, and compliance, whereas in tourism, trust is shaped by emotional engagement and perceived authenticity (Koponen et al., 2023). Studies suggest that anthropomorphized AI (e.g., AI-powered concierges and virtual guides) can enhance trust and satisfaction, but overly scripted AI may lead to skepticism (Blaurock et al., 2024). This highlights a key tourism challenge—AI must be intelligent and engaging without compromising authenticity.

While human trust in AI is well-studied, AI's trust in human decisions remains underexplored. AI does not trust in the human sense but assesses reliability through probabilistic reasoning, pattern recognition, and algorithmic learning (Kissinger et al., 2021). If trained on biased or inconsistent data, AI may reinforce systemic biases or misinterpret user behavior (Blaurock et al., 2024). AI agents adjust recommendations based on past interactions, trust metrics, and confidence thresholds (Azer & Alexander, 2024). In high-stakes tourism scenarios—such as dynamic pricing and AI-driven travel recommendations—AI may override human inputs if data appears conflicting or incomplete (Koponen et al., 2023). This reciprocal trust dynamic shapes AI's role as both a support system and a challenge to traditional decision-making.

Given tourism's highly interactive nature, AI may function as a hybrid intelligence system contributor, combining data-driven insights with human judgment. In this context, new frameworks are needed to explore human-AI trust in addressing biases and decision-making gaps, and to investigate AI's impact on human decision autonomy and trust formation in travel planning, tourism service co-creation, and service recovery. Unlike other service sectors, tourism AI should balance automation with emotional intelligence, ensuring that AI-driven decisions enhance rather than diminish the human-centric nature of tourism services.

3. Methodology

A comprehensive literature review is an effective method for critically assessing research advancements, identifying gaps, and developing new theoretical perspectives (Torraco, 2005). This study employs the Integrative Literature Review (ILR) approach, which integrates research from organizational decision-making and Artificial Intelligence (AI) to provide a holistic and interdisciplinary perspective (de Larrea et al., 2021). ILR is particularly suited for examining emerging topics and advancing theoretical frameworks (Snyder, 2019). The review begins with STS Theory (Trist, 1981; Trist et al., 2013) and incorporates new insights into human-AI decision-making and organizational socialization in hybrid AI environments.

3.1. Data collection and search strategy

This study synthesizes research from multiple disciplines, including decision science, management information systems, human-computer interaction, organizational behavior, and tourism and hospitality. Following the methodological recommendations of Torraco (2005) and Snyder (2019), the integrative literature review of the current study runs in four phases: (a) review design, (b) actual review conduct, (c) analysis and synthesis, and (d) theoretical propositions and proposal of an advanced theoretical framework for future research.

The design phase of the integrative review focused upon the literature on human-AI hybrid managerial decision-making as influenced by the notion of AI organizational socialization; thus, publications across various disciplines were purposefully scanned to determine what is already in the extant literature. Also, suitable structuring of the topic from a conceptual viewpoint took place by adopting STS as the theoretical lens. The integrative review study confirmed the role of STS as an explanatory theoretical mechanism in hybrid human-AI contexts. It also highlighted the potential for integrating various types of AI into decision-making science, contributing to future developments as an active social strand of metacommunities. Specifically, a robust search strategy involved careful selection of keywords with initial scans of the literature followed by small adjustments to better calibrate the focus of the resulting outputs. Priority was given to relevance rather than chronology of the publications identified in the four main searches. Specifically, the keyword searches focused on indexing based on the source, title, keywords, abstracts, subjects to retrieve sources about: (a) human-AI collaborative decision-making in light of the organizational socialization of AI teammates, (b) the role of STS in a hybrid human-AI intelligence context, (c) the STS and relevant critical points, and (d) STS implementation in tourism and hospitality industries.

3.2. Keyword sets and screening process

The keyword sets included:

- *("human-AI collaboration" OR "human-AI symbiosis" OR "hybrid intelligence" OR "human-AI team") AND "decision-making" AND "industry 4.0″ AND ("organizational socialization" OR "organisational socialization"),*
- *("socio-technical systems theory" OR "sociotechnical systems theory") AND "decision-making" AND ("human-AI collaboration" OR "human-AI symbiosis" OR "hybrid intelligence" OR "human-AI team"),*
- *"critique" AND "socio-technical systems theory" AND decision-making,*
- *"socio-technical systems theory" AND "decision making" AND ("tourism" OR "hospitality")*

Searches were processed through *Worldcat Discovery Service* to achieve an enhanced coverage of 41 different online databases (OCLC Developer Network, 2024). We focused on literature published between 2017 and 2024, wherein the research on human-AI teaming towards forming sociotechnical collaborative decision-making systems has been rapidly evolving (Storey et al., 2024).

The second phase included peer-reviewed articles, conference papers, and book chapters with interdisciplinary relevance. Articles in popular magazines, white-papers, and non-peer reviewed journals were excluded. A five-step staged review process was employed during this phase: first, involving a preliminary review of all abstracts; second, excluding the sources making general references to the topic but not actually offering conceptual depth and significant insights; third, proceeding with article reviews; fourth, the reference list of the articles that underwent in-depth review were checked for any sources that could be highly relevant. Finally, this led to adding a few more sources in the final set of publications. These relevant articles were then downloaded and saved for further reading. In the third phase, the literature was analyzed and synthesized with a focus on STS, viewed through the lens of hybrid human-AI teaming and organizational socialization.

Specific results and numbers of papers retained per search:

- 42 publications on hybrid human-AI decision-making as influenced by organizational socialization process, 10 retained
- 30 publications on STS in AI decision-making, 12 retained (Table 1)
- 277 publications critiquing STS in decision-making, 17 retained
- 149 tourism-focused STS studies, 8 retained (Table 2)

3.3. Data analysis and theoretical integration

A concept-centric approach (Webster & Watson, 2002) was used to synthesize literature, categorizing findings based on hybrid human-AI decision-making and STS applications. Data analysis followed open coding and comparative methods, allowing unconstrained theme extraction (Merriam, 2001). This process led to the development of theoretical propositions and the formulation of a new STS-based framework for human-agentic AI synergy. The proposed model reflects the hybrid and transformative nature of human-AI socialization in organizational settings, aligning with the evolving dynamics of cyber-physical-social systems in tourism.

4. AI organizational socialization for human-AI collaborative decision-making

Human-AI teaming is increasingly prevalent, involving independent AI agents or forming integrated human-AI systems, such as centaurs and cybernetic organisms (Thiele, 2021). Scholars advocate for human-AI symbiosis in organizations, combining human intuition with AI's analytical power, which enhances decision-making effectiveness (Abbas et al., 2023). Research shows that hybrid intelligence systems outperform both humans and AI alone by leveraging their respective strengths (Peeters et al., 2021). There is need for AI systems to not only process information logically, but also consider relational and emotional dynamics, enabling more empathetic, supportive, and human-like interactions (Butlin et al., 2023).

The development of AI systems capable of understanding and interacting with human emotions and cultural contexts is becoming increasingly important. While AI lacks true emotions, affective computing allows AI to recognize and respond to human emotions, facilitating natural and supportive interactions (Dhimolea, Kaplan-Rakowski, & Lin, 2022). Still, AI agents can simulate empathetic and socially appropriate responses (Huang & Rust, 2024), and understand human emotions via algorithmic cognitive processing frameworks, with these responses being based on data and programming rather than actual feelings (Lindgren, 2024; Mallick et al., 2024). AI agents' ability to simulate empathy and engage in context-aware socialization influences human attitudes, societal norms, and decision-making processes (Lu et al., 2022). This reciprocal human-AI relationship fosters mutual adaptation, collective intelligence, and symbiotic growth (Yao, 2023).

In hybrid decision-making, AI and humans enhance each other's capabilities (Longoni & Cian, 2022). Optimized human-AI collaborative decision-making can be achieved by aligning three interrelated design domains: (a) allocating human-AI functions effectively, (b) devising the human-AI decision-making system properly, and (c) integrating AI collaboration into organizational workflows. Beyond efficiency gains, AI-human teaming can boost creativity, trust, and minimize AI's negative impact on jobs (Peeters et al., 2021). Ethical principles such as transparency, justice, and autonomy are crucial for ensuring AI aligns with human values (Richards et al., 2023). Scholars emphasize participatory and value-based design, recommending user involvement in AI development to align agentic AI systems with human needs and values

Table 1
Review of publications on human-AI collaborative decision-making through the lens of AI socialization.

