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Effective human–AI work design for collaborative decision-making

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Abstract

Purpose – With the increase in the adoption of artificial intelligence (AI)-based decision-making, organizations are facilitating human–AI collaboration. This collaboration can occur in a variety of configurations with the division of labor, with differences in the nature of interdependence being parallel or sequential, along with or without the presence of specialization. This study intends to explore the extent to which humans express comfort with different models human–AI collaboration.

Design/methodology/approach – Situational response surveys were adopted to identify configurations where humans experience the greatest trust, role clarity and preferred feedback style. Regression analysis was used to analyze the results.

Findings – Some configurations contribute to greater trust and role clarity with AI as a colleague. There is no configuration in which AI as a colleague produces lower trust than humans. At the same time, the human distrust in AI may be less about human vs AI and more about the division of labor in which human–AI work.

Practical implications – The study explores the extent to which humans express comfort with different models of an algorithm as partners. It focuses on work design and the division of labor between humans and AI. The finding of the study emphasizes the role of work design in human–AI collaboration. There is human–AI work design that should be avoided as they reduce trust. Organizations need to be cautious in considering the impact of design on building trust and gaining acceptance with technology.

Originality/value – The paper's originality lies in focusing on the design of collaboration rather than on performance of the team.

Keywords Human–AI team, Human–AI decision-making, Collaboration, Trust, Role clarity

Paper type Research paper

1. Introduction

In the last decade, there has been an increase in the use of artificial intelligence (AI) for decision-making in organizations (Burton *et al.*, 2019; Ghosh *et al.*, 2019). The World Economic Forum (2020) highlighted that AI has cost-saving potential for businesses. As we understand, AI brings benefits like increased efficiency, reduced errors and more accurate results leading to improved strategic outcomes (Davenport and Kirby, 2015; Davenport *et al.*, 2020; Paschen *et al.*, 2020). Organizations are readily incorporating AI across different functions and processes in the capacity of advisors and decision-makers (Cremer, 2020; Fountaine *et al.*, 2019; Daugherty *et al.*, 2019; Brynjolfsson and McAfee, 2017). The technological advancement in AI opens opportunities for diverse knowledge-intensive work with humans (Seeber *et al.*, 2020). Researchers emphasized that when humans and AI collaborate effectively, they can achieve collective intelligence that improves decision-making (Burton *et al.*, 2020; Huang *et al.*, 2019; Metcalf *et al.*, 2019; Schoemaker and Tetlock, 2017). This augmentation can help humans make unbiased judgments, better decisions, greater creativity in task performance and bounded rationality in finding solutions (Burton *et al.*, 2019; Kahnemann *et al.*, 2016).

Ethical approval: This research does not contain any studies performed with animals by any of the authors. The procedures followed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent: Informed consent was obtained from all the individual participants included in the study.

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This is based on the common logic of specialization, where each takes on a task that they are distinctly better at performing (Jarrahi, 2018; Murray *et al.*, 2020; Seeber *et al.*, 2020). For example, in hiring, first AI is used to screen many applications and shortlist candidates based on an identified criterion, after which humans conduct an in-depth interview of the shortlisted candidates. Emerging perspectives propose that AI-based systems can be "considered a member of a team" (Parry *et al.*, 2016); thereby, their adoption and integration require an "informed, prudent and realistic approach" (von Krogh, 2018). As Puranam (2021), in his recent work, has highlighted, the most interesting question is not whether humans can beat a machine or vice versa but how best the two forms of intelligence can collaborate and how organizations can contribute to this. Organizations are exploring different forms of human–AI collaborations to improve managerial performance and make better decisions (Murry *et al.*, 2020; Shrestha *et al.*, 2019; Haesevoets *et al.*, 2021).

Organizations are investing in AI, but they are yet to experience the anticipated benefits, thus calling it a failure (Fountaine *et al.*, 2019). A Deloitte (2017) report studied senior managers working on more than 150 AI projects, where 47% of the respondents found it challenging to integrate AI with the existing people, processes and systems. Studies have highlighted the gap in the application of AI in manager roles (Allas *et al.*, 2018) due to the limited understanding of the interplay between humans and AI (Kellogg *et al.*, 2020; Traumer *et al.*, 2017). The literature on humans and AI reiterates the role of trust in technology adoption (Glikson and Wooley, 2020). The lack of knowledge of AI, its capability and its role in diverse situations also contribute to acceptance apprehension (Mahmud *et al.*, 2022). Xu *et al.* (2022) have highlighted the challenges with human–AI collaboration and also the potential opportunities which exist in this. They cautioned and encouraged researchers to focus on a human-centric approach with a design goal for human–AI interactions. Researchers have emphasized the need to adapt, interact and integrate these systems with human behavior (Lichtenthaler, 2018; Glikson and Woolley, 2020). Researchers emphasized that there would be transformation and rearchitecting of an organization to collaborate with AI (Iansiti and Lakhani, 2020). This revolution of technology will impact the structure of the workforce, how jobs are designed and task related to it, and how decisions are made (Brynjolfsson *et al.*, 2018; Huang and Rust, 2018; Kellogg *et al.*, 2020; Wirtz *et al.*, 2018; Oldham and Fried, 2016; Waschull *et al.*, 2020). With the inclusion of AI in a different task, there would be partial automation included with a new form of division of labor between humans and AI. Unfortunately, in the past, most AI collaborations have been technology-centered (Shneiderman, 2020; Xu *et al.*, 2019). It is important to note that in the past, studies focused on AI than on the need of humans for systems' usage or efficiency and effectiveness, which has resulted in the failure of AI integration in organizations (Langer *et al.*, 2021; Yampolskiy, 2019). There is a gap in the literature on how the introduction of technology will influence work design (Smith and Carayon, 1995; Puranam, 2021). Researchers have identified the change in the relationship between humans and technology with the emergence of AI (Makarius *et al.*, 2020). There is a need to explore new work designs to make this collaboration effective (Parker and Gorte, 2020; Puranam, 2021).

