

Allocative Skill:
Measurement from Assignment Games

by

Xiaoyin Li

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Professor Marti G. Subrahmanyam
Professor Christina Wang
Professor Wendy Jin

Faculty Advisers

Professor Andrew Caplin

Thesis Adviser

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Abstract

This paper focuses on workers' decision-making ability regarding resource allocation, which is defined as the allocative skill, and its impact on their full-time labor earning. In this research, a model combining production theory and attention theory is adopted, in which allocative skill refers to the marginal product of attention. I use two assignment games to measure subjects' allocative skills independently. During the process, they either work as managers assigning workers to different tasks so as to maximize the output, or serve as workers who aim to finish a given task under resource constraint. The result of the surveys indicate that allocative skill is strongly correlated with income, and is the most decisive factor after taking into consideration the score of Ravens test (IQ), Berlin Numeracy Test (statistical numeracy), Goleman's EI Competency Test (Emotional Intelligence), and other demographic information such as age, gender, and education level. In addition to analyzing various assessments and factors, this study delves into a comparison between two assignment games, examining how their unique features affect the measurement of subjects' abilities. This comparative analysis enriches the interpretation of the experimental results.

Keywords: income determinants; resource allocation; decision-making; production theory; attention theory

Preface

In a world marked by dynamic labor markets and evolving economic landscapes, understanding the intricacies of workers' decision-making processes is important, as the explanatory power of productivity as a decisive factor on income is decreasing. Especially after the shock of the pandemic and the rise of AI technology, this trend continues and moreover, has been accelerated in an irreversible way. Consequently, the ability of workers to make informed decisions regarding resource allocation across various domains is now highly valued in the workplace. This raises interesting questions about how to quantify this skill and demonstrate its impact on wages.

Under the guidance of my mentor and building on existing literature, this paper aims to measure the so-called allocative skill, and explore its pivotal role in shaping an individual's full-time labor earnings.

Chapter 1. Introduction

This chapter provides a brief overview of the background about the current labor market, highlighting the increasing importance of workers' decision-making ability regarding resource allocation and its impact on their income. It also introduces the methodology to answer the main research question, as well as the feasibility and difficulty of the approach. The chapter concludes with the significance and the potential contribution of this project.

1.1 Background Introduction & Literature Review

Nowadays, workers' productivity, which is simply measured by the number of tasks they can do in a certain time period, is less valued in a variety of jobs, while their decision-making ability plays a more decisive role. Machines increasingly replace people in routine job tasks (Deming 2021). The development of AI-related technology further required people's competence in handling irreplaceable jobs that contain less routine work, while the shock from the pandemic makes jobs more demanding. Ojiyi noted that, "One theme that keeps coming up is how AI is affecting job displacement. Some authors argue that AI will lead to significant job losses, particularly in routine and repetitive tasks. Others, however, suggest that AI will create new job opportunities as it augments human capabilities" (2023). But the two opinions are not necessarily conflicting, if we use decision intensity as the cutting line. Artificial intelligence only serves as supportive roles in high decision-intensity jobs, while leading to job replacement in low decision-intensity work¹. In the same paper, he even describes AI's role as "[supporting]

¹ To measure decision intensity, I refer to the approach of evaluating job categories based on three dimensions using data from the Occupational Information Network (ONET) collected by the US Department of Labor, and transfer the values to cardinal numbers (Caplin et al. 2023).

decision-making processes by automating repetitive tasks and reducing human error” (Ojiyi et al. 2023).

According to Jain et al., and Poba-Nzaou et al., jobs in the realm of healthcare and education are positively affected by AI, which even creates new job opportunities in these industries (2021). Jobs in these categories are among the ones with highest decision intensity on average. On the other hand, jobs that contain repetitive routine work with low decision intensity are at higher risk of being replaced. For example, manufacturing jobs related to assembly and machining may be affected, while 90% of tasks related to cashiers and other regular sales professions will be replaced by self-checkout, robots that scan shelves, virtual assistants, and common warehouse automation systems (Buchmeister et al. 2019, Agrawal et al. 2019, Hawksworth and Berriman 2018). The pandemic thus accelerated this process, making workers with low decision-making ability less valued. The impact will be long-lasting as it is predicted that 42% of the job lost will not be recovered (Hite and McDonald 2020). Taking a closer look at the jobs heavily impacted by the pandemic, it disproportionately affected the hotel and restaurant industry (Gulyas and Pytka 2020). These types of jobs are the ones with comparatively low decision intensity.

According to the data from the National Bureau of Statistics, managerial staff, professional and technical staff have higher annual salary on average from 2018 to 2022, followed by clerical staff, and lastly social production service, life service personnel, and manufacturing workers. This trend generally follows the hypothesis regarding the positive correlation between decision intensity and salary, and stays true after being broken down into different regions based on geographic location. Then, by using data that is further divided into job categories in different industries, the correlation still exists.

1.2 *Methods & Methodology*

This paper adopted the theory and created assessment methods aimed at measuring individuals' proficiency in making sound decisions regarding resource allocation. Workers need to do proper resource allocation while obtaining information is costly. In real life, it can either be a manager assigning workers to different tasks, or workers allocating limited resources to complete a given task. In either case, they have to choose an attention strategy and form their own belief, so as to do the most efficient allocations. This requires us to evaluate their individual variations in marginal cost of attention holding all other factors constant. Its reciprocal, the marginal product of attention, is then defined as the allocative skill. To further explore the causal relationship between allocative skill and income, I conducted an online study using the platform Credamo, where participants are recruited and compensated for completing tasks, including the assignment game. Additionally, I collect demographic information including their jobs and monthly income.

I mainly use two types of assignment games. The first one is the work-task assignment game. The participants serve as managers who assign workers to different tasks so as to maximize the output. Workers have heterogeneous productivity over different tasks, and their productivity is represented by a matrix with $n \times n$ blocks where n is both the number of workers and the number of tasks. Each worker's productivity of each task is indicated by the saturation of the color block. The assignment must follow one-to-one mapping, which means each worker must be assigned to one and only one task, and each task must be assigned to one and only one worker. I calculate the score by comparing the outcome of the assignment to baseline and ceiling scores. The former is the expected output from random guessing, and the latter is the maximized

output from optimal assignment. The worker-task assignment game serves as the major part of the experiment.

The train-station assignment game is carried out in a parallel manner. In this game, participants serve as workers who have to complete a given task under resource constraints. During the survey, the participants need to assign different trains to their corresponding station on a $n \times n$ board by designing the routes with a constraint on the total number of rails they can use. The ordinal rank differences based on the participant's performance is used as the test result.

The result from the experiment shows a robust correlation between allocative skill and income, even after controlling for factors such as age, gender, education, statistical numeracy and IQ. Moreover, allocative skill turns out to be the strongest predictor among all test results.