Author(s) Year	Description	Methodology	Main Outputs/contributions	Future Directions
van Diggelen et al. (2019)	An overview of the current state of the art in Human-AI agent teaming which envisions a novel interaction form where humans and AI behave as equal team partners.	Conceptual/theoretical synthesis, based on scenario analysis. Experimental and neural networks research has been conducted using semantic anchoring, followed by a prototyping development procedure.	Proposed a technical architecture and framework for social artificial intelligence in human-AI agent teaming, based on the concept of Social Artificial Intelligence Layer. Relevant social capabilities are based on proactive communication, dynamic task allocation and fit-for-purpose collaboration.	To develop more effective autonomous system architectures and create combinations of highly immersive human-AI agent teaming interaction. To explore validation methods for human-AI agent teaming considering the long-term aspects of teaming.
Seeber et al. (2020)	A research agenda that collaboration researchers can use to investigate the anticipated effects of designed machine teammates based on the qualified opinions of collaboration researchers.	A survey based on 819 research questions which collected three subsamples; undergone a multistep analysis procedure: an iterative approach of qualitative content analysis consisting of content structuring and inductive theme analysis	The analysis revealed three design areas: machine artifact design, collaboration design, and institution design. The second part of the results addresses the dualities in the form of concept dichotomies that could arise from human–AI collaboration.	To acquire evidence for the (non) existence of dualities from organizations as early adopters of machine teammates. Also, explore the extent of suggested association dichotomies to possibly explain changes in collaboration when a machine teammate is present.
Reis et al. (2020)	Explores the pros and cons of the use of service robots in the hospitality industry and to practice, by presenting the architectural and technological characteristics of a fully automated plant based on a relevant case.	A systematic literature review methodology was employed. Content analysis of 397 selected articles was conducted; encoded similar terms, and, through their grouping to identify categories and subcategories for patterns and relationships.	It is important that robots are equipped with social interaction skills, though still quite limited. Human-conscious deliberative architectures for social robots have been designed to team with humans in decision making, and collaborative tasks in executing shared activities.	To conduct empirical studies on social robots. Future studies on social robots to find suitable and adaptable solutions for contemporary hotels. Theoretical studies, are of great importance to new research in this nascent field alongside empirical ones.
Peeters et al. (2021)	Regarding human–AI agents teaming a balanced combination of humans with AI, and social artificial intelligence is needed to obtain a truly intelligent system.	An online survey of 570 useable cases; hypothesis testing conducted via CB-SEM	A design framework that adopts elements from three distinct perspectives of employing AI, which supports measurement, prediction, and mitigation of AI from societal aspects.	Consider objectives established at the collective level alongside local human-centric performance. A coherent design methodology for human-AI teaming and a multi-level view on the effects of AI.
Horváth (2023)	Interaction and cooperation with cyber-physical systems (CPSs) is multi-dimensional and socialization of CPSs plays a key role. Intellectualization, and adaptation, are key to decision-making.	A position paper based on Conceptual/theoretical synthesis of selected interdisciplinary research publications.	To depict the current situation, to cast light on some general issues, and to point at some foreseeable general trends, needs, and opportunities concerning the design of new generation CPSs.	How decision-making is influenced by aggregation, management, and exploitation of the growing amount of synthetic systems knowledge produced by CPSs.
Herrmann & Pfeiffer (2022)	Teaming of humans with AI agents is attainable if the whole organizational structure is integrated in the process, rather than just individual human agents.	Existing research studies are extended through an empirical exploration of two cases of AI employment in predictive maintenance.	A systematic framework proposing a set of four loops, and organizational practices enabling adoption and maintenance of AI agents.	Focus on the co-evolution of humans and AI-agents in organizational practices. Important to consider sociology of work, sociology of organization, and science & technology.
Cadden et al. (2022)	Examine the role and potential contribution of organizational culture as enabler of successful AI-agents integration.	Deductive approach, a sample of 261 organizations, analyzed though CFA and CB-SEM.	The influential role of culture in addition to the technical and business enablers when integrating AI into organizational structures and processes.	Examines how the need for resources changes through time, as operations become more autonomous, including synergies and symbiotic supply chains.
Chowdhury et al. (2022)	To examine and theorize on the organizational resources needed to achieve AI capability and business benefits by integrating the resource-based view and knowledge-based view frameworks.	A two-study approach was taken. The first one tested a model via hypothetical scenario method. The second one involved a qualitative study via focus group, and a lab experiment with 184 participants.	Investigated the impacts of travelers' cognitive assessments and affective evaluations.	Future studies to focus on the boundary conditions that impact travelers' evaluations with AI-based recommendation systems
Ritz et al. (2023)	Reviewing contemporary onboarding in light of the role AI plays in supporting various organizational processes, including hiring personnel and innovation.	A two-stage approach, with a) literature review of 30 papers, and b) six interviews based on a semi-structured interview guide.	This research evaluates the potential of AI to improve integration of new employees. It may help organizations design Industry 4.0-informed onboarding processes.	Future research to use it for shedding light on the potential of AI to facilitating humans successfully integrate into organizational structures.
Zheng et al. (2023)	Focuses on the integration of AI agents into the organizations by combining theory of technological adoption with the theory of organizational socialization.	A design-based case study approach in a large conglomerate via designing and proposing a Human-AI collaboration platform.	It provides a digital capability framework and relevant strategies for integrating AI agents into the organization and for achieving decision-making optimization	Future research to investigate how AI agents could optimize the design for better organizational socialization in a human-AI partnership scheme.
Bankins et al. (2024)	An overview of how current state of AI technologies currently reshape human work in the context of human-AI symbiosis.	Critical reflection paper discussing based on selected literature	Human-AI collaboration requires humans to develop high AI literacy to know how to work effectively with AI.	Future research to develop strategies for enhanced job designs and employees to be upskilled so they feel supported within a resilient.
Lindgren (2024)	Focuses on exploring the social roles of humans and AI forming hybrid intelligence, as influenced by transparency and sense of control.	A critical and progress review type of paper based on selected literature coming mainly from computer science and information management	As set of eight research challenges is recommended focusing on the design aspects of the emergent and blended roles of humans with AI agents.	Future research to develop structures for determining human-AI interactions from both functional and social aspects as per designed transformations in the STS.

Source: Developed by authors.

Table 2
STS theory in tourism and hospitality.

Author(s), publication year	Description	Methodology	Main outputs/contributions	Future Directions
Lim et al. (2017)	Drawing on STS theory, it proposes a smart tourism design framework and sets up an interactive mobile app for smart sustainable systems.	The cyclic process of design science methodology was implemented to create a smart tourism design model.	A new theoretical framework and a prototype of a software app are provided. Research contributes to the information systems literature.	Future research may focus on advancing the proposed framework and app in creating a more holistic approach.
Nyaboro et al. (2021)	Research explores how the comparative elements of tourism destinations could leverage on the competitive qualities via STS theory toward smart tourism design.	It implements a design thinking process via two field studies and a set of semi-structured interviews with stakeholders at two destinations.	It proposes a model for enhancing tourism destination competitiveness, and sociotechnical design features are embodied in an interactive mobile app.	Future studies to focus on eliciting additional social attributes from stakeholders for more accurate and diverse design features.
Lee et al. (2022)	Drawing on STS and social capital theories, it explores workers' job performance and retainment in food delivery services via crowdsourcing platforms.	A hypothetico-deductive approach and a sample of 267 responses from food delivery workers were analyzed via covariance-based structural equation modeling.	This study linked the dimensions of social capital with the technical system risks. The key role of social mechanisms in the virtual workplace is demonstrated.	Future studies to explore social factors other than crowdsourced workers' trust, toward the theorization of tourism STS.
Liu et al. (2022)	It models social-and-technical system enablers to examine the behavioral mechanisms towards Airbnb platform use from hosts' perspective.	A useable sample of 323 responses was finally utilized to test the hypothesized model via covariance-based structural equation modeling.	This paper suggests ways for accommodation platform managers to manage various enablers for supporting hosts in service provision.	Future research to include external environmental factors as well as individual characteristics in theoretical modelling.
Yan et al. (2022)	Drawing from STS theory, it examines corporate social responsibility as enabler of participative decision-making in hybrid working environments.	A synthesis of hospitality management literature, corporate social responsibility, and employee health and safety management.	A four-dimensional conceptualization towards a single framework to examine service employee health and safety at hybrid working contexts.	Future studies to focus on forthcoming radical changes in the work environment as per the role of human-AI collaboration.
Wang et al. (2023)	Sociomateriality is proposed for investigating the dynamics developed between tourists and their smartphones in group decision-making.	Two groups of 40 tourists were recruited to conduct a process-tracking study to identify different scenarios of group decision-making via NVivo.	It showcases the continuous interactions of tourists with technology, and smartphones involvement in group decision-making.	Future theorization via STS theory to facilitate decision-making research and move beyond diffusion of new tech and tourist experiences.
Park et al. (2023)	Research investigates the stressors experienced by hosts and the concept of technostress.	A sample of 157 Airbnb hosts was collected via Qualtrics and the hypothesized model was analyzed via PLS-SEM.	Employing STS theory, it identifies the catalysts across the social and technology dimensions.	Future research may explore other platform-specific factors and types of services with sociotechnical perspective.
Lim et al. (2024)	It investigates the role of team autonomy and task interrelationship in the overall team dynamics and effectiveness.	A sample of 312 tourism and hospitality employees was used, and the hypothesized model was analyzed via SEM (R Lavaan).	Team-level autonomy and task interdependence positively influence team performance. Organizations employ transparent systems to avoid resource misuse.	Future research to examine the role of influence of national culture on team design effectiveness and team performance.

Source: Developed by authors.

(Lindgren, 2024).