In human–AI collaboration, the work design plays a critical role as it influences the acceptance of AI as a member of a team and the collaborative outcomes (Seeber *et al.*, 2020). There are various forms in which the design of the human–AI collaboration can be structured (Shreshtha *et al.*, 2019). Across industries, the most commonly used form of human–AI collaboration is AI-advised human decision-making, where the inputs of the machine aid the decision of the human, and the machine acts as a tool in making the decision. With the advancement of machines, in another form, human and AI collaboration would result in a decision with mixed-initiative and emerging team behavior (Bansal *et al.*, 2019; Angwin *et al.*, 2016; Leyer and Schneider, 2021) as Yablonsky (2021) has elaborated well on different categories of AI analytical application like descriptive, diagnostic, predictive, prescriptive and augmented in organizations. This paper is based on the theoretical proposition of Puranam (2021), who proposes different configurations of human–AI collaboration for work designs. Puranam (2021) highlights the distinctive nature of human–AI collaboration, with its differences from human interaction and technology adoption due to the potential in the system for mutual adjustment. Drawing comparison with organizations, human–AI collaboration is also an organization that is a goal-directed multiagent system, and the goal of the system is to make the decision. As the literature suggests, decisions in the multiagent system have a distinctive feature where sometimes the accuracy can improve through pooling and error cancellation (Surowiecki, 2004; Larrick and Soll, 2006; Rokach, 2010). In most of the knowledge work as humans and AI come together to make decisions, the aggregation of inputs can improve quality accuracy. Researchers have urged the need to understand how the task might be shared between humans and AI and the consequences of the different choices (Parker and Grote, 2020). Puranam (2021) elaborates that in human–AI collaboration, decision-making can be seen in two dimensions (1) nature of interdependence and (2) extent of heterogeneity of knowledge or skill needed in the task (Burton and Obel, 1984; Milgrom and Roberts, 1990; Raveendran *et al.*, 2020). Any two tasks are interdependent when the value created by both tasks is different from the sum of value created by performing each task independently. In knowledge-based decision-making, the interdependence of tasks can be *sequential,* where the decision is an input for another or the value of their joint, *parallelly* produced output is super (or sub) additive (Christansen and Knudsen, 2013). Specialized knowledge of each can be used when each member focuses on a task that matches their capability. For instance, there can be a pooling of estimates of profits in parallel to make a better investment decision or a machine to act as a second opinion for a medical diagnosis. This design is to explore configurations that might produce the best result for any given decision task.

Based on the above collaboration work design, the present study proposes that different work designs will influence humans–AI collaboration while engaging in a task (Hackman and Oldham, 1976; Parker and Goter, 2020). Work design choices need to be proactively considered during technology implementation with the socio-technical system principles for joint optimization (Langer *et al.*, 2021; Makarius *et al.*, 2020). The present study aims to understand how AI influences humans as knowledge workers who act as collaborative partners in different work designs. The paper tries to empirically test the proposed configuration to assess the impact on trust, role clarity and feedback preferences. The paper's originality lies in focusing on the design of collaboration rather than on performance. Theoretically, the paper situates itself in the field of designing and improving human–AI collaboration in the workplace. It also adds to the literature on trust and role clarity in human–AI relationships with insight into a collaborative team setting. At a practical level, the study contributes to implementing AI in an organization and its work design structures. The finding of the study indicates human readiness to collaborate with AI as teammates in a decision-making task. The present study uses a human-centric approach to identify the preference for collaboration with AI, which is evaluated through trust, clarity of role and preferred feedback in different work designs. The analysis aims to explore if human trust in AI is a function of (1) replacing human colleagues with AI, (2) the configuration of the division of labor (3) or a combination of both. The rest of the paper is structured as follows: Section 2 presents past literature on human–AI collaboration with work designs and trust, role clarity and feedback. Section 3 focuses on the research methodology. Following this, Section 4 focuses on results and Section 5 the discussion. Then Section 6 elaborates on the theoretical and practical implications, and Section 7 focuses on the limitations and further studies. Finally, Section 8 concludes the paper.

2. Past literature

Organizations are readily deploying AI for making and executing many management decisions (Duggan *et al.*, 2020), thereby leading to an increase in interest by academicians in the implication of their adoption in organizations (Myhill *et al.*, 2021; Bucher *et al.*, 2021). In the management field, researchers are focusing on collaboration between humans and AI since both are assumed to have complementary strengths to make better decisions (Jarrahi, 2018; Raisch and Krakowski, 2021). In this section, the paper highlights some of the literature on human–AI collaboration. Further, it elaborates on different work design configurations that are possible in human–AI teams. It also highlights relevant literature on trust, clarity of role and preferred feedback of humans when collaborating with AI.

Studies in the past have shown how collaboration has led to improved outcomes like reading radiology images (Wang *et al.*, 2016), an increase in IQ in business teams (Wilcox and Rosenberg, 2019), improved team performance of human players in the online game (Shirado and Christakis, 2017), increased efficiency of different processes in organizations, which include decision-making, greater flexibility in systems, increase in the scale of actions of the organization and personalization of information (Wilson and Daugherty, 2018). While there is great appreciation for the potential of AI to revolutionize organizations, there is some level of uncertainty about its consequences on people and organizations (Bedué and Fritzsche, 2022). Frick (2015) highlights, "as these machines evolve from tools to teammates, one thing is clear, accepting them will be more than a matter of simply adopting new technology" (p. 146). For collaborative initiatives, it is important to understand the influence of AI on human perception leading to the behavior of acceptance or avoidance of AI. Avoiding AI undermines usage to make decisions, thus, inhibiting collaborative human–AI teams.

With the increased use of AI for decision-making, researchers are exploring how humans use decision support by AI systems (Burton *et al.*, 2019) and if humans are aversive to the recommended decisions by automation (Dietvorst *et al.*, 2015; Prahl and Van Swol, 2017) or appreciate the recommendation (Logg *et al.*, 2019). Lindebaum shared that "algorithms in organizational decision-making are perpetuated by the striving for an ideal state of reality that is impacted by the ambition of reaching perfect rationality in decision-making" (Lindebaum *et al.*, 2020). Most of the past research in AI-based decision-making is about acceptance and usage (Cao *et al.*, 2021; van Esch and Black, 2019). There is little work on human and AI collaboration tasks and work design (Seeber *et al.*, 2020).

