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Exploring collaborative decision-making: A quasi-experimental study of human and Generative AI interaction

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ABSTRACT

This paper explores the effects of integrating Generative Artificial Intelligence (GAI) into decision-making processes within organizations, employing a quasi-experimental pretest-posttest design. The study examines the synergistic interaction between Human Intelligence (HI) and GAI across four group decision-making scenarios within three global organizations renowned for their cutting-edge operational techniques. The research progresses through several phases: identifying research problems, collecting baseline data on decision-making, implementing AI interventions, and evaluating the outcomes post-intervention to identify shifts in performance. The results demonstrate that GAI effectively reduces human cognitive burdens and mitigates heuristic biases by offering data-driven support and predictive analytics, grounded in System 2 reasoning. This is particularly valuable in complex situations characterized by unfamiliarity and information overload, where intuitive, System 1 thinking is less effective. However, the study also uncovers challenges related to GAI integration, such as potential over-reliance on technology, intrinsic biases particularly 'out-of-the-box' thinking without contextual creativity. To address these issues, this paper proposes an innovative strategic framework for HI-GAI collaboration that emphasizes transparency, accountability, and inclusiveness.

1. Introduction

The release of ChatGPT on November 30, 2022 [1], coincided with the aftermath of a global pandemic, was within a period characterized by significant societal and technological transformations. Before the introduction of Generative AI (GAI), 'traditional AI', which requires structured data for model construction and information processing, including neural networks, evolutionary algorithms, decision trees, random forests, support vector machines, and k-means clustering were already widespread [2]. Traditional AI was integrated into applications that influenced pricing, inventory management, logistic optimization, content recommendation etc., but were somewhat restricted in their functionality and had difficulties in directly interacting with users [3]. In contrast, GAI technologies such as ChatGPT introduced a user interface that made AI both accessible and a regular part of daily technology use [4]. This made a significant shift towards direct human-AI collaboration [5]. This ease of use and direct interaction has ushered in a new era of machine-driven intelligence, where technological advances have outpaced organizational understanding of their effective management and exploitation.

In the traditional paradigms of organizational decision-making, human intelligence (HI) whether individual or collective, is distinguished by a blend of intuitive perception, emotional sensitivity, and cultural cognizance, that resonates across scenarios, from executing immediate, task-specific objectives [6] to strategizing for comprehensive, long-term aspirations [7]. These intrinsic human cognitive abilities inject creative and deep-seated insights into the strategic framework, thus equipping the organization with the fitness to adeptly steer through market fluctuations, competitive pressures, and technological advancements [8]. Where teams must interact dynamically with constantly changing external variables, the comprehensive range of human cognitive skills is essential for plotting pathways through ambiguous situations and capitalizing on the opportunities that such adaptability affords [9]. However, cognitive, and heuristic biases, essentially 'rule of thumb' or 'mental shortcuts' evolved for information-processing efficiency [10], can sometimes be advantageous but often constrict perception and engender systematic errors in judgment, frequently leading to distorted reasoning and suboptimal decision-making outcomes [11]. High reliance on familiar biases can overshadow data-driven analysis. The latest iteration, GPT-4o ("o" for "omni"), expands on GPT-4 with 1.76 trillion

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parameters, trained on a diverse corpus of internet-sourced texts. It enables more natural human-computer interaction by processing multimodal inputs (text, audio, image, video) and responding, including to audio inputs, within an average of 320 ms—comparable to human response times in conversation. Leveraging its extensive pre-training across vast textual datasets, it augments human decision-making by serving as a cognitive extension. This provides a chain-of-thought through a real-time interactive chatbot interface [12]. The adeptness of the model to interactively produce recommendations at a marginal incremental cost, coupled with its ability to process a wide array of data inputs, be it visual, textual, or numerical, makes it particularly advantageous for organizations limited by budgetary and technical infrastructure constraints. Serving as a 'neutral enabler', the model encourages a broader investigation of innovative options that challenge the conventional individual and group decision-making rules and shortcuts that are commonplace in organizational decision making [13].

In many respects, the strengths of AI are the weaknesses of HI. Automation technologies, including machine learning (ML) and robotics, are increasingly integral to daily life and have substantial impacts on the workplace. Initially limited to repetitive manufacturing tasks, automation now extends to more complex roles: robots operate alongside physicians in surgeries and analyze medical images [14], while analytics drive route optimization [15,16], autonomous vehicles [17,18] and enhance resilience [19,20]. Machines excel in both routine and complex tasks due to their precision, strength, and indefatigability [21]. Despite their precision and efficiency, machines rely heavily on the quality of the data they trained and are bound by mathematical principles. This limitation is significant when it comes to creative or 'out-of-the-box' thinking, areas where human intuition and flexibility still hold the upper hand [15]. Moravec's Paradox underscores this phenomenon, suggesting that AI finds it easier to manage high-level cognitive tasks, like chess-playing, than it does with tasks requiring context understanding, such as interpreting human emotions [22]. It is critical to distinguish these attributes driven by GAI from true 'intelligence'. Current systems lack a semantic understanding of their outputs, indicating a significant gap in the development of truly intelligent machines [23]. Additionally, the capacity for reasoning, especially common-sense reasoning, remains uniquely human and elusive for GAI. This leads to the two main research questions: *"How does GAI affect the dynamics of collaborative decision-making between HI and AI?"* and *"What are the potential challenges and opportunities that arise from this interaction?"*

As the adoption and innovation of GAI accelerate, we are in a crucial phase known as the 'Inter-AI period' [24]. This is a critical window where humans have the opportunity to establish the norms and values that will guide AI development, shaping its use and integration into society [25,26]. During this fleeting period, as GAI evolves, the ability to influence its direction diminishes, with established norms and values becoming increasingly embedded within the technology [27]. It is essential, both for technological advancement and also for ensuring that the combined decision-making capabilities of HI and GAI are optimized, positively impacting societal structures and interactions in the long term [28]. A third supplementary research question arises: *"How can we develop an ethical framework that* supports *effective and responsible decision-making in environments where HI and GAI collaborate?"*

Despite the widespread implementation of GAI in various contexts, empirical research on its specific impact on human decision-making dynamics, particularly in minimizing biases and improving HI and GAI collaboration decision quality remains limited. This pioneering study employs a quasi-experimental pretest-posttest design to assess how GAI can recalibrate human decision-making, targeting the minimization of biases that impede objective human cognition. By methodically evaluating the opportunities and challenges concerning how GAI reshapes HI and AI collaborative decision-making, the research is poised to offer transformative insights for refining organizational strategy and decision-making structures. Such findings promise to advance the decision-making body of knowledge and offer actionable strategies within an ethical framework for integrating GAI into organizational practices.

The remainder of this paper is organized as follows: Section 2 presents the theoretical underpinnings of HI and AI decision-making, with the integration of instinctive thinking and systematic analytical thinking through HI and AI collaboration. Section 3 details the quasi-experimental methodology employed. This is followed by Section 4, which discusses the execution of a four-group decision-making quasi-experiment. Section 5 offers a synthesis of the data through both qualitative cognitive mapping and quantitative statistical examination. Section 6 provides a comprehensive recapitulation of the research findings, extracts implications, acknowledges the limitations, and proposes research avenues for the future.

2. Literature review

2.1. Cognitive heuristics and bias in human intelligence decision-making

In the transformative period of the late 1960s and early 1970s, the seminal work of Amos Tversky and Daniel Kahneman introduced a paradigm shift in the understanding of human judgment and cognitive decision-making. They pioneered the 'cognitive heuristics and biases' framework posited when faced with uncertainty [29], where individuals often rely on a collection of heuristics techniques rather than engage in comprehensive algorithmic processing [30]. The concept rapidly changed the boundaries of academic psychology and the study of business operational decision-making [31–33].

Heuristics bias is characterized by the reliance of an individual on initial information to make subsequent judgments, implying that once an anchor is set, there is a tendency for estimates or decisions to incline toward it [34]. When extending the analysis to group decision-making, the anchoring bias can have compound effects. A dominant initial opinion in a group can disproportionately influence the consensus, swaying collective judgment regardless of its initial validity [35]. In operational decisions, for instance, this type of anchoring can lead to the 'bullwhip effect', where small variations in demand can be amplified across supply chain tiers. As group dynamics often amplify biases through social mechanisms such as groupthink, where the desire for overoptimism and ingroup favoritism results in an irrational decision-making outcome [36]. However, the adoption of structured group strategies that combine debiasing techniques and collaborative deliberation has been found to reduce the potential for groupthink, where the role of 'devil's advocates' [37]; 'Delphi and focus group' [38]; and 'nominal group technique' [39] in such settings is pivotal; by consistently questioning established assumptions, they encourage a thorough examination of information, thus preparing an environment of critical reflection and productive debate.

Group decision-making harnesses the collective cognitive capabilities of individuals, which can be instrumental in identifying and improving individual biases—a phenomenon referred to as 'collaborative cognition' [40,41]. When groups cultivate a culture of critical evaluation and encourage open discussion, they are more likely to engage in reflective thinking, thereby reducing their dependence on heuristic shortcuts [42]. Typically, the adage 'two heads are better than one' holds true, indicating that groups outperform individuals in intellectual tasks, thereby significantly reducing anchoring bias [35]. However, the absence of definitive answers in group settings often leads to decisions influenced by anchoring bias, where collective judgments skew towards higher anchors due to a unified preference. This leads to the insufficiency of collaboration alone in guarding against such cognitive distortions [43]. To bridge this gap, the inclusion of AI as an 'neutral adjudicator' within group decision-making frameworks serves as an element of unbiased evaluation, akin to the role of an independent arbitrator, thereby offering a methodological countermeasure to the natural inclination of groups towards convergent biases [44,45].

2.2. Cognitive bias reduction and algorithmic bias introduction in AI decision-making

Cognitive heuristics, which serve as mental shortcuts, frequently leads to systematic deviations in judgment and decision-making [46]. To combat such biases, AI algorithms leverage a diverse array of techniques derived from ML, deep learning, and data science, underpinned by statistical theory, and designed for computational effectiveness. With, for instance, classification algorithms, including Support Vector Machines (SVM) and Random Forests (RF), recognize categorical outcomes from input data [47,48]. Regression techniques, like linear regression and its extensions for handling non-linear relationships facilitate predictive forecast analytics that foster multi-criteria data-driven decision-making [49,50]. Clustering algorithms, including K-Means and Hierarchical Clustering, identify inherent groupings with data [51,52]. Supervised and unsupervised learning techniques are both critical in detecting patterns and anomalies within large datasets [53]. Building upon the foundational capabilities of supervised and unsupervised learning, GAI functions on the paradigm of ML known as transformer models [3]. GAI enhances decision support by instantaneously delivering information and emulating interactive human discussion. This process involves extracting information from vast datasets, which may reduce cognitive biases engendered by information saturation and selective retrieval, consequently orienting decision-makers toward a more equitable and exhaustive viewpoint [54,55].

However, the effectiveness of GAI in reducing heuristics biases and achieving a better result is dependent on the quality and diversity of the data input fed into the system where biases in training data can lead to skewed AI decisions, a phenomenon known as algorithmic bias [56,57]. This is particularly pervasive in GAI, where the quality of the generated outputs is tightly linked to the data on which the model is trained [58]. Consequently, if biases trace the underlying datasets, the GAI is liable to sustain these in its interactions. The susceptibility of AI to 'prompt engineering' and the deliberate manipulation of input prompts further aggravate this problem [59]. The phenomenon of prompt engineering within GAI may start a feedback loop wherein prejudiced prompts obtain correspondingly biased responses, thereby undermining the capacity to effectively reduce heuristic biases [60]. Concurrently, to ensure that algorithm-driven decisions are equitable, AI systems are increasingly secured with protocols designed for bias detection and mitigation, including fairness-aware and accountability ethical frameworks that proactively recalibrate algorithmic computations to recognize and rectify potential biases [61] and the Explainable AI (XAI) strives to make reasoning transparent and trustworthy [62]. The concept of Human-in-the-Loop (HITL) within the domain of XAI represents an intersection where human intuition and expertise complement the computational efficiency of AI, particularly in decision-making processes. This underscores a symbiotic relationship that leverages the strengths of both HI and AI to improve outcomes and mitigate biases [63,64].

2.3. Balancing system 1 intuition and system 2 analysis with conversational AI-HI collaboration

Fast-and-slow dual-process decision-making proposes two distinct but interconnected reasoning systems, referred to as 'System 1'- automatic, quick, and often subconscious thinking and 'System 2'-deliberate, slow, and conscious reasoning [65]. System 1 processing operates in an intuitive and efficient manner, rapidly generates responses based on pattern-recognition, is enriched with emotional context, and utilizes stereotypes and heuristics [66]. Contrastingly, System 2 is characterized by its abstract and deliberate nature, inherently slower, and requires significant cognitive effort, fortified by computationally demanding, driving its methodical and reasoned decision-making [67]. The effectiveness of System 1 lies in its ability to swiftly produce decisions in urgent scenarios or when rapid assessments are needed. However, this quickness often results in sacrifices to the precision and thoroughness typically provided by more analytical and time-consuming processes of System 2. Therefore, there is a call for effective decision-making, which requires a balanced interplay between System 1 and System 2 [68,69]. The integration of human cognitive abilities with advanced AI, specifically GAI, offers a tactical approach to neutralize natural human biases inner System 1 by reinforcing the analytical capabilities of System 2 [70]. The identification of heuristic bias including anchoring [71], and the integration of AI feedback mechanisms [72], represents an advancement in the mitigation of cognitive bias driven by System 1 by encouraging the engagement of System 2 analytical thinking in decision-making processes.

GAI, by harnessing extensive open-access databases, improves human cognitive operations, particularly fortifying the deliberative and analytical capabilities central to System 2 thinking [73]. Providing immediate access to a wide array of information and insights derived from data, counters the natural biases and heuristic shortcuts frequently associated with System 1 [74]. The HITL paradigm in GAI serves as an interactive cognitive assistant, prompting individuals to engage in deeper inquiry and reflection, thereby mitigating the tendency toward rapid, potentially biased conclusions [75]. In collaborative contexts, the integration of diverse human perspectives with the computational power of GAI facilitates the navigation of collective biases, enabling the formulation of balanced and 'external' viewpoints for consideration. The iterative nature of the HITL feedback loop assures that the contributions of AI to decision-making are consistently honed and realigned with dynamic human values and insights [76]. Moreover, the dialogic capabilities of GAI foster an environment of iterative questioning and refinement of thought processes, representative of System 2's introspective nature [77]. Hence, GAI emerges as a dynamic force, guiding decision-makers towards a path of deliberate and considered reasoning, substantially reducing the tendency for biases and snap judgments [78]. This collaborative model empowers both individuals and groups to exploit the proficiency of GAI in processing extensive open-source data while preserving the essential human faculties for ethical and value-based judgments, and problem-solving in decision-making processes [79]. A weak human plus machine plus better process has proven to be more effective than either a strong machine alone or a strong human plus machine plus inferior process [80].

3. Methodology

Experimental methods are becoming more central in AI and HI interactions, as the rising popularity of large language models strengthen experimental techniques and deepens understanding of the interactions [81–83]. Quasi-experimental pretest-posttest design is widely adapted in decision-making research to infer causal relationships by controlling variables and observing outcomes [84,85]. Although pretest-posttest design does not establish causality as definitively as randomized controlled trials, it offers a methodologically sound alternative for examining the interplay between various decision-making agents when randomization is not feasible [86]. This approach facilitates the observation of how specific interventions (GAI in the context of this research), impact decision-making outcomes, providing substantial evidence to either support or dispute theoretical models [87,88]. Through the strategic manipulation of variables in a controlled environment, the experiments are designed to reduce the impact of external variables, thus strengthening the validity of the findings, and greatly enriching the comprehension of cognitive processes within decision-making [89].