Successful human-AI teaming depends on AI organizational socialization, mirroring the socialization process of teams consisting solely of human members and human team dynamics (Jain et al., 2022). This way AI agents can assimilate into organizational structures, policies, and cultures, fostering trust and adaptability (Larson, 2021). AI organizational socialization refers to the mutual adjustment of humans and AI teammates to affective, cognitive, and behavioral demands, ensuring interoperability and decision-making quality (Jarrahi, 2018; Larson, 2021). Nonetheless, practical implementation remains a critical challenge for researchers and practitioners (Peeters et al., 2021).

Table 1 summarizes human-AI collaborative decision-making research, highlighting key technical and organizational enablers through the lens of AI organizational socialization. AI's role in automated social tasks (e.g., online recommendations and eWOM) underscores the importance of cultural adaptation in AI integration (Lyons et al., 2023). Effective AI-human socialization requires an adaptive organizational culture that fosters critical reflection and continuous learning (Cadden et al., 2022). Despite growing awareness, cultural alignment and AI socialization remain underexplored, calling for a sociotechnical breakthrough in human-AI collaboration design.

5. STS theory and new system design in organizations

5.1. STS theory, design qualities, and new technologies

Sociotechnical Systems (STS) Theory lost prominence in the 1980s–1990s due to industrial engineering approaches like lean manufacturing and business process re-engineering (Mumford, 2006). However, its relevance resurged post-2010 with rapidly evolving work environments, requiring integration of technology and organizational structures to support dynamic teams and resource applications. STS remains a powerful framework for system design, fostering collaboration and problem-solving (Eason, 2013; Trist et al., 2013). The concept of sociotechnical design focuses on how human agents interact with advanced technological subsystems, ensuring AI integration aligns with human needs, skills, and objectives rather than following a rigid, technology-driven path (Pasmore et al., 2019). These hybrid groupings would contribute to co-creating optimal sociotechnical designs in an organizational setting (Lindgren, 2024).

Internal supervision and leadership at the team level require encouragement and responsible autonomy (Walker, 2015). The social component in STS plays a critical role in value creation, affecting leadership, autonomy, and employee commitment, which in turn boosts organizational resilience and performance (Makarius et al., 2020; Chowdhury et al., 2022). However, external factors, such as financial crises and technological advancements, continuously reshaping workplace ethics and organizational culture, necessitating ongoing adaptation of sociotechnical designs (Pasmore et al., 2019).

STS originally analyzed human groups, but today it includes human-AI collaborations in multi-agent settings. AI acts as a bridge between social and technical domains, improving stability and reducing non-linear organizational behaviors (Walker, 2015). While Industry 4.0 research has prioritized technical optimization, effective STS design requires balancing social and technical elements (Sony & Naik, 2020). Joint-optimization remains central to STS (Walker, 2015; Xu et al., 2024), where human skills are combined with AI-driven data monitoring and decision analysis (Stylos et al., 2021). This human-AI interaction fosters hybrid intelligence, reshaping STS in cyber-physical-social systems (Abbas et al., 2023).

5.2. STS theory in tourism

STS theory was identified as an effective framework for experience-centered tourism systems and started appearing in the published literature from 2017 onwards (Lim et al., 2017). Its popularity in tourism draws from the industry's rapidly shifting work environments and the evolving nature of value production. Table 2 summarizes key studies integrating STS into tourism and hospitality.

STS applications in smart tourism can help organizations offer tourists smart apps with well-designed sociotechnical features to enhance their visitation experiences (Nyaboro et al., 2021). These studies emphasize the importance of integrating societal values into decision-making, leading to competitive advantages. However, researchers call for more precise design features and sustainable research frameworks reflecting the recent advances in service co-creation and organizational development (Nyaboro et al., 2021). Further studies stress the impact of AI and human-AI collaboration on tourism workflows and service blueprints (Yan et al., 2022). Building theories based on the interaction between the technical and social aspects of tourism provides a unique chance to study peer-to-peer decision-making in managing tourism services. Research on online platforms, sharing economies, and metaverse services provides insights into peer-to-peer decision-making in co-created tourism experiences (Liu et al., 2022). Trust is a critical factor, influencing AI adoption in tourism, as employees and consumers navigate risk, networking, and social influences (Lee et al., 2022).

Beyond structural integration, spatial and temporal factors also shape tourism-related decision-making, yet they remain underexplored (Jin & Cai, 2022). Real-time, location-based data collection is key to influencing tourist behavior via AI-driven recommendations (Wang et al., 2023). This is even more important in the case of agentic AI hybrid systems, due to the advanced in-design capabilities of the respective STS. As agentic AI agents (robotics, chatbots, avatars) advance, their role in tourism decision-making will expand, requiring further STS-driven research.

5.3. Critique on STS theory: toward embracing the hybrid human-AI era

STS theory has evolved across disciplines, but its application often leans either toward social or technical aspects, rather than balancing both (Baxter & Sommerville, 2011). Over time, its core principles have been diluted, making it difficult to maintain a consistent theoretical foundation (Eason, 2013). Some scholars argue that STS has fundamental limitations, particularly in achieving true joint optimization, where both social and technical subsystems are given equal weight (Abbas & Michael, 2022). In practice, early STS applications often favored social adaptation over technological transformation, rather than co-evolving both elements (Kelly, 1978; Pasmore, 1982). This oversight limited STS's ability to anticipate new technological paradigms (Mumford, 2006). Furthermore, Coiera (2007) recommended avoiding an overly critical view of technology and instead advocated for a balanced and constructive approach. Nowadays, this is becoming even more imperative due to advances in AI.

Another key challenge is that technological advancements frequently overshadow social considerations, making integration difficult (Stahl, 2007). STS models often adjust social factors in response to technology rather than integrating sociotechnical design from the outset (Abbas & Michael, 2022). Moreover, ambiguity in STS definitions and levels of abstraction complicates its practical application, especially with AI-driven transformations (Baxter & Sommerville, 2011). Advanced AI, such as robotic agents, blends both social and technical roles, challenging the traditional binary division of STS components (Eason, 2001).

Existing STS frameworks struggle to explain human underperformance, often attributing failures to system shortcomings rather than individual responsibility (Baxter & Sommerville, 2011). Additionally, empirical research on STS remains limited, as measuring social components is more complex than evaluating technical factors (Baxter & Sommerville, 2011). Proponents of STS have also failed to adapt the theory to rapidly changing global business ecosystems (Pasmore, 1995). STS ideological debates did not prove beneficial for theory advancements and prevented from keeping up with technical and organizational developments. To remain relevant, STS must evolve to embrace the hybrid human-AI era, requiring constant monitoring, data-driven adaptability, and decision-making integration.

5.4. From systems thinking to flow/process thinking in decision-making

STS acknowledges that social-technical integration creates complex, emergent interactions, sometimes leading to unpredictable outcomes (Walker, 2015). This complexity is especially pronounced in service organizations, where workflows are dynamic and non-linear. However, STS originally developed in mass production settings, making its direct application to service industries problematic (Hirschhorn et al., 2001). The distinct characteristics of contemporary service organizations must be thoroughly examined when applying STS in the Industry 4.0 era.

To address the challenges of applying STS theory in service settings, systems thinking is expanding toward process thinking, which emphasizes flow, continuous adaptation, and emergent decision-making (Zhichang, 2007). As technological advancements accelerate, STS needs to evolve beyond static system models to account for ongoing, iterative processes (Pasmore et al., 2019). Process thinking presents challenges, as interactions produce multiple, indeterminate outcomes, requiring flexible methodologies (Cloutier & Langley, 2020). Observed decisions often represent just one of many potential pathways, reinforcing the need for adaptive decision frameworks (Shipp & Jansen, 2021).

6. Synergistic Hybrid Transformative Dynamic Flows framework

6.1. Key attributes towards building a hybrid dynamic decision-making system

Organization systems should adapt and evolve to survive, necessitating periodic reviews and ongoing design efforts. Sociotechnical human-computer networks are not mere extensions of social networks but complex adaptive systems that evolve continuously (Shet & Pereira, 2021). Open systems are best suited for handling uncertainty and change, ensuring resilience and adaptability (Eason, 2013). In Industry 4.0, aligning social and technical components with organizational processes is essential for optimizing human-AI teaming. A purely technical approach that ignores local participation limits adaptability. Instead, strategic planning should involve stakeholders, ensuring that systems evolve rather than being rigidly "rolled out" (Abbas & Michael, 2022). Development teams must understand sociotechnical interactions, focusing on how technology and people co-adapt (Baxter & Sommerville, 2011). STS design requires strategic decision-makers to understand trends, resources, competition, and the commitment of agents, shaping the system's design purpose.

Three key Industry 4.0 trends shape hybrid human-AI teaming. First, organizations are dynamic networks and not static entities. Internal and external elements co-evolve, requiring continuous adaptation (Pasmore et al., 2019). In these networks, optimization should be treated as a shared goal among various organizational agents. Second, ongoing organizational 'shape-shifting' emphasizes the need for ongoing organizational design to maintain customer serviceability, development, and performance. Technology continuously alters work processes, requiring strategic flexibility (Dixit et al., 2022; Johansen, 2017). Third, AI-driven decision-making decentralization largely shapes shared decisions in hybrid systems. Power shifts from centralized control to distributed AI-human collaborations involves frequent deliberations across hybrid system agents, requiring transparent governance (Pasmore et al., 2019).

