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Human-AI cooperation: Modes and their effects on attitudes

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A B S T R A C T

Since advancements in artificial intelligence (AI) have allowed AI to live and work with humans as independent agents, it has become increasingly common for people to cooperate with autonomous AI agents, which is known as human-AI cooperation (HAIC). The purpose of this research is to explore the various modes of HAIC and their effects on people's attitudes. The current paper presents a between-group study conducted by dividing samples into two groups, i.e., a human–human cooperation group and a HAIC group. A total of 1367 samples are investigated. By employing confirmatory factor analysis, we identify-four modes of HAIC: interdependent exploitation, independent exploitation, interdependent exploration, and independent exploration. By conducting a multigroup comparative analysis, we find that people prefer interdependent exploration modes and dislike independent exploitation and independent exploration modes when cooperating with AI. Our study provides insights into the modes of HAIC and the effects of these modes on people's attitudes.

1. Introduction

Given the continuing improvement of artificial intelligence (AI) technology, AI that can act independently of people is gradually emerging. For example, the AI used in many games can function autonomously without relying on humans. In games such as Warcraft 2 and DOTA 2, the ability of AI has even surpassed that of humans (Vinyals et al., 2019; Ecoffet et al., 2021). In addition to games, AI with autonomous capabilities has also emerged in the medical, financial, legal, and military fields (Rahwan et al., 2019). When autonomous AI emerges in large numbers, a primary problem that humans face in this context pertains to ways of cooperating with autonomous AI, a task which is called human-AI cooperation (HAIC) (O'Neill et al., 2020). HAIC does not lie in the far future; for example, in the gaming world, the phenomenon of human players teaming up with AI is already very common (Rosenfeld et al., 2017; Walliser et al., 2019). Inevitably, various modes of cooperation between humans and AI emerge, and previous research has not yet explored these modes of cooperation or determined whether these modes have different effects on human attitudes. Answering these two questions can allow us to understand the modes of HAIC that humans are more willing to accept, which can help us investigate HAIC in further depth.

Previous studies have reported inconsistent perceptions of HAIC. Negative attitudes toward HAIC exist among some people who believe that AI lacks creativity (Luo et al., 2019) and who therefore refuse to work with autonomous AI (Ishowo-Oloko et al., 2019; Musick et al., 2021). However, other people believe that AI is able to process data efficiently and that HAIC can reduce the cognitive load on humans who are members of a work team. Therefore, HAIC can improve performance, and so the attitudes of these people toward AI collaborators are positive (Hillesheim & Rusnock, 2016). We believe that the different attitudes toward HAIC can be

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interpreted from the different modes of HAIC. If AI is allowed to explore unknown areas of cooperation, it is likely to fail to meet people's expectations; however, if AI is allowed to undertake analytical computational tasks in cooperation with humans, its performance is likely to be enhanced substantially (Fan et al., 2010). Therefore, the modes of HAIC that can enhance people's attitudes toward cooperation must be explored in further detail, as these modes have not been studied thoroughly.

The main purposes of this paper are to classify HAIC modes and to study people's attitudes toward various HAIC modes. The goal of this study is to focus on the gaps in previous research. First, in the future, there will be many modes of HAIC just as there are many modes of human–human cooperation, so classifying the modes of HAIC can help us improve our understanding of how humans cooperate with AI. However, previous studies have only proposed the concept of HAIC (O'Neill et al., 2020), and less attention has been given to the modes of HAIC. Second, previous studies have not explored the differences in preferences and attitudes across different modes of HAIC. This question pertains to the types of cooperation with AI in which people prefer to engage.

Based on cooperation theory (Stern & Reve, 1980; Chen et al., 1998), we examine the behavioral orientation of cooperation—dependence versus independence (Millot & Debernard, 2007; Makarius et al., 2020)—and the goal orientation of cooperation—exploitation versus exploration (March 1991; Camisón et al., 2018)—and derive four HAIC modes from these two dimensions of cooperation: interdependent exploitation, independent exploitation, interdependent exploration and independent exploration. Interdependent exploitation occurs when humans and AI rely on one another to optimize the existing resources via cooperation; independent exploitation occurs when humans and AI act independently and use existing resources effectively via cooperation; interdependent exploration occurs when humans and AI rely on one another and collaborate to explore external resources via cooperation; and independent exploration occurs when humans and AI divide the work and explore external resources individually via cooperation. In the following, we further verify these four HAIC modes and investigate whether people exhibit different attitudes toward the four HAIC modes compared to their attitudes toward human–human cooperation, thus allowing us to analyze the modes of cooperation with AI that people prefer.

This paper is structured as follows: first, we explain the basic concept of HAIC and supply relevant definitions. Subsequently, we describe the theory of cooperation and propose HAIC modes based on this theory. Then, we design and administer the questionnaire based on the hypothesis and use structural equation modeling (SEM) to study the HAIC modes. Confirmatory factor analysis is conducted to justify the four modes of HAIC cooperation, and the impact of various HAIC modes is explored in further detail via a multigroup SEM comparison between "human-AI cooperation" and "human-human cooperation". Finally, conclusions and future research perspectives are discussed.

2. Literature review

2.1. Concept of HAIC

HAIC refers to the process by which humans and autonomous AI cooperate to accomplish tasks to achieve a common goal (O'Neill et al., 2020). When O'Neill et al. (2020) proposed this concept, the main context was the fact that digital technologies are subjective and that autonomous AI teammates can perform more dynamic task functions than ever before. AI has long been viewed as a tool to assist human decision-making, but technological advances have allowed AI to act autonomously (Rahwan et al., 2019), such that AI can participate in teamwork activities with human beings. The concept of HAIC was implicit during early studies of automation. Woods (1996) argued that automated systems can be introduced into human teams when those systems are considered to be independent agents. Rich and Sidner (1997) showed that highly automated systems can participate in human teamwork but that such systems must adhere to the principles of human–human cooperation. Two conditions must be met to achieve HAIC. First, the AI involved in HAIC must be an autonomous entity that can perceive and act on its surroundings, which allows it to perform tasks that could previously be performed only by humans (Wynne & Lyons, 2018; Köbis et al., 2021). Second, in the case of HAIC, AI should play a unique role on the team rather than merely serving as a tool (Lyons et al., 2018).

HAIC has gradually become a hot topic in recent years, largely due to advances in AI that have allowed HAIC to advance from pure concept to reality (O'Neill et al., 2020), and given the fact that AI's emotional, behavioral, and cognitive abilities have become closer to those of humans, AI can truly be treated as a teammate (Lyons et al., 2018; McNeese & McNeese, 2020).