The experiment process develops methodologically (as shown in Fig. 1) [90,91], commencing with 'Experiment Preparation', where research problems are defined and objectives are set, leading to the selection of cases and contexts. The 'Pretest Phase' then measures group decision-making baseline data without GAI interventions. With the 'Intervention Phase', specific GAI is introduced, and subsequent outcomes are then measured in the 'Posttest Phase' to detect any changes

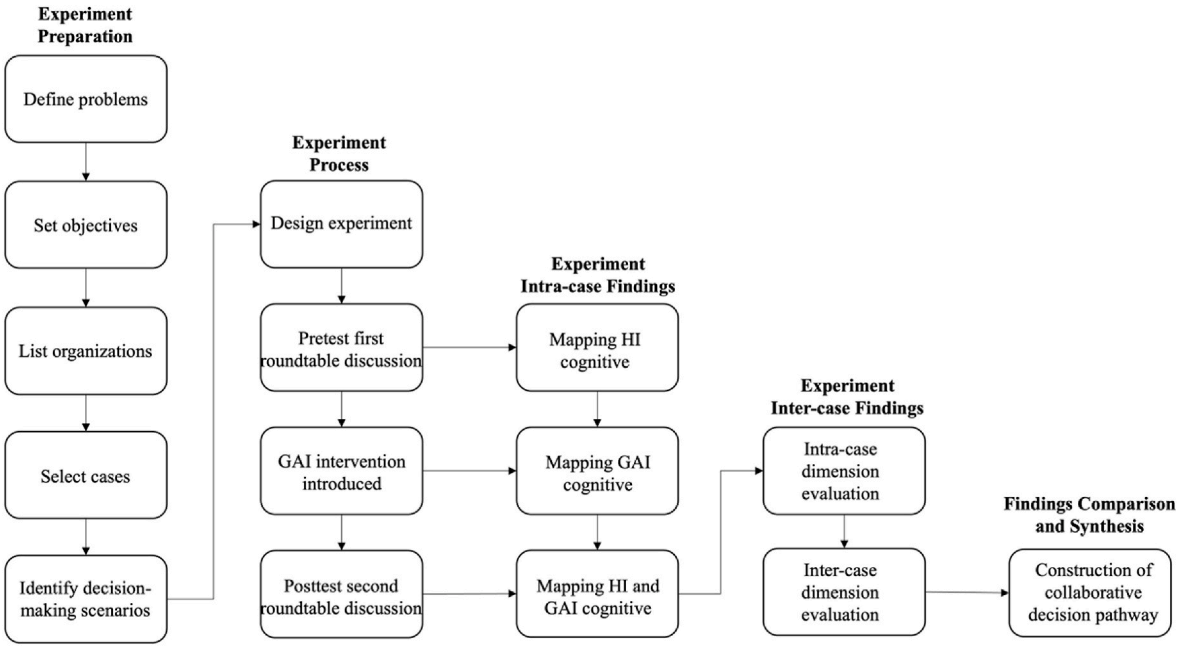

Fig. 1. Experimental procedures.

attributable to the intervention. The 'Inter-Findings Analysis' examines the cognitive interplay between HI and GAI, and the 'Findings Comparison and Synthesis' phase compares data pre- and post-interventions, analyzing homogeneity and heterogeneity to forge a comprehensive understanding of the interactions between HI and GAI in decision-making processes.

3.1. Group decision-making scenario selection

The selection process began with compiling an extensive list of global organizations recognized for their advanced operational decision-making practices, sourced from the authors' extensive LinkedIn network. These organizations were approached with a detailed description of the scope of the study, information about the research team, and a summary of the intended experiment process to confirm their interest and ability to contribute meaningfully from the outset. Upon receiving a response, the authors restated the research objectives and asked the highest level about their readiness to collaborate. We also committed to assuring the confidentiality of the data throughout and sharing the complete report of the study with the participants. The study encompassed three cases and four scenarios and involved interviews with 14 experts in the sectors of Food Delivery Services, Transportation Investment, and Public and Media Relations (Table 1).

When setting sample controls and defining the research boundaries, this research focused on several critical factors, including the geographic spread of the participating organizations, the sectors in which they operate, and their history of adopting AI in decision-making processes to protect the validity and reliability of the research findings. In the data provided, cases A and B showed a traditional approach to decision-making, primarily relying on human insight and expertise, where the decision-making process typically involved employee research, ideation sessions, and executive-level decision-making. On the other hand, case C from the dataset had incorporated AI into their data analysis methods, which marked a departure from solely human-based decision-making approaches. This experience with AI, although not extending to GAI, was particularly relevant to our study. By integrating cases heavily dependent on HI with those that already significantly benefit from AI, the study aims to bridge the gap between traditional and emergent decision-making mechanisms, offering a forward-looking perspective on the evolution of HI and GAI organizational decision-making.

3.2. Experiment design procedures

The experiment phase for this study spanned from September 2023 to January 2024. This period was chosen to accommodate the availability of participants and to ensure a sufficiently long interval for

Table 1
Overview of the participants.

Cases	Industry	Scenario	Code	Nature of work	Year of experience
A-Canada-2014	Food Delivery Services	Decision-Driven Market Launch and Growth	A1	Business Growth Specialist	4
			A2		5
			A3		3
			A4		6
B-China-2019	Transportation Investment	Logistics Optimization Decision	B1	Logistics Optimization Specialist	10
			B2		10
			B3		2
			B4		7
		Targeted Market Penetration Decision	B5	General Manager	20
			B6	Operations Specialist	10
			B7		10
			B8		8
C-China-1996	Public and Media Relations	Strategic Digital Marketing Decision	C1	Digital Marketing Specialist	3
			C2		3

observing varied decision-making scenarios and their outcomes. The experiment was designed to examine the assistance of GAI in group decision-making, particularly focusing on cognitive processes to diminish human biases and improve collaboration to mitigate the combined biases of AI and GHI in group decision-making tasks, thereby contributing to short-term operational and long-term strategic decision-making.

3.2.1. Pretest first-roundtable discussion: human intuition-based decision-making

Initially, participants were gathered for a 30-min discussion session where they focused solely on their collective knowledge and instinct to tackle a set of four fundamental 'what' and 'how' questions. The purpose here was to capture a clear picture of how the nature of group decision-making unfolds and to note the typical patterns and potential biases that arise when humans work together to solve problems without any algorithm-based guidance. This establishes a foundational understanding of group decision-making that would later serve as a reference point for comparing the impact of GAI integration.

3.2.2. GAI intervention introduced decision-making

In the subsequent stage of our procedure, which spanned an identical time frame of 30 min, the dynamics of the experiment shifted to incorporate the capabilities of ChatGPT 4.0 into the decision-making process. In this phase, human participants were presented with the same set of scenarios as before. However, unlike the initial round, they now had the advantage of ChatGPT's computational insights. As the questions unfolded, ChatGPT's initial responses were prompted by a directive to answer based on the provided background data, with a predefined directive *'given the background information, answer Qs'***.** Once the initial answers were given, the participants could invoke a deeper level of analysis by signaling ChatGPT to *'continue, show more insights'*.

3.2.3. Posttest second-roundtable discussion: HI and GAI collaborative decision-making

The posttest second-round 30 min roundtable discussion was dedicated to a systematic analysis of the collaborative HI and GAI decision-making cognitive processes. This was supported by a structured 1–5 scale Likert evaluation scale; metrics are shown in Table 2. For instance, Intuitive Judgment reflects the innate human capability to make decisions based on instinct and heuristics, a quality yet to be replicated authentically by GAI. Cognitive Overload and Heuristics Bias emphasize the limitations and potential pitfalls in human decision-making, highlighting areas where GAI can offer significant support. Experience-based decision-making underscores the value of leveraging past knowledge, a trait that GAI is beginning to emulate through learning algorithms. GAI, on the other hand, introduced dimensions such as Consistency and Transparency, crucial for establishing GAI as a reliable and understandable decision-support tool. Adaptability pointed to the ability of GAI to modify its decision-making protocols dynamically, a complement to human flexibility. However, the dimension of Algorithmic Bias served as a cautionary note, signifying the need for vigilance and continuous refinement of GAI systems. The collaborative dimensions, Complementarity, Conflict Resolution, Synergy, and Efficiency provided a holistic view of the potential combination of GAI and HI. Complementarity and Synergy specifically addressed how GAI could augment human capabilities, creating a symbiotic relationship that enhances decision-making prowess. Conflict Resolution and Efficiency captured the goal of collaborative decision-making: to harmonize diverse viewpoints and optimize resource utilization, ultimately aiming for decisions that are both effective and sustainable.

3.3. Data analysis

The analysis was carried out in two steps: analysis of intra-case scenarios and searching for inter-case patterns.

During the pretest-posttest experiment intra-case scenarios, cognitive mapping was utilized as a critical analytical instrument, providing enhanced clarity to the multifaceted nature of HI and GAI decision-making processes. This clarity was achieved through the methodical interpretation of consistent responses derived from group discussions alongside the data generated from training GAI systems. The utilization of cognitive mapping was important in deconstructing the complex cognitive processes that underpin the creation of scenarios. Since its incorporation into the Strategic Options Development and Analysis framework and its association with soft systems methodology in 1995 [115], cognitive mapping has stood as a tool for deciphering the complexities inherent in strategic and operational management challenges, particularly those that are poorly structured and require holistic analysis [116,117]. A cognitive map is constructed with nodes, which are connected by directional arrows [118]. These nodes, sometimes referred to as vertices or points, symbolize the concepts or ideas perceived to be relevant to the problem or scenario under investigation. The arrows, or edges, delineate the perceived relationships or linkages between these concepts, suggesting a sense of directionality or cause-and-effect.

Upon finalizing the collaborative cognitive maps, research transitioned to quantitatively assessing intra and inter-case scenarios using a 1–5 scale in alignment with the predefined metrics in Table 2. This

Table 2
Dimensions of HI and GAI collaborative decision-making evaluation.

	Dimensions	Definition	References
HI	Intuitive Judgment	Decision-making is based on gut feelings, heuristics, and immediate perception without the explicit use of rational processes or analytical reasoning.	[92–94]
	Cognitive Overload	A state where an individual is overwhelmed by the amount of information processing required, exceeding their cognitive capacity.	[95,96]
	Heuristics Bias	The cognitive shortcuts that simplify decision-making lead to systematic errors or biases in judgment.	[42,97]
	Experience-Based Decision-Making	Using knowledge from prior experiences to inform current decision-making.	[98]
GAI	Consistency	The measure of stability and predictability in the outputs of AI, particularly after it has been subjected to the training rounds.	[99,100]
	Transparency	The clarity with which the decision-making process of an AI system is conveyed and made understandable to human users.	[101,102]
	Adaptability	The capacity to change decision-making strategies in response to new information or changing directives.	[103,104]
	Algorithmic Bias	The degree to which AI consistently leans towards a certain outcome or deviates from the true value during decision-making.	[105,106]
HI and GAI collaboration	Complementarity	The degree to which the integration of AI augments the capabilities of human decision-making processes, resulting in a collective output that surpasses what either could accomplish in isolation.	[107,108]
	Conflict Resolution	The process of resolving disagreements to reach a satisfactory decision for all parties involved.	[109,110]
	Synergy	The level of cooperative interaction between artificial intelligence systems and group decision-making processes, particularly through the iterative cycles of data training and application.	[111,112]
	Efficiency	Making decisions in a way that maximizes outcomes while minimizing the use of time and resources.	[113,114]

quantitative assessment permitted an evaluation of HI and GAI individually, as well as an appraisal of their collaborative efficacy in response to the posed experimental inquiries. The use of statistical averaging in both horizontal and vertical analyses was important in distilling individual responses into a cohesive understanding of the collective performance of HI and AI interfaces. Horizontally, it helped average out the individual responses across the different metrics for each case, ensuring that the evaluation within each scenario was balanced and bias minimized. Vertically, it aggregated the scores across all cases, providing an overarching measure of effectiveness and allowing for a comparison between the distinct scenarios. The merging of these two approaches provided a multi-dimensional perspective on the data. This improved the reliability of the findings by counterbalancing individual variance in hypothesis verification.

The final analytical scope was then increased through frame analysis, a prevalent technique within the domain of managerial cognition. This approach divides cognitive frames into two distinct categories: diagnostic frames, which explain the existing status quo, and prognostic frames, which forecast prospective developments [119]. Adopting this dualistic categorization, the study analyzed the current symbiosis of HI and GAI and projected its forward-moving trajectory within real-world decision-making.

4. Results

During this detailed phase of the analysis (Fig. 2), the experts engaged in three stages of cognitive mapping construction. In the pretest first-roundtable discussion and intervention stage, human intelligence cognitive (HIC) and GAI cognitive (GAIC) were constructed respectively. The collaboration HIC and GAIC cognitive map was created in the posttest second-roundtable discussion. To generalize the result, a rating scale was provided to participants (Table 2), which assessed both the decision-making capabilities of HI and GAI independent and their collaborative effectiveness in decision-making.

4.1. Scenario 1- decision-driven market launch and growth

Launched in 2014 in Vancouver, Company A has distinguished itself in the technology sector with its innovative delivery network model, facilitating everyday services from food delivery to various convenience offers. Its expansion has been notable in key urban areas in North America, Australia, and the United Kingdom. Now eyeing the European landscape, the company aims to transplant its successful service model to invigorate community engagement, with a strategic focus on Ireland. In preparation for the planned expansion into the food delivery market of Ireland, the forthcoming discussion by a panel of four experts will focus on four critical questions: *Q1*: To establish a successful operation in Ireland, what specific tangible assets and intangible resources must Company A procure and prepare? *Q2*: Considering the objective of diversifying and growing Company A's service offerings, what potential Ireland-based partners or enterprises could align with the strategic objectives for expansion? *Q3*: In what ways can Company A utilize Ireland's social media trends and influencer circles to cultivate a strong market presence and drive demand for the food delivery service? *Q4*: Within the framework of Ireland's urban landscape, what distinct operational challenges might arise?

4.1.1. Pretest first-roundtable discussion

HI focuses initially on securing essential operational assets like premium office locations and custom vehicle fleets (Fig. 3). This focus shifts towards integrating these assets more strategically by appointing local representatives for cultural integration, highlighting a move from basic operational setups to deeper strategic integration within the community. HI's approach to partnerships starts with basic alliances with local food establishments and educational institutions and evolves to include tech firms and government agencies, widening the scope of strategic partnerships. In operations, HI addresses specific challenges like architectural idiosyncrasies and population density, gradually incorporating solutions for weather adaptability and cultural diversity in workforce planning, thus shifting from immediate logistical solutions to long-term operational strategies.

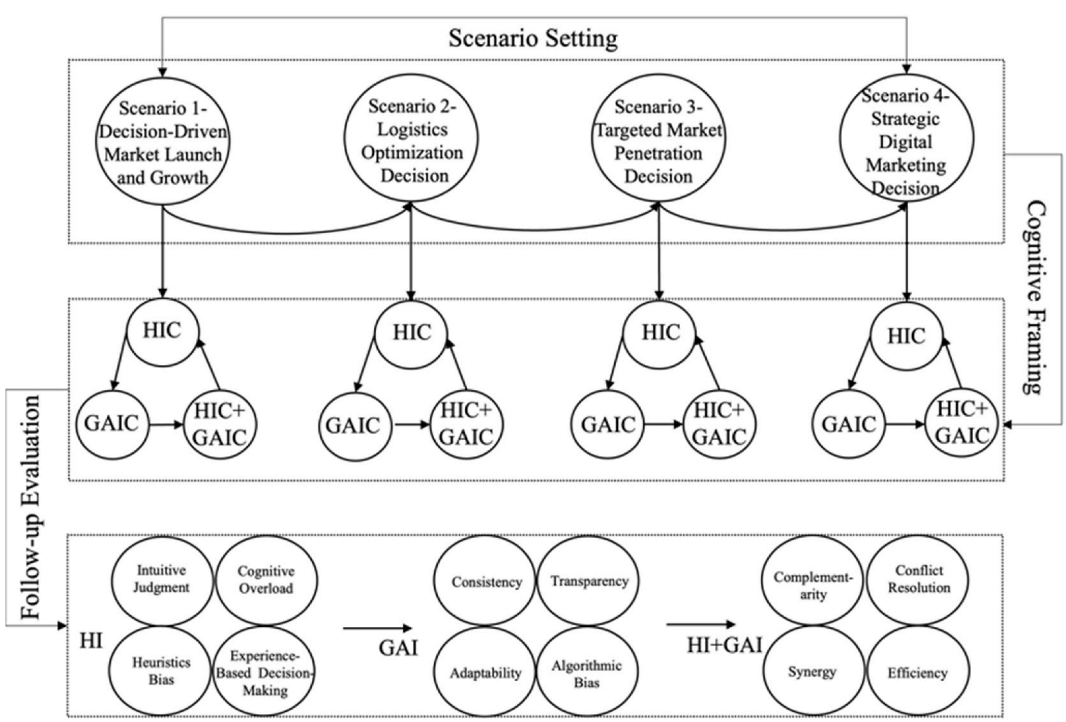

Fig. 2. Analysis procedure.

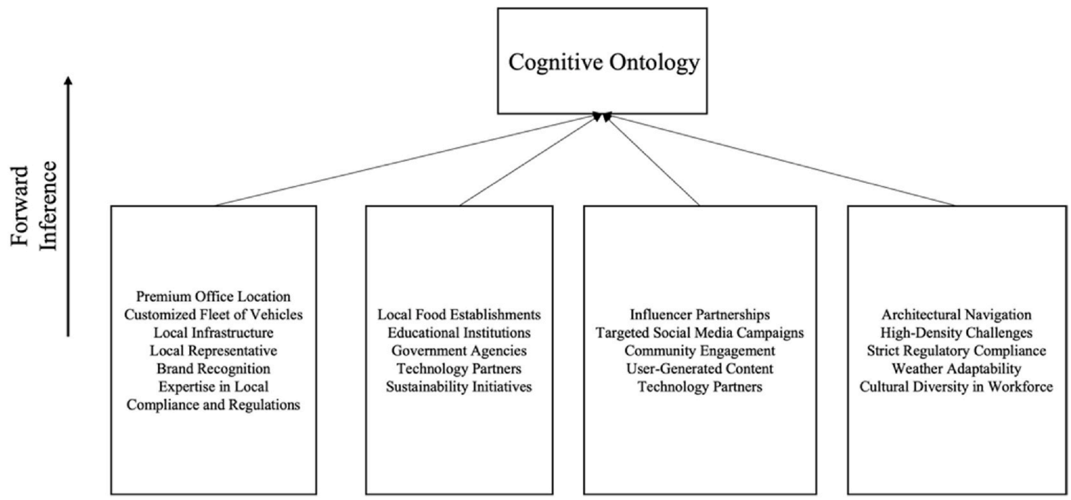

Fig. 3. Scenario 1-HI cognitive map.