From these critical discussion points, the following propositions emerge:

P1: STS should adopt process thinking to reflect human-AI decision-making flows, rather than focusing solely on actors.

P2: Human-AI teaming depends on temporal dynamics (action flows), which are crucial for effective hybrid decision-making and business transformation.

P3: Mutual socialization between humans and AI enhances transformative learning and teamwork.

P4: AI agents' social role in hybrid decision-making is critical for tourism organizations.

6.2. Synergistic Hybrid Transformative Dynamic Flows framework for tourism and hospitality

This study proposes a conceptual, process-based theoretical framework that builds on and updates Trist's (1981) sociotechnical systems theory for application in smart business ecosystems. The Synergistic Hybrid Transformative Dynamic Flows framework integrates Caldwell et al.'s (2022) hybrid human-AI teaming principles with Baygi et al.'s (2021) action flow model, toward optimizing decision-making in tourism and hospitality (see Fig. 2). A series of interrelated components serve as the foundational pillars of the framework. The decision-making process is initiated by specific inputs and shaped by key resources—organizational, AI, and human—alongside clearly defined goal prioritization from human, AI, and organizational perspectives. Underpinning these processes are human and organizational values, which provide essential conceptual grounding for the framework.

Capabilities and competencies are important for human agents, AI agents, and the organization as a whole. s noted by Alter (2024), intelligent machines need to develop a range of distinct capabilities, categorized under four dimensions of technological smartness: (a) information processing (e.g., capturing, storing, and manipulating information); (b) external action-taking (e.g., sensing, communication, coordination, and control); (c) self-regulation (e.g., self-monitoring, correction, and adaptation); and (d) knowledge acquisition (e.g., learning, classification, and evaluation). To assess and coordinate the performance of AI systems with human-like competencies, three interactive capabilities—cognitive, relational, and emotional intelligence—are particularly important (Chandra et al., 2022). Potential tools that exemplify these capabilities include emerging agentic AI systems such as PromptLayer Workflows and AutoGen (Kulkarni et al., 2023), which support the development of cognitive AI architectures. To support human–AI socialization and integrated teaming, the conceptual framework proposed in this study encourages collaborative decision-making between human and AI agents, particularly within strategic management contexts in tourism and hospitality.

The framework emphasizes *five core design actions* for effective hybrid human-AI agency:

Bi-directional Situational Awareness – Humans rely on intuition, emotions, and aesthetics, while AI uses data analytics for context-based decision-making (Mallick et al., 2022).

High-Performance Human-agentic AI Interface – Ensuring seamless interaction between AI and human users through adaptive interfaces.

Distributed/Shared Decision-Making – Task allocation based on human-AI strengths, leading to better decision outcomes (Bardhan et al., 2020; Trist et al., 2013).

Action-Oriented Feedback Mechanism – Enhancing AI performance and accountability.

Transformative Emergence – AI systems dynamically adjust to new business environments and market conditions.

In complex hybrid organizational ecosystems, prioritizing role allocation based on the strengths of human and AI agents is essential for achieving task effectiveness. The Synergistic Hybrid Transformative Dynamic Flows framework also underscores the importance of transparency in decision-making, which fosters trust, enhances collaboration, and promotes optimal hybrid system performance (Lyons et al., 2023).

Effective human–AI teamwork requires mechanisms that actively foster and repair trust, especially in dynamic decision-making environments such as tourism. Trust repair plays a central role in evaluation and feedback processes and consists of three interrelated components: responsibility attribution, structural regulatory frameworks, and social equilibrium (Lyons et al., 2023). Responsibility attribution involves assigning accountability within hybrid decisions—such as those related to site selection, travel planning, or event management—ensuring that both human and AI contributions are appropriately assessed. Structural mechanisms refer to the regulatory and procedural frameworks that enable smooth, coordinated collaboration, while social equilibrium is maintained through positive reinforcement or corrective actions that help build and sustain trust. Collectively, these components create a feedback-rich environment that promotes collective attunement, allowing tourism organizations to adapt and evolve in increasingly AI-augmented contexts.

Within this framework, evaluation focuses on the quality of task division, the strength of trust-building processes, and the overall performance of the hybrid system (Heyder et al., 2023). A key element of this adaptive capacity lies in the transformative emergence phase, which facilitates innovation through the design and application of Intelligent Choice Architectures (ICAs)—structured, decision-support systems that guide collaboration between humans and AI. This phase is shaped by two critical constructs: generativity, defined as the ability of technology to trigger emergent change through dynamic interaction, and legitimation, which ensures that such technologies are socially and organizationally accepted (Pentland et al., 2022). While generativity drives improvements in service quality and responsiveness, legitimation anchors these advances within broader institutional and cultural contexts.

Although several ICAs have been discussed in the literature—including the Great Power Shift ICA (Schrage & Kiron, 2025) and RAGENTIC (Retrieval-Augmented Generation–Enhanced Multi-Agent Architecture)—these architectures serve as conceptual blueprints for building socially informed, knowledge-rich environments in which human and AI agents can collaborate effectively. For example, agentic RAG systems can dynamically retrieve and incorporate external knowledge to support complex, adaptive decision-making in tourism operations (Zhang et al., 2024).

In the proposed model, AI operates as a context-aware decision-support system, designed to augment rather than replace human expertise. Its primary responsibilities lie in tasks such as data processing, forecasting, optimization, and pattern recognition—areas where the speed, scale, and consistency of algorithmic computation surpass human capacity. However, these capabilities are not autonomous; they are bounded by the limitations of training data, programmed objectives, and system constraints. To more precisely define the nature of AI's role, we introduce the concept of "AI conscientiousness"—referring to the system's capacity to function responsibly within ethical, strategic, and situational boundaries. This includes leveraging tools such as confidence

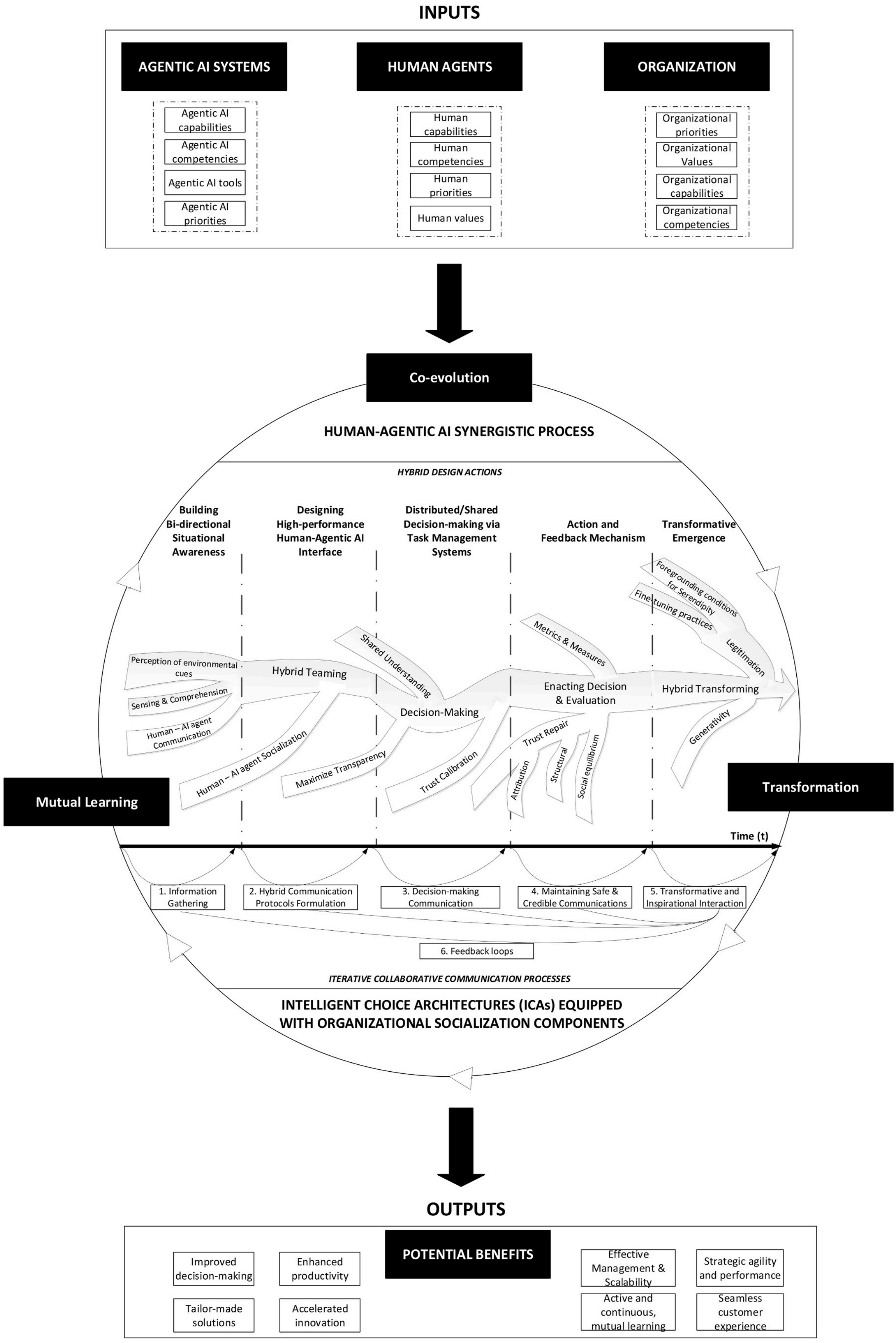

Fig. 2. Hybrid Transformative Dynamic Flows framework.
Source: Developed by authors based on Baygi et al. (2021) and Caldwell et al. (2022).

scoring, explainability techniques, and rule-based logic to ensure its outputs are transparent, contextually relevant, and aligned with organizational values.