2.2. HAIC mode based on cooperation theory

Although previous studies have provided definitions of HAIC, we do not yet understand the modes in which human and AI can cooperate, so we must first delineate the various modes of HAIC based on cooperation theory. The theory of cooperation originated in the previous century (Deutsch, 1949) and has since been developed and refined (Henrich & Muthukrishna, 2021). This theory considers cooperation to be a joint activity between partners to achieve mutually compatible goals (Tjosvold, 1988), in which context the goals of the organization influence the behavioral orientations of both partners and the behaviors of both partners affect goal realization simultaneously (Schuster, 2002). Behaviors and goals are core factors associated with cooperation (Chen et al., 1998; Stern & Reve, 1980; Brito et al., 2014). Therefore, cooperation theory considers behaviors and goals to be the two most important dimensions of the cooperation process. Behavioral dimensions can be divided into two categories—interdependent and independent (Millot & Debernard, 2007; Makarius et al., 2020)—and goal dimensions can also be divided into two categories—exploitation and exploration (March 1991; Camisón et al., 2018).

2.2.1. Behaviors of Cooperation: Independence and interdependence

Humans and AI can behave independently of one another when cooperating (Millot & Debernard, 2007); for example, humans and AI can play different roles in accomplishing a task, analyzing and making decisions regarding their respective subtasks without interfering with one another (McNeese et al., 2018; Ishowo-Oloko et al., 2019). Humans and AI can also behave interdependently when working; for example, AI focuses on tasks that process data to support humans in making decisions (Raisch & Krakowski, 2021; Sowa et al., 2021). The classification of independent and interdependent cooperative behaviors has been addressed by previous studies. Hake and Vukelich (1972) argued that cooperative processes are interdependent when the behaviors of the collaborators can influence each other, whereas in the case of relative independence, individuals on a team are rewarded for their own efforts without regard to the behaviors of other team members (Nass et al., 1996). Some concepts of independence and dependence have also been applied to the HAIC field. Sowa et al. (2021) argued that there are two diametrically opposed HAIC models: according to one model, humans work completely independently of AI and there is no interaction between humans and AI, while according to the other model, humans and AI complement and depend on one another, with the machine even becoming an extension of the human brain, such that the two collaborators reach a level of full synergy. Makarius et al. (2020) also mentioned the concepts of independence and symbiosis in the case of HAIC, in which context independence involves humans dividing the work with AI and acting independently of one another in a highly automated situation, and symbiosis involves AI and humans making decisions collaboratively to achieve their goals interdependently.

Two forms of cooperative behaviors occur in HAIC: interdependent and independent behaviors. As seen above, the relationship between humans and AI in the context of interdependent behavior is complementary, such that the behavior of one party has an impact on the behavior of the other. The relationship between humans and AI in the context of independent behavior is unrelated, and each party handles its tasks independently.

2.2.2. Goals of Cooperation: Exploration and exploitation

The goals of cooperation with AI can be divided into exploration and exploitation (March 1991; Claus & Boutilier, 1998). The concepts of exploration and exploitation have frequently been applied in the field of organizational management (March 1991). Exploration includes searching, changing, risk-taking, experimenting, gaming, being flexible, discovering, and innovating, while exploitation includes optimizing, selecting, producing, ensuring efficiency, screening, realizing, and executing. Exploration essentially involves experimenting or engaging in external exploration to develop entirely new ideas, while exploitation focuses on refining and extending existing capabilities and technologies to obtain additional benefits. Kang et al. (2007) noted that exploration is a process of creativity via external increments, which aims at the acquisition of new resources and knowledge via processes of creation and search. Exploitation, on the other hand, is a process of intrinsic resource optimization that optimizes and refines existing resources via analysis and combination (Levinthal & March 1993; Camisón et al., 2018). The different structures of exploration and exploitation have an impact on organizational performance, and these two concepts have been widely used as an analytical structure in the field of management research (He & Wong, 2004; Holmqvist, 2004). Organizations must pursue the goals of exploration and exploitation to achieve optimal performance and thus ensure long-term viability in a changing environment (Holmqvist, 2004).

During cooperation, the pursuit of exploration and exploitation goals is necessary, and we use these exploration and exploitation goals as a classification dimension for the HAIC modes. We believe that HAIC can have two types of goals: a goal of exploration is to develop unknown areas or create new paradigms and a goal of exploitation is to collaborate to optimize existing areas, use existing paradigms, and improve existing resources.

In summary, in accordance with the two dimensions of cooperation, i.e., behavior and goals, we obtain four HAIC modes:

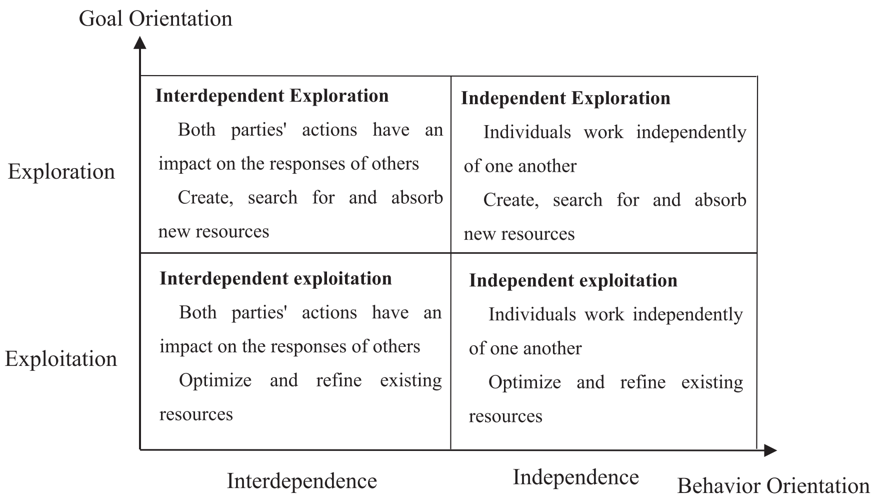

Fig. 1. HAIC modes based on cooperation theory.

interdependent exploitation, independent exploitation, interdependent exploration and independent exploration (Fig. 1). Interdependent exploitation occurs when humans and AI depend on one another and optimize existing resources; independent exploitation occurs when humans and AI use existing resources independently; interdependent exploration occurs when humans and AI develop external resources interdependently; and independent exploration occurs when humans and AI act independently and explore external resources. Therefore, a hypothesis is formulated as follows:

H1: There are four HAIC modes: interdependent exploitation, independent exploitation, interdependent exploration, and independent exploration.