4.1.2. GAI intervention introduced

GAI starts by examining distribution centers and logistics technologies to optimize the basic infrastructure of operations (Fig. 4). This analysis soon progresses to incorporate advanced network technologies. In terms of partnerships, GAI begins by identifying diverse potential partners across various sectors, later expanding this to include connections with organic stores and city council initiatives. This growth in partnerships illustrates GAI's ability to broaden its focus from individual sectors to a more comprehensive community and governmental engagement. In marketing, GAI transitions from focusing on influencer networks and localized content to adopting data-driven campaigns and diverse content strategies, showing a shift towards more inclusive and effective marketing methods.

4.1.3. Posttest second-roundtable discussion

The collaboration between HI and GAI leverages the strengths of both approaches to form a more comprehensive operational strategy (Fig. 5). Initially focusing on combining asset security with advanced technological integration, this partnership soon develops a unified approach that seamlessly integrates cultural insights with sophisticated logistics solutions (See Appendix 1 for the collaboration thinking shift). For example, the collaboration starts with a focus on educational and local business partnerships, which evolves into a holistic strategy encompassing a wide range of educational, business, and technological partnerships. This integration enhances the overall growth and adaptability of operations. In marketing, the collaboration merges traditional human touchpoints with AI-driven techniques, creating more dynamic and impactful engagement strategies.

According to Table 3, the pretest scores across the four questions (Q1 to Q4) reflected these limitations, with average scores of 4 for intuitive judgment, 3.75 for experience-based decision-making, 3.06 for cognitive overload and 2.44 for heuristics bias. After the first round of GAI training, the average scores were 3.5 for consistency, 3.38 for transparency, 3.63 for adaptability, and 3.19 for algorithmic bias. These scores indicate a moderate level of predictability and clarity in the GAI outputs, as well as some initial responsiveness to new information. Following the second round of training, there were notable improvements in most areas: consistency increased slightly to 3.63, transparency rose significantly to 4.13, and adaptability improved markedly to 4.38. However, algorithmic bias increased to 3.69, indicating that while the AI

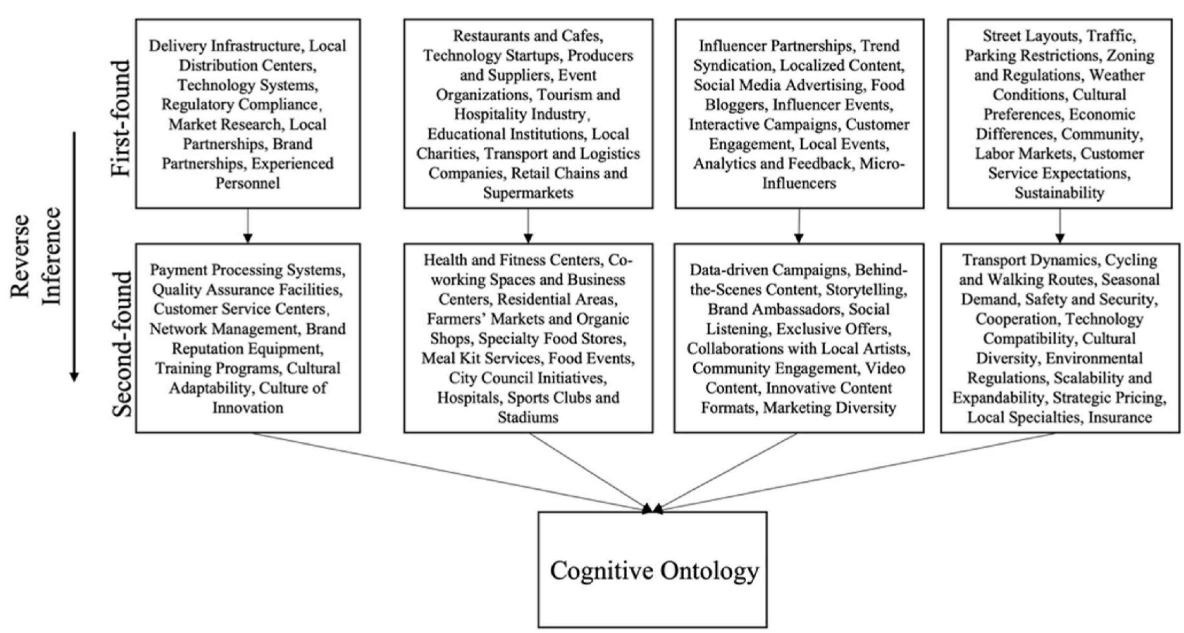

Fig. 4. Scenario 1-GAI cognitive map.

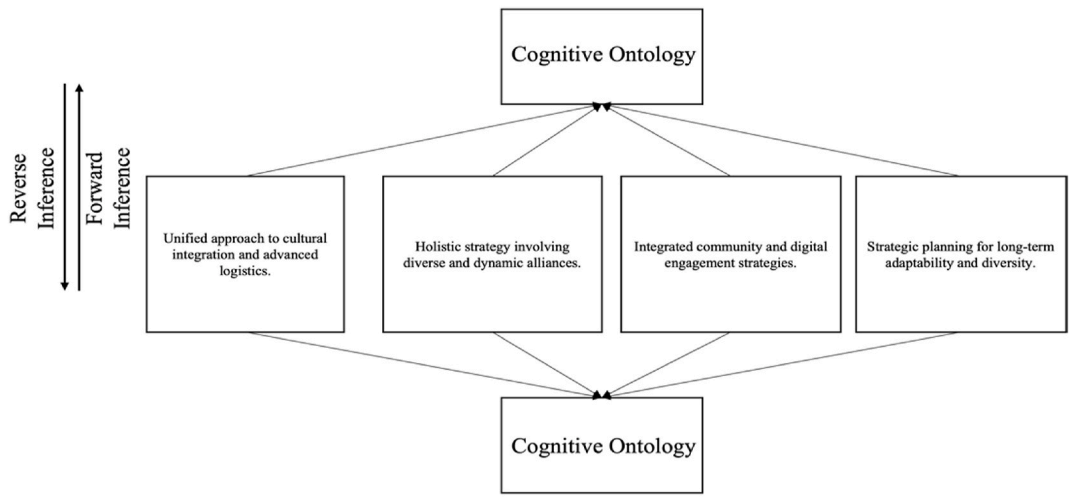

Fig. 5. Scenario 1-HI and GAI cognitive map.

system became more transparent and adaptable, it also showed a higher tendency towards biased decision-making. The posttest second-roundtable discussion scores revealed enhancements in key dimensions such as complementarity, conflict resolution, synergy, and efficiency. Specifically, complementarity, which measures how well GAI improves human decision-making, scored 3.75. Conflict resolution, the ability to resolve disagreements effectively, scored 3.69. Synergy, reflecting the cooperative interaction between GAI systems and human decision-making, scored 3.5. Finally, efficiency, which measures decision-making that maximizes outcomes while minimizing time and resources, scored 3.63.

4.2. Scenario 2- logistics optimization decision

Mining operations in Location F face logistical challenges due to the lack of direct rail transport, which requires the consideration of multimodal transportation methods to move sand and aggregate to Location Q, a significant demand center. A panel of four experts convened to deliberate on the following issues: *Q1*: Given the hazards associated with direct highway transportation and the advantages of integrated highway and railway systems, what alternative pathways could be employed to reduce delays and refine cost efficiency? *Q2*: How could transportation methods be coordinated to facilitate the efficient transfer of materials while also adhering to the sustainable development objective of minimizing the environmental impact? *Q3*: What strategic partnerships could be formed with local authorities and organizations to facilitate real-time updates on road conditions, thus ensuring efficient communication and the maintenance of smooth transportation pathways? *Q4*: In the face of ongoing road maintenance or unforeseen closures, what contingency plans can be developed that minimize environmental impact and guarantee uninterrupted traffic flow?

4.2.1. Pretest first-roundtable discussion

HI initially advocates for a “hub-and-spoke” system to manage congestion and boost cost efficiency effectively (Fig. 6). As the strategy develops, it includes using GPS and real-time data analytics to optimize routing, moving from basic traffic management to advanced, data-driven routing solutions. For transportation, starting with the use of electric or hybrid trucks for shorter hauls, HI evolves into creating a centralized logistics platform that facilitates smooth transitions between different transport modes, reflecting a shift from improving individual elements to integrating entire logistics operations.

4.2.2. GAI intervention introduced

GAI starts by suggesting a variety of transportation methods, including short-sea shipping and intermodal transportation, to tackle logistical challenges (Fig. 7). The approach soon expands to include even more sophisticated solutions like pipeline conveyance and adopting hub-and-spoke models, showing a progression towards creating a complete multimodal transportation system. In logistics management, GAI first recommends optimization software and regular scheduling for rail transport, and then advances to support collaborative logistics frameworks that ensure synchronized scheduling across different modes. This shows how GAI transitions from promoting initial technology use to enhancing entire systems, improving the efficiency of logistics operations substantially.

4.2.3. Posttest second-roundtable discussion

Shown in Fig. 8, starting with a focus on congestion management and cost efficiency improvements, the partnership of HI and GAI quickly integrates advanced data analytics and comprehensive transport strategies (See Appendix 2 for the collaboration thinking shift). For example, HI concentrates on practical, on-the-ground improvements such as electric mobility and transport synchronization, while GAI introduces systemic enhancements. Together, they create a cohesive strategy across various transport modes. This collaboration effectively addresses immediate operational improvements and develops strategies for long-term resilience and environmental sustainability, showing a proactive and strategic approach to complex logistical challenges.

As shown in Table 4, in the first roundtable discussion, the average scores for HI namely, intuitive judgment, cognitive overload, heuristics bias, and experience-based decision-making were 2.63, 1.88, 2.94, and 2.5, respectively. After GAI intervention, the initial consistency and transparency scores were 2.81 and 2.38, respectively, while adaptability and algorithmic bias were rated at 2.56 and 2.25. In the second round of intervention, transparency slightly improved to 2.81. Consistency, adaptability, and algorithmic bias significantly increased to 3.23, 3.13 and 3.06, respectively. The results show consistently high average scores across metrics in HI and GAI collaboration, with complementarity at 3.5, conflict resolution at 3.69, synergy at 3.56, and efficiency also at 3.56 (see Table 5).

4.3. Scenario 3- targeted market penetration decision

Transportation Investment Enterprise B is considering an expansion into the fine-washed sand market, targeting the launch of a product line characterized by high standards of quality, eco-friendliness, and innovative features appropriate for the local construction sector. Addressing environmental issues and the potential for climate-induced disruptions in production is critical to balance the opportunities with the inherent

Table 3
Scenario 1-dimension evaluation.

	HI				GAI					HI and GAI			
	Pretest first-roundtable discussion				GAI intervention introduced					Posttest second-roundtable discussion			
	Intuitive Judgment	Cognitive Overload	Heuristics Bias	Experience-Based Decision-Making	Training	Consistency	Transparency	Adaptability	Algorithmic Bias	Complementarity	Conflict Resolution	Synergy	Efficiency
Q1	(3, 4, 3, 5) 3.75	(4, 2, 2, 4) 3	(2, 3, 2, 2) 2.25	(4, 4, 4, 5) 4.25	1st	(2, 4, 3, 3) 3	(4, 5, 2, 4) 3.75	(3, 3, 3, 4) 3.25	(2, 3, 3, 3) 2.75	(4, 4, 4, 4) 4	(5, 4, 4, 3) 4	(4, 4, 3, 3) 3.5	(3, 5, 3, 5)
					2nd	(3, 4, 4, 4) 3.75	(4, 5, 3, 4) 4	(4, 4, 4, 4) 4	(3, 3, 3, 3) 3				4
Q2	(3, 5, 4, 4) 4	(2, 4, 2, 5) 3.25	(2, 3, 3, 2) 2.5	(1, 5, 4, 5) 3.75	1st	(3, 5, 3, 4) 3.75	(2, 5, 2, 5) 3.5	(3, 4, 3, 5) 3.75	(2, 3, 4, 4) 3.25	(4, 4, 3, 5)	(4, 5, 3, 4) 4	(3, 5, 3, 3) 3.5	(2, 4, 3, 3)
					2nd	(3, 3, 4, 3) 3.25	(4, 4, 4, 4) 4	(4, 5, 4, 5) 4.5	(4, 5, 5, 5) 4.75	4			3
Q3	(4, 4, 3, 5) 4	(2, 3, 1, 5) 2.75	(2, 2, 3, 2) 2.25	(2, 3, 5, 4) 3.5	1st	(2, 4, 3, 4) 3.25	(5, 3, 2, 3) 3.25	(5, 5, 2, 3) 3.75	(2, 4, 4, 4) 3.5	(3, 5, 3, 4)	(4, 3, 3, 5)	(4, 4, 2, 4) 3.5	(3, 5, 3, 4)
					2nd	(3, 4, 3, 3) 3.25	(5, 4, 3, 5) 4.25	(5, 5, 2, 5) 4.25	(2, 5, 4, 3) 3.5	3.75	3.75		3.75
Q4	(4, 5, 3, 5) 4.25	(3, 3, 3, 4) 3.25	(3, 2, 3, 3) 2.75	(2, 4, 3, 5) 3.5	1st	(3, 5, 4, 4) 4	(2, 2, 4, 4) 3	(5, 3, 3, 4) 3.75	(3, 4, 3, 3) 3.25	(2, 5, 2, 4)	(1, 4, 2, 5)	(1, 5, 3, 5) 3.5	(4, 5, 2, 4)
					2nd	(4, 4, 5, 4) 4.25	(4, 5, 4, 4) 4.25	(5, 5, 4, 5) 4.75	(3, 4, 4, 3) 3.5	3.25	3		3.75
AVG.	4	3.06	2.44	3.75	1st	3.5	3.38	3.63	3.19	3.75	3.69	3.5	3.63
					2nd	3.63	4.13	4.38	3.69				

risks of this venture. The success will depend on its ability to navigate operational complexities, capitalize on strategic opportunities, and integrate the new product with its long-term vision. In preparation for market entry, a panel of four experts has been convened to address four key questions. *Q1*: What strategies could be adopted to reduce costs while enhancing profitability in this new market? *Q2*: What potential partnerships or collaborative relationships might be advantageous in our entry into the market? *Q3*: What measures will be taken to ensure a resilient and reliable supply chain to meet market demand? *Q4*: How can the brand be positioned to gain a strong foothold in the fine-washed sand market?

4.3.1. Pretest first-roundtable discussion

HI strategies initially focus on leveraging economies of scale and adopting energy-efficient technologies to reduce costs (Fig. 9). The approach soon evolves into a dynamic pricing strategy that responds to changing market demands, showing a progression from cost-focused strategies to more flexible, market-driven approaches. In terms of partnerships, starting with local builders and eco-certification bodies, HI broadens its scope to include joint ventures with regional transport firms, enhancing the entire logistics chain. This growth from niche partnerships to comprehensive logistical collaborations underscores an expanding understanding of market integration and operational effectiveness.

4.3.2. GAI intervention introduced

GAI strategies start by using predictive analytics to enhance operational efficiency, such as securing long-term supplier contracts to reduce costs and improve workflow (Fig. 10). As these strategies develop, GAI focuses more on optimizing the entire value chain and introduces dynamic pricing to better respond to market changes. This marks a transition from focusing merely on operational efficiency to adopting more complex, integrated approaches that use data for comprehensive management of the value chain. In logistics, GAI employs technologies like GPS and blockchain to improve efficiency and ensure transparency. These tools also help support wider objectives such as fostering a circular economy, demonstrating how AI can move from enhancing logistical operations to advancing broader environmental and sustainability initiatives.

4.3.3. Posttest second-roundtable discussion

The collaboration between HI and GAI strategies leverages both human insight and AI analytics to craft sophisticated and resilient operational frameworks (Fig. 11). Initially, this partnership focuses on integrating cost-effective production methods with market adaptability strategies (See Appendix 3 for the collaboration thinking shift). As the collaboration deepens, it incorporates advanced analytics and real-time data into decision-making processes, merging cost-efficiency with agile responses to market conditions. For example, in supply chain management, the combination of HI's diversified strategies and GAI's technological applications develops into robust systems that are not only resilient but also future direction. This collaborative approach enhances immediate operational efficiency and also prepares the organization to face future challenges dynamically and effectively.