In recent work, Haesevoets *et al.* (2021) have studied the willingness of managers to include machines in the decision-making process, where they found the willingness to accept a cooperative partnership with AI, but as long as humans have the perception that their input and judgment make the decision. Davenport (2016) has emphasized that human–AI collaboration is not possible without the support of human intervention and guidance. Studies have also emphasized evaluating the position of humans in this partnership (De Cremer, 2019; De Cremer and Kasparov, 2021). Research suggests that this relationship is more sophisticated than it was assumed, where employees will not simply follow AI decision-making (De Cremer, 2019, Cremer, 2020). Sowa *et al.* (2021), in a multi-stage study focusing on different types of AI and modes of collaboration with humans, found that humans encouraged human–AI collaboration than complete automation. De Cremer and McGuire (2022) found that humans have opposed the use of AI in a leadership role as they considered them to be less fair. At the same time, they found that humans are open and willing to establish a partnership with AI as teammates but led by humans. Humans want to find an equilibrium of cooperation in a human–AI partnership. Thus, there is a gap in understanding of how this equilibrium can be created and what would be the best mode for humans and AI to collaborate in a productive form. Researchers have identified the need to understand the division of labor between humans and algorithms (Grønsund and Aanestad, 2020) for social and technical convergence (Makarius *et al.*, 2020).

2.1 Work design

2.1.1 Division of labor. As we begin to divide work between humans and AI, there can be allocation of specific tasks between humans and AI, along with specific order in which the inputs of AI are presented to humans (Silverman, 1992; van Dongen and Maanen, 2013; Grønsund and Aanestad, 2020). Considering the nature of interdependence, there is a parallel and sequential form of collaboration between humans and AI (Puranam, 2021; Endsley, 2017). The system's heterogeneity provides for the logic of division of labor with specialization in which each performs different, non-overlapping subtasks based on their respective skills and capabilities (Agarwal *et al.*, 2018; Dellermann *et al.*, 2019). Humans and AI perform different (sub-) tasks with varying output types, and their output is combined. Human–AI teams involve redefining task division and task allocation (Puranam, 2021) to exploit their advantages in terms of superior output and lower cost (Canetti *et al.*, 2019; Murray *et al.*, 2020). For example, in a hiring task, AI can do the first subtask of screening applications and shortlist candidates, and humans can conduct an in-depth interview. A configuration is a specific relation between humans and AI with some form of division of tasks and responsibilities (Grønsund and Aanestad, 2020). There are several possible configurations, but the following six are identified for the context of the study.

Parallel without specialization: A parallel decision-making system with no difference in specialization is, e.g. "While picking a stock to invest in, Human and Algorithm make assessments independently on same data, and the stock is picked for investment only when both agree." Past literature emphasizes that system designers support that parallel system produces greater efficiency (Endsley, 2017). The advantage of this system can be by providing validation to the decisions of humans, and these systems can help increase the effectiveness of the decisions produced. The possible disadvantages of these systems can be on doubling effort with an inefficient use of resources. In such collaboration, there can be increased apprehension toward AI for job loss by humans, leading to avoidance of AI (Donepudi *et al.*, 2020).

Parallel with specialization: In this form of collaboration, humans and AI process different elements of decision simultaneously, e.g. "While writing a report on a company's stock for a client, Human analyzes the qualitative part of the information and Algorithm analyses quantitative part of the information, the report integrates both to make a final recommendation." The possible advantages of this system are efficiency and effectiveness of decision-making (Endsley, 2017). The potential disadvantage of this system is the lack of understanding of humans about the decision-making process of AI (Bader and Kaiser, 2019).

Sequential: In a sequential form of interdependence, there is a flow of decisions in which one system shares the inputs followed by the inputs (Puranam, 2021; Endsley, 2017). In sequential interdependence, the differences in specialization can also impact the process of decision-making. Within a sequential system, there are two possible ways of integrating inputs of an AI, either before or after human processes the available information (Endsley, 2017; Guerlain *et al.*, 1999). *Sequential without specialization (AH):* In this collaboration, AI makes the decision and shares it with humans, and the human does the same task again. "While picking a stock for a client, the first Algorithm may make a recommendation, and then the human offers a "second opinion." Stock is selected only if both agree." The advantage of such collaboration can be that humans can rely on the algorithm to make the decision, and these outputs can force humans to look more deeply into their decisions. The potential benefit of this system can be to increase efficiency (Onnasch *et al.*, 2014) and improve decision quality (Kuncel *et al.*, 2013), subject to validation of AI. The potential disadvantages of this system are that it can influence humans' decisions, limiting the scope of the output given by AI (Endsley, 2017).

Additionally, research in automation has shared that such systems can initially be perceived as highly reliable, leading decision-makers to follow the decision of AI without looking at additional information or potentially contradicting information, leading to overdependence (Lee and See, 2004). Also, these systems can make humans "reduced to the role of [. . .] recipient of the machine's solution" (Silverman, 1992, p. 111), thus reducing the acceptance of AI. The usage of such division of labor also diminished the reputation of decision and loss of opportunity to show the expertise of humans (Arkes *et al.*, 2007; Nolan *et al.*, 2016).

Sequential with specialization (AH): In this, the inputs of AI come before human processes the information, e.g. "While picking a stock for a client, Algorithm does the processing of quantitative data, Human integrates that with insight from qualitative data and produces final report and recommendation." In such a division of labor, each input is integrated. The potential benefit of this system is using each to the best advantage. There can be an increase in information processing speed and greater diversity in information processed as humans receive input and finalize decisions. They can be perceived to have greater control over the process. The potential disadvantage of this situation is the lack of knowledge and understanding of information processed and the decision given by AI (Gillath *et al.*, 2021; Kellogg *et al.*, 2020).

Sequential without specialization (HA): In this form of collaboration, when the humans receive the input of the algorithm after they have made their decision, e.g. "While picking a stock for a client, the first Human may make a recommendation, and then Algorithm offers a "second opinion." Stock is selected only if *both* agree" (Endsley, 2017; Guerlain *et al.*, 1999). In this system, the AI works as an additional source of information that humans can use after they have processed the information (Silverman, 1992). Such division of labor can act as critique or provide feedback to the human decision (Sharit, 2003; Silverman, 1992). In addition to the correctness of a decision, such division of labor can provide an additional point of view to the decision. This division of labor can provide compensation for the loss of reputation of humans and highlight the role of an expert. In addition, that can encourage thorough processing of information and help find better rationales for decisions (Nolan *et al.*, 2016; Guerlain *et al.*, 1999). The potential benefit of such systems is that they can counterbalance human heuristics in decision-making (Derous *et al.*, 2016; Raghavan *et al.*, 2020). It is essential to note the possible disadvantages of this system; it does not reduce work for humans. There can also be an increase in time consumed for processing additional information or exploring different perspectives (Endsley, 2017).

Sequential with specialization (HA): In collaboration, human processes their set of information and give it to AI, e.g. "While picking a stock for a client, Human does the processing of qualitative data, Algorithm integrates that with insight from quantitative data and produces the final report." The advantages of this condition are similar to conditions with specialization with a greater diversity of view and faster processing of information. The potential disadvantage of this configuration can be a loss of control perceived by humans as AI makes the final decision (Kellogg *et al.*, 2020).