Different from the approaches in previous research, the worker-task assignment game aims at eliminating the numerical representation, so as to alleviate the impact of math related ability, as well as giving a one-time clear presentation of all relevant information within one graph. The train-station assignment game further takes into consideration the complexity of real-life scenarios, offering a more dynamic way when it comes to a worker who receives a given task and has to complete it with limited resources. Taking the vital role of emotional intelligence in the workplace into consideration, an EI test based on Goleman's EI Competency Model is also implemented in the survey.

This study adds to what we already know about attention skills in the job market. By understanding how individuals perform at work, this research can help companies make better decisions about hiring and training, while giving individuals new insight into the determinants of their income.

Chapter 2. Mapping the Assignment Games to Theory

This chapter introduces the theoretical framework drawn from existing literature and illustrates how two assignment games align with this framework. It also explains how allocative skill is defined, as well as pointing out the key factors that should be taken into consideration when it comes to designing the assignment games, so that they can both serve as qualified tests to capture individual variance in their decision-making ability about resource allocation. Moreover, it describes the workplace scenarios each experiment simulates and their corresponding characteristics. This session facilitates the transition to the subsequent chapter, which delves deeper into the experimental design and implementation of these assignment games.

Worker-Task Assignment Game

In the worker-task assignment game, players act as managers assigning tasks to different workers. Each question includes n tasks and n workers. Workers can only handle one task each, and all tasks must be assigned. The aim is to assign tasks to workers in a way that maximizes the total output. The game requires players to distribute attention strategically and understand the comparative advantage of each worker towards the tasks. So, it is possible to think of the assignment game as a test that assesses both cognitive and strategic abilities. See Figure 1 for detailed questions.

To begin with, participants have their own prior beliefs about workers' productivity. As attention is costly, participants choose their own attention strategy to acquire information, which follows rational inattention literature (Mackowiak et al. 2023). Then they form a posterior belief and do the allocation based on that to maximize the output. By defining an attention production

function and proving that it is convex with diminishing marginal cost of attention, the decreasing slope of the tangency line causes the agent to optimally pay more attention and produce higher expected output (Caplin et al. 2023).

Thus, this setting matches the theory in which participants try to solve the following equation during the assignment game:

$$V_j(a, \omega) = \max_{P_j \in P(A)} \sum_a \sum_{\omega} y_j(a, \omega) P_j(a | \omega) \mu_j(\omega) - c_j K(P_j)$$

At the individual level, c_j refers to the agent's marginal cost of attention, and its inverse α_j is the marginal product of attention, which is defined as the allocative skill (Caplin et al. 2023). A is the set of all possible assignment of factors, and a is an assignment which satisfies $a \in A$. ω is the state of the world that participants refine their belief about. $K(\cdot)$ is the attention cost function. According to Blackwell, Mackowiak et al., Kamenica and Gentzkow, we can use a joint distribution $y(a, \omega)$ to represent the choice of signals and the choice of actions, as there is a unique mapping between them (1953, 2023, 2011). $P(a | \omega)$ is the state-contingent assignment probabilities. Thus, the agent “develops a joint attention-action strategy - reflected in the term $P(a | \omega) \mu(\omega)$ - that maximizes expected output in any possible state, taking into account their prior beliefs and the cost of acquiring information $c K(P)$ ” (Caplin et al. 2023).

$$P_j(a | \omega) = \frac{\exp(\alpha_j y_j(a, \omega))}{\sum_{b \in A} \exp(\alpha_j y_j(b, \omega))}$$

The above equation further shows that “if we impose symmetry then we can derive α_j for every participant using data on observed assignments and outputs” (Caplin et al. 2023). By assuming the cost function in the form of the Shannon mutual information, and identifying necessary conditions for optimality of the weighted logit form according to Matejka and McKay, the above

equation is derived (2015). Here, ω is the true state, a refers to the chosen assignments, and α_j represents the allocative skill of each participant j . $y_j(a, \omega)$ measures the ex post output, and $y_j(b, \omega)$ measures the counterfactual outputs from every other choices ($a, b \in A$). Thus, by using the data from the survey result, we can obtain the ordinal ranking of α_j for all participants.

The experimental setup closely aligns with the theory above. Both workers and tasks are labeled generically with numbers to ensure that, from the outset, participants perceive them as equivalent. This approach satisfies the condition of symmetry between workers and job tasks. The set of possible actions is finite and known, as there are $n!$ possible assignments in total.

Furthermore, I standardize the information provided to participants, the time used for making assignments, and the overall complexity of the tasks. Participants are compensated based on their performance and are selected from an online platform where payment rates are predetermined, ensuring that utility is directly linked to output. The payment amounts are modest enough to mitigate concerns regarding risk aversion.

Train-Station Assignment Game

From another perspective, workers are assigned to specific tasks in the workplace. For each worker, the goal is to finish the task with given information, as well as resources such as time or energy. In this case, the ability to make wise decisions about resource allocation according to their processing of information becomes critical to their success in completing the tasks, thus impacting their wages.

The train-station assignment game in the survey mimics the scenario where participants know they should finish a task, but have limited resources to complete it. During the survey, the participants need to assign different trains to their corresponding station on a $n \times n$ board by

designing the routes. Meanwhile, there is a constraint on the total number of rails they can use. This requires the participants to absorb all the given information, and pave the rails according to their prior beliefs. Moreover, the decision regarding the route design of each square on the checkerboard may take them closer to accomplishing the goal, or farther away instead, since the multiple trains needed to be assigned, along with the constraints and rules which will be described in detail in the following sections, add to the complexity of this puzzle. Thus, by receiving information signals, i.e., the situation on the board, the participants also have to revise and form posterior beliefs through their attention strategies, so as to get the expected output and achieve the goal.

The action set is known and finite, both regarding all possible ways to pave the rails without the constraint on the maximum number of rails being used, which is 14^{n^2-k} (n is the length of the board and k is the number of trains on the board), and all possible ways to lead the train to its corresponding station.

The participant will either pass or fail the game, so as to ensure their prior belief is symmetric, as there is no information telling them ahead of time that they should give priority to fulfilling the requirement of a certain type of train. The information is fixed as long as the setting on the board is the same, and we also make sure that the participants fully understand the basic rules before formally playing the assignment game. After they finish each game, the puzzle will change, which requires participants to find routes again with a new set of information. The time available to complete each assignment game is fixed, and the difficulty of the puzzles are evaluated according to their complexity level. We can thus implement a section-level adaptive measure to calculate the final score for all participants, which makes it possible to efficiently

reveal an appropriate range of scores with a smaller number of test questions. Thus, it is possible to use a similar approach and get the ordinal rank differences of all subjects.