In the pretest first-roundtable discussion, the average scores for HI's intuitive judgment, cognitive overload, heuristics bias, and experience-based decision-making were 2.75, 2.56, 3.31, and 2.69, respectively. These results suggest that participants moderately relied on intuition and prior experiences while making decisions. They experienced a moderate level of cognitive overload, indicating some difficulty in processing information. The high score in heuristics bias implies that participants frequently used cognitive shortcuts, which may have led to systematic errors in their judgment. Following the GAI intervention, initial scores for consistency, transparency, adaptability, and algorithmic bias were 2.88, 2.81, 2.75, and 2.69, respectively. In the second evaluation, these scores improved to 3.31, 3.56, 3.56, and 3.13. This

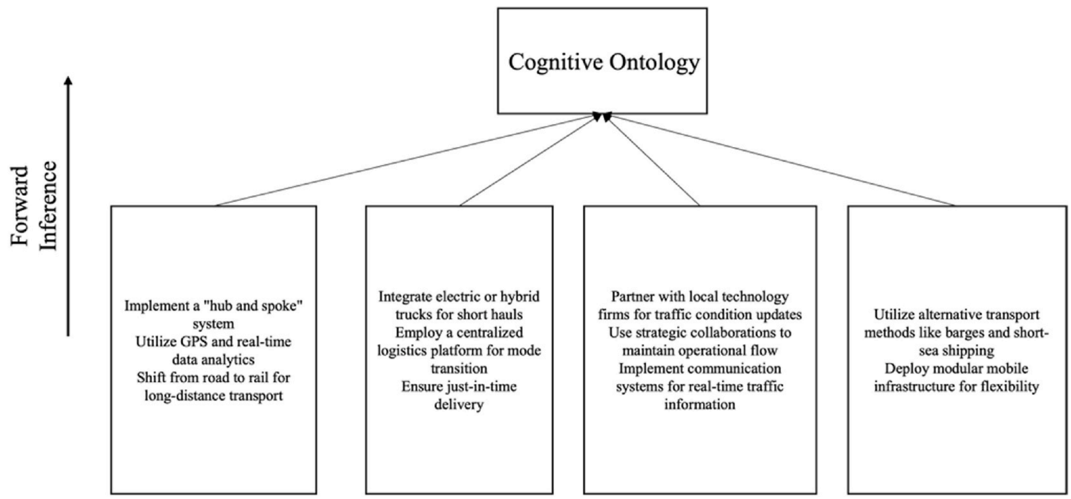

Fig. 6. Scenario 2-HI cognitive map.

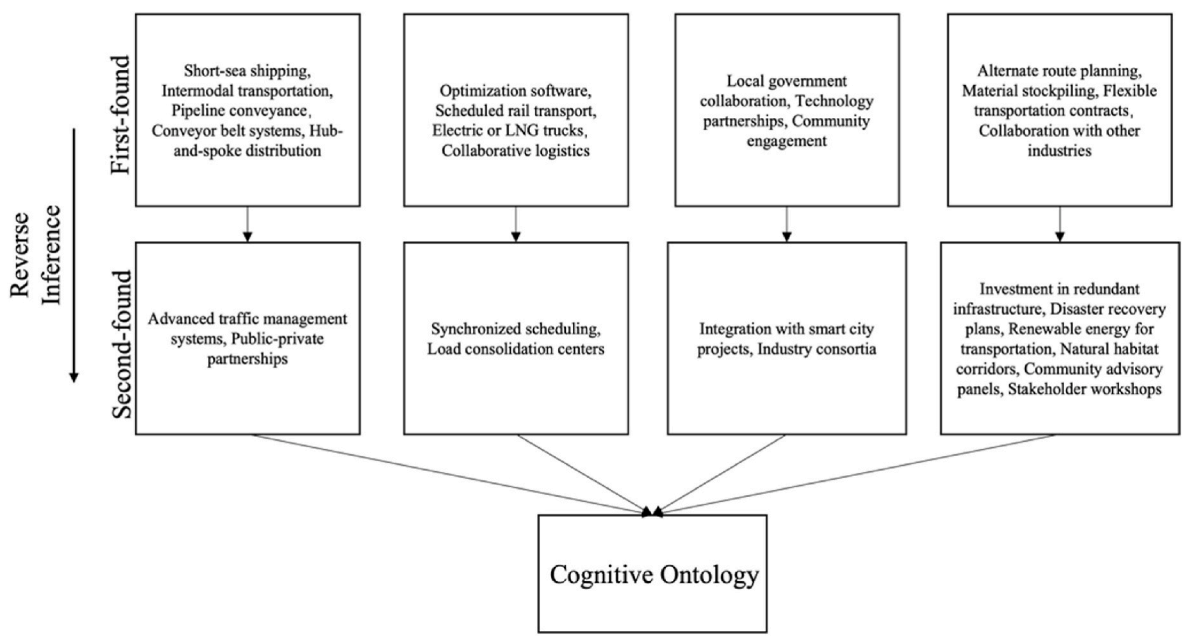

Fig. 7. Scenario 2-GAI cognitive map.

indicates that the intervention led to better consistency, and adaptability in AI decision-making, though it also showed a slight increase in bias. In the posttest second-roundtable discussion, the average scores for complementarity, conflict resolution, synergy, and efficiency were 4.13, 3.81, 3.81, and 3.81, respectively. These high scores indicate that the integration of GAI significantly enhanced the group's decision-making capabilities, showing strong synergy and efficient collaboration. Conflict resolution was also effective, contributing to satisfactory outcomes for all parties involved. The overall results reflect a successful augmentation of human decision-making processes through GAI, leading to better collective outputs and efficient use of resources.

4.4. Scenario 4- strategic digital marketing decision

One of the renowned social media and e-commerce platforms of China, Media X is gearing up for the Singles' Day (Double 11) event, which is a highly popular online shopping festival. This year, the focus of D is to leverage the advantages of its platform to boost sales in the cosmetics industry. *Q1*: What specific data should be collected before the Double 11 event to ensure readiness for data-driven initiatives, thus providing insights for the cosmetics industry and strengthening marketing strategies? *Q2*: How to optimize targeted content publication and promotion during Double 11 to maximize engagement and conversion rates in the cosmetics industry? *Q3*: What approaches should be taken to effectively manage user interactions, and adjust content and promotional strategies at various stages before, during, and after the event to maximize the impact of the Double 11 event? *Q4*: How to construct performance metrics to evaluate and improve the outcomes of the Double 11 event, promoting strategic optimization for future events in the cosmetics industry?

4.4.1. Pretest first-roundtable discussion

HI begins with straightforward data collection on consumer behaviors, such as identifying peak browsing times and product preferences (Fig. 12). This knowledge is then used to develop more agile supply chain processes that respond swiftly to consumer feedback, reflecting a dynamic approach to managing operations and customer interactions. For example, by starting with a simple content calendar based on

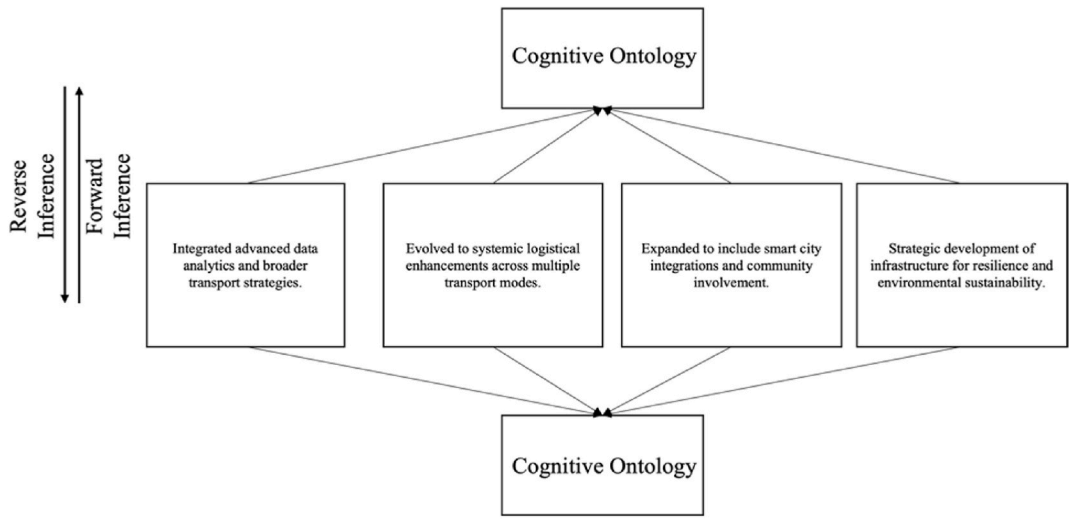

Fig. 8. Scenario 2-HI and GAI cognitive map.

audience preferences, HI practitioners later integrate more interactive elements like live streams and flash sales, aiming to maintain customer engagement through ongoing, real-time activities. This evolution shows a shift from static planning to a more fluid, responsive strategy that continuously adapts to consumer feedback and enhances overall engagement.

4.4.2. GAI intervention introduced

GAI focuses on deeply analyzing consumer behavior and inventory dynamics to optimize marketing tactics (Fig. 13). Starting with data on how consumers interact with products and services, GAI uses real-time analytics to adjust marketing strategies promptly. For example, by analyzing feedback from audience participation, GAI moves towards utilizing sophisticated tools that predict trends and consumer preferences, enhancing the strategic foresight in marketing. This process adapts to current consumer behavior and proactively shapes future marketing strategies by anticipating changes in the market and consumer demands, using predictive modeling to plan for expansion and increased market engagement.

4.4.3. Posttest second-roundtable discussion

When HI and GAI work collaboratively, the approach to market strategies becomes highly integrated and dynamic (Fig. 14). Initially, this collaboration combines human-driven insights with AI's data processing capabilities to create a comprehensive view of market conditions (See Appendix 4 for the collaboration thinking shift). For instance, combining HI's understanding of content strategy with GAI's analytical insights leads to the development of marketing campaigns that are both creative and data driven. This integrated approach allows for real-time adjustments based on a deep understanding of market dynamics and consumer behaviors. The collaboration extends to performance metrics as well, where traditional sales-focused indicators are enhanced with AI's ability to incorporate broader consumer insights, turning basic data collection into a sophisticated, insight-driven strategy that optimizes both market presence and consumer engagement.

In scenario 4-dimension evaluation (Table 6), the average scores of HI were: intuitive judgment (2.5), cognitive overload (1.5), heuristics bias (2.13), and experience-based decision-making (4). These results indicate that participants relied heavily on experience-based decision-making, faced low cognitive overload, also prone to less heuristics bias. Their intuitive judgment was moderate, suggesting a balanced approach between gut feelings and rational analysis. The GAI intervention results showed stable scores for consistency (2.75) across both rounds, with improvements in transparency (from 3 to 3.13) and adaptability (from 2.88 to 3.38). However, algorithmic bias increased from 3.38 to 3.63, indicating that while the GAI became more transparent and adaptable, it also exhibited a higher degree of bias in its decision-making processes post-intervention. Considering HI and GAI collaboration, the scores for complementarity (4.25), conflict Resolution (3.63), synergy (4.38), and efficiency (3.88) indicate strong overall performance. The high scores in complementarity and synergy reflect effective collaboration and mutual enhancement among participants, while the good score in efficiency shows productive use of resources and time. Conflict Resolution, although lower than the other metrics, still demonstrates considerable ability to manage and resolve disagreements.

5. Discussion

In familiar scenarios 1 and 4, participants could rely heavily on past experiences. However, in unfamiliar scenarios 2 and 3, their decision-making processes shifted significantly. Specifically, the lack of relevant experience meant that participants could not rely as much on experience-based decision-making, leading to a greater reliance on intuitive judgment and potentially increasing the risk of cognitive biases such as heuristics [120]. The moderate to low scores in cognitive overload suggest that while participants were not overwhelmed by the volume of information, their decision-making process might still be influenced by their instincts or first impressions in the absence of reasoning [93]. This shift highlights a critical challenge in human decision-making: when familiar patterns are absent, there is an increased likelihood of defaulting to intuition rather than methodical reasoning. This can be problematic in new scenarios where gut feelings may not be the best guide, but that is where GAI helps.

As GAI evolved, the interventions across two training rounds reveal significant enhancements in consistency, adaptability, and transparency. Consistency in ML systems refers to the ability of the algorithm to produce consistent results even when exposed to varying data inputs, a principle anchored in robust optimization [121]. This concept ensures that the model remains effective and accurate under a range of different scenarios and perturbations, critical for applications requiring high reliability across diverse environments. Adaptability, on the other hand, highlights the GAI's increased flexibility in integrating and responding to new information. This feature is grounded in transfer learning and adaptive learning, which allow a model to apply knowledge learned from one domain to problems in new domains effectively [122]. Such a capability is vital for dynamic systems that operate in real-time environments where the input data can change unpredictably. Lastly, the enhancement in transparency involves making the GAI's

Table 4
Scenario 2-dimension evaluation.

	HI				GAI					HI and GAI			
	Pretest first-roundtable discussion				GAI intervention introduced					Posttest second-roundtable discussion			
	Intuitive Judgment	Cognitive Overload	Heuristics Bias	Experience-Based Decision-Making	Training	Consistency	Transparency	Adaptability	Algorithmic Bias	Complementarity	Conflict Resolution	Synergy	Efficiency
Q1	(2, 3, 3, 2)	(2, 2, 2, 2)	(4, 3, 2, 2)	(2, 2, 2, 3)	1st	(2, 3, 3, 3) 2.75	(2, 4, 3, 2) 2.75	(3, 2, 2, 3) 2.5	(2, 1, 3, 1) 1.75	(2, 5, 4, 4)	(4, 4, 4, 4)	(3, 4, 3, 4)	(4, 5, 2, 3)
	2.5	2	2.75	2.25	2nd	(3, 2, 4, 3) 3	(3, 2, 3, 3) 2.75	(3, 2, 2, 4) 2.75	(3, 3, 3, 2) 2.75	3.75	4	3.5	3.5
Q2	(2, 3, 3, 2)	(2, 2, 2, 3)	(3, 3, 3, 4)	(2, 2, 2, 5)	1st	(3, 3, 2, 3) 2.75	(1, 1, 2, 3) 1.75	(2, 3, 3, 4) 3	(3, 4, 3, 4) 2.75	(3, 3, 4, 5)	(3, 4, 2, 5)	(4, 5, 3, 3)	(4, 4, 3, 3)
	2.5	2.25	3.25	2.75	2nd	(4, 3, 2, 4) 3.25	(2, 2, 4, 2) 2.5	(3, 4, 4, 4) 3.75	(4, 2, 4, 4) 3.5	3.75	3.5		3.5
Q3	(3, 3, 3, 2) 2.75	(2, 2, 1, 1) 1.5	(3, 2, 4, 3) 3	(2, 2, 3, 3) 2.5	1st	(2, 3, 3, 3) 2.75	(4, 3, 2, 3) 3	(2, 1, 2, 2) 1.75	(2, 2, 3, 4) 2.75	(3, 4, 3, 3)	(4, 3, 4, 4)	(4, 4, 3, 4)	(4, 3, 4, 4)
					2nd	(3, 2, 4, 3) 3	(2, 3, 3, 2) 2.5	(3, 2, 2, 4) 2.75	(3, 3, 3, 4) 3.25	3.25	3.75	3.75	3.75
Q4	(2, 2, 3, 2) 2.25	(2, 2, 1, 2) 1.75	(3, 2, 3, 3) 2.75	(2, 3, 3, 2) 2.5	1st	(3, 2, 3, 4) 3	(2, 1, 3, 2) 2	(4, 2, 3, 3) 3	(2, 1, 2, 2) 1.75	(2, 5, 2, 4)	(3, 3, 3, 5)	(2, 4, 3, 4)	(4, 4, 3, 3)
					2nd	(3, 2, 2, 4) 3.67	(3, 2, 4, 5) 3.5	(2, 3, 4, 4) 3.25	(3, 2, 3, 3) 2.75	3.25	3.5	3.25	3.5
AVG.	2.63	1.88	2.94	2.5	1st	2.81	2.38	2.56	2.25	3.5	3.69	3.56	3.56
					2nd	3.23	2.81	3.13	3.06				

Table 5
Scenario 3-dimension evaluation.