Some of the recent literature highlighted the importance of trust (Glikson and Woolley, 2020), role clarity (Makarius *et al.*, 2020) and feedback preferences (Parker and Gorte, 2020) in human–AI collaboration. The different collaboration configurations will impact the perceived level of trust, clarity of role and preference of feedback experienced by humans as they collaborate with AI.

2.1.2 Trust. One of the most commonly referred definitions of trust is by Mayer *et al.* (1995), "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party." This definition is not limited to human–human trust, thus allowing us to consider trust between humans and AI (Wang *et al.*, 2016). Literature highlights the critical factor of trust as a predictor of technology acceptance and adoption of response from a machine (Hoff and Bashir, 2015; Schaefer *et al.*, 2016; Glikson and Wolley, 2020). In particular, trust is critical to the human–AI relationship because of AI behavior's perceived risk and non-determinism (Davis, 2019). The usage of the machine's inputs acts as evidence of trust in the machine (Madhavan and Wiegmann, 2007; Sniezek and Van Swol, 2001), specifically in decision-making tasks (Lee *et al.*, 2013). Hoff and Bashir (2015) emphasized the differences in how trust unfolds between technology and humans. Research suggests that, mainly in the case of technology, trust is built before experience (McKnight *et al.*, 2002). Some dispositions, situations and past experiences can influence an employee to trust and integrate the AI system (Hoff and Bashir, 2015). The performance, process and purpose of AI systems drive the development of trust (Glikson and Wooley, 2020). Past research highlights that there can be numerous contextual factors that can influence trust in AI (Alsheibani *et al.*, 2019; Mc Knight *et al.*, 2002); thus, there is still a gap in the literature on how trust can be managed when designing for human–AI collaboration.

2.1.3 Role clarity. As humans and AI converge, having a clear expectation of the role of AI systems is essential for humans. The management should support humans to understand how their tasks are different from or related to the task of the AI (Makarius *et al.*, 2020). Developing this understanding endorses the comprehension of humans as they interact with machines. Bauer *et al.* (2007) identify role clarity in building an understanding of the expectation of a role. For managers collaborating with AI, a better understanding of responsibilities and tasks within roles helps develop clear expectations that address ambiguity, negative anticipation and uncertainty, impacting performance and commitment (Brougham and Haar, 2018). Makarius *et al.* (2020) propose that managers and human resource experts should help clarify the role of AI systems to employees for better comprehension and collaboration between them, leading to the development of trust. Studies have found that in the human–machine team, developing shared cognition, where members of the team get the capabilities of their teammates, can be helpful for the performance of these teams (Cooke *et al.*, 2013; Demir *et al.*, 2020). Studies have found that humans perceive greater clarity of role with machines when there is an opportunity to interact and understand the machines, thus leading to better performance (Walliser *et al.*, 2019). The perceived clarity in their role in human and machine collaboration in decision-making can help accept AI as teammates.

2.1.4 Feedback. Feedback concerning job and work characteristics focuses on the mastery of the job. Hackman and Oldham's (1976) work on work characteristics emphasizes the role "knowledge of results" has in enhancing motivation. Apart from the motivation effect, they influence performance to enable and support learning. Studies have shared how introducing feedback with complex technology can help an unsuccessful empowerment project (Leach *et al.*, 2001). Parker and Gorte (2020) recognize how the introduction of technology has the potential to enable and reduce feedback. The use of technology and the widespread availability of data can be devolved to make decisions and understand how the task fits the bigger picture. However, technology up-gradation also can reduce feedback leading to loss of skill, as there is decreased awareness of humans with only passive monitoring. When conditions exceed the capability of technology, the conditions of reduced feedback make it difficult for a human to control (Norman, 1990). Studies have cautioned on the overdependence on automation with the implication of skill loss (Newell and Marabelli, 2015). Some of the latest studies have encouraged finding joint human and automation systems that are mutually dependent and work on common goals (Dominiczak and Khansa, 2018). Hence, feedback is crucial for this process. One of the earlier works of Zuboff (1988) in automation shows how feedback can have two strategies, "automate" or "information," where "automate" is for automation of the process that can help to replace humans. At the same time, "information" allows humans to make complex decisions. The above literature highlights that feedback is critical for supporting learning and performance in human–AI collaboration. Thus, feedback preference in work design is crucial for effective performance, as this encourages better engagement with AI and the system and reflects the interest of humans to collaborate.

3. Research methodology

3.1 Data collection and sample

For the study, two separate surveys were created – A and B. In survey A, humans assume to collaborate with another human as a teammate; in survey B, humans assume they are collaborating with AI. An online survey platform Qualtrics was selected to construct the survey. The researchers identified networking organizations in different countries – India, Denmark, Singapore and Malaysia, to send out the survey. These organizations had a vast network of knowledge workers across industries and regions. They agreed to share the survey instead of reporting the research findings. The survey was titled "The Bionic Readiness Survey" with a tag line "Laying the foundation of Human–AI collaboration." The link to the survey was shared with a brief introduction to the connections of the networking organizations. Participation in the study was voluntary, and by clicking, they gave consent to share their responses. The online link to the survey was circulated using the networking organizations and their connection. The sample was collected over three months.

As mentioned, surveys A and B had six collaboration configurations for decision-making. Any person agreeing to take the survey was randomly assigned to survey A or B by the platform. Those who took the study were randomly given any one of the surveys. In survey A or B, the participant was randomly shown two out of the six collaboration configurations. There was a description of the situation in each configuration in words and a pictorial illustration. Further, an example of an actual situation that depicts the configuration was given to support the understanding. In response to each configuration, the participants were asked to share their perception of the level of trust, clarity of role and preferred feedback style in each configuration. Upon completing the survey, the participant filled a short AI aversion scale. After completing the responses, demographic details were collected – age, gender, organization size and primary job.

The participants who received survey A got the following instruction "*Imagine . . . that a new teammate has been introduced to work alongside you as a colleague to help make decisions. Assume that your teammate is comparable in effectiveness and efficiency with you. How do you feel about each of these configurations in which you might work with them?*" While participants who received survey B were given the following instructions "*Imagine . . . that an Artificial Intelligence (AI) powered machine has been introduced to work alongside you as a colleague to help make decisions. Assume that the AI is comparable in effectiveness and efficiency to a typical human for its assigned tasks. How do you feel about each of these configurations you might work with the algorithm?*" After reading the information, the participants in each survey received two random configurations and responded to the survey questions.