2.3. The effect of HAIC mode on Attitude

Previous studies have reported various attitudes toward HAIC. On the one hand, some people have negative sentiments toward HAIC. Luo et al. (2020) showed that salespeople experience aversion when working with AI coaches and thus reject training by AI coaches. Ishowo-Oloko et al. (2019) highlighted the trade-off between transparency and efficiency in HAIC and noted that people are more reluctant to work with AI when the AI's identity is disclosed. People have an inherent bias against AI, which is perceived to lack creativity and empathy (Luo et al., 2019); thus, HAIC generally underperforms human–human cooperation (Musick et al., 2021). Other researches have suggested that people may be receptive to HAIC. Nass et al. (1996) manipulated interdependence in the context of cooperation and found that attitudes were more positive under conditions of interdependence than under conditions of independence. Fan et al. (2010) argued that AI has advantages with respect to computationally intensive activities such as information processing and filtering, that humans are better at prediction and reasoning, and that AI can help reduce the cognitive load on humans, thus resulting in effective HAIC. The research by Hillesheim and Rusnock (2016), on the other hand, suggested that if people believe that AI is reliable, then HAIC yields higher performance.

We believe that people's attitudes toward HAIC can be interpreted from the perspective of the different modes of HAIC. First, due to the behavioral differences across different modes of cooperation, people may have divergent attitudes. For example, people who prefer to work interdependently with one another to accomplish tasks do not necessarily prefer to work independently, while people who prefer to work independently to accomplish tasks do not necessarily prefer to work interdependently (Brannon et al., 2015). Therefore, we believe that cooperation modes influence people's attitudes. Second, people's attitudes may also differ across the four modes of HAIC. On the one hand, interdependent modes in HAIC can create a shared understanding among team members (Gao et al., 2012), and AI working closely with humans rather than dividing that work can promote higher performance (Daugherty & Wilson, 2018) and more positive attitudes (Longoni et al., 2019; Longoni & Cian, 2022). People are averse to the notion of AI making automated decisions independently of humans but are more willing to accept AI when AI takes into account humans' opinions in the process of decision-making and when it performs tasks interdependently with humans (Dietvorst et al., 2016). On the other hand, people who do not trust AI can be flexible and are reluctant to allow AI to perform highly subjective exploration-type tasks that require creativity, such as recommending jokes or making dating plans (Yeomans et al., 2019; Castelo et al., 2019). However, people are more receptive to AI in the limited context of exploitation-type tasks, such as numerical computation and estimation (Logg et al., 2019). We therefore believe that the HAIC mode in question influences people's attitudes and that people are more willing to work with AI in the interdependent exploitation mode.

2.3.1. Attitudes toward independent vs Interdependent cooperation modes

In the interdependent cooperation HAIC mode, humans and AI complement one another by performing their respective roles, which can demonstrate the advantages of AI while ensuring compliance with human needs (Sowa et al., 2021). In the independent cooperation HAIC mode, humans and AI work independently without interacting with one another based on mutual trust between humans and AI (Park et al., 2021).

On the one hand, the interdependent mode is more suited to the respective capabilities of humans and AI and facilitates the complementary strengths of each party (Fan et al., 2010). AI has the advantage of superior computational power, with a lower error rate and a longer working time, AI is better suited to relatively fixed and large-scale tasks. While humans have the advantage of being more comfortable with situations that involve emotional expressions and judgments and are thus better suited for flexible and random tasks (Sowa et al., 2021). In an interdependent mode, AI focuses on computing and processing data to support humans in the task of solving unstructured and abstract problems (Musick et al., 2021). This complementary model has been widely accepted. Longoni et al. (2019) found that in the medical field, patients prefer AI to work with human doctors to diagnose themselves rather than working with independent AI to give a diagnosis. The research by Sircar et al. (2021) also suggested that AI and engineers should work together interdependently to ensure that data are processed correctly. The complementary properties of humans and AI thus provide a foundation for an interdependent cooperation mode.

On the other hand, an independent cooperation mode requires that humans have sufficient trust in AI (Park et al., 2021), but the degree of trust between humans and AI frequently does not reach the expected level. Humans doubt the subjective judgment ability of AI, thereby reducing trust in autonomous AI (Castelo et al., 2019). Distrust in AI is also related to the low degree of AI transparency (Ishowo-Oloko et al., 2019). Because people are not familiar with the internal operations of AI, it is often difficult for humans to entrust significant aspects of certain tasks to independent AI for completion (Cadario et al., 2021). This lack of trust in AI makes it necessary for HAIC to occur within the limits of human control (Dietvorst and Bharti, 2020). In summary, the following hypothesis is proposed:

H2: In HAIC, there is a preference for an interdependent rather than an independent cooperation mode.

2.3.2. Attitudes toward exploration vs Exploitation cooperation modes

The exploration mode of HAIC requires humans and AI to explore external resources, which is a process that requires a certain degree of innovation and flexibility (March 1991). In contrast, in the exploitation mode, humans and AI work together to optimize known resources, which is a process that is well suited to the AI's skill at computing using existing data (Castelo et al., 2019).

AI tends to be deficient in terms of its ability to innovate, which constrains HAIC from employing an exploration mode. Since algorithms are often based on summaries of existing specifications on the basis of previous experience, AI is known as a problem-oriented application of technology (Alter, 2021), and in many cases that lack over-engineered aspects, AI does not cope well with newly generated problems, thus resulting in its inability to complete certain tasks (Mowforth & Bratko, 1987). In addition, AI's ability to innovate depends heavily on its data input; however, the collection of high-quality data is a challenging task (Roden et al., 2020), and biased results from biased data are common (Li & Huang, 2020). Furthermore, AI does not possess a motivation to innovate. Because AI agents do not possess cognition and perspective, additional human judgment concerning the solutions proposed by AI is often required in cases of innovative exploration (Musick et al., 2021). Therefore, in HAIC, people are reluctant to allow AI to perform innovative and expansive exploration tasks.

In contrast, the exploitation mode focuses on optimization, and most work accomplished in this mode is rather stable and repetitive, which is in line with the properties of AI (Longoni et al., 2019). It is believed that AI is better suited to standardized and repetitive tasks (Nissenbaum & Walker, 1998). Research by Castelo et al. (2019) suggested that people prefer AI to perform objective and repetitive tasks, such as analyzing and computing data, rather than subjective and innovative tasks. Therefore, in the exploitation mode, AI can better cooperate with humans, thus increasing the efficiency of the entire collaborative process. Therefore, the following hypothesis is formulated:

H3: In HAIC, there is a preference for an exploitation rather than an exploration cooperation mode.

Based on cooperation theory and the preceding discussion, we propose our research model (Fig. 2).