	HI				GAI					HI and GAI			
	Pretest first-roundtable discussion				GAI intervention introduced					Posttest second-roundtable discussion			
	Intuitive Judgment	Cognitive Overload	Heuristics Bias	Experience-Based Decision-Making	Training	Consistency	Transparency	Adaptability	Algorithmic Bias	Complementarity	Conflict Resolution	Synergy	Efficiency
Q1	(2, 3, 3, 2)	(3, 3, 2, 2)	(3, 3, 3, 4)	(3, 3, 2, 3)	1st	(3, 4, 2, 2) 2.75	(3, 3, 3, 2) 2.75	(2, 3, 2, 3) 2.5	(2, 2, 2, 3) 2.25	(4, 5, 4, 4) 4.25	(4, 4, 4, 3) 3.75	(5, 4, 3, 4) 4	(4, 5, 3, 4) 4
	2.25	2.5	3.25	2.75	2nd	(3, 2, 3, 4) 3	(4, 3, 3, 4) 3.5	(3, 3, 4, 4) 3.5	(3, 3, 3, 3) 3				
Q2	(3, 3, 4, 3)	(2, 4, 2, 4)	(3, 4, 3, 3)	(2, 2, 3, 3)	1st	(3, 2, 3, 3) 2.75	(2, 3, 2, 5) 3	(3, 2, 3, 3) 2.75	(2, 3, 4, 4) 3.25	(5, 4, 4, 4) 4.25	(4, 4, 4, 4) 4	(3, 4, 5, 3) 3.75	(3, 4, 4, 4) 3.75
	3.25	3	3.25	2.5	2nd	(3, 3, 4, 3) 3.25	(4, 4, 4, 4) 4	(3, 4, 4, 3) 3.5	(4, 3, 4, 3) 3.5				
Q3	(3, 2, 3, 3)	(2, 3, 2, 3)	(4, 2, 4, 3)	(2, 3, 3, 2)	1st	(2, 4, 3, 4) 3.25	(3, 3, 2, 3) 2.75	(2, 5, 2, 3) 3	(2, 3, 3, 4) 3	(3, 4, 4, 5) 4	(4, 4, 3, 4) 3.75	(3, 4, 4, 4) 3.75	(4, 5, 4, 4) 4.25
	2.75	2.5	3.25	2.5	2nd	(3, 4, 3, 3) 3.25	(4, 4, 3, 3) 3.5	(4, 5, 2, 3) 3.5	(2, 3, 4, 3) 3				
Q4	(3, 4, 2, 2)	(2, 2, 3, 2)	(4, 4, 2, 4)	(2, 4, 3, 3)	1st	(2, 2, 4, 3) 2.75	(3, 2, 4, 2) 2.75	(3, 2, 3, 3) 2.75	(2, 2, 2, 3) 2.25	(3, 5, 4, 4) 4	(4, 4, 3, 4) 3.75	(4, 3, 4, 4) 3.75	(3, 4, 3, 3) 3.25
	2.75	2.25	3.5	3	2nd	(4, 3, 5, 3) 3.75	(4, 3, 2, 4) 3.25	(3, 3, 4, 5) 3.75	(3, 2, 4, 3) 3				
AVG.	2.75	2.56	3.31	2.69	1st	2.88	2.81	2.75	2.69	4.13	3.81	3.81	3.81
					2nd	3.31	3.56	3.56	3.13				

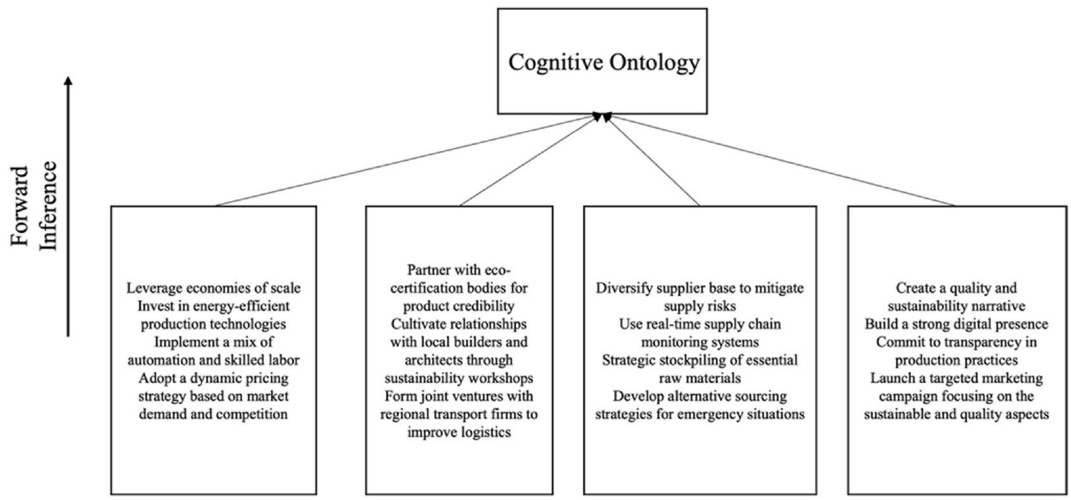

Fig. 9. Scenario 3-HI cognitive map.

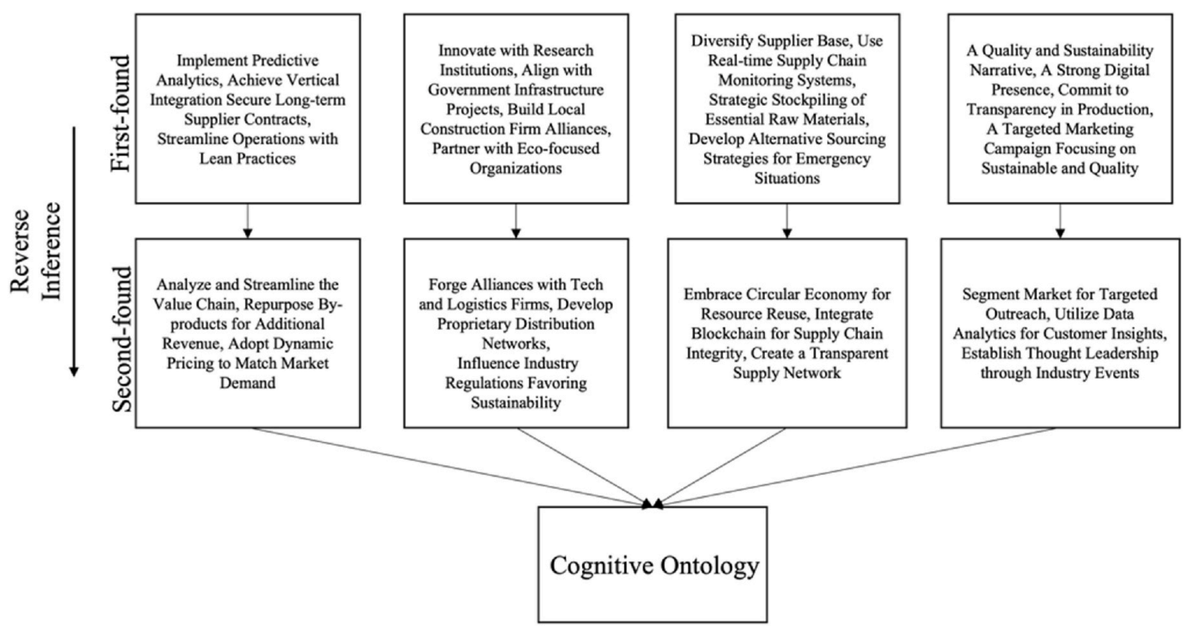

Fig. 10. Scenario 3-GAI cognitive map.

decision-making processes more understandable. XAI aims to make the operations of AI systems more transparent and the results easier to interpret, thereby increasing the trustworthiness and facilitating easier debugging and improvement of AI systems [123,124]. As shown in Table 7, businesses can effectively leverage the enhanced features of GAI, consistency, adaptability, and transparency, to foster innovation, optimize operations, and enhance customer engagement.

Specifically, the outcomes produced by ChatGPT, when mixed with expert analyses, revealed distinct variations indicative of the inherent differences in cognitive processing between GAI and human expertise. ChatGPT employs reverse inference, a hallmark of System 2 reasoning, characterized by a methodical dissection and subsequent reconstruction of present conditions to unearth foundational elements [125]. This process is inherently slower and more deliberate, requiring comprehensive examination by GAI to synthesize a holistic view. Experts have acknowledged the innovative and forward-thinking suggestions made by ChatGPT in scenarios. In digital marketing, A2 highlighted "AI's suggestions for digital marketing strategies in Ireland are exceptional, showing good points that we had not considered before." This demonstrates ChatGPT's ability to offer fresh and valuable insights. In logistics, B3 appreciated the GAI's alignment with contemporary practices: "The GAI's proposal for a hub and spoke system is in line with the latest logistics practices … using real-time data is revolutionary for our operations." Similarly, for supply chain resilience, B7 noted, "I'm particularly impressed with ChatGPT's recommendations … Integrating technology like blockchain for transparency is a forward-thinking approach." "The GAI's detailed analysis and utilization of user behavior analytics to enhance our Singles' Day event, alongside its approaches to managing customer interactions, are both targeted and innovative". "ChatGPT's recommendations for data-driven strategies to engage customers during Singles' Day are particularly noteworthy for their ingenuity." (C1, C2)

Despite these appreciates, criticisms highlight ChatGPT's limitations. Expert A1 expressed concerns about overlooked crucial cultural aspects: "The AI's suggestions seem to overlook the importance of face-to-face interactions in Ireland's business culture." This comment underscores a significant gap in ChatGPT's comprehension of local business dynamics. Additionally, some experts pointed out the impracticality of

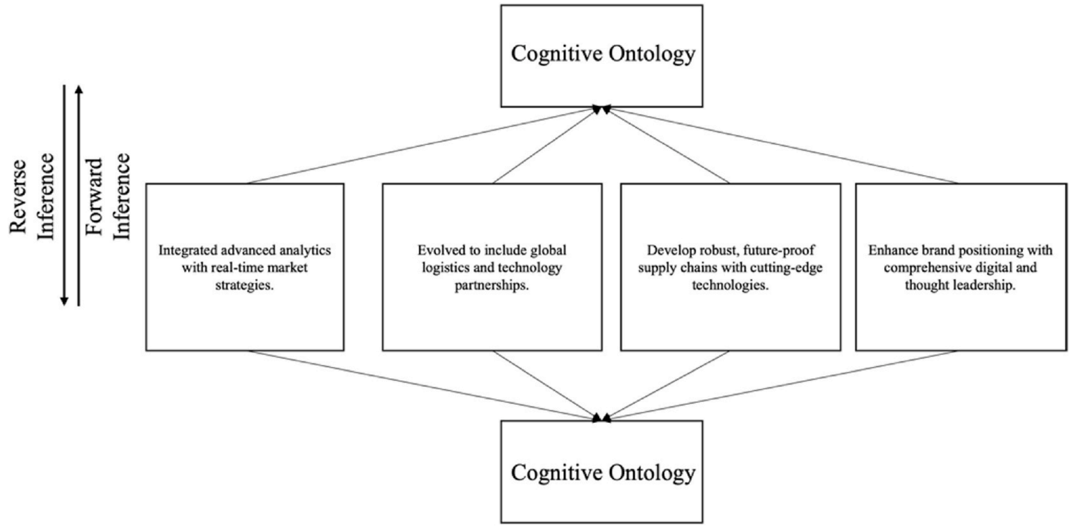

Fig. 11. Scenario 3-HI and GAI cognitive map.

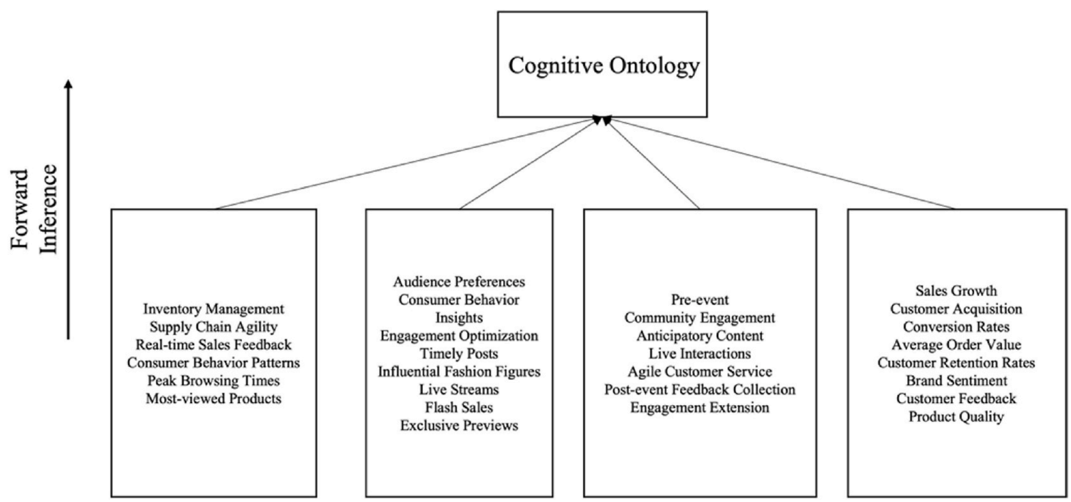

Fig. 12. Scenario 4-HI cognitive map.

certain suggestions. Expert B4 remarked on the logistical recommendations: "Yes, the pipeline transport and short-sea shipping are good options, but they may be very difficult to achieve due to real-world constraints." Experts B1 and B2 critiqued the practicality of AI-generated strategies, stating, "The GAI's suggestions tend toward the idealistic, particularly with the proposed integration of public-private partnerships, which could fundamentally alter the nature of the project." Expert B8 commented on market strategies: "While the AI's method in market segmentation is systematic, it overlooks the emotional and psychological drivers of consumer behavior. For our brand strategies to be effective, a deeper understanding of human touch and the importance of interpersonal relationships in B2B interactions is essential." Further emphasizing the limitations of GAI in qualitative assessment, experts C1 and C2 observed, "The reliance of GAI on performance metrics predominantly overlooks qualitative elements such as customer experience and brand loyalty, which are indispensable for sustained success in our industry. Both negative and positive qualitative feedback are crucial." A1, A2, C1, and C2 noted that the utilization of consumer data, while based on a beneficial concept, failed to consider necessary data protection regulations, which may result in practices that fall short of ethical standards. Despite undergoing a two-round training process, experts (B4, B8) have indicated that the outcomes of the second-round training substantially surpass contextual expectations. These statements reflect a consensus among experts that while GAI can provide extensive data-driven analysis, it may not fully grasp the contextual, human-centric elements that are vital in certain business sectors [24], particularly those involving human relationships and perceptual branding.

As evidence, across all scenarios, an increase in algorithmic bias was noted despite improvements in other areas. For example, in Scenario 1, algorithmic bias increased from 2.69 to 3.13 post-intervention, and in Scenario 4, it rose from 3.38 to 3.63. In each scenario, as the GAI system became more transparent and adaptable, it also started to exhibit more pronounced biases. This could be a result of the GAI system overfitting to specific patterns in the training data or prioritizing efficiency over fairness [126]. Algorithmic bias occurs when an AI system produces results that are systematically prejudiced due to erroneous assumptions in the ML process [127]. These biases can arise from various sources, including biased training data, flawed algorithms, or unintended consequences of the system's design and deployment. In the context of decision-making, algorithmic bias can lead to unfair or suboptimal outcomes, affecting the credibility and trustworthiness of GAI systems [128]. This could be due to the GAI system learning and reinforcing existing biases present in the data it was trained on or due to the system's algorithms prioritizing certain types of information over others. Such biases can be particularly problematic in scenarios requiring

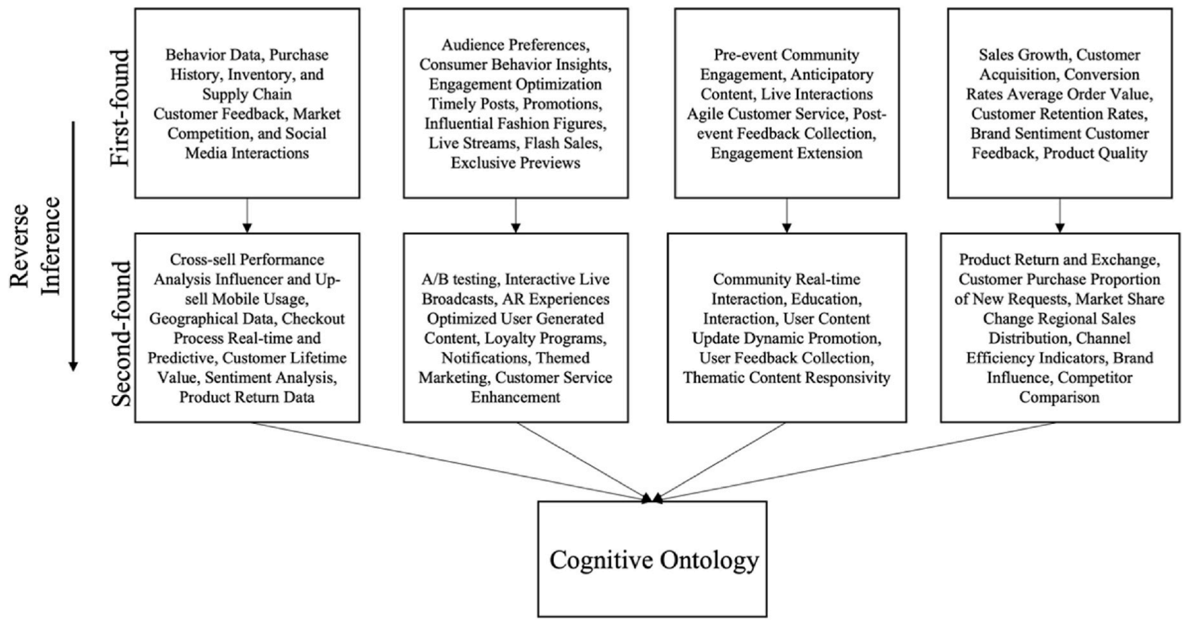

Fig. 13. Scenario 4-GAI cognitive map.