Overall, this assignment game has the following advantages. Firstly, it uses a visualized setting that contains various and relatively complex information that is rich enough to mimic the situation in real life. It is neither entirely numeric based which makes it suspected to be related to participants' arithmetic ability, nor does it require keyboard input speed like the Train of Thought test from Lumocity where participants need to react quickly before the train passes certain nodes of the track. Meanwhile, we can still fix the information received by participants, since this assignment game is composed of finite ingredients: the size of the board, the location of the trains and their corresponding stations, other settings on the map (like roadblocks), and the maximum number of rails they can use. Secondly, the design of this assignment game is natural and relatively easy to follow. Paving rails to assign trains to their stations is intuitively understandable, so that we only need to ensure that the participants understand the rules correctly at the very first place. In the survey, a tutorial with videos and illustration, along with a sample test is available to the participants before they formally start to answer the questions. In addition, the assignment game allows participants to choose their attention strategy to refine the prior beliefs they begin with, and form posterior belief based on the signals they receive, which for example, can be the situation on the board after they pave the rails halfway. Each move, which refers to deciding the route design for a certain square, may take the participant one step closer to their goal, but may also lead them farther away. Moreover, the interaction with and the limitation from the environment is clearly shown and displayed in the game as the situation on the board instead of being a relatively vague concept behind the scene that determines other production factors. The setting on the board represents the state of the world, but the participants still need

to choose a set of signals to refine their belief so as to better understand it, so that they can get the desired outcome and reach their goal. Lastly, there are multiple ways to interpret this assignment game. It can be a worker using resource allocation to complete an assigned task, and it can also be a manager making decisions to allocate resources to different workers so that they can each finish their own work. In the latter case, the constraint on the number of rails still represents limited resources, while avoiding the trains to crash refers to the situation where the work of one employee may have a linkage effect on other people's work. But since we give the trains and stations general labels, and the participant will either pass or fail the game, which means we do not give priority to any task or worker, the participants' beliefs are still guaranteed to be symmetric.

Chapter 3. Experimental Design

This chapter provides a comprehensive explanation of the assignment game designs, as well as addressing their potential limitations and proposing solutions. Additionally, it provides an overview of survey design as a whole and explains the rationale behind the selection of the platform for implementation.

3.1 *Assignment Game Design*

For the worker-task assignment game, the participants need to finish 15 allocations at three difficulty levels. During the assignment game, they are asked to observe workers' productivity on different tasks from a given $n \times n$ matrix, and assign n workers to n tasks by one-to-one mapping. As is shown in Figure 1, the matrix is made up of blocks with different saturation, and darker blocks mean higher productivity. The block on row x , column y represents the productivity of worker x doing task y , where $x \in \{1, 2, \dots, n\}$ and $y \in \{1, 2, \dots, n\}$. Participants can also look at the reference bar to figure out the relationship between the saturation of blocks and their corresponding value. This allows the participants to have an idea of the workers' comparative advantage by one sight, being able to match the blocks with exact numbers when needed, while making sure that they are not simply adding up the numerical values.

The difficulty levels are determined by the size of the matrix, i.e., the number of rows and columns, which is n . The participants sequentially solve problems with 3×3 matrices, 4×4 matrices, and 5×5 matrices. The total number of possible assignments is $n!$. By writing functions in Python accordingly in both recursive and non-recursive ways, I double-check with the worker-task question design, so that each question has only one allocation that can maximize the total output. In this case, when holding the size of the matrix constant, the possibility of getting the

correct answer either from random guessing or from all possible assignments remains the same, thus controlling the complexity of the questions within the same difficulty level.

The participants have to pass a color test that examines their sensitivity regarding color saturation. They also have the chance to go through sample questions, so that they can better understand the rules of this assignment game and avoid potential issues about technical difficulty along with interaction design before they continue. All participants have the same time constraints for the assignment games.

I calculate the score of each assignment by comparing the outcome to baseline and ceiling using $50 \times 2^{\frac{x-\bar{x}}{x^*-\bar{x}}}$, where x is the total output of the participant's assignment, \bar{x} is the baseline from random guessing, and x^* is the ceiling. This formula calculates the score of the assignment at a scale of 100, and when the output is lower than the result from random guessing, participants get lower marginal returns compared to those whose assignment yields an output that is above the baseline. The assignment gets increasingly harder to increase the output by one unit the more it gets closer to the ceiling, and participants get rewarded for that as the marginal return of output on scores is increasing. Given that the assignment game design along with the assumption of random guessing gives symmetry to all numbers inside the matrix, the baseline is calculated by: $\frac{1}{n} \sum_{j=1}^n \sum_{i=1}^n x_{ij}$, where n is both the number of rows and columns of the productivity matrix, i refers to the row element x is in, and j refers to the column element x is in.

It can also be derived from $\frac{\sum_{j=1}^n \sum_{i=1}^n x_{ij} \cdot (n-1)!}{n!}$.

For the train-station assignment game, the participants are asked to finish a set of allocation puzzles, in which they have to design routes for different trains to go to their corresponding station under certain constraints.

The board is in the shape of a $n \times n$ checkerboard. In each square, the rail can be paved in any direction that leads the train from one square to another, while both squares should be next to the square where the rail is located. The rails can cross, but they must end up leading to the same square on one end. As Figure 5 in the Appendix shows, for each square, there are 14 different ways to pave the rails. Each train is initially located on one of the squares with a starting direction represented by an arrow, and there is a rail underneath it. Thus, if we use k to represent the total number of trains, there are 14^{n^2-k} possible ways of paving the rails. If we take the constraint on the number of rails, or to say, the maximum number of squares we can use into consideration, as well as the fact that given the direction of the train on the previous square, only 5 ways of paving the rail on its neighboring square make sense: forward, left, right, forward left, forward right. This gives us a total number of $\sum_{i=1}^m 5^i \cdot p_i$ ($m \leq n^2 - k$ and $m, n, k \in \mathbb{N}^*$), where m is the maximum number of rails the participants can use, and p represents how many possible combinations there are if the participant actually uses i rails in total. As for the notation for the squares, we define the rows to be row 1 to row n from bottom to top, and the columns to be column 1 to column n from left to right. Similar to the naming of squares of the chessboard, we get the bottom row of squares being notated as $(1, 1), (1, 2), (1, 3), \dots, (1, n)$, and the square at the top right corner to be (n, n) . The stations are located at the edges of the board, which is represented by the elements in the set $\{(x, y) \mid x \in \{0, n+1\}, y \in \{1, 2, \dots, n\} \text{ or } x \in \{1, 2, \dots, n\}, y \in \{0, n+1\}\}$. (See Figure 3 in the Appendix for graphic illustration). Suppose we place a train on a 4×4 board at $(1, 3)$ with an initial direction heading to the right, and its corresponding station located at $(5, 2)$, Figure 6 shows all possible routes guiding the train to the station. It is clear that when n gets larger, the possible ways of paving the rails goes to infinity, which matches the fact that in reality, the workers face an infinite number of possible decisions about

how to deploy factors of production in order to complete their tasks. In the assignment game, since m , n , and k are treated as constants, we can thus prove that the participants' action set is known and finite with the previous calculation regarding the number of possible assignments.