3. Research methods

To test the effectiveness of the HAIC model and its effects on cooperative attitudes empirically, we designed a questionnaire and conducted a survey based on a Defense of the Ancients (DOTA) scenario. DOTA is a multiplayer online battle arena in which five players form a team and cooperate to destroy the opponents' ancients to achieve victory. When a team is formed, AI can be selected as a teammate, thus leading to the formation of a human-AI cooperative team. The AI in DOTA can operate automatically and can even outperform humans (Ecoffet et al., 2021). Therefore, HAIC is very common in the DOTA scenario, thus meeting the contextual requirements of this study. In addition, empirical studies of HAIC in game scenarios are common (Hillesheim & Rusnock, 2016; O'Neill et al., 2020; Musick et al., 2021). We constructed a questionnaire for the HAIC model based on previous studies, and after validating

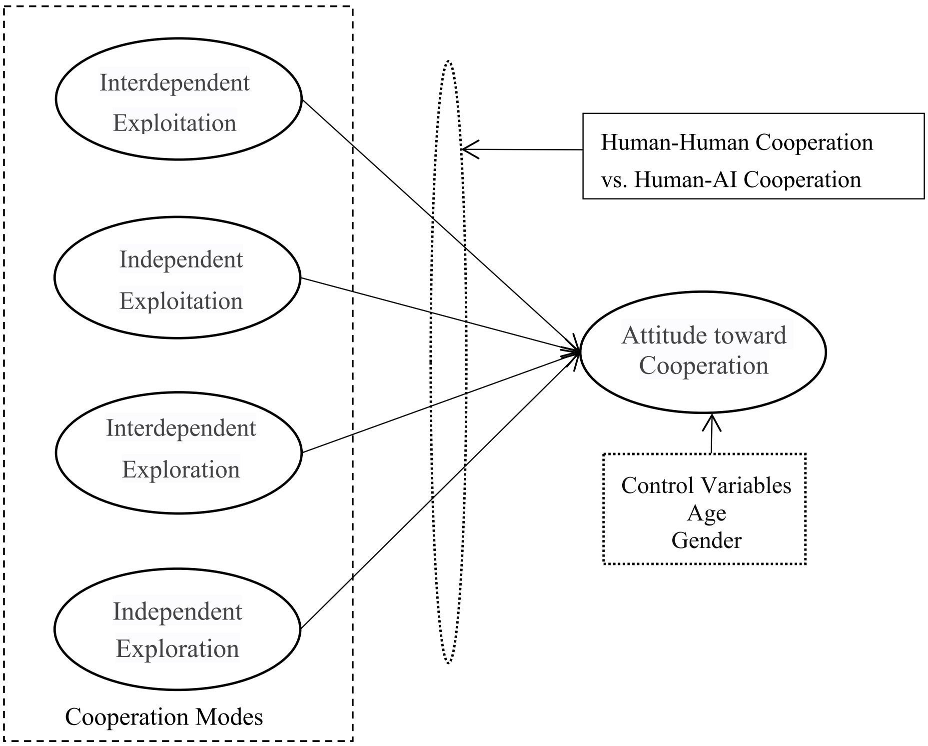

Fig. 2. Proposed Research Model.

this questionnaire for reliability and validity, we conducted a confirmatory factor analysis using AMOS 22 software (Bollen, 1989).

3.1. Measures

The items used in the HAIC questionnaire were drawn from previous studies pertaining to cooperation theory, and we adapted concepts from the literature and applied them to the game scenario to ensure the consistency of our study. Specifically, the concepts of exploitation and exploration were derived from March (1991) and Camisón et al. (2018), where exploitation is defined as optimizing the allocation of existing resources, exploiting the team's intrinsic potential, and improving the efficiency of existing resources in cooperation, while exploration is the acquisition of external resources and innovative activities and external territorial expansion. The concepts of independence and interdependence were derived from the definitions provided by Millot and Debernard (2007) and Makarius et al. (2020), according to whom independence occurs when the collaborating parties do not interfere with each other and operate in isolation while interdependence occurs when the collaborating parties complement, support and rely on one another. Thereby, the items for the four HAIC modes were designed by reference to these concepts in combination with game scenarios (Mora-Cantallops & Sicilia, 2018); in addition, we designed items for cooperative attitudes based on the study by Park et al. (2021) (see Table 1). All items were measured on a seven-point Likert scale. In addition, we added gender and age as control variables. To ensure the validity of the content, five students who were familiar with AI teammates in the game and who had experience playing cooperatively with AI teammates were invited to complete the questionnaire. After asking questions regarding the clarity of the questionnaire measurements, these students finally agreed on the content of the questionnaire.

3.2. Data collection

The participants were divided into two groups to measure cooperation in two situations, i.e., human–human cooperation and HAIC, so that these groups could be compared in a subsequent study. The participants were grouped randomly for measurement and were first asked whether they had experience playing DOTA. If participants answered "yes", they were allowed to answer the subsequent questions. For the HAIC group [human–human cooperation group], the participants were further asked whether they had previously participated in a team with an AI [other humans] to play the game, and those who answered "yes" were asked to answer additional questions. Subsequently, the participants were asked to imagine teaming up with other AI [other humans] to play the game. Thereafter, they answered questions regarding the modes of cooperation. Then, we implemented a control check between groups by asking the participants whether they imagined playing in a group with AI [other humans] when answering the questions to verify the validity of the grouping. Finally, the participants completed measures of their demographic characteristics.

Table 1
The HAIC questionnaire with all the final items.

Construct		Items	Supporting literature
Interdependent Exploitation	A1	I tend to operate in a complementary way with my teammates when optimizing the allocation of available resources (e.g., Jungling together)	March (1991), Mora-Cantallops & Sicilia (2018), Makarius et al. (2020)
	A2	I tend to act together with my teammates when exploiting the inner potential of the team (e.g., distributing money, buying equipment for each other)	
	A3	I tend to work with teammates who depend on each other when it comes to improving the efficiency of existing resources (e.g., healing each other)	
Independent Exploitation	B1	I tend to do my own tasks with my teammates when optimizing the allocation of available resources (e.g., Jungling alone)	March (1991), Millot & Debernard (2007), Camisón et al. (2018), Mora-Cantallops & Sicilia (2018)
	B2	I tend to act separately from my teammates when exploiting the inner potential of the team (e.g., spending money alone, buying equipment separately)	
	B3	I tend to divide actions with my teammates when it comes to improving the efficiency of existing resources (e.g., self-healing)	
Interdependent Exploration	C1	I tend to act in a complementary manner with my teammates when obtaining external resources (e.g., clearing the enemy minions together)	March (1991), Camisón et al. (2018), Mora-Cantallops & Sicilia (2018), Makarius et al. (2020)
	C2	I tend to collaborate with my teammates in creative activities to accomplish tasks (e.g., attacking enemy heroes together)	
	C3	I tend to work with teammates who depend on each other when expanding the area externally (e.g., attacking enemy defense towers together)	
Independent Exploration	D1	I tend to operate independently of my teammates when obtaining external resources (e.g., clearing enemy minions independently)	March (1991), Millot & Debernard (2007), Mora-Cantallops & Sicilia (2018)
	D2	I tend to operate separately from my teammates when carrying out innovative activities (for example, attacking enemy heroes alone)	
	D3	I tend to split up with my teammates when expanding externally (for example, attacking enemy defense towers alone)	
Attitude toward Cooperation	ATC1	The teamwork in the game is a pleasant experience for me	Park et al. (2021)
	ATC2	I would like to cooperate with my teammates in the game against each other	
	ATC3	Its good to participate in the game with my teammates in a cooperative manner	