Humans, by contrast, retain responsibility for high-level reasoning, contextual interpretation, and ethical deliberation, especially in complex or uncertain situations. The division of labor is based on complementarity: AI handles data-driven, repetitive, or large-scale tasks, while human agents provide oversight, interpret outputs, and make final decisions. For instance, in dynamic pricing, AI may forecast demand and suggest optimal rates, but pricing adjustments remain the responsibility of human managers, who align these recommendations with broader business strategies and customer expectations. Clarifying this division of roles is essential for building trust, ensuring transparency, and supporting accountability in hybrid teams. The framework thus promotes a collaborative model, in which AI augments rather than replaces human decision-making—reinforcing a sociotechnical perspective grounded in balance, mutual learning, and adaptive systems thinking.

In support of continuous improvement, the framework also highlights two key mechanisms: AI-driven serendipity and fine-tuning. Serendipity captures the system's ability to identify and leverage

Table 3
Portraying the roles of AI agents and human counterparts to specify Hybrid Transformative Dynamic Flows stages in the case of a pricing strategy tourism model.

Hybrid design actions / Collaborative communication processes	Bi-directional Situational Awareness	Designing High-performance Human-Agentic AI interface	Shared decision-making via Task Management systems	Action & Feedback Mechanism	Transformative Emergence
Information gathering	• AI agents and humans being aware of content and context, respectively. • Tourism Market demand • Competitors' pricing strategies • Tourist preferences/ patterns	• Design parameters input of the tourism Agentic AI-human systems	• Setting up tourism destination scenario simulations of cultural events	• Agentic AI system monitors decision actions taken, and feedback is provided to human agents to refine future decisions	• Input from insights provided by human tourism agents and AI agents
Hybrid communication formulation	• Agentic AI monitors tourism market trends and human managers offers insights on strategy and context	• Analyzing visual user/ interface pricing parameters (AI agents • Balancing size of multi-agent systems (Both) • Devising real-time human-guided AI learning (human prompted, AI implemented) • Efficient data exchange (Both)	• Tourism task Management systems allocate tasks according to human and AI agents' strengths	• Mutual verification and confidence in tourism indicators and service goals performance via Agentic AI-human socialization (Both)	• Formulating combined insights by both human tourism agents and AI agents
Decision-making communication	• Two-way human-AI communications to establish channel for supporting decision-making readiness	• Introducing collaborative tools to facilitate communication and task management (human prompted) • Infused Human-AI interaction & immediacy (Both)	• AI agents to handle data analysis and initial pricing recommendations • Human agents to review and adjust AI-agent recommendations based on intuition and expertise • Tourism System capability • Efficiency orientation • Human-AI conflict	• The decided tourism pricing strategy is applied across various online booking platforms • Impact of existing/new travel regulations on pricing of visitation	• Create innovative solutions
Maintaining safe and credible communications	• Two-way human-AI communications to maintain situational awareness	• Introducing collaboration tasks (for human-AI agentic systems) with monitoring capabilities	• Secure documentation and storage of decision-making outcomes	• Safeguarding hybrid resiliency • Tackling tourism management task complexity • Reducing information uncertainty via secure communication protocols • Problem diagnosis and treatment	• Proactivity in hybrid responsiveness • Transparency • Accountability
Transformative and inspirational communication	• AI agents identify real-time big data from online sources • Human tourism agents draw information from human and AI agents	• Design AI-human interface includes dashboards demonstrating predictive analytics, and scenario simulations • Introduce hybrid brainstorming sessions to foster innovative pricing strategies	• Recommendations for tourism activities from hybrid Agentic AI-human systems, according to external conditions (traffic, weather etc.)	• Human tourism managers adjust AI outputs and evaluate potential impact on pricing • AI agents feedforward for substantial improvement of destination-related services	• Creativity • Entrepreneurial thinking • Team innovation • Disruptive innovation • Prediction accuracy
Feedback loops	• Rapid situational alterations in technological, social, business environments • Incorrect interpretation	• Perceived Human-AI team viability • Human-AI tourism system control balance • Social judgments • Failure to build a synergistic interface	• Ethical and moral considerations • Forced interaction • Degree of ambidextrous human-AI team competency	• Human-AI Bargaining power • Lack of adequate guest personalization	• Checking the degree of tourism system Cybersecurity • Checking the degree of ambidextrous innovation

Sources: Developed by authors based on Castillo et al., 2021; Li et al., 2019.

unexpected opportunities—a crucial capability in volatile or emerging markets—while fine-tuning refers to iterative refinement through ongoing human–AI interaction (Busch & Barkema, 2022). Together, these mechanisms help validate and legitimize the human–AI partnership, enhancing trust and performance in tourism decision-making.

To bridge the conceptual framework with practical application, we identify a set of key variables that inform effective human–AI teaming in tourism settings. These include contextual factors (e.g., market dynamics, traveler profiles), task types (e.g., forecasting, optimization, personalization), and interaction mechanisms (e.g., feedback loops, override protocols). Understanding and aligning these variables is essential for designing systems that pair AI capabilities with human judgment in a way that is ethical, transparent, and effective. Table 3 presents these variables as a foundation for developing and testing hybrid decision-making models, with an emphasis on optimizing destination pricing strategies in tourism organizations.

7. Discussion and conclusions

7.1. Discussion

The dynamic and rapidly evolving nature of tourism industry processes—combined with broader societal shifts toward the emergence of hybrid meta-tourism environments—necessitates that tourism organizations adopt optimized and synergistic approaches to decision-making. In particular, there is growing potential in leveraging hybrid human–AI teaming to enhance organizational agility and strategic responsiveness (Abbas & Michael, 2022; Tuomi et al., 2025). This article proposed a conceptual framework for optimizing managerial decisions through a process- and flow-based lens, integrating the effects of agentic AI–human organizational socialization into tourism decision-making contexts.

The Synergistic Hybrid Transformative Dynamic Flows framework was introduced to offer a conceptual explanation for how modern managerial decision-making in tourism can be supported and transformed through human–AI interactions. Drawing from emerging literature, the framework emphasizes the transformative potential of such interactions, grounded in the premise that both human and AI agents can participate in social processes and collaborate in shared tasks (McDonald & Pearson, 2019). These interactions shape the ways decisions are made, and ultimately, how organizations respond to complex tourism environments. Bridging the dynamic and context-sensitive human ecosystem with the calculative and data-driven AI ecosystem requires meta-learning and co-evolution between human and AI agents. This suggests a direction for future tourism research that centers on understanding how these agents influence one another, and how such reciprocal shaping can inform both the design and use of AI within the sector. As AI agents increasingly engage in social interactions with human counterparts, their influence extends beyond technical functions and into managerial decision-making practices. They become participants in the broader process of knowledge creation, problem-solving, and adaptation within tourism organizations. This highlights the importance of acknowledging AI's role not just as a tool, but as a meaningful contributor to organizational intelligence.

7.2. Conclusions

In conclusion, AI impacts the social dimension of decision-making by facilitating and participating in human–AI collaboration. Recognizing AI as a form of artificial decision-maker elevates its role alongside human agents in shaping hybrid decision systems. The proposed conceptual framework underscores how such hybrid systems depend on iterative processes of socialization, trust-building, and adjustment between human and AI agents. These interactions support more effective and resilient decision-making practices within tourism businesses. By promoting a process-based perspective, the framework highlights how hybrid transformations in decision-making can be achieved through social equilibrium, legitimation, and the co-evolution of human–AI teams. At a societal level, a broader shift is underway toward the formation of hybrid communities, in which humans and intelligent machines increasingly operate as collaborative agents (Cimini et al., 2020). AI agents enhance human capabilities and performance not merely as extensions, but as contributors to new forms of hybrid intelligence. This integration fosters the development of diverse meta-communities across regions and service sectors—particularly in tourism—where the fusion of human and machine intelligence reshapes the production of services and the nature of managerial decision-making. Embracing this transformation calls for a reevaluation of how tourism researchers and practitioners conceptualize service delivery and organizational decision systems in an age of hybrid intelligence.

7.3. Limitations and suggestions for future research

Recent advancements in the tourism industry, coupled with growing challenges and rapid technological and societal shifts, have heightened the need for more effective predictive and adaptive models to guide decision-making in hybrid human–AI contexts. While human–AI collaboration is already a tangible reality in tourism, this study offers a conceptual framework informed by process thinking and sociotechnical systems (STS) theory to guide the integration of AI agents into managerial decision-making processes. However, several limitations should be acknowledged. First, although the proposed Synergistic Hybrid Transformative Dynamic Flows framework presents a structured approach for incorporating AI into tourism decision-making, its practical implementation may be constrained by issues such as data availability, data quality, and system interoperability across different organizations. The framework assumes a high degree of real-time data flow and system connectivity, which may not always be feasible due to privacy concerns, regulatory environments, or varying levels of technological readiness among tourism businesses.

