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Enhancing the Elementary School's Students' Analytic Thinking and Decision-Making Abilities Through AI-Assisted Program in the GM5 Game Playing Activities

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The purpose of the GM5 game is to train children to overcome the challenge of computational thinking and decision making. Through step-by-step analysis, thinking, and calculation, finding ways to not be defeated by opponents can be figured out in their minds deeply. When playing this game, there are 5 time-limited steps including selecting cards, analyzing combinations of cards' risk vectors, assessment of opponents, planning allocations, and tricking opponents. The chain-reaction of logic analysis, mathematical operations, and intrigues involved in the game playing are quite complicated. Therefore, this game has a great potential to enhance the player's thinking and decision-making abilities. Nevertheless, a systematic learning scheme and assistance tools are in demand for attaining deeper educational purposes. As a result, this research develops an AI program to assist students to rethink their own strategies reflexively and adopts a 5-E learning cycle for students to develop systemic game-playing abilities, experiences and mindsets.

Keywords: AI, computational thinking, decision-making, 5-E learning cycle, game playing activity, STEM

Introduction

Learning how to program can help children improve their logical thinking ability, critical thinking ability and learning ability (Papert, 1980). Computational thinking proposed by Dr. Wing (2006; 2008) is an essential ability for problem-solving, including procedure and algorithms, abstraction, and data analysis. Computational thinking in information society is a necessary competence for the digital natives and should be cultivated from elementary school stage (Department of Education of Taipei City Government, 2018). Conducting coding education in elementary schools became an important educational policy in many countries because coding education has positive effect on the learners' computational thinking ability. In the cybernetic era, being aided by the developments of AI technology and education technology (edtech), digital natives can enhance their strategic thinking and decision-making abilities to deal with complex problems in an increasingly complicated and unpredictable world.

Toddlers learn from games, that is, "Learning by Playing" is the ideal and natural learning way. Education

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is also required to create situations that can bring students active learning in achieving good learning experiences. Some e-learning researches (Erhel & Jamet, 2013; Huang, Huang, & Tschopp, 2010; Kim, Park, & Baek, 2009; Moreno-Ger, Burgos, Martínez-Ortiz, Sierra, & Fern_andez-Manj_on, 2008; Prensky, 2003) revealed that game-based learning is a competitive activity which can enhance learners learning motivation or improve the development of cognitive skills, or it can be the form of simulations that allow students to practice their skills in a virtual environment. Promoting strategic thinking and decision-making abilities of children is an important mission of education, and thus the main purpose of the edutainment method developed in this study is to enhance children's strategic thinking and decision-making abilities by utilizing the game of "GM5" (note the Acknowledgement at the end of this paper) through a process of "Learning by Playing". Through the teaching and game-playing process, many students found the difference between their own human intuitive decisions and the "rationally optimal" systemically calculated strategies and tactics by the AI program, and help them to invoke quantitative reasoning for strategic thinking by using the computational AI program. Once the students see the "counter-intuitive magic" through this training process, they will deeply appreciate that adaptation to systemic computational methodology for solving problems is definitely a necessary survival skill in the AI-dominated future. Therefore, through this game-based learning activities and experiences with AI programs, students can learn the steps of computational strategic thinking and decision-making, and furthermore, comprehend and mimic the progressive works to establish a set of their own supervisory rules for innovating a personal AI assistant for decision-making.

Decision-Making Training Modular Contents of GM5

We define a *domino* as a contextual module of training contents to be a game card, mainly consisting of the following components:

(C1) Domino Title & Description—Describing the narrative contents of a scene (scenario) faced by the game player;

(C2) Domino Image—The illustration of the scene so that the player can quickly recognize and easily remember the domino during a game competition;

(C3) Domino Risk Vector—The combination of five integer numbers in a scale running from -5 to 5 to indicate how the situation in the narrative scene benefit or damage the cartoon characters—Stark, Bondi, Monique, Omar and Howard, respectively.

Figure 1. A set of 10 dominos.

How to Play the Game GM5—Multi-Scenario/Multi-Allocation Game Mechanisms

When playing in the two-player game mode, each player alternates his/her game role between "challenger" and "defender" according to the basic rules shown as follows:

1. 10 dominos are placed on the table initially, and the players have 3 minutes to read and remember them.

2. After a coin-toss to decide the order, the two players pick a domino at a time in turn to collect 5 dominos in hand, serving as the set of offense dominoes to challenge each other.