Data were collected via Credamo, a questionnaire collection platform similar to MTurk that guarantees the quality of the sample (Gong et al., 2020), and the participants completed the questionnaire in exchange for money. A total of 1367 valid questionnaires (Human-AI cooperation: N = 691; Human-Human Cooperation: N = 676) were returned. Table 2 shows the demographic information of our respondents in detail. Within the valid sample, 61.4 % of participants were male, and 38.6 % were female. The majority of the respondents were under the age of 30 (87.8 %) and had received higher education at a university or college (92.9 %).

4. Data analysis and results

We used confirmatory factor analysis (CFA) to assess the structure of the HAIC model. Specifically, we modeled and analyzed the structural equations using AMOS 22 software.

4.1. Reliability and validity

First, we tested the model fit. We examined the full sample (N = 1367), the HAIC sample (N = 691), and the human–human cooperative sample (N = 676). In the reliability test, the composite reliability (C.R.) and Cronbach's alpha (Alpha) values were above 0.7. In the convergent validity test (Table 3), loading exceeded 0.7 for almost all factors, and the average variance extracted (AVE) exceeded 0.5 (Table 3). In the discriminant validity test, the square root of each AVE was greater than the correlation coefficient between the constructs (Table 4). These results indicate that the participants were able to distinguish among the four modes of cooperation, and so H1 was validated (Bollen, 1989).

4.2. Structural model analysis

After testing the model to ensure reliability and validity, we assessed the fit of the overall model and the two submodels. The results show that the measurement model has a good model fit. The minimum discrepancy divided by its degrees of freedom (CMIN/DF) were all <5, thus indicating that the hypothesized model has a good fit (Carmines and McIver, 1981), and the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the normed fit index (NFI), the tucker-lewis index (TLI), and the comparative fit index (CFI) were all>0.9, thereby exceeding the recommended threshold for good model fit (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA) was<0.08, which also indicated a good model fit (Hu & Bentler, 1999).

4.3. Group comparison analysis

To examine the effects of the various HAIC modes on attitudes toward cooperation, we employed a multigroup SEM approach to compare the effects of human–human cooperation to those of HAIC on attitudes toward cooperation (Anderson & Gerbing, 1988). The results are detailed in Table 6. The following primary conclusions were obtained. First, in HAIC, the mode of independence has a nonsignificant negative effect on attitudes toward cooperation, which indicates that people reject the notion of AI working independently and prefer to work interdependently with AI, thereby validating H2. Furthermore, compared to human–human cooperation, the influence of the interdependent exploitation mode on attitudes toward cooperation is greater in HAIC, and the positive direction indicates that people are more willing to exploit internal resources in close collaboration with AI, which also validates H2 and H3.

5. General discussion

This paper examines HAIC modes and their effect on attitudes toward cooperation. It is inspired by two facts. First, advances in AI are progressively increasing the efficiency of work, and autonomous AI agents are able to participate as teammates in human teamwork-related tasks, thus overturning the longstanding scenario in which AI operate under human control (O'Neill et al., 2020). Specifically, the continuing emergence of HAIC has caused it to occur in multiple modes. Secondly, people exhibit different attitudes

Table 2
Demographic information.

Variable	Category	Human-AI Cooperation (N = 691)		Human-Human Cooperation (N = 676)		Full samples (N = 1367)	
		Numbers	Percentage	Numbers	Percentage	Numbers	Percentage
Gender	male	430	62.2 %	410	60.7 %	840	61.4 %
	female	261	37.8 %	266	39.3 %	527	38.6 %
Age	<18	9	1.3 %	14	2.1 %	23	1.7 %
	18–25	398	57.6 %	393	58.1 %	791	57.9 %
	26–30	200	28.9 %	186	27.5 %	386	28.2 %
	30–40	67	9.7 %	72	10.7 %	139	10.2 %
	>40	17	2.5 %	11	1.6 %	28	2 %
Education level	High school or below	60	8.7 %	37	5.5 %	97	7.1 %
	Undergraduate or bachelor	515	74.5 %	496	73.4 %	1011	74 %
	Postgraduate	102	14.8 %	128	18.9 %	230	16.8 %
	Doctor or above	14	2 %	15	2.2 %	29	2.1 %

Table 3
Reliability and convergent validity analysis for the full sample (N = 1367) and sub-samples: Human-AI Cooperation(N = 691) vsHuman-Human Cooperation(N = 676).

Construct	Item	Full sample (N = 1367)				Human-AI Cooperation (N = 691)				Human-Human Cooperation (N = 676)			
		Factor loading	AVE	C.R.	Alpha	Factor loading	AVE	C.R.	Alpha	Factor loading	AVE	C.R.	Alpha
Interdependent	A1	0.728	0.544	0.781	0.755	0.670	0.508	0.756	0.729	0.757	0.541	0.779	0.783
	A2	0.734				0.758				0.755			
Exploitation	A3	0.750				0.708				0.693			
Independent	B1	0.835	0.682	0.866	0.866	0.849	0.684	0.866	0.866	0.819	0.680	0.864	0.865
	B2	0.838				0.835				0.841			
Exploitation	B3	0.805				0.796				0.814			
Interdependent	C1	0.714	0.520	0.764	0.782	0.779	0.591	0.812	0.812	0.629	0.462	0.719	0.717
	*C*2	0.745				0.782				0.641			
Exploration	C3	0.703				0.744				0.761			
Independent	D1	0.823	0.608	0.822	0.816	0.793	0.594	0.814	0.810	0.855	0.626	0.832	0.823
	D2	0.682				0.695				0.666			
Exploration	D3	0.826				0.819				0.838			
Attitude to cooperation	ATC1	0.864	0.691	0.869	0.865	0.869	0.720	0.885	0.882	0.848	0.637	0.838	0.830
	ATC2	0.889				0.897				0.872			
	ATC3	0.732				0.774				0.657			

Table 4
Discriminant validity analysis for the full sample (N = 1367) and sub-samples: Human-AI Cooperation(N = 691) vsHuman-Human Cooperation(N = 676).