Second, the framework's applicability across diverse tourism sectors remains uncertain. Differences in organizational structures, service delivery models, and customer engagement strategies may affect how well the framework translates to specific domains such as hospitality, destination management, or tour operations. As such, further empirical validation is required to refine and tailor the framework for different industry contexts. Third, while this study conceptualizes AI-driven decision-making within an STS perspective, the specific roles and effectiveness of various AI agents—including chatbots, humanoid robots, and advanced agentic AI systems—warrant deeper exploration. The adoption of AI has significant implications for employee roles, customer experience, and ethical considerations, including algorithmic bias, transparency, and the interpretability of AI outputs. These dimensions merit further critical attention to ensure ethical, responsible, and inclusive AI integration in tourism settings.

This study primarily emphasizes human trust in AI; however, the reciprocal dynamics of trust—how AI systems "trust" or assess the reliability of human input—remain underexplored. As Kissinger et al. (2021) argue in The Age of AI, AI systems do not trust in the human sense but instead rely on probabilistic reasoning, learned patterns, and confidence scores based on historical data and user behaviour. If trained on biased or inconsistent data, these systems may internalize skewed perceptions, overemphasizing dominant patterns and ignoring critical but less frequent outliers in decision-making processes. Understanding this dynamic is particularly important in high-stakes tourism and hospitality environments, where service quality and safety often depend on effective and transparent decision-making.

Given the increasing reliance on AI-assisted decisions in tourism, future research should investigate how AI agents assess and respond to human decisions, including how confidence scoring, interpretability mechanisms, and override protocols shape the effectiveness of hybrid teaming. The bidirectional nature of trust in human–AI collaboration must be better understood to ensure ethical alignment and functional synergy between agents. To this end, empirical research is essential to test and refine the conceptual assumptions and structural relationships proposed in this framework. As Meng et al. (2024) underscore in their group decision-making study, empirical validation and interaction-aware consensus mechanisms are critical for refining structured models—principles that are equally vital for testing AI-integrated frameworks in tourism. Scenario-building exercises applied to specific tourism service contexts, supported by experimental design methods, can help test the relationships and dynamic flows depicted in Fig. 2 and Table 3. Additionally, observation-based approaches—including structured, unstructured, or non-participant observations—could yield valuable insights into the behavioural dynamics between human and agentic AI agents. Human–AI interaction studies can further support the generalization of patterns and inform optimization strategies using multicriteria decision-making models.

Finally, employing Explainable AI (XAI) techniques—such as cognitive modelling—could help evaluate the alignment between AI-generated explanations and human understanding, offering insight into collaboration quality and trust development. By addressing these limitations and building on the conceptual foundation proposed here, future studies can strengthen predictive models, enhance AI integration strategies, and improve decision-making practices for tourism organizations operating within increasingly complex digital ecosystems. By critically acknowledging these limitations and proposing avenues for empirical validation, this study lays a foundation for more nuanced, ethically grounded, and context-sensitive integration of AI into tourism decision-making, advancing both theoretical and practical understandings of hybrid human–AI collaboration.

CRediT authorship contribution statement

Nikolaos Stylos: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Fevzi Okumus:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Irem Onder:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation.

Impact statement

This article introduces the Hybrid Transformative Dynamic Flows framework to explain modern managerial decision-making in the travel and tourism industries, highlighting the transformative nature of human-AI interactions through a process/flow thinking approach, by incorporating the influences of AI-human socialization.

The proposed framework conceptualizes tourism decision-making as a hybrid, process-driven model where AI is not just a tool but an active social agent influencing organizational socialization, managerial decision-making, and service co-creation. Human-Agentic AI socialization can contribute to high (er) hybrid team effectiveness toward enhancing the quality of shared decisions made and ultimately lead to the substantial increase of the organizational outputs in terms of measured benefits.

At the societal level, there is a shift toward hybrid communities by combining human intelligence and AI at the cellular level; this may significantly advance modern societies' capacity to create diverse metacommunities across different regions and sectors.

Declarations of competing interest

None.

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Nothing to declare.

References

Abbas, S. M., Liu, Z., & Khushnood, M. (2023). When human meets technology: Unlocking hybrid intelligence role in breakthrough innovation engagement via self-extension and social intelligence. *Journal of Computer Information Systems, 63*(5), 1183–1200.

Abbas, R., & Michael, K. (2022). Socio-technical theory: A review. In S. Papagiannidis (Ed.), *TheoryHub book*. Retrieved from http://open.ncl.ac.uk.

Abedin, B., Meske, C., Junglas, I., Rabhi, F., & Motahari-Nezhad, H. R. (2022). Designing and managing human-AI interactions. *Information Systems Frontiers, 24*(3), 691–697.

Alter, S. (2024). Principles for analyzing, designing and evaluating the situated use of intelligent machines. *Information Technology & People, 37*(7), 2523–2550.

Azer, J., & Alexander, M. (2024). Human-Machine Engagement (HME): Conceptualizing AI's role in service experiences. *Journal of Service Research*. https://doi.org/10.1177/10946705241296782

Bankins, S., Hu, X., & Yuan, Y. (2024). Artificial intelligence, workers, and future of work skills. *Current Opinion in Psychology*. https://doi.org/10.1016/j.copsyc.2024.101828

Bardhan, I., Chen, H., & Karahanna, E. (2020). Connecting systems, data, and people: A multidisciplinary research roadmap for chronic disease management. *MIS Quarterly, 44*(1), 185–200.

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with computers, 23*(1), 4–17.

Baygi, R. M., Introna, L. D., & Hultin, L. (2021). Everything flows: Studying continuous socio-technological transformation in a fluid and dynamic digital world. *MIS Quarterly, 45*(1), 423–452.

Bednar, P. M., & Welch, C. (2020). Socio-technical perspectives on smart working: Creating meaningful and sustainable systems. *Information Systems Frontiers, 22*(2), 281–298.

Binz, M., & Schulz, E. (2023). Using cognitive psychology to understand GPT-3. *Proceedings of the National Academy of Sciences, 120*(6). https://doi.org/10.1073/pnas.2218523120

Blaurock, M., Büttgen, M., & Schepers, J. (2024). Designing collaborative intelligence systems for employee-AI service Co-production. *Journal of Service Research*. https://doi.org/10.1177/10946705241238751

Bock, D. E., Wolter, J. S., & Ferrell, O. C. (2020). Artificial intelligence: Disrupting what we know about services. *Journal of Services Marketing, 34*(3), 317–334.

Busch, C., & Barkema, H. (2022). Planned luck: How incubators can facilitate serendipity for nascent entrepreneurs through fostering network embeddedness. *Entrepreneurship Theory and Practice, 46*(4), 884–919.

Butlin, P., Long, R., Elmoznino, E., Bengio, Y., Birch, J., Constant, A., Deane, G., Fleming, S. M., Frith, C., Ji, X., Kanai, R., Klein, C. Lindsay, G., Michel, M., Mudrik, L., Peters, M. A. K., Schwitzgebel, E., Simon, J., & VanRullen, R. (2023). Consciousness in artificial intelligence: Insights from the science of consciousness. arXiv preprint arXiv:2308.08708.

Cadden, T., Dennehy, D., Mantymaki, M., & Treacy, R. (2022). Understanding the influential and mediating role of cultural enablers of AI integration to supply chain. *International Journal of Production Research, 60*(14), 4592–4620.

Caldwell, S., Sweetser, P., O'donnell, N., Knight, M. J., Aitchison, M., Gedeon, T., … Conroy, D. (2022). An agile new research framework for hybrid human-AI teaming: Trust, transparency, and transferability. *ACM Transactions on Interactive Intelligent Systems, 12*(3), 1–36.

Casares, A. P. (2018). The brain of the future and the viability of democratic governance: The role of artificial intelligence, cognitive machines, and viable systems. *Futures, 103*, 5–16.

Castillo, D., Canhoto, A. I., & Said, E. (2021). The dark side of AI-powered service interactions: Exploring the process of co-destruction from the customer perspective. *Service Industries Journal, 41*(13–14), 900–925.

Chaffer, T. J., Goldston, J., & A I, G. D. (2024). *Incentivized symbiosis: A paradigm for human-agent coevolution* (pp. 1–24). arXiv preprint arXiv:2412.06855.

Chandra, S., Shirish, A., & Srivastava, S. C. (2022). To be or not to be… human? Theorizing the role of human-like competencies in conversational artificial intelligence agents. *Journal of Management Information Systems, 39*(4), 969–1005.

Chawla, C., Chatterjee, S., Gadadinni, S. S., Verma, P., & Banerjee, S. (2024). Agentic AI: The building blocks of sophisticated AI business applications. *Journal of AI, Robotics & Workplace Automation, 3*(3), 1–15.

Chen, D., Youssef, A., Pendse, R., Schleife, A., Clark, B. K., Hamann, H., … Nagpurkar, P. (2024). *Transforming the hybrid cloud for emerging AI workloads. arXiv preprint arXiv:2411.13239*.

Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research, 144*, 31–49.

Cimini, C., Pirola, F., Pinto, R., & Cavalieri, S. (2020). A human-in-the-loop manufacturing control architecture for the next generation of production systems. *Journal of Manufacturing Systems, 54*, 258–271.

Cloutier, C., & Langley, A. (2020). What makes a process theoretical contribution? *Organization Theory, 1*(1). https://doi.org/10.1177/2631787720902473

Coiera, E. (2007). Putting the technical back into socio-technical systems research. *International Journal of Medical Informatics, 76*, S98–S103.

Davis, M. C., Challenger, R., Jayewardene, D. N., & Clegg, C. W. (2014). Advancing socio-technical systems thinking: A call for bravery. *Applied Ergonomics, 45*(2), 171–180.
de Larrea, G. L., Altin, M., Koseoglu, M. A., & Okumus, F. (2021). An integrative systematic review of innovation research in hospitality and tourism. *Tourism Management Perspectives, 37*. https://doi.org/10.1016/j.tmp.2021.100789
Dhimolea, T. K., Kaplan-Rakowski, R., & Lin, L. (2022). Supporting social and emotional well-being with artificial intelligence. In *Bridging human intelligence and artificial intelligence* (pp. 125–138). Cham: Springer International Publishing.
Dillion, D., Tandon, N., Gu, Y., & Gray, K. (2023). Can AI language models replace human participants? *Trends in Cognitive Sciences, 27*(7), 597–600.
Dixit, A., Jakhar, S. K., & Kumar, P. (2022). Does lean and sustainable manufacturing lead to Industry 4.0 adoption: The mediating role of ambidextrous innovation capabilities. *Technological Forecasting and Social Change, 175*. https://doi.org/10.1016/j.techfore.2021.121328
Dutta, D., & Kannan Poyil, A. (2024). The machine/human agentic impact on practices in learning and development: A study across MSME, NGO and MNC organizations. *Personnel Review, 53*(3), 791–815.
Eason, K. (2013). Afterword: The past, present, and future of sociotechnical systems theory. *Applied Ergonomics, 45*(2), 213–220.
Endsley, M. R. (2023). Supporting human-AI teams: Transparency, explainability, and situation awareness. *Computers in Human Behavior, 140*, Article 107574.
Felin, T., & Holweg, M. (2024). Theory is all you need: AI, human cognition, and causal reasoning. *Strategy Science, 9*(4), 346–371.
French, A. M., & Shim, J. P. (2024). From artificial intelligence to augmented intelligence: A shift in perspective, application, and conceptualization of AI. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-024-10562-2
Gretzel, U. (2011). Intelligent systems in tourism: A social science perspective. *Annals of Tourism Research, 38*(3), 757–779.
Heyder, T., Passlack, N., & Posegga, O. (2023). Ethical management of human-AI interaction: Theory development review. *The Journal of Strategic Information Systems, 32*(3). https://doi.org/10.1016/j.jsis.2023.101772
Hirschhorn, L., Noble, P., & Rankin, T. (2001). Sociotechnical systems in an age of mass customization. *Journal of Engineering and Technology Management, 18*(3–4), 241–252.
Horváth, I. (2023). Designing next-generation cyber-physical systems: Why is it an issue? *Journal of Integrated Design and Process Science, 26*(3–4), 317–349.
Huang, G. I., Karl, M., Wong, I. A., & Law, R. (2023). Tourism destination research from 2000 to 2020: A systematic narrative review in conjunction with bibliographic mapping analysis. *Tourism Management, 95*. https://doi.org/10.1016/j.tourman.2022.104686
Huang, M. H., & Rust, R. T. (2024). The caring machine: Feeling AI for customer care. *Journal of Marketing*. https://doi.org/10.1177/00222429231224748
Ibrahim, M. N., Ribeiro, M. A., & Nsom Kimbu, A. (2024). Redirecting slack resources to social and environmental issues: A cross-cultural analysis of tourism firms post-crisis. *Journal of Travel Research*. https://doi.org/10.1177/00472875241260333
Jain, R., Garg, N., & Khera, S. N. (2022). Effective human–AI work design for collaborative decision-making. *Kybernetes, 52*(11), 5017–5040.
Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586.
Jin, H., & Cai, W. (2022). Understanding the smartphone usage of Chinese outbound tourists in their shopping practices. *Current Issues in Tourism, 25*(18), 2955–2968.
Johansen, B. (2017). *The new leadership literacies: Thriving in a future of extreme disruption and distributed everything*. Berrett-Koehler Publishers.
Kim, H., So, K. K. F., Shin, S., & Li, J. (2024). Artificial intelligence in hospitality and tourism: Insights from industry practices, research literature, and expert opinions. *Journal of Hospitality & Tourism Research*. https://doi.org/10.1177/10963480241229235
Kissinger, H., Schmidt, E., & Huttenlocher, D. (2021). *The age of AI: And our human future*. Little, Brown and Company.
Koponen, J., Julkunen, S., Laajalahti, A., Turunen, M., & Spitzberg, B. (2023). Work characteristics needed by middle managers when leading AI-integrated service teams. *Journal of Service Research*. https://doi.org/10.1177/10946705231220462
Kulkarni, A., Shivananda, A., Kulkarni, A., & Gudivada, D. (2023). LLMs for enterprise and LLMOps. In *Applied generative AI for beginners: Practical knowledge on diffusion models, ChatGPT, and other LLMs* (pp. 117–154). Berkeley, CA: Apress.
Larson, L. E. (2021). *Leading teams in the digital age: Team technology adaptation in human-agent teams., media, technology and society* (Vol. 2021). United States Ann Arbor: Northwestern University ProQuest Dissertations & Theses, Article 28714297.
Lee, S., Chang, H., & Cho, M. (2022). Applying the sociotechnical systems theory to crowdsourcing food delivery platforms: The perspective of crowdsourced workers. *International Journal of Contemporary Hospitality Management, 34*(7), 2450–2471.
Li, J. J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management, 73*, 172–181.
Lim, C., Mostafa, N., & Park, J. (2017). Digital omotenashi: Toward a smart tourism design systems. *Sustainability, 9*(12), 2175.
Lindgren, H. (2024). Emerging roles and relationships among humans and interactive AI systems. *International Journal of Human-Computer Interaction*, 1–23. https://doi.org/10.1080/10447318.2024.2435693
Lindgren, S., & Holmström, J. (2020). A social science perspective on artificial intelligence: Building blocks for a research agenda. *Journal of Digital Social Research (JDSR), 2*(3), 1–15.
Liu, Y., Zhang, M., & Wang, Y. (2022). Understanding the determinants of service providers' contribution behaviors on peer-to-peer sharing accommodation. *Current Issues in Tourism, 25*(22), 3657–3674.
Longoni, C., & Cian, L. (2022). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing, 86*(1), 91–108.
Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., … Bao, J. (2022). Outlook on human-centric manufacturing towards Industry 5.0. *Journal of Manufacturing Systems, 62*, 612–627.
Lyons, J. B., Hamdan, A. I., & Vo, T. Q. (2023). Explanations and trust: What happens to trust when a robot partner does something unexpected? *Computers in Human Behavior, 138*. https://doi.org/10.1016/j.chb.2022.107473
Majid, G., Tussyadiah, I. P., Kim, Y. R., & Pal, A. (2023). Intelligent automation for sustainable tourism: A systematic review. *Journal of Sustainable Tourism, 31*, 2421–2440.
Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research, 120*, 262–273.
Mallick, R., Flathmann, C., Duan, W., Schelble, B. G., & McNeese, N. J. (2024). What you say vs what you do: Utilizing positive emotional expressions to relay AI teammate intent within human–AI teams. *International Journal of Human-Computer Studies, 192*. https://doi.org/10.1016/j.ijhcs.2024.103355
Mallick, R., Sawant, S., McNeese, N., & Chalil Madathil, K. (2022). Designing for mutually beneficial decision-making in human-agent teaming. In *Human factors and ergonomics society annual meeting* (Vol. 66, pp. 392–396). CA: Los Angeles: Sage, 1.
McDonald, K. R., & Pearson, J. M. (2019). Cognitive bots and algorithmic humans: Toward a shared understanding of social intelligence. *Current Opinion in Behavioral Sciences, 29*, 55–62.
Melville, N. P., Robert, L., & Xiao, X. (2023). Putting humans back in the loop: An affordance conceptualization of the 4th industrial revolution. *Information Systems Journal, 33*(4), 733–757.
Meng, F.-Y., Zhao, D.-Y., Gong, Z.-W., Chu, J.-F., Pedrycz, W., & Yuan, Z. (2024). Consensus adjustment for multi-attribute group decision making based on cross-allocation. *European Journal of Operational Research, 318*(1), 200–216.
Mercuur, R., Dignum, V., & Jonker, C. M. (2020). Integrating social practice theory in agent-based models: A review of theories and agents. *IEEE Transactions on Computational Social Systems, 7*(5), 1131–1145.
Merriam, S. B. (2001). Andragogy and self-directed learning: Pillars of adult learning theory. *New Directions for Adult and Continuing Education, 2001*(89), 3–96.
Mumford, E. (2006). The story of socio-technical design: Reflections on its successes, failures and potential. *Information Systems Journal, 16*(4), 317–342.
Nechesov, A., Dorokhov, I., & Ruponen, J. (2025). Virtual cities: From digital twins to autonomous AI societies. *IEEE Access, 13*, 13866–13903. https://doi.org/10.1109/ACCESS.2025.3531222
Nyaboro, J., Park, K., & Park, J. (2021). M-Tour: A new socio-technological design application for destination competitiveness in Egypt. *Industrial Management & Data Systems, 121*(6), 1152–1166.
OCLC Developer Network. (2024). WorldCat search API developer-level access to WorldCat – for bibliographic holdings and location data. available at: www.oclc.org/developer/api/oclc-apis/worldcat-search-api.en.html.
Ozmen Garibay, O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., … Xu, W. (2023). Six human-centered artificial intelligence grand challenges. *International Journal of Human-Computer Interaction, 39*(3), 391–437.
Park, J. E., Lee, E., Kim, J. Y., & Koo, C. (2023). 'Platform stress': Exploring a new type of stress in the sharing economy. *Current Issues in Tourism*, 1–15.
Pasmore, W., Winby, S., Mohrman, S. A., & Vanasse, R. (2019). Reflections: Sociotechnical systems design and organization change. *Journal of Change Management, 19*(2), 67–85.
Peeters, M. M., van Diggelen, J., Van Den Bosch, K., … Raaijmakers, S. (2021). Hybrid collective intelligence in a human–AI society. *AI & Society, 36*, 217–238.
Pentland, B. T., Yoo, Y., Recker, J., & Kim, I. (2022). From lock-in to transformation: A path-centric theory of emerging technology and organizing. *Organization Science, 33*(1), 194–211.
Rajesh, S., Abd Algani, Y. M., Al Ansari, … Balaji, S. (2022). Detection of features from the internet of things customer attitudes in the hotel industry using a deep neural network model. *Measurement: Sensors, 22*. https://doi.org/10.1016/j.measen.2022.100384
Reis, J., Melão, N., Salvadorinho, J., Soares, B., & Rosete, A. (2020). Service robots in the hospitality industry: The case of Henn-na hotel, Japan. *Technology in Society, 63*. https://doi.org/10.1016/j.techsoc.2020.101423
Richards, D., Vythilingam, R., & Formosa, P. (2023). A principlist-based study of the ethical design and acceptability of artificial social agents. *International Journal of Human-Computer Studies, 172*. https://doi.org/10.1016/j.ijhcs.2022.102980
Ritz, E., Donisi, F., Elshan, E., & Rietsche, R. (2023). Artificial socialization? How artificial intelligence applications can shape A new era of employee onboarding practices. *In HICSS*, 155–164.
Roodbari, H., & Olya, H. (2024). An integrative framework to evaluate impacts of complex tourism change initiatives. *Tourism Management, 100*. https://doi.org/10.1016/j.tourman.2023.104829
Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN computer science, 2*(3), 160.
Sarker, A., Ul Islam, T., & Islam, M. R. (2024). A review on recent trends of bioinspired soft robotics: Actuators, control methods, materials selection, sensors, challenges, and future prospects. *Advanced Intelligent Systems*. https://doi.org/10.1002/aisy.202400414
Schelble, B. G., Flathmann, C., McNeese, N. J., Freeman, G., & Mallick, R. (2022). Let's think together! Assessing shared mental models, performance, and trust in human-agent teams. *Proceedings of the ACM on Human-Computer Interaction, 6*, 1–29.