A total sample of 309 participants was captured. On analysis of the result, 23 responses were discarded (10 due to missing data and 9 could not answer the attention question and 4 were in a straight line). In survey A, there were 151 respondents where there were 94 males (62.2%), 52 females (34.4%), 1 non-binary (0.6%) and 4 (2.6%) preferred not to say. The average age of the participants in survey A was 43.7 years (SD = 14.05). In survey B, there were 135 respondents where there were 92 males (68.7%), 41 females (30.3%) and 2 (0.8%) participants who preferred not to say. The average age of participants in survey B was 40.7 years (SD = 13.78). The demographic details of the sample were collected on the primary job and organizational size. The details are presented in Table 1.

3.2 Measures

Jian *et al.* (2000) adaptions were used to assess the trust. The reliability coefficient of the scale was found to be 0.873. One of the items included was "I am confident in this form of collaboration between me and the algorithm at work." The scale was measured using a 1–5 Likert scale. The same scale was adapted for human teams' interaction, and the item included read, "I am confident in this form of collaboration between my teammates at work and me."

Variable	Category	Frequency	Percentage
Gender	Male	186	65.03%
	Female	93	32.51%
	Other	7	2.44%
Age	18–24	37	12.93%
	25–34	73	25.52%
	35–44	50	17.48%
	45–54	65	22.72%
	55–64	41	14.33%
	65- above	20	6.99%
Primary job	Student	46	16.08%
	Making decision	74	25.87%
	Managing people	49	17.13%
	Producing physical products	2	0.69%
	Producing intangible outputs	52	18.18%
	Providing services	63	22.02%
Organization size	1–10	20	6.99%
	11–50	50	17.48%
	51–200	46	16.08%
	201–500	28	9.79%
	501–1,000	32	11.18%
	1,001–5,000	25	8.74%
	5,000 and above	85	29.72%

Table 1. Demographics description of the sample

Role clarity was assessed using Hassan (2013). The reliability coefficient of the scale was found to be 0.888. One of the items included was, "In this form of collaboration between me and the Algorithm, I would know exactly what I am supposed to do." The same scale was adapted for human teams' interaction, and the item included read, "In this form of collaboration between my teammate and me, I would know exactly what I am supposed to do." The aversion towards AI was measured using an adapted version of the fear-based xenophobia scale (Van der Veer *et al.*, 2013). The reliability coefficient for the scale was found to be 0.87. One of the items included was "Interacting with and using AI makes me uneasy." The scale was measured using a 1–5 Likert scale.

4. Results and analysis

Linear regression was used to analyze the results. First, we examined the predictors for AI aversion. After controlling for the use of AI, the effect of age, gender, primary job and organizational size were assessed for aversion to AI. The result indicates there was a significant effect of age and primary on aversion to AI (Table 2). As age increased, there was a decrease in aversion towards AI. The result also shared that people in decision-making roles had a greater aversion to AI. Further, Table 3 represents the descriptive data for surveys A and B.

The data were analyzed on the three identified research questions as fore mentioned. First, given AI as a colleague, which configuration gives the highest trust, role clarity and feedback. To analyze this in a human–AI dyad, the effect of the six collaborative configurations was measured on trust, role clarity and feedback preference using linear regression. The six conditions were independent variables in which configuration 1 was used as a reference condition. After controlling for aversion to AI, the effect of the condition was measured successively first on trust, then on role clarity and feedback preference (Table 4). For the trust, there was a statistically significant difference in configuration 3, i.e. there was a lower level of trust experienced when this configuration was presented. For role clarity, there was a statistically significant difference in configuration 2, i.e. there was a greater level of role clarity expressed by humans in this configuration. Humans expressed no statistically significant preferred form of feedback in human–AI dyads for feedback.

The second research question assessed for any configuration is whether there is a difference between a colleague being AI vs human on trust, role clarity and feedback. To assess if the result of the human–AI dyad (Table 4) is not a result of the identity of the collaborator being AI, a second analysis was done by comparing the collaborator being a human. After controlling for AI aversion and comparing human vs AI conditions, this analysis showed the effect on trust, role clarity and preferred feedback (Table 5). For the trust, there was a statistically significant difference in configuration 4, i.e. there was an increase in

Table 2. Predictors for AI aversion

Variable	β	SE	t	p	R^2	F-statistics
Age	−0.06980	0.03359	−2.078	0.0385*	0.025	4.49* (df = 2, 284)
Gender	0.06155	0.09999	0.616	0.5386	0.014	2.49 (df = 2, 284)
Primary job (making decisions)	−0.30901	0.16182	−1.910	0.0472*	0.037	1.84* (df = 7, 279)
Organization size	0.03244	0.02091	1.552	0.1217	0.020	3.52 (df = 2, 284)

Note(s): Significant codes: "*" 0.05 "." 0.1 " " 1
Source(s): Primary

Table 3. Descriptive for survey A and survey B, mean and standard deviation

	Survey A			Survey B		
Variables	Trust	Role clarity	Feedback	Trust	Role clarity	Feedback
Config-1	4.64 (1.02)	4.38 (1.25)	0.55 (0.50)	4.81 (1.12)	4.43 (1.25)	0.57 (0.50)
Config-2	4.72 (1.09)	4.87 (0.99)	0.55 (0.50)	4.77 (0.61)	4.65 (1.18)	0.46 (0.50)
Config-3	4.53 (1.22)	4.61 (1.18)	0.54 (0.50)	4.31 (1.13)	4.24 (1.13)	0.40 (0.49)
Config-4	4.46 (1.17)	4.41 (1.16)	0.64 (0.48)	4.82 (1.06)	4.80 (0.97)	0.58 (0.49)
Config-5	4.83 (0.95)	4.67 (1.08)	0.71 (0.45)	5.05 (0.75)	4.82 (0.89)	0.40 (0.49)
Config-6	4.60 (1.16)	4.55 (1.19)	0.62 (0.49)	4.74 (1.01)	4.51 (0.98)	0.53 (0.50)

