Enhancing Strategic Sophistication: A Novel Approach for Expert Negotiators and Non-Experts

Keywords: Learning; Strategic Sophistication; Negotiators; Experimental Economics; App

JEL codes: C72, C73, C90, M53

Abstract

A distinctive aspect of human intelligence lies in its capacity to optimize decision-making in interactive settings based on the potential actions of others, a phenomenon known as strategic sophistication. This ability is pivotal in strategic interactions, where predicting others' actions, anticipating their beliefs about our possible actions, and making decisions based on such beliefs are essential. This competence holds particular relevance in negotiation, where achieving a compromise between demand and offer necessitates a thorough understanding of the counterpart's true objectives and the compromises they would be willing to accept. Despite extensive behavioral research revealing human behavioral flaws in strategic interactions, there's limited knowledge about the differences in strategic thinking abilities between expert negotiators and those not primarily involved in negotiation within their professional domain. Additionally, there's little understanding of the potential for enhancing strategic sophistication in expert negotiators and any variations in their ability to learn strategic behavior compared to individuals inexperienced in negotiation. In this innovative study, both non-expert individuals and expert negotiators are given the opportunity to learn through a specially designed app aimed at improving decision-making skills in complex strategic environments. Using a between-subject design, we compare the learning achieved by expert negotiators and non-expert individuals after extensive training with this app. Analysis of choice and belief elicitation data reveals that practicing with this app significantly increases participants' strategic abilities. Crucially, this improvement is more notable among expert negotiators, indicating a greater adaptability to feedback received during the training phase. Our findings offer new insights into the factors influencing learning in strategic interactions and shed light on differences in learning between expert negotiators and individuals with no experience in negotiation. Finally, our results emphasize the app's effectiveness in enhancing strategic skills across individuals, irrespective of their initial abilities.

1. Introduction

In our daily lives, decision-making is a constant occurrence. While some decisions may be straightforward, such as choosing between an apple and an orange, we often find ourselves in more complex situations where outcomes hinge not just on our decisions but also on the actions of others. Strategic interactions, as these scenarios are termed, demand optimal decision-making based on the ability to form accurate beliefs about others' intentions (first-order beliefs) and others' expectations of our potential actions (second-order beliefs). In this regard, the term "strategic sophistication" refers to the capacity to engage in high-quality and complex recursive reasoning, involving multiple steps of strategic thinking about both others and oneself. Game theory serves as a valuable tool to model strategic interactions and explore individuals' strategic sophistication in interactive settings, utilizing games (Figure 1). Extensive experimental evidence from games has unveiled significant heterogeneity in strategic sophistication. Contrary to the assumptions of classical game theory, which presupposes full rationality and correct beliefs (Nash, 1950), most players do not adhere to strategic rationality. They often fall short of applying all possible steps of recursive reasoning and instead rely on costless heuristics in their decision-making processes. For instance, some players make decisions without considering others' incentives and potential actions, and the majority do not form second-order beliefs (Polonio et al. 2015, Polonio & Coricelli 2019).

A prominent model to characterize heterogeneity in strategic sophistication is the Cognitive Hierarchy model (CH, Camerer et al., 2004; Chong et al., 2016). The CH model delineates choice behavior through hierarchical levels of strategic thinking. Each player endeavors to anticipate the strategic level of their counterpart(s) and then optimally responds to this belief by employing a more sophisticated strategy. The hierarchy start with players employing random choices (level-0); then introduces level-1 players, who optimally respond to the belief that all other players are level-0; one step further there are level-2 players, who believe that the potential opponents are no more sophisticated than level-1, and so forth, expanding the depth of strategic thinking until behavior approximate the equilibrium predictions. This theoretical framework posits heterogeneity in individuals' strategic sophistication, contrasting with the Nash equilibrium, which presupposes the perfect rationality of agents possessing consistent beliefs about others' forthcoming actions and making optimal choices based on those expectations. This diversity in strategic thinking can be attributed to various factors, which can be categorized into two main groups. First, heterogeneity in strategic thinking is associated with variations in participants' beliefs regarding others' levels of strategic thinking (Costa-Gomes & Weizsäcker 2008; Polonio & Coricelli, 2019). Second, the execution of complex strategies involving more than one step of strategic thinking necessitates diverse cognitive abilities, including mentalizing, fluid intelligence, working memory, cognitive reflection, and representation skills (Alaoui & Penta, 2016, 2022; Brañas-Garza et al., 2012; Crawford, 2003; Goodie et al., 2012; Grosskopf & Nagel, 2008; Kiss et al., 2016; Zonca et al. 2020).