Construct	Full sample (N = 1367)					Human-AI Cooperation(N = 691)					Human-Human Cooperation(N = 676)				
	A	B	C	D	ATC	A	B	C	D	ATC	A	B	C	D	ATC
Interdependent Exploitation(A)	**0.737**					**0.713**					**0.736**				
Independent Exploitation(B)	0.080	**0.826**				−0.026	**0.827**				0.188	**0.825**			
Interdependent Exploration(C)	0.676	0.028	**0.721**			0.701	−0.009	**0.769**			0.655	0.068	**0.680**		
Independent Exploration(D)	0.165	0.382	0.076	**0.780**		0.057	0.361	0.076	**0.771**		0.256	0.394	0.069	**0.791**	
Attitude to cooperation(ATC)	0.602	0.004	0.661	−0.016	**0.831**	0.692	−0.088	0.650	−0.012	**0.848**	0.484	0.114	0.660	−0.035	**0.798**

Notes: Diagonal elements (in bold) are the square root of AVEs of constructs.

Table 5
Fitting index for the full sample (N = 1367) and sub-samples: Human-AI Cooperation(N = 691) vsHuman-Human Cooperation(N = 676).

	Full sample (N = 1367)	Human-AI Cooperation (N = 691)	Human-Human Cooperation (N = 676)	Expectation
CMIN/DF	4.636	2.573	3.331	<5
GFI	0.958	0.954	0.940	>0.9
AGFI	0.940	0.935	0.915	>0.9
NFI	0.947	0.944	0.920	>0.9
TLI	0.947	0.956	0.928	>0.9
CFI	0.958	0.965	0.943	>0.9
RMSEA	0.052	0.048	0.059	<0.08

Table 6
Sub-group analysis between Human-AI Cooperation sample (N = 691) and Human-Human Cooperation sample(N = 676).

Path	Path coefficient		
	Human-AI Cooperation	Human-Human Cooperation	Zs_{core}
Interdependent Exploitation->Attitude to cooperation	0.463***	0.117*	−4.625***
Independent Exploitation->Attitude to cooperation	−0.057 ns	0.111***	2.981***
Interdependent Exploration->Attitude to cooperation	0.329***	0.586***	3.756***
Independent Exploration->Attitude to cooperation	−0.043 ns	−0.149***	−1.247 ns

Notes: ns: non-significant, *p < 0.1, **p < 0.05, ***p < 0.01.

toward HAIC (Fan et al., 2010; Ishowo-Oloko et al., 2019), thus suggesting the existence of variables that can influence people's attitudes toward HAIC. In this context, our study provides new theoretical implications, practical implications and directions for future research.

5.1. Theoretical implications

The first theoretical contribution of this paper is the delineation of the four HAIC cooperation modes. Cooperation between humans and AI will become the norm in the future (Rahwan et al., 2019), but previous research related to HAIC has focused on the concept of such cooperation and the factors that influence it (O'Neill et al., 2020) and has not investigated the modes of HAIC. This paper explores the classification dimensions of HAIC with respect to behavior-oriented and goal-oriented cooperation based on cooperation theory and thereby proposes a new model of HAIC modes. In this research, HAIC is classified into four modes—interdependent exploitation, independent exploitation, interdependent exploration, and independent exploration—thus making a theoretical contribution to the study of HAIC (Table 5).

The second theoretical contribution of this paper is its discovery of the mode of HAIC that is preferred by humans. In the context of HAIC in the DOTA scenario, people are more receptive to the interdependent exploitation mode of cooperation than to other such modes. Previous studies have explored scenarios in which people engage in HAIC. For example, people accept AI when their teammates are not revealed to be AI (Ishowo-Oloko et al., 2019; Luo et, al, 2019). High levels of interdependence when humans work with AI teammates can also promote positive attitudes (Nass et al., 1996). We show empirically that HAIC has a stronger effect on cooperative attitudes than human–human cooperation in the interdependent exploitation mode, which provides a reference for understanding the way in which humans prefer to cooperate with AI.

The third theoretical contribution of this paper is that it provides a new perspective to compare the research related to human–human cooperation with that pertaining to HAIC. Our results suggest cases in which HAIC is preferred (i.e., when the cooperation mode is interdependent exploitation) and when human–human cooperation is preferred (i.e., when the cooperation mode is independent exploitation or interdependent exploration). This finding suggests that people are willing to accept AI as a replacement for human teammates only when the AI teammate engages in interdependent cooperation with them and when performing an exploitation-type task such as processing data or computation (Fan et al., 2010; Longoni et al., 2019). Future comparative studies of HAIC and human–human cooperation can also be viewed in terms of different modes of HAIC.

5.2. Practical implications

This paper also makes certain practical contributions. First, although the interdependent mode of HAIC has a positive effect on attitudes toward cooperation with AI, the independent mode has no significant effect in this context. Therefore, when organizations promote AI, they should try to make AI and organizational members cooperate interdependently rather than independently so that the acceptance of AI members by members of the organization can be enhanced. When introducing AI team members, organizations should also emphasize the AI's ability to work interdependently with people rather than the AI's degree of automation.

Second, this paper finds that human–human cooperation and HAIC should be applied in different contexts. Since people prefer the interdependent exploitation mode in HAIC, when managers consider using AI to replace human work, they should focus on tasks that require interdependent cooperation and those that make optimal use of resources that are already available. For example, AI can be used to conduct data analysis and thereby provide advice to humans. However, when the cooperation mode in question is that of independent exploitation or interdependent exploration, people prefer to work with humans rather than AI. Therefore, managers should consider the areas in which AI should be applied when trying to reduce labor costs by implementing AI.

5.3. Limitations and future research

The limitations of our study indicate some opportunities for future research.

First, the HAIC modes do not account for cultural factors. Since HAIC will be a global phenomenon in the future (Rahwan et al., 2019), a cross-cultural test of HAIC modes and their effects on cooperative attitudes is also recommended to verify the stability of the HAIC model and determine whether there are any differences in terms of people's preferences for specific HAIC modes across cultures. For example, in an interdependent culture, people are more likely to cooperate with AI interdependently, whereas in an independent culture, people may accept independent AI (Kitayama et al., 2007).

