Pre-Analysis Plan for "AI, Organizations, and Tacit Knowledge"

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Introduction

Given recent advancements in artificial intelligence (AI) and machine-learning technology, there are increasing concerns that many of today's jobs will become automated and performed by robots or machines. The degree of such automation is unprecedented. A recent report by PWC (2017) estimates that nearly 40 percent of U.S. jobs will be impacted by automation within the next 15 years. In his best-selling book "AI Superpowers: China, Silicon Valley, and the New World Order", Kai-Fu Lee calculates that almost half of all current jobs will become automated. Understanding this labor market phenomena has important implications for firms, governments, and the public at large.

Much of this research has been grounded in a task-based approach introduced by Autor et al. (2003), which focuses primarily on job's technical suitability for automation. While the task-based approach focusing on technical capabilities represents an important first step, organizations are key drivers of technological change, and we must understand the role they will play in the future of work. In this paper, we propose one way to think about organizations in this debate. Grounded in the knowledge-based theory of firm (Kogut and Zander 1992), we theorize about the ways in which tacit versus explicit knowledge affects coordination and team performance, and how the introduction of AI onto a team impacts existing organizational routines. We posit that we can theorize of automation as the transfer of knowledge from an individual to a machine and argue that such transfer is more difficult when knowledge is tacit, so automation will be more difficult to implement for teams whose coordination is based on organizational routines rather than explicit mechanisms. We also test for complementarities between organizational knowledge, AI, and coordination ability. We describe our experimental approach in more details below.

Research design

Our study will be conducted using a randomized lab experiment at the Behavioral Research Lab at Columbia Business School. Groups of four participants will be randomized into different team arrangements to complete a coordination-based game. We describe each component in more details below.

Overview of the game

Participants will be put onto teams of four and play the minigame "Dash and Dine" on Super Mario Party on the Nintendo Switch. A video of the minigame can be found here: `https://www.youtube.com/watch?v=cz1eB-X6a2o`. In the game, teams of four have one minute to grab requested ingredients from tables to complete recipes for points. Each successful recipe is one point, and players must coordinate with the others on their team to complete the recipe. The game has several attractive properties for our purposes: (i) it is a coordination game where communication is required, (ii) outcome

Table 1: Treatment arms in 2x2x2 design

High Coordination AI

	Tacit	Explicit
AI		
Human		

Low Coordination AI

	Tacit	Explicit
AI		
Human		

scores are easily collectable and displayed on the screen at all times, (iii) there is a built-in AI that can easily replace a player, and (iv) no prior experience with the gaming system is necessary for participants.

Teams will play for a total of 15 rounds, but the structure of the team will vary depending on whether the team is randomly assigned to the tacit knowledge or explicit knowledge condition, which we describe below.

2x2x2 factorial design

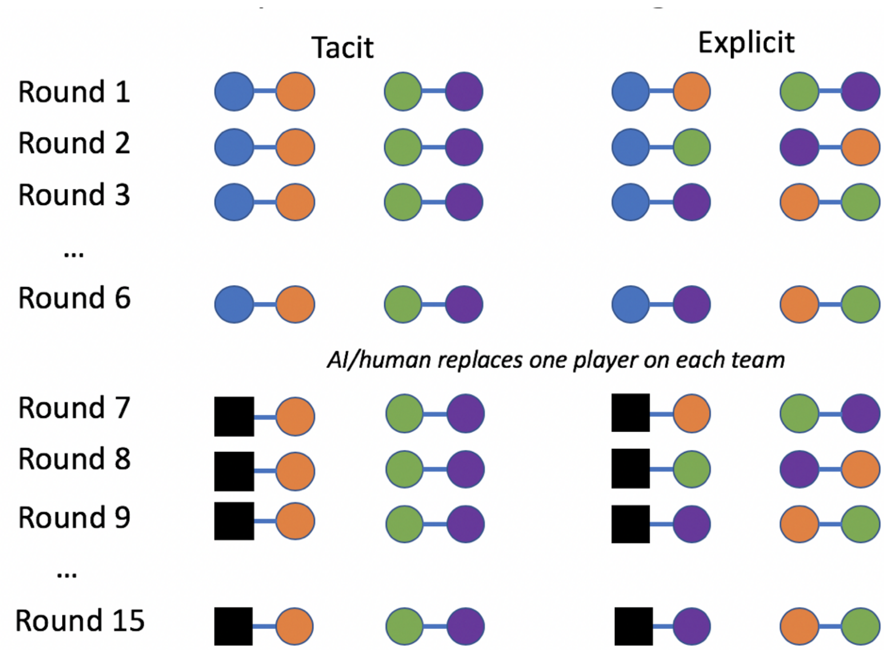
Our experiment will follow a 2x2x2 factorial design. First, teams will be randomly assigned to either the tacit coordination condition or the explicit coordination condition. Second, teams will be randomly assigned to have a team-member replaced by either an AI or by another human player. This treatment arm will allow us to test whether the effects we observe related to tacit-vs-explicit knowledge are unique to AI's or also occur when a new human player is introduced to the team. Third, teams randomized to coordinate with an AI will be randomly assigned an AI with strong or weak coordination ability (though we will focus on only the former this summer). Having three treatment arms allows us to test for complementarity between organizational elements, an important driver of firm organization and strategic decision making. Our treatment arms are displayed in Table 1.