All the trains will start to move at the same time, and all of them have the same speed, so participants also have to pay attention when designing the routes so that the trains won't crash. Inspired by the game Railbound, two additional rules are added to the assignment game. One is that for the rails that cross on the same square, a double-sided arrow should be added to the rail that turns, and whenever the train meets the arrow, it turns. This rule is critical to the design of puzzles. The other rule adds a new pair of ingredients to the puzzles, which is buttons and railings. Each button can control one railing. Whenever a train passes a square that contains a button, the corresponding railing switches from close to open, or open to close according to its current state. This setting not only adds to the complexity and variety of the puzzles, but also mimics the scenario in real life where one worker's task can affect the other's.

3.2 *Potential Problems and Solution*

There exist drawbacks for both game designs. For the worker-task assignment game, given that in order to maximize the output, the subjects need to understand the exact degree of comparative advantage of workers on different tasks, which means it is helpful for them to know how much a worker can do better on one task compared to the other, but the color blocks cannot show this clearly before they map the color blocks to exact numbers. As for the train-station assignment game, its complexity is also its disadvantage. Thus, I should be careful about whether it is similar to an IQ test instead of an assignment game about resource allocation.

The approach to the problem of the work-task assignment game is to try avoiding putting blocks with one level of saturation difference more than two squares vertically and one square horizontally, or two squares horizontally and one square vertically away from each other. Also, participants need to pass a color saturation test before doing this assignment game. For the train-station assignment game, it is necessary to check its correlation with the Raven's Test, so as to both check the degree of similarity for the two tests, and avoid potential collinearity issues in the regression.

As the two assignment games have advantages and disadvantages in different aspects, and mimic two major scenarios for decision-making about resource allocation in the workplace, it is reasonable to carry them out in parallel manner so that they may serve as complements for each other, thus enriching the results of the surveys.

3.3 *Survey Design*²

The assignment game serves as the main component of the survey. At the beginning, the participants go through a tutorial that introduces the basic rules of the assignment game with illustrations and sample question(s). Participants also have to answer some questions correctly to show that they understand the rules before they move on.

For the worker-task assignment game, besides the sample question that assists participants to better understanding the game setting and rules with a 2*2 matrix, the participants also have to pass a color test regarding saturation sensitivity, where they have to choose the color block that has different saturation from the others in the same line. For the train-station assignment game, an example is shown in Figure 7 with description. Figure 9 is another

² The NYU Shanghai IRB, FWA#0002253, has reviewed the application and determined that it is EXEMPT research under Exempt Category 2, based on 45 CFR 46.104.

simplified example that shows how the constraint on the maximum number of rails work, and what it is like to have rails that cross on the same square.

The puzzles are divided into three sections: easy, medium, and hard. The difficulty of the puzzles is positively correlated with the valid length of the board, the number of trains, the number of other valid items on the board (including roadblocks and railings), and is negatively related with the number of possible solutions. For most cases, there is only one correct way to design the route due to the constraint. Valid length of the board means after the puzzle is solved, decreasing one row or one column with all the items on relevant squares while moving the station on the edge correspondingly at the same time will no longer become a solution after the change. For example, if we delete the n^{th} column and there's a station on $(n+1, 1)$, all the items on this column will be removed, and the station will be moved to $(n, 1)$. An item is defined as valid if removing it from the board will increase the number of possible solutions. All participants get the medium-level section as their first section. Then, they will be assigned to a second section according to their performance on the first section. This section-level adaptive measure allows us to efficiently reveal an appropriate range of scores with a smaller number of test questions.

After that, the participants have to finish other assessments: the Raven's test, the Berlin Numeracy Test, and the Emotional Intelligence Test. At last, the survey collects their demographic information including their age, gender, education background, job type, wage, and etc. Check Figure 4 for the flow diagram.

3.4 *Platform*

This study aims at recruiting participants who are at least 18 years old, and work full time. The payment for completing the survey should also be small enough compared to their full-time labor earning to avoid concerns about risk aversion. Finally, I decided to choose Credamo as the platform to carry out this survey for the following reasons: choice of participants, functionality, and quality of the answers.

Credamo allows me to target qualified participants based on their country/region, gender, age, industry, occupation, registered residence, enterprise type, employment status, and etc. This not only limits the participants to working age people with a full-time job, but also enables me to rule out the people who do not meet certain criteria.

Credamo has embedded the function of sketching during the survey, which gives the participants more freedom and also serves as a tool to assist them in finishing the route design for the assignment game. Moreover, the platform enables users to code in Python or R, not to mention recognizing text and objects through screen image.

By upgrading to a premium account, Credamo allows users to have up to 30% of rejection rate, which guarantees the validity of collected answers. It is also possible to give extra monetary awards based on the performance of participants on this platform. This is pretty important as the assignment game along with other assessments and questions may take longer than some other surveys, and the participants are paid by the number of surveys they answer and how many questions are included in each survey.

Chapter 4. Statistical Analysis

This chapter provides a brief overview of the summary statistics of all key variables used in the analysis, including the participants' performance in all tests, their background information, along with a clear depiction of the participant distribution across different game types. It also outlines the total length of the experiment, how payments are calculated, and provides all essential details concerning the experimental setup in the data section. Following this, the chapter transitions into the results section, where a thorough data analysis is conducted, and the key takeaways from the analysis are presented.

4.1 *Data*

Overview

I recruited 378 participants in total for the experiment. The survey is carried out on the online platform Credamo, where most of the eligible participants are from their data mart pool by their pushing algorithm, and another 60 participants access the survey through QR code. All participants are full-time workers in China who are above 18 and below 60 years old. They are paid on the whole survey based on the total number of questions according to the standard payment on the platform, which is 7 RMB per survey. Meanwhile, they are informed beforehand that better performance will lead to extra payment. When it comes to the train-station assignment game, due to its complexity and the increasing difficulty as participants are drawn from the previous test pool, the payment was increased to 10 RMB per survey, resulting in an average of 9.46 RMB per survey. The participants take 2131 seconds on average (around 35 minutes) to finish the whole survey.

Assignment Games

Among all participants who are recruited, 7 failed to answer all the color sensitivity test correctly, 4 failed the attention test, and 47 gave invalid answers for the worker-task assignment game. For example, they did not follow one-to-one mapping in at least one question, and assigned two workers to the same task. This leaves a total of 320 participants for this survey. It is a one-time survey with three rounds of assignment games at different difficulty levels. The first round includes 5 questions with 3*3 productivity matrices, the second round includes 5 questions with 4*4 productivity matrices, and the third round includes 5 questions with 5*5 matrices. Participants spend an average of 5.68 seconds for each assignment. By calculating the scores at 100 points scale, and after round-off operation³, 1.25% of the participants reached the highest score of 98, and 6.25% scored lower than 50. The average score of all the participants for the worker-task assignment game is 84.91.