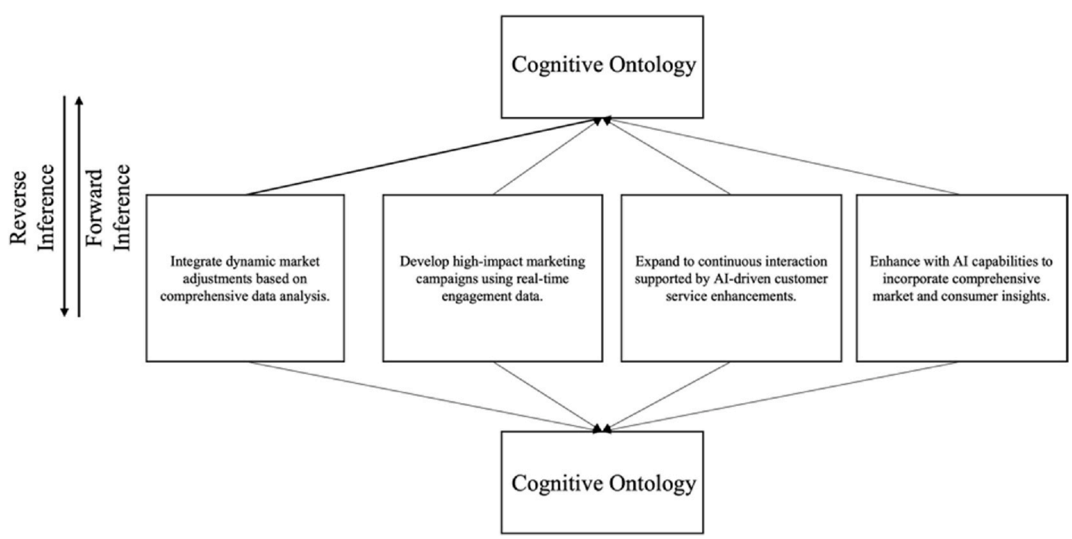

Fig. 14. Scenario 4-HI and GAI cognitive map.

contextual understanding, where a one-size-fits-all approach is inadequate. Therefore, this increase in bias underscores the need for continuous monitoring and adjustment of GAI systems to ensure they remain fair and unbiased. To facilitate the effective application of GAI in business environments, this research proposes the following five protocols for managing GAI bias (Table 8).

The collaboration between GAI and HI highlights a strong complementarity, as evidenced by high scores. This indicates that GAI's capabilities are well-suited to address human weaknesses, and vice versa. Synergy, another highly rated dimension, reflects the seamless integration of human and GAI contributions, suggesting that these entities do not merely coexist but actively collaborate to produce outcomes greater than the sum of their parts. This cooperation likely involves GAI offering real-time data processing and predictive analytics, while human counterparts provide contextual understanding and ethical judgments, thus optimizing decision processes. Efficiency scores highlight that this collaboration significantly reduces the time and resources typically required for complex decision-making. This efficiency is crucial in environments where rapid and accurate decisions are essential, suggesting that GAI not only matches but potentially accelerates human cognitive speed without sacrificing accuracy. However, the slightly lower scores in conflict resolution (Scenario 3 and 4), while still substantial, indicating the need for improved mechanisms to handle disagreements or interpretive discrepancies between human and machine insights [129].

The human capacity for forward inference utilizes accumulated experiences and knowledge to forecast future events, synonymous with System 1 intuition. This type of cognitive processing is swift, instinctive, and often operates below the conscious level [130]. Experts applied their market awareness across scenarios such as launch strategies, logistics, market entry, and digital marketing initiatives. There were discernible overlaps in the outcomes of expert reasoning and those derived from generative models with System 2 reasoning [131]. For instance, infrastructure, educational partnerships, and regulatory frameworks in the first scenario; the hub-and-spoke logistics model, electrification of transport mediums, and technological collaborations in

Table 6
Scenario 4-dimension evaluation.

	HI				GAI					HI and GAI			
	Pretest first-roundtable discussion				GAI intervention introduced					Posttest second-roundtable discussion			
	Intuitive Judgment	Cognitive Overload	Heuristics Bias	Experience-Based Decision-Making	Training	Consistency	Transparency	Adaptability	Algorithmic Bias	Complementarity	Conflict Resolution	Synergy	Efficiency
Q1	(2, 1)	(1, 1)	(2, 2)	(2, 4)	1st	(2, 1) 1.5	(3, 1) 2	(3, 1) 2	(2, 3) 2.5	(3, 3) 3	(2, 3) 2.5	(3, 4) 3.5	(2, 4) 3
	1.5	1	2	3	2nd	(3, 1) 2	(4, 1) 2.5	(5, 3) 4	(3, 3) 3				
Q2	(3, 1)	(2, 1)	(3, 1)	(4, 4)	1st	(4, 2) 3	(4, 4) 4	(4, 3) 3.5	(2, 5) 3.5	(3, 5) 4	(2, 4) 3	(3, 5) 4	(2, 5) 3.5
	2	1.5	2	4	2nd	(2, 2) 2	(3, 4) 3.5	(2, 3) 2.5	(4, 5) 4.5				
Q3	(4, 5)	(2, 1)	(3, 2)	(5, 5)	1st	(4, 3) 3.5	(4, 3) 3.5	(3, 3) 3	(2, 5) 3.5	(5, 5) 5	(4, 5) 4.5	(5, 5) 5	(4, 5) 4.5
	4.5	1.5	2.5	5	2nd	(4, 3) 3.5	(4, 3) 3.5	(3, 3) 3	(2, 5) 3.5				
Q4	(3, 1)	(3, 1)	(2, 2)	(5, 3)	1st	(3, 3) 3	(3, 2) 2.5	(3, 3) 3	(3, 5) 4	(5, 5) 5	(4, 5) 4.5	(5, 5) 5	(4, 5) 4.5
	2	2	2	4	2nd	(4, 3) 3.5	(4, 2) 3	(5, 3) 4	(2, 5) 3.5				
AVG.	2.5	1.5	2.13	4	1st	2.75	3	2.88	3.38	4.25	3.63	4.38	3.88
					2nd	2.75	3.13	3.38	3.63				

Table 7
Guidance of utilizing and improving the feature of GAI.

Consistency	
Utilizing Consistency	By incorporating GAI systems with improved stability, businesses can ensure that their core operations are consistently efficient, leading to smoother and more predictable outcomes.
Adaptability	
Exploiting Adaptability	The adaptability of GAI allows companies to stay responsive to emerging trends and changes in the market landscape. This feature enables businesses to quickly integrate new information and adjust their strategies, maintaining competitiveness and responsiveness without the need for extensive manual intervention.
Transparency	
Emphasizing Transparency	Implementing transparent GAI processes helps in making the decision-making framework of AI systems clear to all stakeholders. This transparency is crucial for aligning with ethical standards and fostering an environment of trust, especially in interactions with customers who seek clarity on how their data is being used and processed.

the second; dynamic pricing models and partnerships with local entities in the third; and strategies for sales growth and supply chain enhancements in the fourth.

It should be noted that, ChatGPT's limitations are notable in the realm of creative or "out-of-the-box" thinking, where human intuition and flexibility have a distinct advantage. Creativity often demands a sophisticated understanding of context and culture, elements that are inherently difficult for GAI to fully comprehend. Human experts excel at interpreting and responding to subtle cues, making innovative connections, and utilizing tacit knowledge gained through experience. These abilities are essential for crafting strategies that deeply resonate with consumers and stakeholders on a personal level. Moreover, creative thinking often involves the ability to perceive relationships between seemingly unrelated ideas and to generate novel solutions. This process involves systematic exploration and the ability to engage in "transformational creativity," where fundamental assumptions are redefined [132]. Human experts are skillful at this form of creativity, as they can draw from a broad spectrum of experiences and contextual knowledge, making intuitive leaps that are difficult for GAI to emulate. In practice, this means that while GAI can provide valuable data-driven foundations, human input is essential for refining these insights into strategies that are culturally, contextually and ethically appropriate [133]. The collaboration between GAI's analytical capabilities and human creativity can lead to more robust and innovative outcomes [134]. Therefore, businesses should leverage GAI for its strengths in data processing and pattern recognition, while relying on human experts for strategic and creative decision-making [135]. This synergy can ensure that GAI-enhanced decisions are efficient, informed, and more importantly, adaptable to complex real-world scenarios, with detailed strategies shown in Table 9.

6. Conclusions

In an era marked by rapid technological advancement, the collaborative dynamics between HI and GAI are reshaping decision-making processes. Through a quasi-experimental pretest-posttest design, this research compares the performance and cognitive strategies of participants before and after the introduction of GAI interventions by seeking to isolate and analyze the specific impacts of GAI on decision-making processes.

Research results highlight the synergistic potential of combining human with machine precision, System 1 with System 2 thinking to achieve superior outcomes in efficiency, creativity, and strategic execution. Particularly in scenarios of human unfamiliarity and information overload, GAI's contributions in providing data-driven support and predictive analytics are shown to significantly alleviate cognitive

Table 8
Guidance of GAI bias.

Monitor and evaluate outputs	
Regular Audits	Businesses should establish a systematic process for regularly reviewing the outputs generated by ChatGPT. This involves setting up periodic audits where the GAI's responses are analyzed for any signs of bias. These audits can be conducted weekly or monthly, depending on the volume and criticality of the GAI's usage. By maintaining ongoing oversight, businesses can promptly identify and address biased outputs before they impact decision-making processes.
Feedback mechanisms	
User Feedback	Creating robust feedback mechanisms is essential for capturing user experiences and identifying biased outputs. Businesses should provide users with easy-to-use channels to report any instances of bias or inappropriate responses from GAI. This feedback should be systematically reviewed and acted upon to refine the GAI's performance. Encouraging users to provide detailed feedback helps in understanding the context of biases, enabling more effective remediation.
Iterative Improvement	Feedback from users should be used to drive iterative improvements in the GAI system. By analyzing the reported issues, businesses can identify patterns of bias and implement changes to address them. This continuous improvement loop ensures that the GAI system evolves to become fairer and more accurate over time.
Transparent usage policies	
Documentation	Maintaining clear and comprehensive documentation on how GAI is used within the business is vital. This documentation should include guidelines on identifying and addressing biased outputs, the process for reporting issues, and the steps taken to mitigate bias. Transparency in usage policies helps build trust among users and stakeholders, ensuring that the GAI system is used responsibly.
Employee Training	Training employees on the responsible use of GAI is critical for minimizing bias. Businesses should conduct regular training sessions to educate employees about the potential biases in GAI outputs and how to report and address these issues. By fostering a culture of awareness and responsibility, businesses can ensure that all users are equipped to handle GAI outputs ethically.
Contextual awareness	
Input Sensitivity	Being mindful of the context and phrasing of inputs provided to GAI can significantly reduce the risk of biased outputs. Businesses should train users to craft inputs carefully, avoiding language that could elicit biased responses from the GAI. By ensuring that inputs are contextually appropriate, businesses can mitigate unintended bias.
Context Review	It is important to review GAI responses within the context they are used to ensure they are appropriate and unbiased. Businesses should establish protocols for context review, where outputs are assessed for their relevance and fairness in the given scenario. This helps prevent misinterpretations and ensures that the GAI system's responses align with business values.
Ethical usage practices	
Ethical Guidelines	Following ethical guidelines for GAI usage is fundamental to reducing algorithmic bias. Businesses should establish and adhere to a set of ethical principles that emphasize fairness, accountability, and transparency in GAI deployment. These guidelines should be integrated into the company's overall governance framework.
Ethics Committee	Businesses should establish an internal ethics committee to oversee the ethical use of GAI. This committee should include diverse stakeholders who can provide different perspectives on ethical issues. The committee's role is to ensure that all GAI-related practices align with the company's values and ethical standards, addressing any biases that may arise.

load and heuristic biases that typically challenge human decision-makers. Moreover, GAI, characterized by significant improvements in stability, adaptability, and transparency, underscores its growing capability to handle diverse and unpredictable data environments effectively. These enhancements ensure consistent performance under varying conditions and enable flexible responses to new information, essential in dynamic decision contexts. The integration of XAI principles further strengthens this dynamic, fostering a deeper trust and understanding of GAI processes among human users.

Table 9
Guidance of the HI and GAI collaboration.

Complementarity	
Task Allocation	Assign tasks optimally by utilizing GAI for generating content, ideas, or solutions that are data-driven, like drafting reports or generating code, while humans handle tasks requiring nuanced understanding, decision-making, and interpersonal interactions.
Tool Integration	Seamlessly integrate GAI tools into human workflows with interfaces that are intuitive and facilitate easy interaction, thus enabling effective collaboration without extensive technical training.
Conflict Resolution	
Define Roles Clearly	Clearly define the roles and responsibilities for both GAI systems and human workers to prevent overlap and reduce potential conflict. This clarity will aid in setting precise expectations and streamline the collaboration process.
Synergy	
Interactive Feedback Systems	Implement systems where GAI and humans can provide continuous feedback to each other. For example, GAI can suggest content strategies based on data trends, while humans can refine these suggestions with contextual knowledge or creative input to enhance relevance and engagement.
Cross-Functional Teams	Promote the development of teams that integrate both GAI tools and human experts. This fosters a collaborative environment where the strengths of each are utilized effectively, driving toward shared business goals.
Efficiency	
Streamlined Workflows	Leverage GAI to automate and accelerate the generation of digital content, analytical reports, or preliminary research, freeing up human collaborators to focus on strategy, creative processes, and complex problem-solving.
Continuous Training and Upskilling	Regularly train human staff to maximize their proficiency with GAI tools, understanding how to best utilize these systems within their roles. Update GAI systems continuously with new data and human feedback to maintain their relevance and effectiveness.
Performance Monitoring	Establish metrics to monitor the effectiveness of GAI in collaboration with human input, assessing improvements in productivity and quality of outcomes. Adjust strategies based on these insights to continuously enhance the collaborative process.

However, this collaboration reveals critical issues such as potential dependency on GAI which could lead to the waste of human decision-making skills and the continuation of biases inherent in the algorithms and data used by GAI systems. Such challenges require monitoring and frequent refinement of GAI systems to ensure decisions are fair and unbiased. Furthermore, the interface between human intuitive and GAI data-driven decision-making can sometimes result in conflicts or misalignments.

Addressing the above-mentioned challenges require a robust ethical framework that prioritizes transparency, accountability, and inclusivity (Table 7). These principles ensure that GAI systems operate robustly and efficiently and remain agile enough to adapt to new challenges and evolving market dynamics. To ensure these standards, it is important to implement comprehensive audits and develop responsive feedback mechanisms. Such measures facilitate the continuous monitoring and refinement of AI outputs, thereby preventing biases and ensuring that operations remain transparent to all stakeholders (Table 8). To conclude, the collaboration between HI and GAI must be strategically managed to combine their respective strengths. Strategic task allocation is essential, allowing GAI to handle data-driven processes while humans oversee tasks that require contextual judgment and interpersonal skills. Enhanced by interactive feedback systems and cross-functional teams, this approach can promote a productive dialogue between HI and GAI. Such collaboration strategies, as outlined in Table 9, can optimize decision-making outcomes, and ensure that the integration of HI and

GAI remains both innovative and responsible. This leads to a productive environment where both human and machine intelligence can collaborate productively and ethically.

For further research opportunities, this research proposes conducting real-life experiments that integrate cognitive neuroscience with GAI technology. These studies should focus on how GAI systems, enhanced with cognitive and neuroscience insights, can improve decision-making processes in various organizational settings. Future research could also focus on collecting input from a wider array of stakeholders, including those impacted by decisions implemented via GAI, to uncover supplementary dimensions of understanding. By examining the interactions between human cognitive functions and GAI capabilities, we can develop more intuitive and effective GAI tools that augment HI.

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CRediT authorship contribution statement

Xinyue Hao: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Emrah Demir:** Writing – review & editing, Supervision, Conceptualization. **Daniel Eyers:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

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Data availability

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Appendix 1

Scenario 1- Decision-driven market launch and growth

Cognitive Entity	Question	Initial Thoughts	Developed Thoughts	Generalized Insights
Human Intelligence Cognitive (HIC)	**Q1**	Focus on securing a premium office location and custom vehicle fleet.	Appointment of a local representative for cultural integration.	Transition from securing basic operational assets to enhancing strategic integration.
	Q2	Basic alliances with local food establishments and educational institutions.	Expanded alliances to include tech firms and government agencies.	Broadened scope from specific to diverse strategic partnerships.
	Q3	Use of social media trends and influencer networks.	Immersive community participation and localized content strategies.	Enhanced focus from influencer engagement to comprehensive community engagement.
	Q4	Addressing architectural idiosyncrasies and population density.	Included weather adaptability and cultural diversity in workforce planning.	From logistical challenges to long-term adaptive strategies in operations.
GAI Cognitive (GAI)	**Q1**	Analysis of distribution centers and logistics technologies.	Incorporation of advanced network technology in operations.	From basic infrastructure setup to integration of advanced technology solutions.
	Q2	Identification of diverse potential partners from various sectors.	Expansion to include organic stores and city council initiatives.	Widening of partnership scope to include broader community and governmental bodies.
	Q3	Initial focus on influencer networks and localized content.	Adoption of data-driven campaigns and diverse content strategies.	Shift from localized engagement to broad-based, data-driven marketing strategies.
	Q4	Recognizing urban layout complexity and regulatory constraints.	Acknowledgment of transport patterns and cultural diversity.	Deepened understanding of urban and regulatory complexities in operations.
Collaborative Cognitive (HIC + GAI)	**Q1**	Combination of asset securing and tech integration discussions.	Unified approach to cultural integration and advanced logistics.	Comprehensive operational strategy combining cultural and technological insights.
	Q2	Early focus on educational and local business partnerships.	Holistic strategy involving diverse and dynamic alliances.	Integration of educational, business, and technological partnerships for growth.
	Q3	Joint use of traditional and digital marketing methods.	Integrated community and digital engagement strategies.	Merging of human touch with AI-driven techniques in marketing for greater impact.
	Q4	Addressed immediate operational and architectural challenges.	Strategic planning for long-term adaptability and diversity.	Unified approach to tackling both immediate and strategic operational challenges.