Coordination via tacit versus explicit knowledge

Our lab experiment will manipulate how knowledge is encoded on teams. Knowledge in organizations can be one of two types. Some knowledge in the firm is explicit, in that it is easy to identify and articulate. In the organizational context, such knowledge is usually codified, as in a firm having manuals, blueprints, or patents that explicitly describe the process in detail. Knowledge in the firm can also be tacit, in that it is difficult to articulate and codify. Michael Polanyi (1966) remarked that "we can know more than we can tell", and this is indeed true within firms. For example, a team of employees may learn to coordinate their actions without any explicit agreement from the group to do so. Tacit knowledge is often encoded in organizational routines that are linked to organizational efficiency. A rich literature in both evolutionary economics (Nelson and Winter 1982, 2002) and the behavioral theory of the firm (Cyert and March 1963) has discussed firms' use of routines to coordinate work. Both of these views theorized that routines helped performance by increasing coordination and decreasing communication costs (Becker and Zirpoli 2008). Since AI adoption involves making organizational explicit, it is natural to study how AI adoption interacts with how knowledge is encoded in the firm.

Our experiment will manipulate the use of routines by interfering with each team's ability to rely more on formal/explicit communication. The organizational learning literature has found that team routines depend on interactions between members that are both repeated and near-identical (Cohen and Bacdayan 1994; Gersick and Hackman 1990). For that reason, we manipulate the degree to which interactions between members are near-identical. We display our manipulation in Figure 1 below.

Figure 1: Outline of experiment



While both teams have repeated interactions (playing the same game) with the members on their teams, the interactions between the tacit team are more identical across rounds— for each round, they play with the same team member (for example, player orange and player blue play together for the first 6 rounds in the tacit condition). Meanwhile, the teams in the explicit condition will alternate partners every round, which we predict will lead to less coordination via routines and increased coordination via verbal and explicit communication.

AI vs human

After the first six rounds, our experiment will randomly replace one of the team members with either an AI or another human player. In Figure 1, this occurs in round 7 when the blue player is replaced by the black box. Teams will be randomly assigned to play with either the AI or another human.

Coordination ability of AI

Our last treatment condition will vary how well the AI can coordinate with the team. We will first run the 2x2 (tacit vs explicit, AI vs human) experiment with an AI with high coordination ability, but in the future we may manipulate the coordination ability of the AI by lowering how well it can coordinate with other players.

Spillovers

Our experimental design allows us to also measure the spillover effects from AI adoption. Because only one of the sub-teams in a team receives the AI player, we can measure how this affects performance on the other sub-team. In Figure 1, the orange player coordinates with the AI (black box), so we can estimate whether this impacts the performance of the green and purple pair. The game requires coordination not only within sub-teams but also across them, and our design allows us to measure these effects to understand not only how AI affects in-unit performance, but also the performance of other divisions of the team.

Hypotheses

We will use our experiment to test three primary hypotheses and one secondary hypothesis.

Our three primary hypotheses center around how tacit versus explicit knowledge affect coordination and performance, and how the introduction of AI onto a team impacts existing organizational routines:

- H1: Coordinating through tacit knowledge/routines increases performance by decreasing communication costs (players in the tacit condition speak fewer words during the game and receive more points)
- H2: The introduction of AI onto a team interferes with existing routines and lowers team performance (performance decreases for teams in both the tacit and explicit conditions when an AI replaces a team player)
- H3: Teams who coordinate through tacit knowledge/routines will see a larger drop in performance than those who communicate via explicit mechanisms when an AI is introduced (the decrease in performance is larger for teams in the tacit condition versus those in the explicit condition).

Our secondary hypothesis aims to test whether the phenomena observed in H1–H3 are unique to AI or would also occur when a new player joins the team

- H4: The introduction of AI onto a team is not the same as introducing a human player onto a team.

We will test H4 by (i) comparing the spillover effects of AI vs human agents, (ii) comparing the direct effects for AI vs human players across the tacit/explicit condition, and (iii) comparing the direct effects for AI vs human players across the AI difficulty conditions.

Empirical Analysis

In order to analyze the data collected from the experiment, we will use both visual methods and regressions.

First, given that we will have 15 rounds of data for all teams, we will plot average performance across time by treatment condition. This will help us visualize the results and aid in presentation purposes.

Second, we will also use regression analysis to more formally analyze the results. In order to estimate the main treatment effects, we will run the following regression (one for the high coordination AI and one for the low coordination AI)

$$y_{i,j,r} = \beta_0 + \beta_1 * Tacit_i + \beta_2 * AI_{i,j,r} + \beta_3 * Tacit_i * AI_{i,j,r} + \epsilon_{i,j,r}$$

In this regression, i indexes teams of 4, j indexes sub-teams of 2, and r indexes rounds. $Tacit_i$ is a binary indicator whether team i was assigned to the tacit condition, $AI_{i,j,r}$ is a binary indicator if subteam j on team i has an AI player on it in round r, and $\epsilon_{i,j,r}$ is the error term (with robust standard errors clustered at the team level). β_1 captures the effect of coordinating using routines in the first six rounds. β_2 captures how the introduction of an AI affects team performance in rounds 7 through 15. β_3 captures the difference in performance following AI introduction for teams coordinating via tacit knowledge versus explicit knowledge.

In addition to this regression, we will also examine three more analyses:

- complementarities: In order to test whether there are complementarities between organizational knowledge, AI, and coordination ability, we will run the above regression with a triple interaction term (but this will occur in the fall).
- spillovers: In order to test for spillover effects, we will run the above regression with an indicator for being in the AI team but not having the AI agent on the sub-team.
- heterogeneity by skill level: We will collect data on player skills prior to the start of the game. We will test for heterogeneous treatment effects by the skill level of the team.