Recent experimental research has explored ways to enhance individuals' strategic sophistication in games, indicating improvements through exposure to feedback (Gill & Prowse, 2016; Knoepfle et al., 2009; Marchiori et al., 2021; Selten et al., 2003), observational learning (Zonca et al., 2021), experience with alternative decision rules (Zonca et al., 2019), and step-by-step training (Verbrugge et al., 2018).

The enhancement of strategic thinking skills is particularly pertinent in the realm of negotiation, where understanding the counterpart's true objectives and acceptable compromises is crucial for reaching a mutually beneficial agreement. Negotiation is a decision-making process where individuals collaboratively determine the allocation of scarce resources (Pruitt, 1983). It arises in situations of conflict without established rules or procedures for resolution, offering a non-aggressive means of seeking agreements. Negotiating for goods such as commodities, money and services is a crucial skill for individuals striving to attain their goals through interaction (Thompson, 1990).

The existing body of literature on decision-making has thoroughly investigated the distinctions between novice and experienced negotiators, providing insights into how different levels of expertise influence strategic choices in interactive scenarios (Babcock & Loewenstein, 1997; Loewenstein & Thompson, 2006; Thompson, 1990). Experienced negotiators display a more sophisticated and strategic approach to decision-making, stemming from their extensive exposure to negotiation contexts. This exposure enables them to recognize patterns, anticipate counterstrategies, and dynamically adapt their approach. Furthermore, experienced negotiators often showcase superior problem-solving skills, an enhanced ability to discern the intentions of their counterparts, and greater proficiency in creating and claiming value during negotiations. Conversely, individuals with low negotiation experience tend to rely on simpler decision-making heuristics, struggling to recognize and respond to complex interactive patterns in dynamic environments. Their limited exposure to diverse strategic scenarios may render them more susceptible to cognitive biases and heuristic errors. Novices may also grapple with accurately assessing the preferences, motivations, and potential strategies of their counterparts.

Studies have delved into the impact of experience on various negotiation facets, including information processing, strategic thinking, and emotional intelligence (Druckman, et al. 1972; Goleman, 1995; Pruitt & Carnevale, 1993; Neale & Northcraft, 1991; Thompson, 2010;). In summary, the literature on decision-making in negotiation underscores significant disparities between expert negotiators and non-expert negotiators, emphasizing the role of cognitive skills in determining the efficiency and optimality of the decision-making process.

Despite this progress, it remains unclear whether individuals who regularly engage in negotiation within a professional context are better equipped to make optimal decisions in broader and less work-specific strategic contexts. Moreover, little is known about potential differences in their ability to learn from the feedback they receive about the behavior of others in these more general strategic environments.

In the current study, we investigate strategic sophistication in Expert Negotiators (EN) and individuals with No Experience in Negotiation (NEN) examining their capacity to learn through a specifically designed app aimed at enhancing users' strategic skills, regardless of their initial competence level. Employing a between-subject design, we measured the initial strategic abilities of EN and NEN individuals, taking into account both the consistency of their choices with the equilibrium and the accuracy of their belief about the action of the counterpart. Subsequently, participants were provided with the opportunity to train using this app, which required them to engage with an algorithm making optimal decisions in interactive games of varying complexity. Following the training phase, participants' strategic abilities were re-evaluated.

The results uncover an initial disparity in strategic competencies between EN and NEN participants, contingent upon the specific game complexity. After training occurs, negotiators exhibit a significantly higher level of performance, both in selecting the equilibrium strategies and in predicting the counterpart’s behavior. This increase in strategic sophistication is further assessed using the CH model, revealing a substantial difference in the attained level of strategic sophistication between the two groups post-app training. Specifically, EN participants reach a level between level-3 and level-4, whereas NEN participants barely reach level-2.

Our results show that our app enhances users’ strategic skills, regardless of their initial proficiency levels. Moreover, we show that expert negotiators adapt their strategic behavior to new counterparts better than non-experts, reaching higher performances. This result highlights the greater ability of individuals working in the field of negotiation in learning and adapting more efficiently to the observed behavior of others.