Source(s): Primary

Table 4. Result for human–AI dyad after controlling for AI

Variable	Trust	Role clarity	Feedback
Constant	4.73	4.34	0.577
Confi-2	−0.04 (0.23)	0.63 (0.25)*	−0.03 (0.11)
Confi-3	−0.50 (0.26)*	0.15 (0.28)	−0.00 (0.11)
Confi-4	−0.21 (0.25)	−0.00 (0.27)	0.08 (0.10)
Confi-5	0.23 (0.24)	0.33 (0.28)	0.13 (0.10)
Confi-6	0.00 (0.26)	0.19 (0.28)	0.00 (0.11)
Constant	4.81 (0.17)	4.34 (0.27)	0.55 (0.09)
Observation	270	270	270
R^2	0.047	1.17	0.49
Residual standard error	0.964	0.035	0.015
F-statistics	2.07* (df = 5, 264)	1.82* (df = 6, 263)	0.66 (df = 6, 263)

Note(s): Significant codes: "*" 0.05 "." 0.1 " " 1
Regression coefficient and standard error reported
Confi- Configuration, df-degrees of freedom

Variable		Regression coefficient and standard error	N	Constant	R^2	Residual standard error	F-statistics
Config 1	Trust	0.21 (0.24)	98	4.88 (0.41)	0.022	1.11	1.04 (df = 2, 95)
	Role clarity	0.09 (0.28)	98	4.57 (0.44)	0.00	1.30	0.23 (df = 2, 95)
	Feedback	0.02 (0.11)	98	0.69 (0.14)	0.01	0.49	0.71(df = 2, 95)
Config 2	Trust	0.11 (0.18)	103	4.90 (0.29)	0.01	0.85	0.65 (df = 2, 100)
	Role clarity	−0.31(0.23)	103	5.03 (0.23)	0.02	1.07	1.01 (df = 2, 100)
	Feedback	−0.05 (0.11)	103	0.55 (0.14)	0.00	0.50	0.18 (df = 2, 100)
Config 3	Trust	−0.04 (0.29)	89	4.58 (0.32)	0.00	1.19	0.33 (df = 2, 86)
	Role clarity	−0.25 (0.30)	89	4.57 (0.31)	0.01	1.19	0.62 (df = 2, 86)
	Feedback	−0.16 (0.11)	89	0.49 (0.13)	0.02	0.50	1.07 (df = 2, 86)
Config 4	Trust	0.49 (0.24)*	101	4.91 (0.28)	0.08	1.09	*4.38 (df = 2, 98)
	Role clarity	0.52 (0.23)*	101	4.79 (0.28)	0.08	1.04	*3.18 (df = 2, 98)
	Feedback	−0.05 (0.10)	101	0.64 (0.13)	0.00	0.49	0.14 (df = 2, 98)
Config 5	Trust	0.22 (0.22)	95	4.56 (0.39)	0.03	0.93	0.77 (df = 2, 92)
	Role clarity	0.14 (0.22)	95	4.12 (0.40)	0.07	0.99	1.84 (df = 2, 92)
	Feedback	−0.29 (0.11)*	95	0.63 (0.13)	0.09	0.48	*3.91 (df = 2, 92)
Config 6	Trust	0.13 (0.27)	87	4.64 (0.35)	0.00	1.14	0.13 (df = 2, 84)
	Role clarity	−0.03 (0.26)	87	4.42 (0.37)	0.00	1.12	0.08 (df = 2, 84)
	Feedback	−0.03 (0.12)	87	0.67 (0.15)	0.01	0.50	0.40 (df = 2, 84)

Note(s): Significant codes: "*" 0.05 "." 0.1 "" 1
Confi- Configuration

Table 5.
Comparing human vs AI as teammate

the level of trust experience in this condition. For role clarity, there was a statistically significant difference found again in configuration 4, i.e. there was greater clarity in role experienced in this condition. For feedback preference, there was a statistically significant difference found in configuration 5, i.e. their lower need for independent feedback in this condition.

To assess the third research question to evaluate if the result found were not a result of configuration, analysis was run across all conditions irrespective of whether the collaborator is human or AI. In this analysis, after controlling for AI aversion, considering configuration 1 as a reference, the effect of all the configurations was seen on trust, role clarity and preferred feedback (Table 6). For the trust, there was a statistically significant difference in configuration 3, i.e. there was lower trust experienced in this condition. For role clarity, there was a statistically significant difference found in configuration 2, i.e. there was greater role clarity experienced as a result of this condition. For preferred feedback, there was a statistically significant condition expressed.

5. Discussion

Even as organizations increasingly adopt AI for managerial decision-making, still there is a gap in the literature for human-centric collaborative work design with AI (Parker and Grote, 2020; Puranam, 2021; Grønsund and Aanestad, 2020; Xu *et al.*, 2022). With this background, the present study addresses the research question of understanding how to organize human–AI collaboration. The paper intends to build a theoretical understanding of work design – the

Table 6.
Comparing the effect of the configuration on trust, role clarity and preferred feedback

Variable	Trust	Role clarity	Feedback
Constant	4.65	4.37	0.577
Confi-2	0.04 (0.16)	0.45 (0.17)*	−0.08 (0.07)
Confi-3	−0.35 (0.17)*	−0.02 (0.18)	−0.10 (0.08)
Confi-4	−0.12 (0.16)	0.16 (0.17)	0.02 (0.07)
Confi-5	0.24 (0.17)	0.34 (0.18)	−0.01 (0.08)
Confi-6	0.02 (0.17)	0.17 (0.18)	−0.05 (0.08)
Constant and standard error	4.65 (0.13)	4.37 (0.14)	0.61 (0.06)
Observation	572	572	572
R^2	0.034	0.026	0.017
Residual standard error	1.051	1.128	0.498
F-statistics	2.279* (df = 7; 566)	1.703* (df = 7; 566)	1.099 (df = 7; 566)

Note(s): Significant codes: "*" 0.05 "." 0.1 " " 1
Regression coefficient and standard error reported
Confi- Configuration

division of labor through task interdependence and heterogeneity of knowledge between humans and AI (Puranam, 2021).

The primary analysis aimed to identify antecedents that predict aversion to AI. The results show age and primary job are significant predictors of AI aversion. The result found that there is a lower level of aversion experienced with an increase in age. These findings are not in sync with the past results where studies have found that age did not influence aversive towards AI (Logg *et al.*, 2019). Though it is cautionary to know that as the experience of people with technology grows, there is constant change in their attitude and behavior in interaction with AI (Sowa *et al.*, 2021). The younger generation may be found to vary more in using AI as they would understand its implication on their job prospects, while those at a later stage of their carrier would not be apprehensive or may even have low level of understanding of AI. Also, the result found that aversion towards AI was greater by people in decision-making roles than in other job roles. This finding aligned with studies where AI decisions are perceived as a black box (Asatiani *et al.*, 2021), which influences the acceptance of inputs. Considering the association of risk with decision-making, people in critical roles can vary using information from an AI that cannot be explained. Another variable evaluated was the hierarchy level of the employee.