For the purpose of comparative analysis, the participants of the train-station assignment game are in the pool of participants who passed both the color sensitivity test and the attention test, as well as giving valid answers for all questions in the worker-task assignment game. A total of 100 surveys were released to the pool, and 66 participants gave valid answers to all questions. The average time participants spend on this survey is around 47 minutes. 1 participant gets 95 percent correct, which is the highest, and the lowest participant gets 10-percent correctness. The 75th percentile of the train-station assignment game scores is 66 percent. Crashing turns out to be the most common mistake, and mismatch has the second highest frequency.

³ Round-off operation is only used in the Data section to show participants' general performance. Neither is this operation applied to the scores used for the regression, nor is the 100-point scale used for data analysis as the scores will be normalized.

Other Assessments

The Raven's Test, which is widely known as the IQ test that requires participants to find patterns through given graphs and choose the one that fills in the last piece, is used in this survey with 15 chosen questions. 14 participants got all the questions correct, and 3 participants scored 0. Regarding the total number of correctly answered questions, the test result has a mean of 8.42, and a standard deviation of 3.80.

The Berlin Numeracy Test is used to evaluate the participants' statistical numeracy with 4 questions adopted from Cokely's research (2012). Check Figure 2 for detailed questions. Among all participants, 48 answered all questions correctly, while 50 got 0 correct answer. Regarding the total number of correctly answered questions, the test result has a mean of 1.99, and a standard deviation of 1.28.

The Emotional Intelligence Test is based on Goleman's four quadrant Emotional Intelligence Competency Model (2002), and evaluates participants' emotional intelligence in four aspects: self-awareness, self-management, social-awareness, and relationship management. The test result is at the scale of 10 points. 8 participants reach the highest score of 9 points, and 4 get the lowest score of 1.75 points. The test score has a mean of 6.38, and a standard deviation of 1.44.

Demographic Information

Participants' basic demographic information, including age, gender, current location based on province and city, education level, major, job type, detailed job category that best matches SOC code of occupation category, and salary. Participants' monthly salary in RMB is collected in the form of a multiple-choice question with different ranges that starts from 0-3000, 3000-6000, 6000-9000, ..., till above 30000. I use the midpoint of each income range as their

salary. There are only 6 participants who chose “above 30000” as their monthly income. The mean of all income data is 11754.55 RMB. The male/female ratio of all participants is 3:2. The average age of all participants is 32. Among all participants, 256 people have an undergraduate degree, 64 people have a master’s degree, 0 people have a doctor’s degree, 14 finish junior college, and the rest don’t have a college degree which means they attended general high school, or technical school, or vocational high school. The education level is higher than the general population, but overall the data is representative.

4.2 Result

The primary hypothesis is that allocative skill, as evaluated by the assignment game, correlates positively with income. For ease of comparison, I normalize the result of the assignment game and all the other assessments. Table 2 showcases regression analyses of income against assignment game scores, while accounting for demographic factors, other cognitive assessments, and additional variables. Although variables are taken into consideration in a one-by-one order as is shown in the table so as to better observe the pattern, the major regression would always be:

$$\begin{aligned} salary_i = & \beta_0 + \beta_1 \cdot Ascore_i + \beta_2 \cdot Rscore_i + \beta_3 \cdot Escore_i + \beta_4 \cdot Bscore_i + \beta_5 \cdot age_i \\ & + \beta_6 \cdot gender_i + \beta_7 \cdot edu1_i + \beta_8 \cdot edu2_i + \beta_9 \cdot edu3_i \end{aligned}$$

where salary refers to participant i ’s monthly income in RMB. Ascore refers to participant i ’s assignment game score, either it is from the worker-task assignment game or the train-station assignment game, or a combined way of calculating the score. Rscore refers to the Raven’s test score, Escore refers to the emotional intelligence test score, and Bscore refers to the BNT score. age is the midpoint of the range in participants’ choice, and gender is a dummy variable where 1 refers to male. The four kinds of education levels are indicated by three dummy variables, for

which $\text{edu1} = 1$ means undergraduate degree, $\text{edu2} = 1$ means master's degree, and $\text{edu3} = 1$ means junior college degree. If only edu is included in the regression, then it refers to whether the participants get a bachelor degree ($\text{edu}=1$) or not ($\text{edu}=0$).

From the correlation matrices, we can see that the worker-task assignment game is only slightly positively correlated with Raven's Test, Berlin Numeracy Test, and very weakly related to Emotional Intelligence Test in a negative way. (Check Table 1 for more details.) According to Table 3, the train-station assignment game basically shares the same result, given that its correlation with all other tests is relatively small, but it has a positive correlation with EI. Surprisingly, the positive correlation between the train-station assignment game and Raven's Test is less strong compared to the correlation between the worker-task assignment game for the same pool of participants, though both turns out to be weakly correlated. This is possibly due to the embedded complexity within the test. According to the result, the route design behavior does not share much similarity with cognition ability of pattern finding. However, it is still possible that it tests test participants' IQ in another aspect that is not captured by the Raven's test. No collinearity issues exist within the regression.

The regression result shows that allocative skill strongly predicts workers' income. A one standard deviation increase in allocative skill increases a worker's monthly income by 1888 RMB. Different from previous approaches, this survey adds emotional intelligence into the controlled tests, considering the vital role it plays in people's career. As a result, emotional intelligence is also a strong predictor of participants' wages. However, even taking all the other tests into consideration, allocative skill is around 1.5 times more decisive than emotional intelligence. Another interesting point is that the Raven's Test, which can be referred to as IQ, is not significant in deciding people's income. This can be explained in two ways. First of all,

allocative skill and emotional intelligence plays an increasingly important role in today's job market. Secondly, the choice of the questions from the Raven's Test impacted the result. The questions are generally more difficult compared to those in surveys that also adopts Raven's Test in previous literature, thus explaining the considerable number of outliers with high wage and low Raven's Test score. Either changing the questions or enlarging the sample size will help us better understand this pattern.

When it comes to the train-station assignment game, though it has a relatively small sample size compared to the previous survey, the result of this parallel survey still provides us with useful insight regarding the research question, especially given that the results can be compared to those from the participants who also did the worker-task survey. In this case, the allocative skill of the same participants remains constant.

From Table 4, the allocative skill measured by the train-station assignment game is significantly and positively correlated with workers' salary. A one standard deviation increase in allocative skill increases a worker's monthly income by 9039 RMB. Emotional Intelligence score remains the second most predictive factor which is significantly correlated with income. After taking the same participants out of the pool who have also taken the worker-task assignment game, the allocative skill from the worker-task assignment game is still positively correlated with income, and one standard deviation increase leads to a rise in worker's monthly income by 2300 RMB. It seems that the train-station assignment game is a more decisive factor when it comes to predicting income. However, we still need to be aware that: first of all, the train-station assignment game examines relatively complex aspects of workers' allocative skill. For example, when it comes to information intake, understanding the rules of this game, which is the abstracting of information from word description and graph illustration, is already testing

their attention strategy even before they officially start to answer the questions. It is also worth noticing that failure to understand the rules won't have an impact on the credibility of survey design and test results. As was mentioned in the previous session, the collected data will be considered as valid if and only if the participants pass the sample questions about rule understanding, and there do not exist invalid answers for the assignment game. Here, attention strategy for understanding the rules means how participants deploy their attention may affect how well they understand the rules in a way that helps them to solve train-station assignments in the right direction. Secondly, compared to the worker-task assignment game, the second assignment game may provide hidden information about how well the participants finish a given task, which might have the potential to indicate their own productivity.