Column Player

Row Player	i	ii	iii
I	59 46	64 74	36 97
II	92 31	85 82	68 22
III	24 17	80 68	46 43

Figure 1. An example of a 3x3 matrix game involving two players: a row player and a column player. Each cell report the outcomes for every possible combination of actions of the two players. The three possible actions for the row player are labelled Action I, Action II, and Action III, while those for the column player are labelled Action i, Action ii, and Action iii. The outcomes for the row player are represented in blue, while those for the column player are represented in red. The outcome of the game is determined by the combination of actions taken by both players. For example, if the row player selects Action I, and the column player chooses Action ii, the row player gains 74 points, and the column player gains 64 points.

2. Methods

2.1 Subject sample and experimental procedures

The current study employed a training and a baseline treatment. The training treatment aimed to investigate the development of learning through the utilization of a dedicated app, while the baseline treatment served as a control condition. The experiment involved 269 participants. Among them, 69 were Expert Negotiators (EN, 56 males, 14 females, mean age: 42, SD: ± 9.21, range: 21 – 60), and 200 were participants with No Experience in Negotiation (NEN) recruited through the online platform Prolific (130 males, 71 females, mean age: 37, SD: ± 11.40, range: 23 – 63).

Expert Negotiators were individuals affiliated with the Intesa Sanpaolo Global Markets Solutions & Financing Business Unit and were recruited through an internal call within the business unit. The internal call was managed via an informal invitation sent through email to potential participants. This invitation email specified the absolute freedom to decide whether to participate in the study. Additionally, the email emphasized the employer's inability to monitor the involvement and the performance of individual employees in the study.

Half of the NEN participants recruited through the online platform Prolific were assigned to the control condition (NEN no-training), and the remaining half were assigned to the training condition (NEN training), while all EN participants were included in the training treatment. All participants were provided with an exhaustive description of all the experimental procedures and were required to sign a written informed consent before taking part in the study. The study was conducted in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki and under a protocol approved by the Area Vasta Nord Ovest Ethics Committee (protocol n. 24579/2018).

The experiment comprised three phases: Assessment, Training, Re-assessment. Figure 2 summarizes the experimental structure. Participants in the no-training treatment participated in the Assessment and the Re-assessment phases only (did not take part in the Training phase).

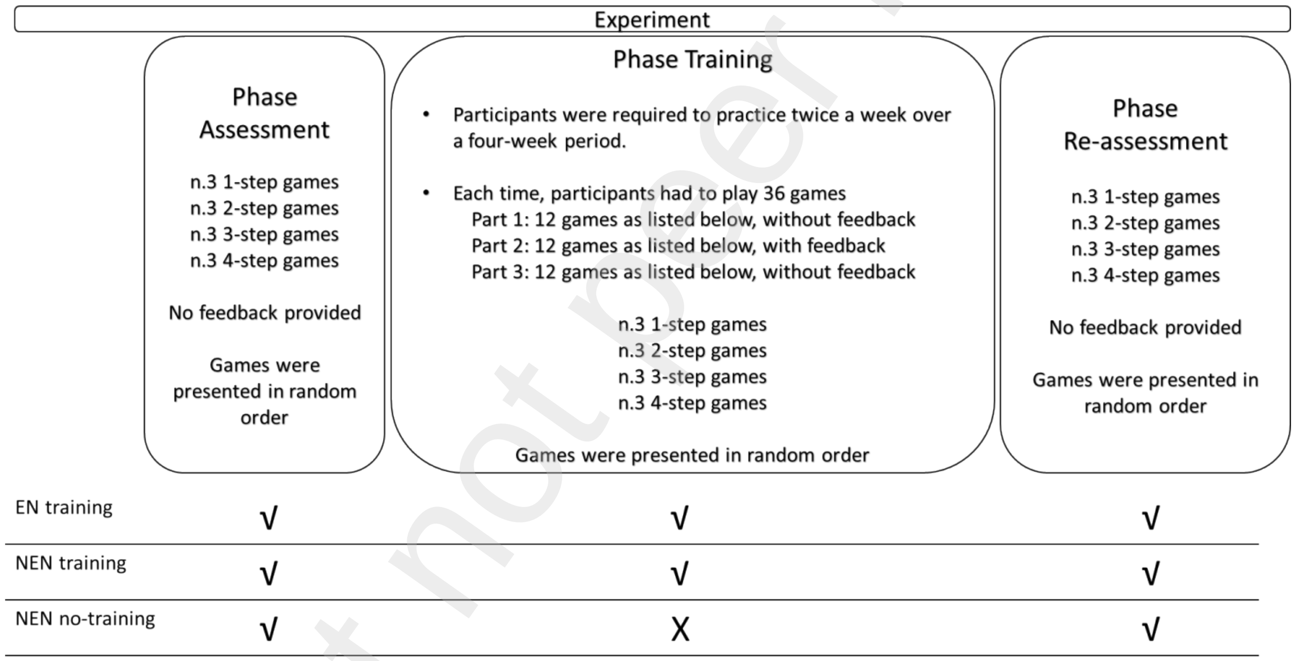

Figure 2. Graphical summary of the experimental design.