The first research question focused on the human–AI dyad to identify configuration with utmost trust, role clarity and preferred feedback. The result found that humans experienced a low level of trust in configurations where they work sequentially with an AI with no specialization difference, and humans receive the inputs from AI. The results found are supported by past literature where humans have shared their apprehension to univocally accept the inputs of AI (Dietvorst *et al.*, 2015; Prahl and Van Swol, 2017). These configurations reduce the role of humans as the recipient of information from the machines (Silverman, 1992), thus reducing their acceptance. In such a configuration, there is a loss of opportunity for humans to show their expertise (Arkes *et al.*, 2007; Nolan *et al.*, 2016). These results are supported by some recent work, where humans have emphasized that they would prefer to lead in human–AI collaboration (De Cremer and McGuire, 2022). The results also found that humans experienced clarity in the role when humans and AI worked parallelly with differences in specialization. Past literature emphasizes that system designers support those parallel systems as they produce greater efficiency (Endsley, 2017). The configuration heterogeneity provides for the logic of division of labor with specialization in which each performs different, non-overlapping subtasks based on their respective skills and capabilities (Agarwal *et al.*, 2018; Dellermann *et al.*, 2019). These collaborations have yielded economic, speed and performance benefits with scale growth (Iansiti and Lakhani, 2020). There were no feedback preferences expressed in this dyad.

The second research question focused on understanding whether there is a difference between a colleague being AI vs human on trust, role clarity and feedback preference. The result found a greater level of trust and clarity of role when humans collaborated with AI than with a human. The configuration was sequential with no specialization differences, and AI made the decision second. In preference of feedback, it was found that there is less need for independent feedback in configurations where there is a difference of specialization between human and AI in sequential condition and human comes second. The results align with past literature, indicating human readiness to collaborate with AI for managerial decision-making (Logg *et al.*, 2019; Haesevoets *et al.*, 2021). These results align with some of the recent work by Langer *et al.* (2021), where humans expressed greater satisfaction and self-efficacy in decision-making when the decision-making system provided their output after humans processed the information. The potential benefit of this system can be to increase efficiency (Onnasch *et al.*, 2014) and improve decision quality (Kuncel *et al.*, 2013), subject to validation of AI. The finding highlights humans' apprehension to collaborate with another human on the same task; this could be due to the anxiety of apparent competition from another human.

The third research question focused on understanding differences across configuration, regardless of whether the colleague is human or AI, on trust, role clarity and feedback. The findings reveal that the humans experienced the lowest trust in a configuration where AI and humans work sequentially with no differences in specialization, and human gave their input second. These findings are in line with the past literature where humans have shared apprehension about blindly following the information of the machines (Dietvorst *et al.*, 2015; Prahl and Van Swol, 2017). The exact configuration also shared lower trust in human–AI dyads. The antecedent analysis also revealed that people in the decision-making role had shared apprehension about using AI. The finding is similar to those of the human–AI dyad, where human does not want to be reduced to the state of being a recipient of information from that of AI. This configuration also reinforces humans' apprehension of the threat of being replaced by AI in jobs (Donepudi *et al.*, 2020). There was high role clarity in the configuration where AI and humans worked sequentially, with differences in specialization, and humans gave their inputs second. This configuration was also found to provide greater clarity in human dyad conditions. Considering human decision-making, the provided configurations allow us to understand possible interactions between humans and AI. Organizational designers can use the patterns to create work designs and divide and allocate tasks between humans and AI.

The result provides an overview of how configuration preferences are influenced when a collaborator is a human or an AI. Further, it also explores how the influence of the configuration is on the level of trust, role clarity and feedback preference irrespective of human or AI collaborator. While there is a configuration where working with an algorithm produces a very low level of trust (sequential without specialization, where humans come second), there is no configuration in which AI as a colleague produces lower trust than humans as a colleague. The humans share a readiness to collaborate with AI, but their distrust is primarily because of the configuration. The human distrust in AI may be more about the configuration of the division of labor in which AI and humans are together than about human vs AI. Considering the future, the study's finding gives clear pointers for organization designers as they design work and allocate tasks between humans and AI. There is a clear preference for collaboration with AI than humans in decision-making. The results show that specialization gives humans greater role clarity in parallel and sequential configurations. To develop greater trust, humans need to be actively engaged in decision-making. There is lower confidence experienced by humans when their role is reduced to that of a recipient of information. There are clear predictors identified that can contribute to the development of aversion towards AI, age and people in a decision-making role. Organizations should take cautious measures as they introduce AI to these identified groups.

6. Implication

6.1 Theoretical implication

Emerging models of human–AI collaboration have theoretically emphasized the role of job design in the acceptance of AI by employees (Makarius *et al.*, 2020; Chowdhury *et al.*, 2022). The study contributes to the gap in the literature on human–AI work design with the division of labor (Parker and Gorte, 2020). The study empirically contributes by highlighting the role of job design in building trust and role clarity through interdependence and heterogeneity between humans and AI. The finding highlights that the work design of human and algorithm in a sequential configuration where AI comes first followed by human, though commonly adopted in practice, contributes to lowering trust in AI. There are system preferences for greater clarity in the role for better collaborative experiences.

The literature on human and AI distinctly emphasize the role of aversion in the adoption of AI in organizational decision-making (Dietvorst *et al.*, 2015; Burton *et al.*, 2019). Researchers have emphasized the lack of clarity on causality for AI aversion and apprehension (Hou and Jung, 2021). The finding of the study highlights that controlling for aversion makes for a greater level of trust in human–AI collaboration that the aversion toward AI could be a result of the configuration in which humans and AI are used rather than the actual AI. The configuration in the form of division of labor can contribute to diminished role and perception of threat with respect to the task leading to avoidance of AI.

As organizations struggle to include AI organizations, researchers are proposing different socio-technical models that can be considered for their socialization (Makarius *et al.*, 2020; Chowdhury *et al.*, 2022). The human's readiness to collaborate with AI is reflected in the result, which contributes to research that explores ways in which humans can be more accepting of the participation of AI in decision-making (Haesevoets *et al.*, 2021; Leyer and Schneider, 2021). The study's finding adds new insight into how work design can influence the clarity of role and development of trust. The influence of work design of human–AI can develop trust, and clarity of role can be insightful.