3. Each player has 10 betting chips and needs to allocate all the 10 chips to bet on the five characters.

4. Let the player winning the coin-toss to be Player A and serve as the challenger first, and then Player A chooses one of his five dominoes to challenge Player B by putting the domino card face-down on the table. Suppose that Player B, the defender, can still remember all his opponent's five dominoes (the scenarios and the risk vectors), then he needs to guess which domino Player A most likely chooses to challenge him and make the "conditionally optimal" betting allocation of the 10 chips on the five characters.

5. The defender computes his/her score by multiplying the numbers of chips placed with the corresponding impact values of the challenging domino's risk vector and summing up, that is, the score is the inner product of the betting allocation vector (A1, A2, A3, A4, and A5) and the risk vector (R1, R2, R3, R4, and R5):

$$\text{Score S} = \text{A1} \times \text{R1} + \text{A2} \times \text{R2} + \text{A3} \times \text{R3} + \text{A4} \times \text{R4} + \text{A5} \times \text{R5} \qquad (1)$$

6. Player A and B take turns as the challenger and defender for 5 rounds.

7. The player with the highest total score is the winner.

A Heuristic Example of Progressive Learning on GM5

The player has to deal with 10 dominos at a time, our experimental data of this study, by observing and recording how students play and compete the game of GM5, revealed that the beginners usually chose to focus on only one or two characters on the domino, the most common practice is to bet all the 10 chips on one single character because they can't remember all the risk vectors of the opponent's 5 dominos. To play the GM5 game well, a student need to systemically develop and utilize his/her abilities of memory, permutation and calculation, but it is very challenging for teachers, through a short course of limited time span, to progressively train students to strengthen and well-organized these abilities to avoid opportunistic strategic thinking and decision-making methods from the very beginning. In order to overcome this learning-curve challenge, this study has built a computer program to recommend "conditional optimal" strategies of betting allocation, and teachers asked students to compare the differences between the computer program's and their own solutions.

By the step-by-step analytical instructions from the interactive computer program, the whole decision-making training process can not only enhance students' strategic thinking and computational skills, but also inspire their interests to co-op with and develop programs of AI personal assistant (PA) in the cybernetic era. The following will show the process with the simplified two-scenario (two dominos) "GM2" case. The two dominos are shown as Figure 2.

Open students' minds. First of all, the students are asked to write down the numbers of betting chips they would like to bet on the five characters, shown as Figure 3.

Figure 2. A pair of two dominos for GM2.

Figure 3. Allocation board.

Based on our experiment data, about 70% of the students filled in with the popular allocation vector (0, 0, 10, 0, and 0), where they figured out that Monique is the "best single" character to bet on with all their chips. Most students took less than one minute to finish the task and were very confident about their decision, and they kept doing the same in the second round to score 80 points in total.

After that, the teacher showed the strategic allocation vector (2, 0, 8, 0, and 0) recommended by the AI program, as shown in Figure 4, and the students' immediate response is a roar of laughter—"It's ridiculous to allocate like that", they said for they thought that it is no way to bet on Stark, because there is risk of getting hit by "-3" in one of the two dominoes in comparison to Monique, which is completely safe in both (the situation is the same for Omar, but Monique is still better than Omar).

The strategy of the computer is (2, 0, 8, 0, and 0), and no matter which card the opponent plays first, it can get 34 points in the first round, and the score in the second round will be 50 for sure by betting either on Stark or Monique with all the 10 betting chips, depending on which domino is left in the second round. Therefore, the total score is 84, as shown in Figure 5, higher than 80 by the students' "consensus best" strategy.

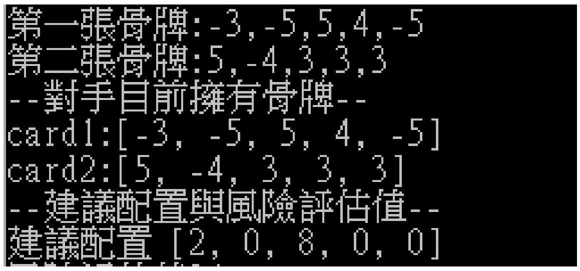

Figure 4. The allocation strategy generated from the AI program (computer screenshot).

Figure 5. The score of the computer is higher than the students' score.