Second, although age and gender were included as control variables in this study, the effects of other personal factors on attitudes toward HAIC modes were not taken into account. Previous research has suggested that attitudes toward AI may vary by occupational group (Li & Huang, 2020). In addition, personal traits may also moderate attitudes toward HAIC modes. For example, people with greater needs for control and uniqueness are more reluctant to engage in cooperation with autonomous AI (Shaffer et al., 2013; Longoni et al., 2019), so future research can explore the influence of personal factors on the impact of HAIC modes.

Finally, this study investigated only the effects of HAIC modes on people's attitudes in the context of the DOTA scenario and did not further investigate the effect of different HAIC modes on individual attitudes in other scenarios. To test the robustness of our hypothesis, future studies can investigate whether the results of this paper are also applicable to other HAIC scenarios by conducting experiments and employing other methods.

6. Conclusion

Based on cooperation theory, this study proposed four modes of cooperation in the context of HAIC: interdependent exploitation, independent exploitation, interdependent exploration and independent exploration. The study also analyzed the impact of these different modes on people's attitudes toward HAIC by reference to survey data collected in the context of DOTA. It was found that different modes of HAIC have different impacts. Compared with human–human cooperation, people prefer the interdependent exploitation mode of HAIC; that is, people prefer interdependent cooperation with AI to optimize and use the available resources. This paper provides a new theoretical framework for HAIC and can thus serve as a reference for further research pertaining to HAIC.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Alter, S., 2021. Understanding artificial intelligence in the context of usage: Contributions and smartness of algorithmic capabilities in work systems. Int. J. Inf. Manage. In Press. Available online 6 August 2021. 10.1016/j.ijinfomgt.2021.102392.
Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: a review and recommended two-step approach. Psychol. Bull. 103 (3), 411–423.
Bollen, K.A., 1989. Structural equations with latent variables. J. A. Stat. Assoc. 35 (7), 289–308.
Brannon, T.N., Markus, H.R., Taylor, V.J., 2015. "Two souls, two thoughts", two self-schemas: Double consciousness can have positive academic consequences for African Americans. J. Pers. Soc. Psychol. 108 (4), 586–609.
Brito, L.A.L., Brito, E.P.Z., Hashiba, L.H., 2014. What type of cooperation with suppliers and customers leads to superior performance? J. Bus. Res. 67 (5), 952–959.
Cadario, R., Longoni, C., Morewedge, C., 2021. Understanding, explaining, and utilizing medical artificial intelligence. Nat. Hum. Behav. 5, 1636–1642.
Camisón, C., Boronat-Navarro, M., Forés, B., 2018. The interplay between firms' internal and external capabilities in exploration and exploitation. Manag. Decis. 56 (7), 2–15.
Carmines, E.G., McIver, J.P., 1981. Analyzing Models with Unobserved Variables: Analysis of Covariance Structures. In: Bohrnstedt, G.W., Borgatta, E.F. (Eds.), Social Measurement: Current Issues. Sage Publications Inc, Beverly Hills, pp. 65–115.
Castelo, N., Bos, M.W., Lehmann, D.R., 2019. Task-dependent algorithm aversion. J. Mark. Res. 56 (5), 1–17.
Chen, C.C., Chen, X.P., Meindl, R.J., 1998. How can cooperation be fostered? The cultural effects of individualism-collectivism. Acad. Manage. Rev. 23 (2), 285–304.
Claus, C., Boutilier, C., 1998. The dynamics of reinforcement learning in cooperative multiagent systems. Proceedings of the Fifteenth National/Tenth Conference on Artificial Intelligence/Innovative Applications of Artificial Intelligence. (AAAI '98/IAAI '98). American Association for Artificial Intelligence, USA, 746–752.
Daugherty, P.R., Wilson, H.J., 2018. Human + machine: Reimagining work in the age of AI. Harvard Business Review Press, Boston, MA.