Appendix 2

Scenario 2- Logistics optimization decision

Cognitive Entity	Question	Initial Thoughts	Developed Thoughts	Generalized Insights
Human Intelligence Cognitive (HIC)	**Q1**	Advocated for a "hub-and-spoke" system to reduce congestion and improve cost efficiency.	Emphasized GPS and real-time data analytics for optimal routing.	From basic congestion management to sophisticated data-driven routing solutions.
	Q2	Initial use of electric or hybrid trucks for short hauls to rail hubs.	Centralized logistics platform for synchronized transport transitions.	Shifted from single-mode improvements to integrated multimodal logistics solutions.
	Q3	Form strategic partnerships for real-time traffic updates.	Past successful partnerships highlighted for ongoing traffic management.	Focused on leveraging technology for efficient and continuous information flow.

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Cognitive Entity	Question	Initial Thoughts	Developed Thoughts	Generalized Insights
	Q4	Utilization of alternative transport methods like barges and short-sea shipping.	Experience-based contingency planning for unexpected road closures.	Enhanced adaptability through diversified and reliable transport alternatives.
GAI Cognitive (GAI)	**Q1**	Proposed a multifaceted approach including short-sea shipping and intermodal transportation.	Extended to pipeline conveyance and hub-and-spoke models.	Broadened from specific solutions to a comprehensive multimodal system.
	Q2	Recommendations for optimization software and scheduled rail transport.	Advanced to collaborative logistics frameworks and synchronized scheduling.	Developed from basic technology adoption to systemic enhancements in logistics.
	Q3	Collaboration with local government and technology companies.	Second phase included integration with smart city initiatives.	Expanded from basic partnerships to integrating with broad-based smart infrastructure.
	Q4	Development of alternate route planning and flexible transportation contracts.	Investment in redundant infrastructure and disaster recovery plans.	Moved from immediate contingency strategies to long-term resilience planning.
Collaborative Cognitive (HIC + GAI)	**Q1**	Combined focus on congestion management and cost efficiency.	Integrated advanced data analytics and broader transport strategies.	Comprehensive approach merging human experience with AI-driven logistical optimization.
	Q2	Early emphasis on electric mobility and transport synchronization.	Evolved to systemic logistical enhancements across multiple transport modes.	Transition from operational improvements to strategic multimodal logistics integration.
	Q3	Joint use of partnerships for traffic management.	Expanded to include smart city integrations and community involvement.	Leveraging both human and AI capabilities for a proactive and dynamic partnership strategy.
	Q4	Addressing immediate operational disruptions with alternate routes.	Strategic development of infrastructure for resilience and environmental sustainability.	Unified focus on long-term operational stability and environmental responsibility.

Appendix 3

Scenario 3- Targeted market penetration decision

Cognitive Entity	Question	Initial Thoughts	Developed Thoughts	Generalized Insights
Human Intelligence Cognitive (HIC)	**Q1**	Emphasize economies of scale and invest in energy-efficient technologies.	Dynamic pricing strategy responsive to market demands.	Shift from cost reduction tactics to dynamic market-driven profitability strategies.
	Q2	Partner with eco-certification bodies and local builders.	Form joint ventures with regional transport firms to streamline logistics.	Expanded from niche partnerships to broader logistics collaborations.
	Q3	Diversify supplier base to enhance supply chain resilience.	Integrate real-time monitoring systems to manage supply chain risks.	From basic risk management to advanced real-time supply chain oversight.
	Q4	Create a brand narrative focused on quality and sustainability.	Develop a marketing strategy that emphasizes environmental responsibility.	Broadened from product-focused branding to comprehensive sustainability leadership.
GAI Cognitive (GAI)	**Q1**	Implement predictive analytics and secure long-term supplier contracts.	Explore value chain optimization and dynamic pricing.	From operational efficiencies to sophisticated value chain and pricing strategies.
	Q2	Suggest partnerships with research institutions and government projects.	Broaden to include technology and logistics companies.	Shift from basic research collaborations to integrative technology partnerships.
	Q3	Use GPS in logistics and blockchain for transparency.	Advocate for circular economy and transparent supply networks.	Evolve from enhancing logistics to creating sustainable and transparent networks.
	Q4	Focus on digital storytelling and defining unique market position.	Introduce market segmentation and thought leadership strategies.	Expand from initial digital presence to comprehensive market and data-driven strategies.
Collaborative Cognitive (HIC + GAI)	**Q1**	Combined focus on cost-effective production and market adaptability.	Integrated advanced analytics with real-time market strategies.	Unified approach merging cost-efficiency with adaptive market strategies.
	Q2	Early emphasis on sustainable practices and local collaborations.	Evolved to include global logistics and technology partnerships.	Transition from local community focus to global, strategic logistical integrations.
	Q3	Address basic supply chain disruptions with diversified strategies.	Develop robust, future-proof supply chains with cutting-edge technologies.	Advanced from immediate solutions to long-term, resilient supply chain systems.
	Q4	Begin with a strong narrative on sustainability.	Enhance brand positioning with comprehensive digital and thought leadership.	Shifted from brand narrative creation to dynamic and interactive market engagement.

Appendix 4

Scenario 4- Strategic digital marketing decision

Cognitive Entity	Question	Initial Thoughts	Developed Thoughts	Generalized Insights
Human Intelligence Cognitive (HIC)	**Q1**	Collect data on consumer behavior patterns, like peak browsing times and most viewed products.	Focus on integrating supply chain agility to adapt to real-time sales feedback.	From basic data collection to dynamic supply chain responsiveness.

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Cognitive Entity	Question	Initial Thoughts	Developed Thoughts	Generalized Insights
	Q2	Create content calendar tailored to audience preferences.	Incorporate live streams, flash sales, and exclusive previews to maximize engagement.	Shifted from planned content publication to real-time, high-impact engagement activities.
	Q3	Engage community with anticipatory content before the event.	Continue engagement with live interactions and agile customer service during and after the event.	Evolved from initial engagement to maintaining momentum through continuous interaction.
	Q4	Establish sales-focused performance metrics like sales growth and customer acquisition rates.	Include qualitative indicators like brand sentiment and product quality feedback.	Broadened from quantitative sales metrics to comprehensive performance evaluation.
GAI Cognitive (GAI)	**Q1**	Analyze consumer behavior and inventory dynamics.	Use real-time analytics to refine marketing tactics.	From analyzing behavior to applying insights for strategic marketing adjustments.
	Q2	Initial focus on analyzing audience participation and feedback mechanisms.	Explore sophisticated analytical tools and trend prediction for marketing refinement.	Moved from feedback analysis to deploying advanced tools for strategic marketing foresight.
	Q3	Use feedback mechanisms to adapt marketing strategies.	Tailor recommendations and strategies through predictive modeling and user experience analysis.	Shifted from adaptive strategies to predictive, proactive market engagement.
	Q4	Project market trajectories and anticipate consumer demands.	Develop AI's adeptness in predictive modeling and market expansion strategies.	Advanced from anticipating market trends to actively shaping market strategies.
Collaborative Cognitive (HIC + GAI)	**Q1**	Combine data-driven insights from human and AI analyses.	Integrate dynamic market adjustments based on comprehensive data analysis.	Unified approach in utilizing real-time data for agile market responsiveness.
	Q2	Merge human content strategies with AI-driven analytical insights.	Develop high-impact marketing campaigns using real-time engagement data.	Integration of strategic content creation with AI-enhanced engagement analytics.
	Q3	Begin with community engagement strategies.	Expand to continuous interaction supported by AI-driven customer service enhancements.	Transition from engagement initiation to sustained interaction and support.
	Q4	Start with basic performance metrics.	Enhance with AI capabilities to incorporate comprehensive market and consumer insights.	From basic metric tracking to deep, insight-driven strategy optimization.

References

[1] OpenAI, ChatGPT. https://chat.openai.com/. (Accessed 10 May 2024), 2023.
[2] Y. Duan, J.S. Edwards, Y.K. Dwivedi, Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda, Int. J. Inf. Manag. 48 (2019) 63–71.
[3] Y.K. Dwivedi, N. Kshetri, L. Hughes, E.L. Slade, A. Jeyaraj, A.K. Kar, A. M. Baabdullah, A. Koohang, V. Raghavan, M. Ahuja, "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy, Int. J. Inf. Manag. 71 (2023) 102642.
[4] A, Wael AL-khatib, Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: a TOE framework, Technol. Soc. 75 (2023) 102403.
[5] V. Giordano, I. Spada, F. Chiarello, G. Fantoni, The impact of ChatGPT on human skills: a quantitative study on twitter data, Technol. Forecast. Soc. Change 203 (2024) 123389.
[6] E.U. Weber, E.J. Johnson, Mindful judgment and decision making, Annu. Rev. Psychol. 60 (2009) 53–85.
[7] E. Bolisani, C. Bratianu, Knowledge strategy planning: an integrated approach to manage uncertainty, turbulence, and dynamics, Journal of Knowledge Management 21 (2) (2017) 233–253.
[8] R.E. Beaty, M. Benedek, P.J. Silvia, D.L. Schacter, Creative cognition and brain network dynamics, Trends in cognitive sciences 20 (2) (2016) 87–95.
[9] S. Gunessee, N. Subramanian, Ambiguity and its coping mechanisms in supply chains lessons from the Covid-19 pandemic and natural disasters, Int. J. Oper. Prod. Manag. 40 (7/8) (2020) 1201–1223.
[10] A.K. Shah, D.M. Oppenheimer, Heuristics made easy: an effort-reduction framework, Psychological bulletin 134(2) (2008) 207.
[11] J.E. Korteling, A. Toet, Cognitive biases, Encyclopedia of behavioral neuroscience (2020) 610–619.
[12] R. Loconte, G. Orrù, M. Tribastone, P. Pietrini, G. Sartori, Challenging ChatGPT'Intelligence'with human tools: a neuropsychological investigation on prefrontal functioning of a large language model, Intelligence (2023) 1–33.
[13] T. Hagendorff, S. Fabi, M. Kosinski, Human-like intuitive behavior and reasoning biases emerged in large language models but disappeared in ChatGPT, Nature Computational Science (2023) 1–6.
[14] P. Gomes, Surgical robotics: reviewing the past, analysing the present, imagining the future, Robot. Comput. Integrated Manuf. 27 (2) (2011) 261–266.
[15] X. Hao, E. Demir, Artificial intelligence in supply chain management: enablers and constraints in pre-development, deployment, and post-development stages, Prod. Plann. Control (2024) 1–23.
[16] E. Demir, K. Huckle, A. Syntetos, A. Lahy, M. Wilson, Vehicle routing problem: past and future, Contemporary Operations and Logistics: Achieving Excellence in Turbulent Times (2019) 97–117.
[17] E. Demir, A. Syntetos, T. Van Woensel, Last mile logistics: research trends and needs, IMA J. Manag. Math. 33 (4) (2022) 549–561.
[18] L. Huang, M. Ladikas, J. Schippl, G. He, J. Hahn, Knowledge mapping of an artificial intelligence application scenario: a bibliometric analysis of the basic research of data-driven autonomous vehicles, Technol. Soc. 75 (2023) 102360.
[19] A. Samadhiya, S. Yadav, A. Kumar, A. Majumdar, S. Luthra, J.A. Garza-Reyes, A. Upadhyay, The influence of artificial intelligence techniques on disruption management: does supply chain dynamism matter? Technol. Soc. 75 (2023) 102394.
[20] J. Hangl, S. Krause, V.J. Behrens, Drivers, barriers and social considerations for AI adoption in SCM, Technol. Soc. 74 (2023) 102299.
[21] W. Wang, G. Gao, R. Agarwal, Friend or foe? teaming between artificial intelligence and workers with variation in experience, Manag. Sci. 0 (0) (2023).
[22] J. Korteling, G.C. van de Boer-Visschedijk, R.A. Blankendaal, R.C. Boonekamp, A. R. Eikelboom, Human-versus artificial intelligence, Frontiers in artificial intelligence 4 (2021) 622364.
[23] J. Kocoń, I. Cichecki, O. Kaszyca, M. Kochanek, D. Szydło, J. Baran, J. Bielaniewicz, M. Gruza, A. Janz, K. Kanclerz, ChatGPT: jack of all trades, master of none, Inf. Fusion 99 (2023) 101861.
[24] N.R. Sanders, The "inter-AI period:" how management mathematics can help shape an AI-enabled future, IMA J. Manag. Math. 35 (2) (2024) 151–162.
[25] N. Rane, ChatGPT, Similar Generative, Artificial Intelligence (AI) for Smart Industry: role, challenges and opportunities for industry 4.0, industry 5.0 and society 5.0, Challenges and Opportunities for Industry 4 (2023).
[26] S.A. Bin-Nashwan, M. Sadallah, M. Bouteraa, Use of ChatGPT in academia. Technology in Society vol. 75, Academic integrity hangs in the balance, 2023, p. 102370.
[27] H.S. Sætra, Generative AI: here to stay, but for good? Technol. Soc. 75 (2023) 102372.
[28] K. Wach, C.D. Duong, J. Ejdys, R. Kazlauskaitė, P. Korzynski, G. Mazurek, J. Paliszkiewicz, E. Ziemba, The dark side of generative artificial intelligence: a critical analysis of controversies and risks of ChatGPT, Entrepreneurial Business and Economics Review 11 (2) (2023) 7–30.
[29] A. Tversky, D. Kahneman, Judgment under Uncertainty: heuristics and Biases: biases in judgments reveal some heuristics of thinking under uncertainty, Sci. Technol. Humanit. 185 (4157) (1974) 1124–1131.
[30] G. Gigerenzer, W. Gaissmaier, Heuristic decision making, Annu. Rev. Psychol. 62 (2011) 451–482.
[31] A. Krawinkler, R.J. Breitenecker, D. Maresch, Heuristic decision-making in the green energy context: bringing together simple rules and data-driven mathematical optimization, Technol. Forecast. Soc. Change 180 (2022) 121695.
[32] S. Villa, J.A. Castañeda, Transshipments in supply chains: a behavioral investigation, Eur. J. Oper. Res. 269 (2) (2018) 715–729.
[33] J. Doyle, U. Ojiako, A. Marshall, I. Dawson, M. Brito, The anchoring heuristic and overconfidence bias among frontline employees in supply chain organizations, Prod. Plann. Control 32 (7) (2021) 549–566.
[34] H. Krijestorac, R. Garg, P. Konana, Decisions under the illusion of objectivity: digital embeddedness and B2B purchasing, Prod. Oper. Manag. 30 (7) (2021) 2232–2251.