When this counter-intuitive result was revealed, the students were taught three basic lessons and principles for STEM education in awe right away:

1. L1. Never underestimate the situation—Even in the simplest 2-domino case, there are something subtle and sophisticated beneath for critical thinking.

2. L2. Don't be biased and overconfident with an all-in bet on one single asset (character), and thus looking for more open diversified allocation possibilities without being confined in a special narrow scope.

3. L3. Math and computation can be fun, and it's awesome to build a computer program to solve complex mind-boggling problems.

Permutation visualization & computer program architecture. In total, there are 1,001 allocation vectors are there for betting the 10 chips on the five characters. Instead of teaching kids with a formula, we use visualization reasoning to help the students figure out all the possible permutations in a sense of complexity in nice order, as shown in Figure 6. Also, the computer programming flowchart is shown as Figure 7.

Table 1

An Example of Allocation Result

Stark	Bondi	Monique	Omar	Howard
10	0	0	0	0
9	1	0	0	0
9	0	1	0	0
9	0	0	1	0
9	0	0	0	1
…	…	…	…	…

Using excel to draw a chart (see Figure 5), total of 1,001 configurations.

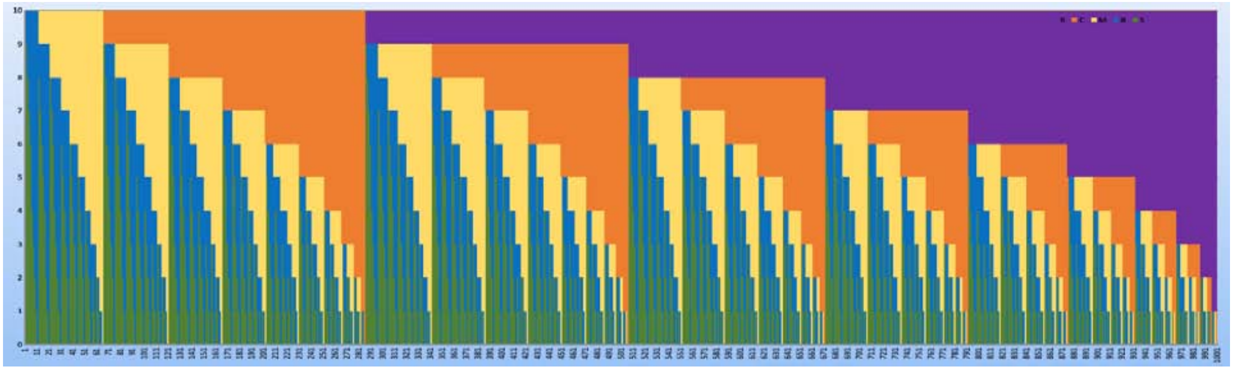

Figure 6. 1,001 allocation vectors.

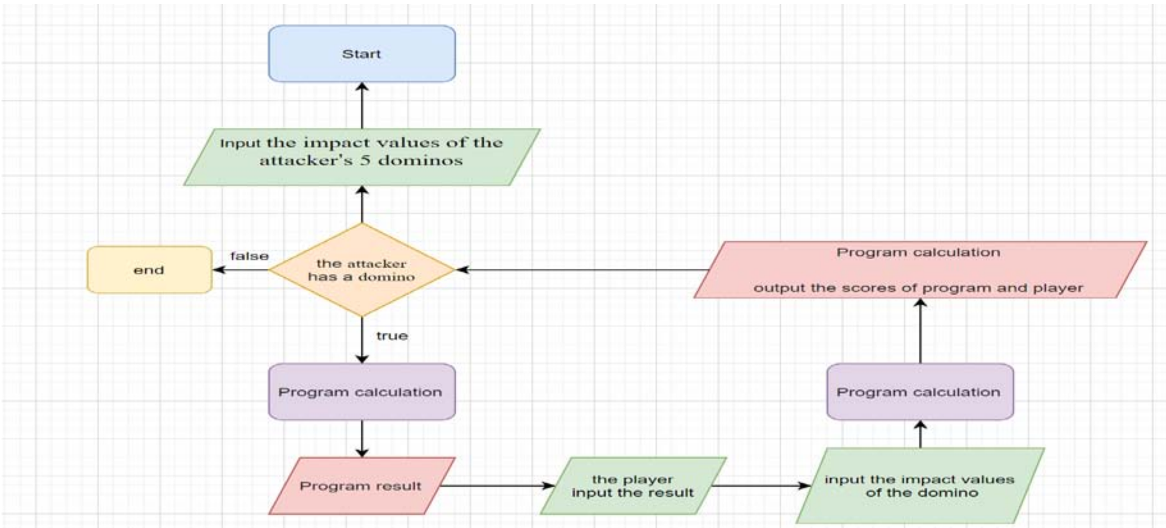

Figure 7. The flowchart of computer programming.