Schintler, L. A., & McNeely, C. L. (2022). Artificial intelligence, institutions, and resilience: Prospects and provocations for cities. *Journal of Urban Management, 11*(2), 256–268.
Schrage, M., & Kiron, D. (2025). *The Great power shift: How intelligent Choice architectures rewrite decision rights*. MIT Sloan Management Review Research Highlight. Available online via: https://sloanreview.mit.edu/article/the-great-power-shift-how-intelligent-choice-architectures-rewrite-decision-rights/. (Accessed 30 January 2025).
Shet, S. V., & Pereira, V. (2021). Proposed managerial competencies for Industry 4.0–Implications for social sustainability. *Technological Forecasting and Social Change, 173*. https://doi.org/10.1016/j.techfore.2021.121080
Shibasaki, R., Hori, S., Kawamura, S., & Tani, S. (2020). *Integrating urban data with urban services. Society 5.0: A people-centric super-smart society*. Hitachi-UTokyo Laboratory (H-UTokyo Lab.).
Shipp, A. J., & Jansen, K. J. (2021). The "other" time: A review of the subjective experience of time in organizations. *The Academy of Management Annals, 15*(1), 299–334.
Shrestha, Y. R., Krishna, V., & von Krogh, G. (2021). Augmenting organizational decision-making with deep learning algorithms: Principles, promises, and challenges. *Journal of Business Research, 123*, 588–603.
Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339.
Sony, M., & Naik, S. (2020). Industry 4.0 integration with socio-technical systems theory: A systematic review and proposed theoretical model. *Technology in Society, 61*. https://doi.org/10.1016/j.techsoc.2020.101248
Stahl, B. C. (2007). ETHICS, morality, and critique: An essay on Enid Mumford's socio-technical approach. *Journal of the Association for Information Systems, 8*(9), 479–490.
Storey, V. C., Hevner, A. R., & Yoon, V. Y. (2024). The design of human-artificial intelligence systems in decision sciences: A look back and directions forward. *Decision Support Systems, 182*. https://doi.org/10.1016/j.dss.2024.114230
Stylos, N., Fotiadis, A. K., Shin, D. D., & Huan, T. C. T. (2021). Beyond smart systems adoption: Enabling diffusion and assimilation of smartness in hospitality. *International Journal of Hospitality Management, 98*. https://doi.org/10.1016/j.ijhm.2021.103042
Thiele, L. P. (2021). Rise of the centaurs: The internet of things intelligence augmentation. In *Towards an international political economy of artificial intelligence* (pp. 39–61). Cham: Palgrave Macmillan.
Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review, 4*(3), 356–367.
Trist, E. L. (1981). *The evolution of socio-technical systems* (Vol. 2). Toronto: Ontario Quality of Working Life Centre.
Trist, E. L., Higgin, G. W., Murray, H., & Pollock, A. B. (2013). *Organizational Choice (RLE: Organizations): Capabilities of groups at the coal face under changing technologies*. Routledge.
Tuomi, A., Tussyadiah, I., & Ascenção, M. P. (2025). Customized language models for tourism management: Implications and future research. *Annals of Tourism Research, 110*. https://doi.org/10.1016/j.annals.2024.103863
Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism. *Annals of Tourism Research, 81*. https://doi.org/10.1016/j.annals.2020.102883
van Diggelen, J., Barnhoorn, J.S., Peeters, M.M., van Staal, W., Stolk, M.L., van der Vecht, B., … Schraagen, J.M. (2019). Pluggable social artificial intelligence for enabling human-agent teaming, 1-23, arXiv preprint arXiv:1909.04492.
Walker, G. (2015). Come back sociotechnical systems theory, all is forgiven…. *Civil Engineering and Environmental Systems, 32*(1–2), 170–179.
Wang, D., Tussyadiah, I., & Zhang, E. (2023). Shaping in-destination group decision-making: The sociomateriality of smartphones. *Journal of Travel Research*. https://doi.org/10.1177/00472875231164980
Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly, 26*. xiii-xxiii (11 pages).
Xu, W., & Gao, Z. (2024). An intelligent sociotechnical systems (iSTS) framework: Enabling a hierarchical human-centered AI (hHCAI) approach. *IEEE Transactions on Technology and Society*. https://doi.org/10.1109/TTS.2024.3486254
Yan, H., Fu, L., & Hu, X. (2022). Harnessing service robots to increase frontline service employees' safety and health: The critical role of CSR. *Safety Science, 151*. https://doi.org/10.1016/j.ssci.2022.105731
Yang, J., Liu, Y., & Morgan, P. L. (2024). Human-machine interaction towards Industry 5.0: Human-centric smart manufacturing. *Digital Engineering*. https://doi.org/10.1016/j.dte.2024.100013
Yao, Y. (2023). Human-machine co-intelligence through symbiosis in the SMV space. *Applied Intelligence, 53*(3), 2777–2797.
Zhang, R., Du, H., Liu, Y., Niyato, D., Kang, J., Sun, S., … Poor, H. V. (2024). Interactive AI with retrieval-augmented generation for next generation networking. *IEEE Network, 38*(6), 414–424.
Zheng, Q., Gou, J., Camarinha-Matos, L. M., Zhang, J. Z., & Zhang, X. (2023). Digital capability requirements: Organizational socialization of AI teammates. *Information Processing & Management, 60*(6). https://doi.org/10.1016/j.ipm.2023.103504
Zhichang, Z. (2007). Complexity science, systems thinking and pragmatic sensibility. *Systems Research and Behavioral Science: The Official Journal of the International Federation for Systems Research, 24*(4), 445–464.

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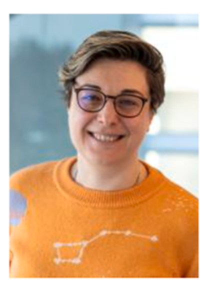

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