[35] T.R. de Wilde, F.S. Ten Velden, C.K. De Dreu, The anchoring-bias in groups, J. Exp. Soc. Psychol. 76 (2018) 116–126.
[36] M.E. Murphy, The nominating process for corporate boards of directors: a decision-making analysis, Berkeley Bus. LJ 5 (2008) 131.
[37] L. Kaufmann, C.R. Carter, C. Buhrmann, Debiasing the supplier selection decision: a taxonomy and conceptualization, Int. J. Phys. Distrib. Logist. Manag. 40 (10) (2010) 792–821.
[38] S. Bhandari, M.R. Hallowell, Identifying and controlling biases in expert-opinion research: guidelines for variations of Delphi, nominal group technique, and focus groups, J. Manag. Eng. 37 (3) (2021) 4021015.
[39] S.G. Sutton, V. Arnold, Focus group methods: using interactive and nominal groups to explore emerging technology-driven phenomena in accounting and information systems, Int. J. Account. Inf. Syst. 14 (2) (2013) 81–88.
[40] J.L. Cybulski, R. Scheepers, Data science in organizations: conceptualizing its breakthroughs and blind spots, J. Inf. Technol. 36 (2) (2021) 154–175.
[41] P.L. Curşeu, R.J. Jansen, M.M. Chappin, Decision rules and group rationality: cognitive gain or standstill? PLoS One 8 (2) (2013) e56454.
[42] M. Ahmad, S.Z.A. Shah, Y. Abbass, The role of heuristic-driven biases in entrepreneurial strategic decision-making: evidence from an emerging economy, Management Decision 59(3) (2021) 669–691.
[43] L. Meub, T. Proeger, Are groups 'less behavioral'? The case of anchoring, Theor. Decis. 85 (2018) 117–150.
[44] J. Manyika, J. Silberg, B. Presten, What do we do about the biases in Al, Harv. Bus. Rev. (2019) 1–9.
[45] F. Cabitza, Biases affecting human decision making in AI-supported second opinion settings, Modeling Decisions for Artificial Intelligence, in: 16th International Conference, MDAI 2019, Milan, Italy, September 4–6, 2019, Proceedings 16, Springer, 2019, pp. 283–294.
[46] C. Werner, A.M. Hanea, O. Morales-Nápoles, Eliciting multivariate uncertainty from experts: considerations and approaches along the expert judgement process, Elicitation: The science and art of structuring judgement (2018) 171–210.
[47] H.A. Owolabi, M. Bilal, L.O. Oyedele, H.A. Alaka, S.O. Ajayi, O.O. Akinade, Predicting completion risk in PPP projects using big data analytics, IEEE Trans. Eng. Manag. 67 (2) (2018) 430–453.
[48] J.-P. Li, N. Mirza, B. Rahat, D. Xiong, Machine learning and credit ratings prediction in the age of fourth industrial revolution, Technol. Forecast. Soc. Change 161 (2020) 120309.
[49] I.H. Sarker, Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective, SN Computer Science 2(5) (2021) 377.
[50] M.D. Rosenberg, B. Casey, A.J. Holmes, Prediction complements explanation in understanding the developing brain, Nature communications 9(1) (2018) 589.
[51] A.M. Ikotun, A.E. Ezugwu, L. Abualigah, B. Abuhaija, J. Heming, K-means clustering algorithms: a comprehensive review, variants analysis, and advances in the era of big data, Inf. Sci. 622 (2023) 178–210.
[52] K. Golalipour, E. Akbari, S.S. Hamidi, M. Lee, R. Enayatifar, From clustering to clustering ensemble selection: a review, Eng. Appl. Artif. Intell. 104 (2021) 104388.
[53] X. Xia, X. Pan, N. Li, X. He, L. Ma, X. Zhang, N. Ding, GAN-based anomaly detection: a review, Neurocomputing 493 (2022) 497–535.
[54] H. Hassani, E.S. Silva, The role of ChatGPT in data science: how ai-assisted conversational interfaces are revolutionizing the field, Big data and cognitive computing 7 (2) (2023) 62.
[55] F.-Y. Wang, J. Yang, X. Wang, J. Li, Q.-L. Han, Chat with chatgpt on industry 5.0: learning and decision-making for intelligent industries, IEEE/CAA Journal of Automatica Sinica 10 (4) (2023) 831–834.
[56] E. Ntoutsi, P. Fafalios, U. Gadiraju, V. Iosifidis, W. Nejdl, M.E. Vidal, S. Ruggieri, F. Turini, S. Papadopoulos, E. Krasanakis, Bias in data-driven artificial intelligence systems—an introductory survey, Wiley Interdisciplinary Reviews: Data Min. Knowl. Discov. 10 (3) (2020) e1356.
[57] N. Kordzadeh, M. Ghasemaghaei, Algorithmic bias: review, synthesis, and future research directions, Eur. J. Inf. Syst. 31 (3) (2022) 388–409.
[58] P.P. Ray, ChatGPT: a comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope, Internet Things Cyber-Phys. Syst. 3 (2023) 121–154.
[59] I. Poola, Overcoming ChatGPTs Inaccuracies with Pre-trained AI Prompt Engineering Sequencing Process, 2023.
[60] J. Zhang, J. Pu, J. Xue, M. Yang, X. Xu, X. Wang, F.-Y. Wang, HiVeGPT: human-machine-augmented intelligent vehicles with generative pre-trained transformer, IEEE Trans. Intell. Veh. 8 (3) (2023) 2027–2033.
[61] S. Tizpaz-Niari, A. Kumar, G. Tan, A. Trivedi, Fairness-aware configuration of machine learning libraries, in: Proceedings of the 44th International Conference on Software Engineering, 2022, pp. 909–920.
[62] A.B. Arrieta, N. Díaz-Rodríguez, J. Del Ser, A. Bennetot, S. Tabik, A. Barbado, S. García, S. Gil-López, D. Molina, R. Benjamins, Explainable Artificial Intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI, Inf. Fusion 58 (2020) 82–115.
[63] J. Ostheimer, S. Chowdhury, S. Iqbal, An alliance of humans and machines for machine learning: hybrid intelligent systems and their design principles, Technol. Soc. 66 (2021) 101647.
[64] V. Choudhary, A. Marchetti, Y.R. Shrestha, P. Puranam, Human-AI ensembles: when can they work? J. Manag. 0 (2023) 1–34.
[65] K. Daniel, Thinking, Fast and Slow, 2017.
[66] D. Arnott, S. Gao, Behavioral economics for decision support systems researchers, Decis. Support Syst. 122 (2019) 113063.
[67] K.L. Milkman, D. Chugh, M.H. Bazerman, How can decision making be improved? Perspect. Psychol. Sci. 4 (4) (2009) 379–383.
[68] A. Diederich, J.S. Trueblood, A dynamic dual process model of risky decision making, Psychological review 125(2) (2018) 270.
[69] B. Bago, D. Frey, J. Vidal, O. Houdé, G. Borst, W. De Neys, Fast and slow thinking: electrophysiological evidence for early conflict sensitivity, Neuropsychologia 117 (2018) 483–490.
[70] F. Fui-Hoon Nah, R. Zheng, J. Cai, K. Siau, L. Chen, Generative AI and ChatGPT: Applications, Challenges, and AI-Human Collaboration, Taylor & Francis, 2023, pp. 277–304.
[71] R. Schwartz, A. Vassilev, K. Greene, L. Perine, A. Burt, P. Hall. Towards a standard for identifying and managing bias in artificial intelligence, NIST special publication 1270(10.6028), 2022, pp. 1–86.
[72] S. Akter, G. McCarthy, S. Sajib, K. Michael, Y.K. Dwivedi, J. D'Ambra, K.N. Shen, Algorithmic Bias in Data-Driven Innovation in the Age of AI, Elsevier, 2021, p. 102387, p.
[73] S. Chandra, A. Shirish, S.C. Srivastava, To be or not to be human? Theorizing the role of human-like competencies in conversational artificial intelligence agents, J. Manag. Inf. Syst. 39 (4) (2022) 969–1005.
[74] N. Shapira, M. Levy, S.H. Alavi, X. Zhou, Y. Choi, Y. Goldberg, M. Sap, V. Shwartz. Clever hans or neural theory of mind? stress testing social reasoning in large language models, arXiv preprint arXiv:2305.14763, 2023, pp. 1–16.
[75] J. Rudolph, S. Tan, S. Tan, War of the chatbots: bard, Bing Chat, ChatGPT, Ernie and beyond. The new AI gold rush and its impact on higher education, Journal of Applied Learning and Teaching 6 (1) (2023).
[76] T. Grønsund, M. Aanestad, Augmenting the algorithm: emerging human-in-the-loop work configurations, J. Strat. Inf. Syst. 29 (2) (2020) 101614.
[77] Y. Qin, S. Hu, Y. Lin, W. Chen, N. Ding, G. Cui, Z. Zeng, Y. Huang, C. Xiao, C. Han. Tool learning with foundation models, arXiv preprint arXiv:2304.08354, 2023, pp. 5868–5869.
[78] Y. Chen, M. Andiappan, T. Jenkin, A. Ovchinnikov, A manager and an AI walk into a bar: does ChatGPT make biased decisions like we do? Available at SSRN 4380365 (2023).
[79] M. Coeckelbergh, H.S. Sætra, Climate change and the political pathways of AI: the technocracy-democracy dilemma in light of artificial intelligence and human agency, Technol. Soc. 75 (2023) 102406.
[80] G. Kasparov, Deep Thinking: where Machine Intelligence Ends and Human Creativity Begins, Hachette UK, 2017.
[81] Y. Shen, K. Song, X. Tan, D. Li, W. Lu, Y. Zhuang, Hugginggpt: solving ai tasks with chatgpt and its friends in hugging face, Adv. Neural Inf. Process. Syst. 36 (2024).
[82] A. Schmidt, P. Elagroudy, F. Draxler, F. Kreuter, R. Welsch, Simulating the human in HCD with ChatGPT: redesigning interaction design with AI, Interactions 31(1) (2024) 24–31.
[83] T. Labruna, S. Brenna, A. Zaninello, B. Magnini, Unraveling chatgpt: a critical analysis of ai-generated goal-oriented dialogues and annotations, in: International Conference of the Italian Association for Artificial Intelligence, Springer, 2023, pp. 151–171.
[84] R.J. Scott, R.Y. Cavana, D. Cameron, Recent evidence on the effectiveness of group model building, Eur. J. Oper. Res. 249 (3) (2016) 908–918.
[85] P. Meissner, T. Wulf, Cognitive benefits of scenario planning: its impact on biases and decision quality, Technol. Forecast. Soc. Change 80 (4) (2013) 801–814.
[86] W.M. Trochim, The regression-discontinuity design, Research methodology: Strengthening causal interpretations of nonexperimental data (1990) 119–139.
[87] Y. Jing, H. Wang, X. Chen, C. Wang, What factors will affect the effectiveness of using ChatGPT to solve programming problems? A quasi-experimental study, Humanities and Social Sciences Communications 11 (1) (2024) 1–12.
[88] H.B. Essel, D. Vlachopoulos, A.B. Essuman, J.O. Amankwa, ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs), Computers and Education: Artificial Intelligence 6 (2024) 100198.
[89] D. Eden, Field experiments in organizations, Annual Review of Organizational Psychology and Organizational Behavior 4 (2017) 91–122.
[90] J. Rogers, A. Revesz, Experimental and Quasi-Experimental Designs, the Routledge Handbook of Research Methods in Applied Linguistics, Routledge, 2019, pp. 133–143, pp.
[91] D.T. Campbell, J.C. Stanley, Experimental and Quasi-Experimental Designs for Research, Ravenio Books, 2015.
[92] H. Plessner, C. Betsch, T. Betsch, Intuition in Judgment and Decision Making, Psychology Press, 2011.
[93] J.S.B. Evans, Intuition and reasoning: a dual-process perspective, Psychological Inquiry 21(4) (2010) 313–326.
[94] A.W. Kruglanski, G. Gigerenzer, Intuitive and Deliberate Judgments Are Based on Common Principles, the Motivated Mind, Routledge, 2018, pp. 104–128, pp.
[95] C. Speier, J.S. Valacich, I. Vessey, The influence of task interruption on individual decision making: an information overload perspective, Decision sciences 30(2) (1999) 337–360.
[96] T.W. Jackson, P. Farzaneh, Theory-based model of factors affecting information overload, Int. J. Inf. Manag. 32 (6) (2012) 523–532.
[97] G. Abatecola, A. Caputo, M. Cristofaro, Reviewing cognitive distortions in managerial decision making: toward an integrative co-evolutionary framework, J. Manag. Dev. 37 (5) (2018) 409–424.
[98] L. Kaufmann, G. Meschnig, F. Reimann, Rational and intuitive decision-making in sourcing teams: effects on decision outcomes, J. Purch. Supply Manag. 20 (2) (2014) 104–112.

[99] F. Di Martino, F. Delmastro, Explainable AI for clinical and remote health applications: a survey on tabular and time series data, Artif. Intell. Rev. 56 (6) (2023) 5261–5315.

[100] A. Lombardi, D. Diacono, N. Amoroso, P. Biecek, A. Monaco, L. Bellantuono, E. Pantaleo, G. Logroscino, R. De Blasi, S. Tangaro, A robust framework to investigate the reliability and stability of explainable artificial intelligence markers of Mild Cognitive Impairment and Alzheimer's Disease, Brain informatics 9(1) (2022) 1–17.

[101] J. Zerilli, A. Knott, J. Maclaurin, C. Gavaghan, Transparency in algorithmic and human decision-making: is there a double standard? Philosophy & Technology 32 (2019) 661–683.

[102] H. Felzmann, E.F. Villaronga, C. Lutz, A. Tamò-Larrieux, Transparency you can trust: transparency requirements for artificial intelligence between legal norms and contextual concerns, Big Data & Society 6 (1) (2019), 2053951719860542.

[103] G.D. Bhatt, J. Zaveri, The enabling role of decision support systems in organizational learning, Decision Support Systems 32(3) (2002) 297–309.

[104] A. Glöckner, T. Betsch, Modeling option and strategy choices with connectionist networks: towards an integrative model of automatic and deliberate decision making, Judgment and Decision making 3 (3) (2008) 215–228.

[105] I. Žliobaitė, Measuring discrimination in algorithmic decision making, Data Min. Knowl. Discov. 31 (4) (2017) 1060–1089.

[106] D. Danks, A.J. London, Algorithmic bias in autonomous systems, Ijcai (2017) 4691–4697.

[107] S. Raisch, S. Krakowski, Artificial intelligence and management: the automation–augmentation paradox, Acad. Manag. Rev. 46 (1) (2021) 192–210.

[108] N.-n Zheng, Z.-y Liu, P.-j Ren, Y.-q Ma, S.-t Chen, S.-y Yu, J.-r Xue, B.-d Chen, F.-y Wang, Hybrid-augmented intelligence: collaboration and cognition, Frontiers of Information Technology & Electronic Engineering 18 (2) (2017) 153–179.

[109] M. Klein, S.C.-Y. Lu, Conflict resolution in cooperative design, Artif. Intell. Eng. 4 (4) (1989) 168–180.

[110] T. Sourdin, The, Judge V Robot?: Artificial Intelligence and Judicial Decision-Making, vol. 41, University of New South Wales Law Journal, 2018, pp. 1114–1133, 4.

[111] M.H. Jarrahi, Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making, Business horizons 61(4) (2018) 577–586.

[112] T. Haesevoets, D. De Cremer, K. Dierckx, A. Van Hiel, Human-machine collaboration in managerial decision making, Comput. Hum. Behav. 119 (2021) 106730.

[113] Y. Peng, Y. Bao, Y. Chen, C. Wu, C. Guo, Optimus: an efficient dynamic resource scheduler for deep learning clusters, in: Proceedings of the Thirteenth EuroSys Conference, 2018, pp. 1–14.

[114] Y.R. Shrestha, S.M. Ben-Menahem, G. Von Krogh, Organizational decision-making structures in the age of artificial intelligence, Calif. Manag. Rev. 61 (4) (2019) 66–83.

[115] C. Eden, Strategic Options Development and Analysis (SODA), 1995.

[116] A. Azar, K.M. Dolatabad, A method for modelling operational risk with fuzzy cognitive maps and Bayesian belief networks, Expert Syst. Appl. 115 (2019) 607–617.

[117] A.M. Sharif, Z. Irani, Exploring fuzzy cognitive mapping for IS evaluation, Eur. J. Oper. Res. 173 (3) (2006) 1175–1187.

[118] A. Samsonovich, B.L. McNaughton, Path integration and cognitive mapping in a continuous attractor neural network model, Journal of Neuroscience 17(15) (1997) 5900–5920.

[119] S.S. Kamble, A. Gunasekaran, A. Ghadge, R. Raut, A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs-A review and empirical investigation, Int. J. Prod. Econ. 229 (2020) 107853.

[120] W.J. Phillips, J.M. Fletcher, A.D. Marks, D.W. Hine, Thinking styles and decision making: A meta-analysis, Psychological Bulletin 142(3) (2016) 260.

[121] D.V. Carvalho, E.M. Pereira, J.S. Cardoso, Machine learning interpretability: a survey on methods and metrics, Electronics 8(8) (2019) 832.

[122] A.M. Roy, Adaptive transfer learning-based multiscale feature fused deep convolutional neural network for EEG MI multiclassification in brain–computer interface, Eng. Appl. Artif. Intell. 116 (2022) 105347.

[123] A. Adadi, M. Berrada, Peeking inside the black-box: a survey on explainable artificial intelligence (XAI), IEEE Access 6 (2018) 52138–52160.

[124] A. Berman, K. de Fine Licht, V. Carlsson, Trustworthy AI in the public sector: an empirical analysis of a Swedish labor market decision-support system, Technol. Soc. 76 (2024) 102471.

[125] T. Hagendorff, S. Fabi, M. Kosinski, Human-like intuitive behavior and reasoning biases emerged in large language models but disappeared in ChatGPT, Nature Computational Science 3 (10) (2023) 833–838.

[126] H. Du, R. Zhang, Y. Liu, J. Wang, Y. Lin, Z. Li, D. Niyato, J. Kang, Z. Xiong, S. Cui. Beyond deep reinforcement learning: a tutorial on generative diffusion models in network optimization, arXiv preprint arXiv:2308.05384, 2023, pp. 1–34.

[127] O.A. Osoba, W. Welser IV, W. Welser, An Intelligence in Our Image: the Risks of Bias and Errors in Artificial Intelligence, Rand Corporation, 2017.

[128] T. Dogru, N. Line, M. Mody, L. Hanks, J.A. Abbott, F. Acikgoz, A. Assaf, S. Bakir, A. Berbekova, A. Bilgihan, Generative artificial intelligence in the hospitality and tourism industry: developing a framework for future research, J. Hospit. Tourism Res. 0 (2023) 1–19.

[129] Y. Kim, J. Lee, S. Kim, J. Park, J. Kim, Understanding users' dissatisfaction with chatgpt responses: types, resolving tactics, and the effect of knowledge level, in: Proceedings of the 29th International Conference on Intelligent User Interfaces, 2024, pp. 385–404.

[130] N. Khatri, H.A. Ng, The role of intuition in strategic decision making, Human relations 53(1) (2000) 57–86.

[131] B.Y. Lin, Y. Fu, K. Yang, F. Brahman, S. Huang, C. Bhagavatula, P. Ammanabrolu, Y. Choi, X. Ren, Swiftsage: a generative agent with fast and slow thinking for complex interactive tasks, Adv. Neural Inf. Process. Syst. 36 (2024).

[132] J. Kim, M.L. Maher, The effect of AI-based inspiration on human design ideation, International Journal of Design Creativity and Innovation 11 (2) (2023) 81–98.

[133] H.O. Khogali, S. Mekid, The blended future of automation and AI: examining some long-term societal and ethical impact features, Technol. Soc. 73 (2023) 102232.

[134] S. Chowdhury, P. Budhwar, G. Wood, Generative artificial intelligence in business: towards a strategic human resource management framework, Br. J. Manag. 0 (2024) 1–12.

[135] X. Hao, E. Demir, Artificial intelligence in supply chain decision-making: an environmental, social, and governance triggering and technological inhibiting protocol, J. Model. Manag. 19 (2) (2023) 605–629.