Figure 8. An example of the second step.

Instructional design of computational reasoning. We can also show the students that although the human brain cannot quickly scan through all the possible allocation vectors in details to find out the "conditionally optimal" strategy, there is a simple structural algebraic explanation behind it.

The first step is to remove "completely dominated" inferior characters. Apparently, no player would bet his/her chips on Bondi because the character's impact factors (the corresponding coordinate values of the risk vectors) are both minus. Moreover, Howards and Omar are also dominated by Monique in the sense that their impact factors are both smaller than Monique's in both the two dominos, and thus chips betted on Monique will always have better returns than these dominated characters. So, we have the two final contenders for the betting chips—Stock and Monique, as shown in Figure 8.

In order to make sure that the "conditionally optimal" allocation strategy does not bet on luck, that is, no matter which domino the challenger uses first to challenge, the strategy will get the same score, we come up with the following simple linear algebraic equation in two unknown variables:

$$\begin{cases} S + M = 10 \\ S * 5 + M * 3 = S * (-3) + M * 5 \end{cases}$$

with the solution $S = 2$, $M = 8$,

where S and M stand for the numbers of chips bet on Stark and Monique, respectively.

The allocation method found by the above systemic reasoning process is very different from most beginners' intuitive "single-bet" method, and after a series of trainings and game competitions in this style of analysis and strategic thinking, the learners' analytical and structural decision-making mindsets can be shaped in a short time to avoid opportunistic moves of intuitive random walk through a complex mind-boggling game process.

Through this activity with two-hour at a time and four-time a month, the teacher repeatedly used different decks of dominos to let students drill and practice going through GM2, GM3, GM4, and GM5 with increased complexity. Every time the students completed a practice, they took notes on their own analysis of the allocation procedure and were asked to express their thoughts. Through this rethinking training process, students can share their peers' ideas and think about the differences between their own logic of allocation and the others. At last they compared it with the strategies of the AI program and modified the allocation logic again. When facing a new deck of dominos, the learners make use of the modified logic to calibrate their strategic thinking, record, and compare through the cybernetic training loop again and again (see Figure 9) to approach better and better game strategies.

5E Discussion on Teaching Activity Design

In this study, the 5E learning cycle of the American BSCS (Bybee & Landes, 1988) was adopted for the development of learning activities, as shown in Figure 10, and is depicted as follows:

Engagement. Due to the attractive contents of the game, students are willing to participate and can actively participate in gaming courses. Teachers use the domino's narrative storylines to motivate students' interests to participate in learning, guide students' minds into the main concepts of the course, link students' existing game play and competition experience with course contents for learning-by-playing, consolidate students' basic mathematical concepts and practices, and monitor the decision-making process of students when playing games.

Explore. Teachers play an assisting role in this phase and inspire students to explore the innovative magic of the game. At this stage, students have enough time to weigh their strategies, discuss the strategies and tactics and even tricks about the science and art of allocation, clarify and propose their explanations based on their intuition and creativity and attain new experiences from their peers.

Explanation. Teachers encourage students to try their best to write down their reasonable explanations for the experience of the previous stage of exploration. After clarifying the concepts, based on the students' ideas, the progressive teaching steps along with game-playing practices are carried out in the learning-improving loop (see Figure 9).