In this case, it is reasonable to assume that by combining the result of the two assignment games with a certain distribution, they may serve as complements for each other, thus having better performance in predicting the workers' full-time labor earning. According to the previous regression, when experimenting on the same group of participants, the train-station assignment game is around 3 times more predictive than the worker. The correlation matrix in Table 3 further shows that the two assignment game scores are weakly correlated with each other. Thus, I define a new assignment game score ComA, where $ComA = 0.2 \times AG1score + 0.8 \times AG2score$. By applying the result to the same regression equation, we can see that the combined assignment score is a stronger predictor of income compared to any of the assignment game scores. (See Table 6 for more details).

Chapter 5. Conclusion

This paper introduces a method for measuring how good people are at making wise decisions about allocating resources, which is called the “allocative skill”. I start with a basic model where people decide how to divide resources to get the most work done. This could be managers assigning tasks to workers or individuals deciding how to use their limited resources efficiently. Since workers have different productivity for different tasks, and different way of resource assignments will impact the final outcome, people must compare options and choose the best one for maximum output.

To understand how people manage their attention, I combined ideas from production theory and attention theory by referencing previous literature. In competitive job markets, those who earn more usually contribute more to their company's success. People who are better at managing their attention tend to make better choices, even when they're dealing with lots of information and limited time. So, we define this skill as the value of the marginal product of attention.

To test this skill, I created two types of assignment games. In these games, participants act as managers assigning tasks to workers to get the most work done, or as workers deciding how to use limited resources to finish a task. They are exposed to different situations and have to make decisions quickly. Their performance is then evaluated based on the output of their allocations. These games challenge players to think fast and make smart decisions, giving us a good idea of how efficient they are at making choices.

Unlike previous studies, the assignment game is simplified in a way that it reduces the need for math skills and presents all the information clearly in one graph. The train-station

assignment game also considers the real-life complexity of tasks, offering a more dynamic way to see how well someone manages their limited resources.

To check if my idea works, I did an online study using the Credamo platform. Participants were recruited online through this platform and paid for doing tasks, including the assignment games. I also collected information about their jobs and monthly income. The results of the study show a strong correlation between allocative skill and income, even after considering factors like education, numeracy skills, and IQ. Allocative skill also turns out to be the most decisive factor among all assessments.

This study builds upon previous literature, and improves understanding of the importance of attention skills in the job market. By viewing attention as a costly resource which differs between individuals, we gain deeper insights into individuals' performance at work. This research can inform better decisions regarding hiring and training practices, ultimately benefiting both individuals and organizations.

Appendix A: Figures

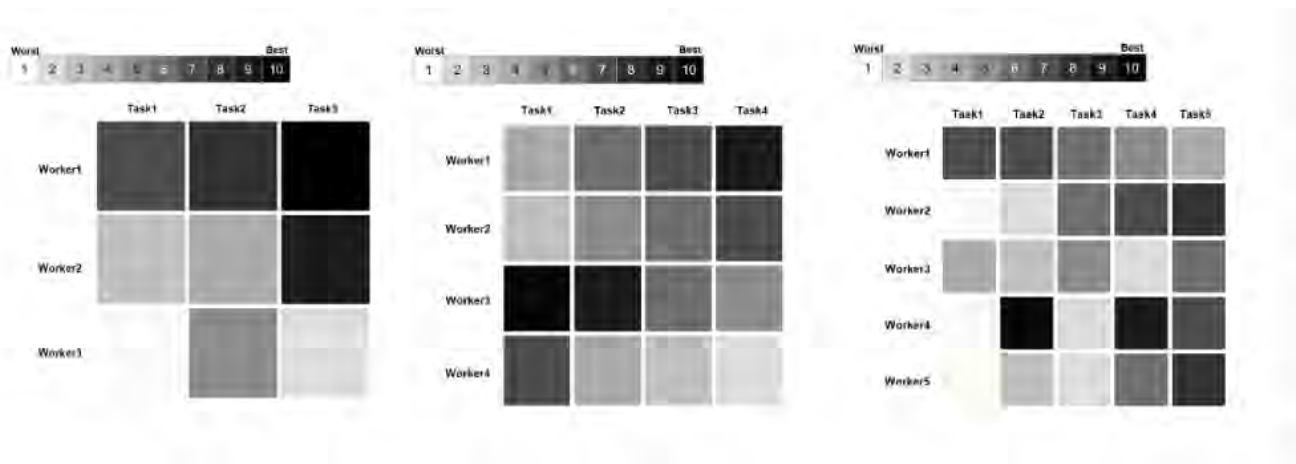


Figure 1: Worker-Task Assignment Game (Examples)

1. Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percent. 25%

2a. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)? 30 out of 50 throws.

2b. Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6? 20 out of 70 throws.

3. In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red? 50%

Figure 2: Berlin Numeracy Test

		(1, n+1)	(2, n+1)	(..., n+1)	(n-1, n+1)	(n, n+1)	
n	(0, n)						(n+1, n)
n-1	(0, n-1)						(n+1, n-1)
.	(0, ...)						(n+1, ...)
.							
2	(0, 2)						(n+1, 2)
1	(0, 1)						(n+1, 1)
		(1, 0)	(2, 0)	(..., 0)	(n-1, 0)	(n, 0)	
		1	2	...	n-1	n	

Figure 3: Train-Station Assignment (Board)