Deutsch, M., 1949. A Theory of Co-operation and Competition. Hum. Relat. 2 (2), 129–152.
Dietvorst, B.J., Bharti, S., 2020. People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error. Psychol. Sci. 31 (10), 1–13.
Dietvorst, B.J., Simmons, J.P., Massey, C., 2016. Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. Manage. Sci. 64 (3), 1155–1170.
Ecoffet, A., Huizinga, J., Lehman, J., et al., 2021. First return, then explore. Nature. 590, 580–586.
Fan, X., McNeese, M., Yen, J., 2010. NDM-based cognitive agents for supporting decision-making teams. Hum. Comput. Interact. 25, 195–234.
Gao, F., Cummings, M. L., Bertuccelli, L. F., 2012. Teamwork in controlling multiple robots. In Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction (HRI '12). ACM, New York, NY, USA, 81-88.
Gong, S.Y., Lu, J.G., Schaubroeck, J.M., et al., 2020. Polluted psyche: is the effect of air pollution on unethical behavior more physiological or psychological? Psychol. Sci. 31 (8), 1040–1047.
Hake, D.F., Vukelich, R., 1972. A classification and review of cooperation procedures. J. Exp. Anal. Behav. 18 (2), 333–343.
He, Z.L., Wong, P.K., 2004. Exploration vs. Exploitation: An Empirical Test of the Ambidexterity Hypothesis. Organ. Sci. 15 (4), 481–494.
Henrich, J., Muthukrishna, M., 2021. The Origins and Psychology of Human Cooperation. Annu. Rev. Psychol. 72, 207–240.
Hillesheim, A.J., Rusnock, C.F., 2016. Predicting the effects of automation reliability rates on human-automation team performance [Conference session]. In: 2016 Winter Simulation Conference (WSC), pp. 1802–1813.
Holmqvist, M., 2004. Experiential Learning Processes of Exploitation and Exploration Within and Between Organizations: An Empirical Study of Product Development. Organ. Sci. 15 (1), 70–81.
Hu, L.-t., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary J. 6 (1), 1–55.
Ishowo-Oloko, F., Bonnefon, J.F., Soroye, Z., et al., 2019. Behavioural evidence for a transparency-efficiency tradeoff in human-machine cooperation. Nat. Mach. Intell. 1, 517–521.
Kang, S.C., Morris, S.S., Snell, S.A., 2007. Relational Archetypes, Organizational Learning, and Value Creation: Extending the Human Resource Architecture. Acad. Manage. Rev. 32 (1), 236–256.
Kitayama, S., Duffy, S., Uchida, Y., 2007. Self as cultural mode of being. In: Kitayama, S., Cohen, D. (Eds.), Handbook of Cultural Psychology. Guilford, New York, pp. 136–174.
Köbis, N., Bonnefon, J.F., Rahwan, I., 2021. Bad machines corrupt good morals. Nat. Hum. Behav. 5, 679–685.
Levinthal, D.A., March, J.G., 1993. The Myopia of Learning. Strateg. Manag. J. 1993, 14 (2), 95-112.
Li, J., Huang, J.S., 2020. Dimensions of artificial intelligence anxiety based on integrated fear acquisition theory. Technol. Soc. 63, 101410.
Logg, J.M., Minson, J.A., Moore, D.A., 2019. Algorithm appreciation: people prefer algorithmic to human judgment. Organ. Behav. Hum. Decis. Process. 151, 90–103.
Longoni, C., Cian, L., 2022. Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. J. Mark. 86 (1), 91–108.
Longoni, C., Bonezzi, A., Morewedge, C., 2019. Resistance to Medical Artificial Intelligence. J. Consum. Res. 46 (4), 629–650.
Luo, X.M., Tong, S.L., Fang, Z., Qu, Z., 2019. Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases. Mark. Sci. 38 (6), 937–947.
Luo, X.M., Qin, M.S., Fang, Z., Qu, Z., 2020. Artificial intelligence coaches for sales agents: caveats and solutions. J. Mark. 85 (1), 1–19.
Lyons, J.B., Mahoney, S., Wynne, K.T., Roebke, M.A., 2018. Viewing machines as teammates: A qualitative study. 2018 AAAI Spring Symposium Series.
Makarius, E.E., Mukherjee, D., Fox, J.D., Fox, A.K., 2020. Rising with the machines: a sociotechnical framework for bringing artificial intelligence into the organization. J. Bus. Res. 120, 262–273.
March, J.G., 1991. Exploration and exploitation in organizational learning. Organ. Sci. 2 (1), 71–87.
McNeese, N.J., Demir, M., Cooke, N.J., Myers, C., 2018. Teaming with a synthetic teammate: Insights into human-autonomy teaming. Hum. Factors. 60, 262–273.
McNeese, M.D., McNeese, N.J., 2020. Humans interacting with intelligent machines: At the crossroads of symbiotic teamwork. In: Living With Robots. Academic Press, pp. 165–197. https://doi.org/10.1016/b978-0-12-815367-3.00009-8.
Millot, P., Debernard, S., 2007. An attempt for conceptual framework for human-machine cooperation. IFAC Proceedings Volumes 40 (16), 347–353.
Mora-Cantallops, M., Sicilia, M.-Á., 2018. Moba games: A literature review. Entertain. Comput. 26, 128–138.
Mowforth, P., Bratko, I., 1987. AI and Robotics; Flexibility and Integration. Robotica 5 (2), 93–98.
Musick, G., O'Neill, T., Schelble, B.G., Mcneese, N.J., Henke, J.B., 2021. What Happens When Humans Believe Their Teammate is an AI? An Investigation into Humans Teaming with Autonomy. Comput. Hum. Behav. 122 (4), 106852.
Nass, C., Fogg, B.J., Moon, Y., 1996. Can computers be teammates? Int. J. Hum.-Comput. Stud. 45 (6), 669–678.
Nissenbaum, H., Walker, D., 1998. Will computers dehumanize education? a grounded approach to values at risk. Technol. Soc. 20 (3), 237–273.
O'Neill, T., McNeese, N., Barron, A., Schelble, B., 2020. Human-autonomy teaming: A review and analysis of the empirical literature. Hum. Factors. Available online 22 October 2020. 10.1177/0018720820960865.
Park, S.S., Tung, C.T.D., Lee, H., 2021. The adoption of AI service robots: a comparison between credence and experience service settings. Psychol. Mark. 38 (4), 691–703.
Rahwan, I., Cebrian1, M., Obradovich, N. et al., 2019. Machine Behaviour. Nature. 568, 477-486.
Raisch, S., Krakowski, S., 2021. Artificial intelligence and management: the automation-augmentation paradox. Acad. Manage. Rev. 46 (1), 192–210.
Rich, C., Sidner, C.L., 1997. COLLAGEN: When agents collaborate with people. Proceedings of the first international conference on autonomous agents (pp. 284-291). ACM. 10.1145/267658.267730.
Roden, B., Lusher, D., Spurling, T.H. et al., 2020. Avoiding GIGO: Learnings from data collection in innovation research. Soc. Networks. In Press. Available online 19 May 2020. 10.1016/j.socnet.2020.04.005.
Rosenfeld, A., Agmon, N., Maksimov, O., Kraus, S., 2017. Intelligent agent supporting human-multi-robot team collaboration. Artif. Intell. 252, 211–231.
Schuster, R., 2002. Cooperative coordination as a social behavior. Hum. Nat. 13 (1), 47–83.
Shaffer, V.A., Probst, C.A., Merkle, E.C., et al., 2013. Why Do Patients Derogate Physicians Who Use a Computer-Based Diagnostic Support System? Med. Decis. Making. 33 (1), 108–118.
Sircar, A., Yadav, K., Rayavarapu, K., et al., 2021. Application of machine learning and artificial intelligence in oil and gas industry. Petrol. Res. 6 (4), 379–391.
Sowa, K., Przegalinska, A., Ciechanowski, L., 2021. Cobots in knowledge work human-AI collaboration in managerial professions. J. Bus. Res. 125, 135–142.
Stern, L.W., Reve, T., 1980. Distribution channels as political economies: A framework for competitive analysis. J. Mark. 44 (Summer), 52–64.
Tjosvold, D., 1988. Cooperation and competitive dynamics within and between organizational units. Hum. Relat. 41 (6), 425–436.
Vinyals, O., Babuschkin, I., Czarnecki, W.M., et al., 2019. Grandmaster level in StarCraft II using multi-agent reinforcement learning. Nature. 575, 350–354.
Walliser, J.C., de Visser, E.J., Wiese, E., Shaw, T.H., 2019. Team Structure and Team Building Improve Human-Machine Teaming With Autonomous Agents. J. Cogn. Eng. Decis. Mak. 13 (4), 258–278.
Woods, D.D., 1996. Decomposing automation: apparent simplicity, real complexity. In: Parasuraman, R., Mouloua, M. (Eds.), Automation and Human Performance: Theory and Applications. CRC Press, New York, NY, pp. 3–18.
Wynne, K.T., Lyons, J.B., 2018. An integrative model of autonomous agent teammate-likeness. Theor. Issues. Ergon. Sci. 19 (3), 353–374.
Yeomans, M., Shah, A., Mullainathan, S., Kleinberg, J., 2019. Making sense of recommendations. J. Behav. Decis. Mak. 32 (4), 403–414.