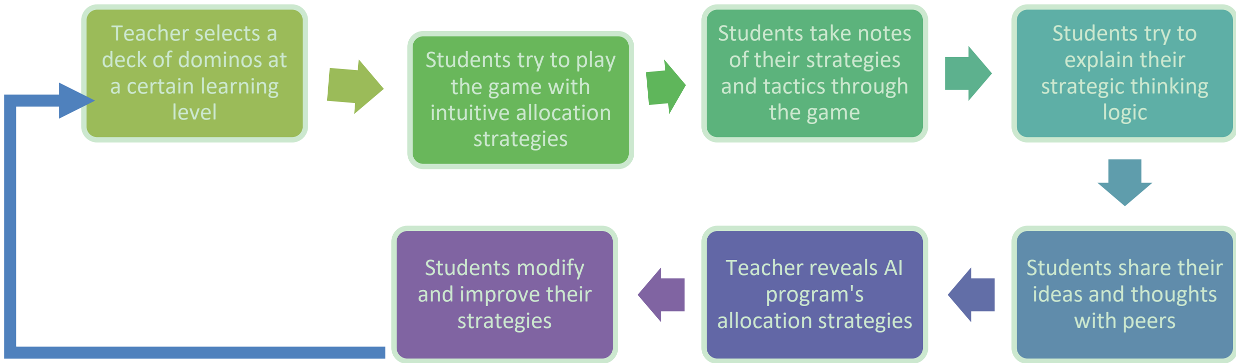

Figure 9. Progressive teaching process and learning loop.

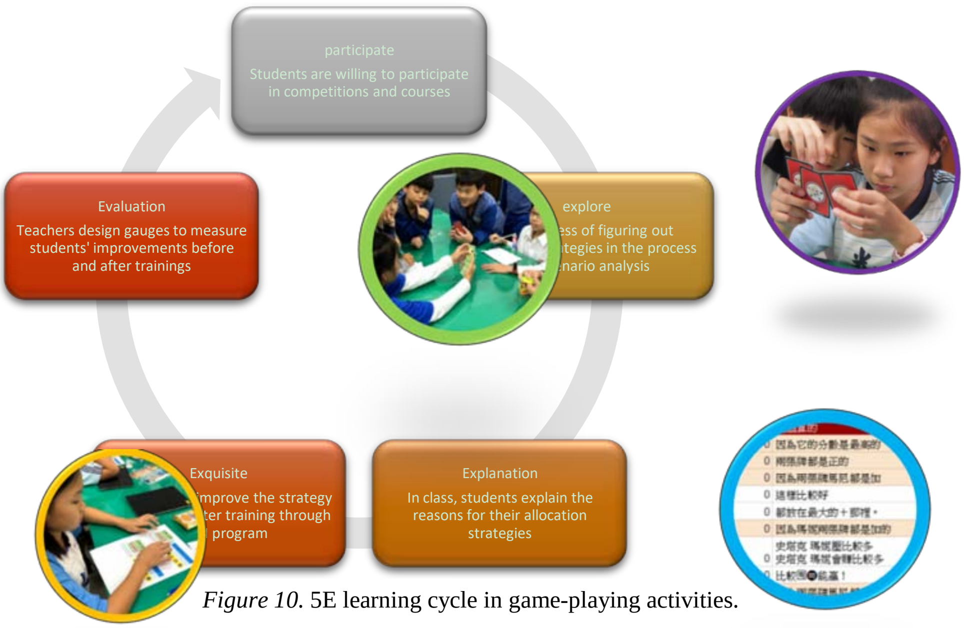

Figure 10. 5E learning cycle in game-playing activities.

Elaboration. In the refinement stage, students should be able to apply the concepts they have learned to solve new problems, and be able to clearly perceive the difference of the solutions before teaching, and try to express their own ideas and new concepts they have learned. The teachers also encourage the students to challenge the AI program by checking the assumptions and domain knowledge the AI program calls upon to calculate the "conditionally optimal" strategies and brainstorming for improving the AI assisting experience.

Evaluation. Throughout the teaching process, there are continuous and iterated evaluation processes. Students receive self-assessment of their own performances, other students' performances, and self-improvement evaluation before and after teaching. This stage helps students introspect and reflect their progression based on the meta-cognition theory.

AI Program-Assisted Training Experiences

At the beginning of this teaching program before the AI computer program was designed, there was no clear direction for allowing students to play freely, and it was impossible to monitor and analyze the students' thinking process. Moreover, sometimes even for teachers themselves, it was very hard to comprehend and explain the logic behind strategies for complex gaming situations. However, through this computer-program aided research, students' feedbacks are recorded and analyzed one by one, and the context of teaching had been gradually summarized so as to provide a gradient roadmap showing students' learning journey of systematically improving their strategic thinking and decision-making abilities.

Take student No. 1 as an example, before teaching, his recklessly intuitive allocation strategy was 10 all-in. The idea was that he felt that the score was the highest (see Figure 11), but after teaching, he targeted the same brand. After observing the combinations of positive and negative impact factors on the five characters (as shown in Figure 12), he made different allocation decisions by adopting the computer-program aided thinking. Take student No. 2 as another example. Before training, he would only look for a character with highest impact values in the domino's risk vector each time (see Figure 11). After training through the teaching process, he would scan through more characters and was willing to diversify his allocation bets (see Figure 12).