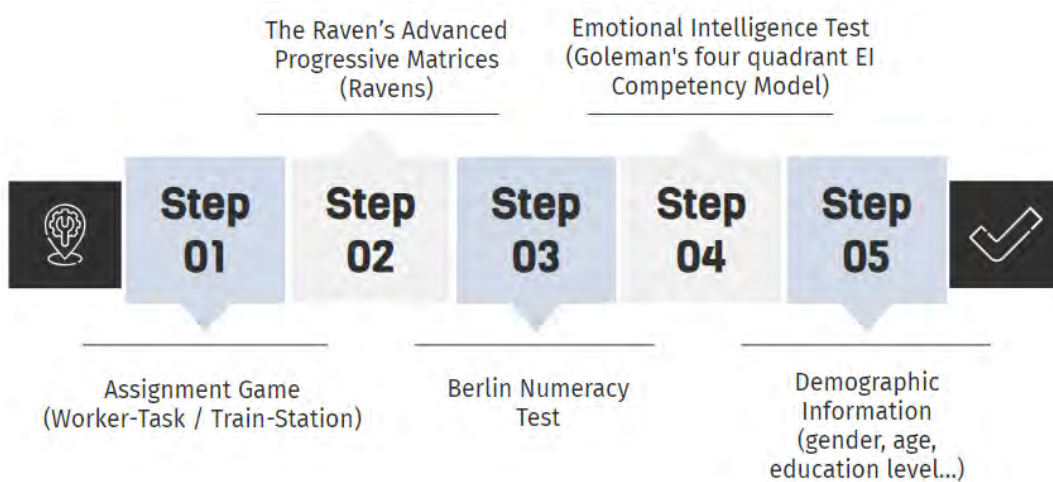


Figure 4: Flow Chart

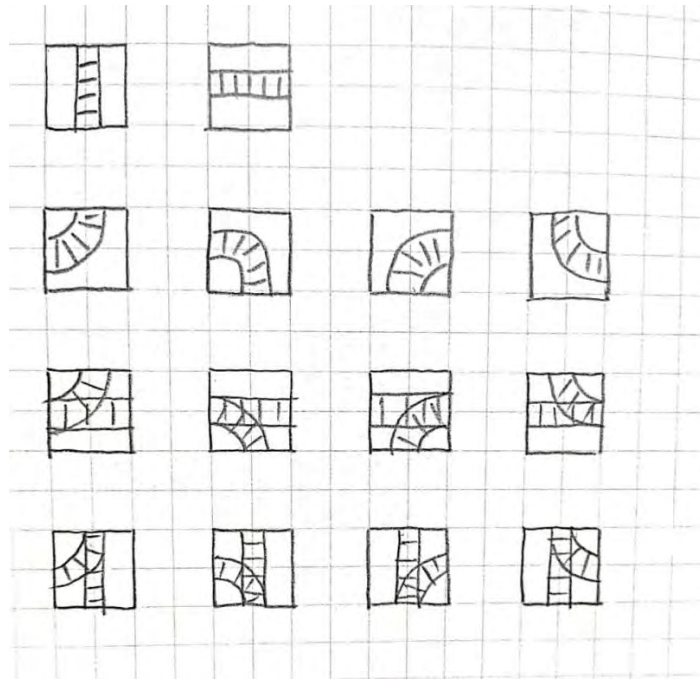


Figure 5: Train-Station Assignment Game (rails)

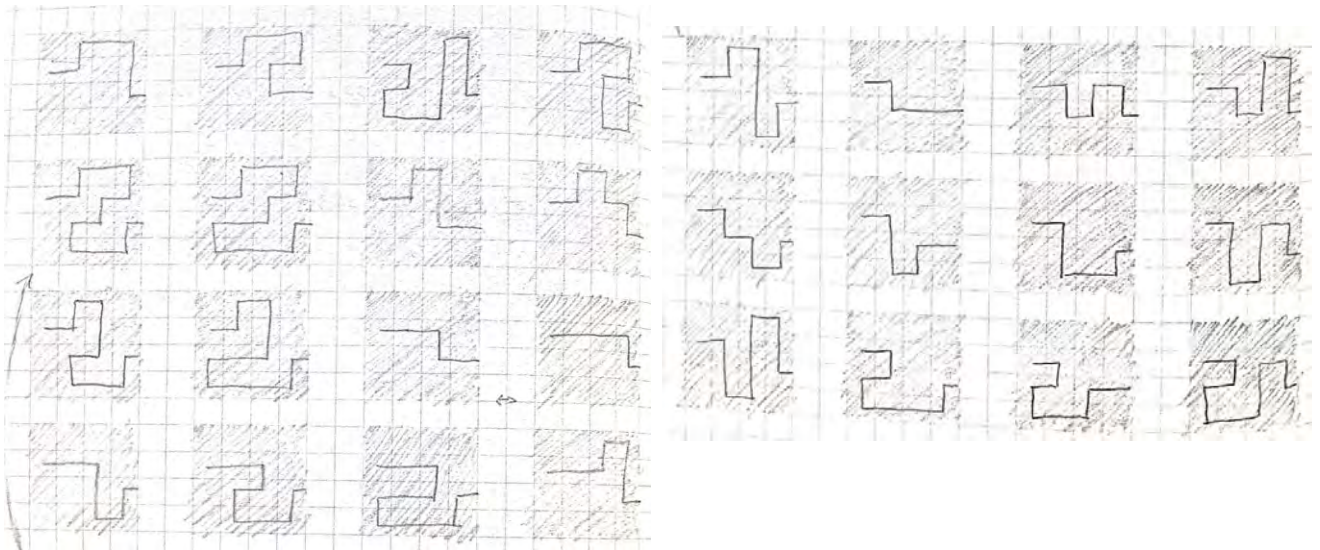


Figure 6: Train-Station Assignment Game (Free route illustration)



Figure 7: Sample Question 1

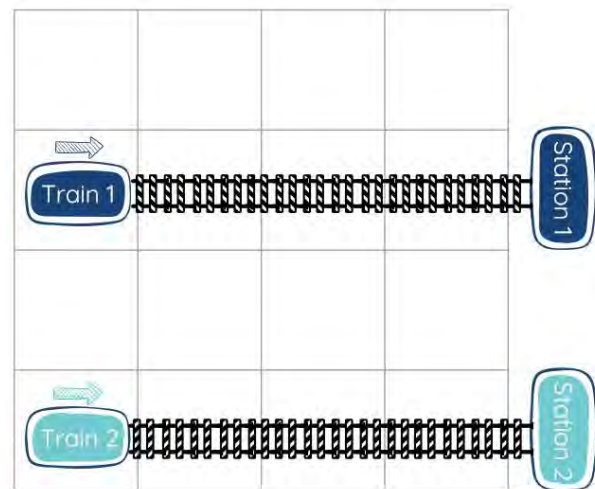


Figure 8: Answer to Sample Question 1

Notes: At the beginning, the participants will go through a tutorial that introduces the basic rules of the assignment game. As is shown in Figure 7, two trains are located on the 4×4 board, and the two stations are located on the edge as their destination. The goal is clear: participants have to design the path so that each train goes to the station that matches its color. The initial directions of the trains are represented by the arrows, and there exist rails underneath the starting position of all trains. Both trains have the same speed as they move. In each block, the rail can be paved in any direction that leads the train from one block to another, while both blocks should be next to the block where the rail is located. The rails can cross, but they must end up leading to the same direction. There are various ways to realize this goal, and the participants know nothing ahead of time about what route to choose. Then, the participants are given a limited number of rails, which is the same as limiting the number of blocks they can use to pave the rails. In the tutorial, the maximum number of rails given is 6, so that there is only one possible answer (Figure 8).