6.2 Practical implication

Many empirical reports emphasize that humans and AI can augment and produce better results than either can do alone (Bader and Kaiser, 2019; Grover *et al.*, 2020; Wang *et al.*, 2016). Acknowledging that human–AI collaboration is the future work model (Cremer, 2020; Jarrahi, 2018; Seeber *et al.*, 2018), organizations are struggling to create a balance between humans and AI (Schrage, 2017). We understand that humans are aversive to the advice generated by AI (Dietvorst *et al.*, 2015; also see Bigman and Gray, 2018; Lee, 2018; Önkal *et al.*, 2009). To answer this question, the study shares insight into different effective and ineffective work designs that can be useful to make this augmentation productive and AI more accepting in decision-making situations.

At the onset, the result of the study indicates the readiness of humans to collaborate with AI (Logg *et al.*, 2019). Thus, it is critical to understand different factors inhibiting this collaboration. There is enough evidence showing a lack of consideration of social and organizational factors while introducing techno-centric changes; the study directs organization designers to proactively shape work design alongside human-centered technologies to produce benefits (Clegg and Shepherd, 2007; Parker and Grote, 2020). Organizations need to acknowledge the role of aversion in influencing the acceptance of AI. The highlighted role of age and the primary job of decision-makers can contribute to aversion towards AI. Literature suggests that there can be different ways in which this can be addressed, like building understanding about the capability of the AI and not letting it be perceived as a "black box" (Gillath *et al.*, 2021; Adadi and Berrada, 2018). The organization should focus on building knowledge about AI through training than can help build greater acceptability of machines in making decisions.

As the literature suggests that automation is of the task and not a job (Aggarwal *et al.*, 2018), there is a need to design better the division of labor between humans and AI on different tasks considering interdependence and heterogeneity. As organizations increasingly adopt human AI in decision-making, the most frequently used design is when humans receive the inputs of AI and process the information further. Ironically the finding of the study highlights that under this condition, there is decreased trust experienced by humans. The finding clearly says that humans will only trust AI when it is not a threat to their role. They share the need for greater control over AI and the final decision in collaborative decisions (Haesevoets *et al.*, 2021). Since many organizations use this model, there is clear evidence that such configuration reduces trust in AI and greater aversion towards them. This form of collaboration is reduced to the role of receiving inputs from the machine, where they cannot express their expertise, thus increasing their perception of the threat of AI taking over their jobs. It is essential to introduce an algorithm that humans understand and have some control over in organizations. Humans should have the freedom to control the algorithm's output (Dietvorst *et al.*, 2018). Though the nature of interdependence does not significantly impact the division of labor, it can be parallel or sequential; heterogeneity of knowledge affects trust and greater clarity of their role in the collaboration. The work design between humans and AI can develop clarity on the role. Understanding each other's context helps humans develop greater acceptance of AI.

7. Limitation and further studies

There are some limitations in the studies. When we are drawing a comparison between humans and AI as collaborative partners in the two surveys, we compare between groups. There is an inherent advantage with this situation as we get an unbiased evaluation of each decision-maker separately, but this does not evaluate humans' preference by explicitly asking collaboration configuration preference when a collaborator is human or AI. Another limitation was that the configurations were presented as decision-making scenarios. The participants were asked to imagine themselves in this collaborative decision-making scenario, which can be a constraint. Future research should extend the work and complement the finding by exploring the perception of trust and role clarity experienced by people in actual work setups collaborating with AI in decision-making scenarios. If budget allows, researchers should evaluate different work designs adopted in a different work setting, where humans and AI may be in parallel or sequential settings with differences of specialization present or not. Comparison of them can give better insight into acceptance of work design with AI. The scenarios presented to the participants were not real-life scenarios that operate in a complex and stressful work environment as managers. There could be differences in a situation where the task and the consequence of making a wrong decision would be high are complex. Under such highly contextual conditions, would there be a difference in collaboration preference? Future studies should explore job-specific decision-making and its impact on AI's collaborative preferences.

8. Conclusion

As organization experts' design work for human–AI collaboration, they should consider the division of labor for the interdependence of tasks and heterogeneity of knowledge between them, as it has a significant role in adopting AI. Different configurations influence trust and role clarity with AI than actual algorithm influencing. The study brings to the forefront the readiness of humans to collaborate with AI as teammates in collaborative decision-making. There is a clear need for using a human-centric view to adopt AI in decision-making roles (Xu *et al.*, 2022). The analysis found that the configuration of human–AI produces lower trust than others. Also, there is no configuration in which AI as a colleague produces lower trust than humans. In contrast, some configurations contribute to greater trust and role clarity with AI as a colleague. The human distrust in AI may be less about human vs AI and more about the division of labor in which human–AI work. To ensure greater trust, it is essential to make humans feel secure in their roles. They would not want their role to be reduced to being recipients of information from AI.

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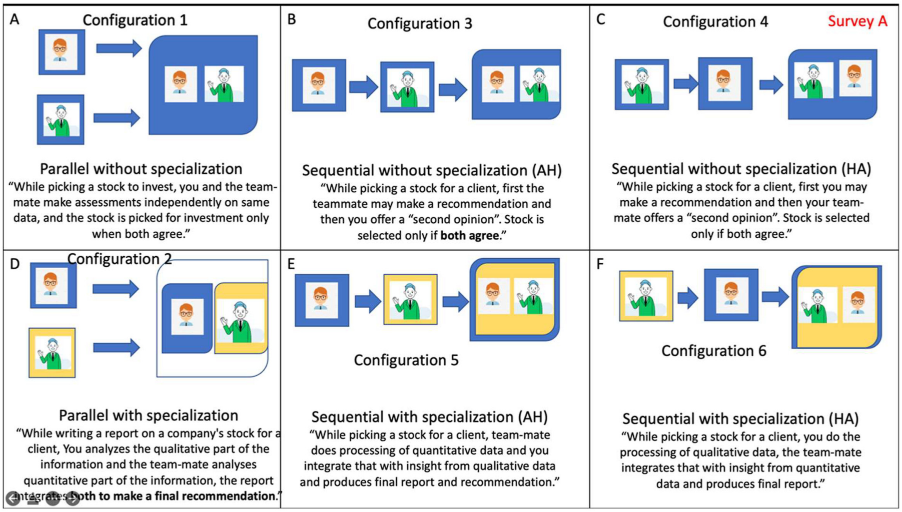
Appendix

Survey A



Survey B