NAME	Stock	Bondi	Monique	Omar	Howard	配置的想法是?
AI	2	0	8	0	0	電腦算的
1 號同學	0	0	10	0	0	因為它的分數是最高的
	0	0	10	0	0	兩張牌都是正的
2 號同學	0	0	10	0	0	因為兩張牌馬尼都是加
	0	0	5	5	0	這樣比較好
	0	0	9	1	0	都放在最大的＋那裡。
	0	0	10	0	0	因為瑪妮兩張牌都是加的
	3	0	6	1	0	史塔克 瑪妮壓比較多 史塔克 瑪妮會賺比較多
	5	0	5	0	0	比較囤可能贏！
	0	0	10	0	0	因為兩張牌馬尼都是加

Figure 11. Pre-training student self-evaluation form with allocation notes.

NAME	Stock	Bondi	Monique	Omar	Howard	配置的想法是?
AI	2	6	2	0	0	電腦算的
2 號同學	7	1	2	0	0	因爲史塔克正的比較多邦迪有兩張是正的
	9	0	1	0	0	把他的最後一張騙走
	6	3	1	0	0	Only these three have plus.
	3	6	2	0	0	邦迪扣的比較少 瑪妮 史塔克有正
	5	0	5	0	0	這樣比較好
	5	5	0	0	0	因為幾乎都是+的~
	6	2	1	1	0	因為史塔克、邦迪、瑪妮、奧馬爾都有正的
	3	4	3	0	0	邦迪扣比較少 史塔克 瑪妮有正
1 號同學	2	6	2	0	0	因為史塔克只有一個加，邦迪扣少加多瑪尼也只有一個加
	5	3	2	0	0	壓在比較多＋的地方
	6	4	0	0	0	這樣才不會被扣太多分

Figure 12. Student self-assessment form with allocation notes after training.

Conclusions

The motivation for the development of this game-based learning program is that students, without good trainings, often try to be opportunistic or find special tricks to win the game, bypassing the game mechanism design for critical and systemic thinking, and are very likely to stick to some biased strategies while partially or mainly betting on luck. Therefore, after many discussions with the participating teachers, this study intended to establish an AI augmentation program to systemically showing teachers and students that, as a matter of fact, there are still lots of room to improve for decision-making so that the program can open their mind first and provide them a compass to navigate through a complex decision-making jungle. With the aid of this tool, students will have more fun and patience to progressively improve their strategic thinking abilities and decision-making skills in a systemic and sustainable way. In the meantime, teachers and parents are glad to see that this progressive training process can unknowingly help students gradually shape a decent mindset for decision making through the 5-E learning cycle.

According to Dr. Jenher Jeng, the inventor of the game GM5, this game's training mechanisms have three very far-reaching implications which all aim to incubate the next generation to be great citizens in the AI era:

1. Open societies—In the modern era of misinformation on social media, decision-makings of voting based on bias, prejudice or even hatred is so hazardous to democratic societies that, as justified by this study, people who can be very narrow-minded and intuitively biased since childhood need to be trained to have an open mind with decent decision-making senses and skills;

2. Rational markets—The algorithmic trading robots are taking over capital markets and swarm AIs are moving market sentiments like the Robin hood rally among millennial stock investors in more and more frenetic manners to cause bigger and bigger market bubble and crash risks, and thus similarly, investors need to be educated and trained from childhood to acquire rational decision-making senses and skills with knowledge in muscle memory to overcome greed and fear in fundamental humanity;

3. Cybernetic courses—The profound linear algebra training of computing allocation strategies over complex probabilistic permutations of dominos' allocation vectors and risk vectors can establish a solid systemic mathematical training foundation-program, enriched by interdisciplinary knowledge contents embedded in dominos, to incubate a generation of AI application designing talents.

Therefore, we believe that this study is only the tip of an iceberg to motivate more educational professionals in STEM/STEAM education. To carry this study to next levels, we suggest the future research studies should design more advanced courses in the above three principal implications with longer monitoring processes and broader international co-ops, build cloud-based sharing platforms, host competitions and design pre-training and post-training gauges to measure and compare how students improve their decision-making skills and change their mindsets in different cultural backgrounds during the training process at different levels.

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