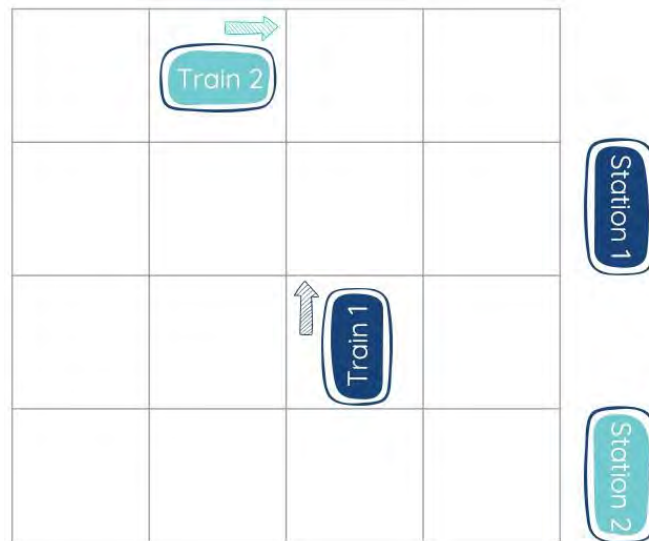


Figure 9: Sample Question 2

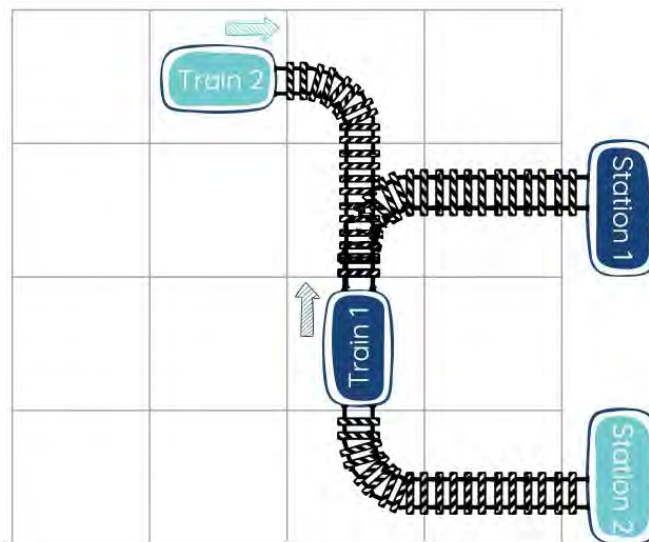


Figure 10: Answer to Sample Question 2

Notes: In more complicated scenarios, the trains may crash into each other or fail to reach its station. For the above example, the maximum number of rails given is 5. Thus, the participants have to ensure that Train 1 and Train 2 will not crash on the rail that crosses. As is shown in Figure 10, Train 1 passes the intersected point first, and then Train 2 crosses this point.

Appendix B: Tables

	AG1	Ravens	BNT	EI	age	gender	edu1	edu2	edu3
AG1	1								
Ravens	0.2160	1							
BNT	0.2678	0.3350	1						
EI	-0.0538	0.1619	0.0103	1					
age	0.0477	-0.1228	-0.1625	0.0954	1				
gender	0.1712	0.0373	0.2604	0.0843	0.1321	1			
edu1	-0.0450	0.0667	0.0278	0.0708	-0.1152	0.0730	1		
edu2	0.0865	-0.0535	0.0531	0.0238	0.0445	-0.0645	-0.8503	1	
edu3	-0.1188	0.0629	-0.1626	-0.1283	0.1323	-0.0441	-0.3721	-0.1012	1

Table 1

Notes: Correlation matrix for worker-task assignment game, other assessments, and demographic information. Naming is directly from the abbreviation explained in the text, as well as in the regression part in the result session.

	(1)	(2)	(3)	(4)	(5)
Allocative Skill (AG1)	3,390*	4,407**	5,026***	1,535**	1,888**
	[1,855]	[1,863]	[1,909]	[748]	[914]
Ravens Test		-2,400	-3,019	-1,590	-1,074
		[1,748]	[1,971]	[983]	[1,428]
Emotional Intelligence			2,964***	1,461**	1,360**
			[1,112]	[786]	[657]
Berlin Numeracy Test					-1,332*
					[767]
Demographic Controls				X	X
R-Squared	0.0147	0.0340	0.0608	0.1709	0.1742

Table 2

Notes: Regression result for worker-task assignment game, adding other assessments and demographic information accordingly. Standard error is presented in the brackets.

	AG1	AG2	Ravens	EI	BNT	age	gender	edu
AG1	1							
AG2	0.1184	1						
Ravens	0.0791	0.0289	1					
EI	-0.2639	0.2031	-0.1876	1				
BNT	0.1963	0.1465	0.2005	-0.3336	1			
age	-0.0499	0.0631	-0.2312	0.0676	-0.3124	1		
gender	-0.1749	0.3352	-0.3418	0.1158	0.0903	0.4950	1	
edu	-0.1613	-0.3175	0.0699	0.0278	0.0755	-0.1873	-0.2082	1

Table 3

Notes: Correlation matrix for train-station assignment game and the worker-task assignment game within the same participant pool, along with other assessments, and demographic information. AG1 refers to the test score of the worker-task assignment game, while AG2 refers to the other.

	(1)	(2)	(3)	(4)	(5)
Allocative Skill (AG2)	11,290*** [1,141]	10,490*** [1,353]	9,986*** [1,270]	9,431*** [1,229]	9,039*** [1,191]
Ravens Test			81*** [17]	93*** [20]	83*** [21]
Emotional Intelligence				741** [287]	1,045*** [250]
Berlin Numeracy Test					45** [17]
Demographic Controls		X	X	X	X
R-Squared	0.5986	0.7389	0.7767	0.7965	0.8156

Table 4

Note: Regression result for train-station assignment game, adding other assessments and demographic information accordingly. Standard error is presented in the brackets. Note that in column 3 - EI ($p = 0.012$), and in column 4 - BNT ($p=0.011$).

	ComA	Ravens	EI	BNT	age	gender	edu
ComA	1						
Ravens	0.0329	1					
EI	0.1868	-0.1876	1				
BNT	0.1563	0.2005	-0.3336	1			
age	0.0598	-0.2312	0.0676	-0.3124	1		
gender	0.3227	-0.3418	-0.1158	0.0903	0.4950	1	
edu	-0.3239	0.0699	-0.0278	0.0755	-0.1873	-0.2082	1

Table 5

Notes: Correlation matrix for combined score of the assignment games within the same participant pool, along with other assessments, and demographic information. ComA refers to the combined test result. See text for detailed description.

	(1)	(2)	(3)	(4)	(5)
Allocative Skill (ComA)	13,919*** [1,706]	12,793*** [1,694]	12,165*** [1,595]	11,478*** [1,544]	10,981*** [1,507]
Ravens Test			82*** [17]	95*** [20]	85*** [21]
Emotional Intelligence				802*** [288]	1,096*** [250]
Berlin Numeracy Test					43** [17]
Demographic Controls		X	X	X	X
R-Squared	0.5980	0.7274	0.7659	0.7892	0.8071

Table 6

Note: Regression result for the combined score of the assignment games, adding other assessments and demographic information accordingly. Standard error is presented in the brackets.

Note that in column 5 - BNT ($p=0.016$).

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