In all phases, participants interacted with an algorithm (referred to as the computer) programmed to consistently follow the equilibrium strategy. Participants were informed at the beginning of each phase that the computer would play rationally, seeking to maximize its own payoff, without adjusting its strategy throughout the experiment or adapting its choices to those of the participant. They were also informed that the algorithm selected its actions assuming that the participant would act rationally to maximize earnings. The decision to pair participants with an artificial opponent aligns beliefs and controls for unregulated adjustments in the level of strategic sophistication that might occur with a human counterpart (see Agranov et al., 2012). While this control comes at the expense of limiting generalizability, as interactions with an artificial counterpart may prompt different strategic considerations than human interactions, it ensures a more controlled testing environment.

The initial phase (Assessment) aimed to evaluate each participant's initial level of strategic sophistication. During the Assessment, participants played a series of 12 two-person 3x3 games. Among these, three games had a dominant strategy for the row player (i.e., the participant) but no dominant strategies for the counterpart (referred to as 1-step games). Another three games had a dominant strategy for the column player (i.e., the computer) but no dominant strategies for the row player (referred to as 2-step games). Three games had a dominated strategy for the row player and are solvable in three steps of iterated elimination of dominated strategies (referred to 3-step games). Finally, three games had a dominated strategy for the column player and are solvable in four steps of iterated elimination of dominated strategies (4-step games). An extensive description of the four games is provided in the next section.

In each round (each game) of the experiment, participants had to select one of the three available actions (Action 1, Action 2, Action 3) and indicate the probability with which they expected the counterpart to choose the first, second, or third column (Action-1, Action-2, Action-3). To state their beliefs, participant had to associate a probability to each of the counterpart's actions, choosing a value between 0 (certainty that the computer would not choose that action) and 100 (certainty that the computer would choose that action). Figure 3 provides a graphical representation of how the choice task and belief elicitation were presented to participants in the app. The aim of eliciting participants' beliefs was to assess whether the potential increase in strategic skills after training with the app is accompanied by more accurate beliefs about the counterpart's behavior. This evaluation aimed to ascertain whether improved strategic skills resulted not only from heuristics ensuring safe and sufficiently optimal choices but from a deeper understanding of computer incentives and a more accurate prediction of the rational counterpart's action in each specific game.

During the Assessment phase, participants received no feedback regarding the computer's choices or the game outcomes. Consequently, in this initial evaluation phase, participants could not learn from their previous decisions. Participants faced no time constraints during the task, and the phase had an overall duration of approximately twenty minutes.

Following the completion of the Assessment phase, participants in the training treatment were instructed to practice for approximately four weeks, engaging in a full practice session twice a week.

During the Training phase, participants played 36 games, presented in three parts of 12 games each. In each part, the games presented had a structure similar to the one of the games seen in the Assessment phase, but the information provided was differed. In part 1, participants played 12 games without feedback; in part 2, they received feedback on the computer's choice and the outcome of the interaction; lastly, in part 3, participants played again 12 games without any feedback. Figure 2 presents a representation of the experimental structure, while Figure 3 offers a screenshot of the task as displayed in the app. A detailed description of the app can be found in Section A.3 of the Supplementary Material.

At the end of each session (after part 3 was over), participants received a summary table detailing their performance across the three parts. This summary table included the total points obtained out of the available total and the average accuracy of their belief statements. The summary provided participants with the opportunity, after each training session, to assess their progress and compare their improvement with their previous sessions.

The chance to engage in a feedback session allowed participants to carefully consider the rationale behind the counterpart's chosen actions in each game, assess the optimality of the outcomes, evaluate the accuracy of their beliefs regarding the counterpart's expected behavior, and compare the efficacy of the action they selected with alternative actions.

EN participants practiced using an especially developed app, installed on their mobile phones, while NEN participants recruited through the Prolific platform were asked to connect to a web version of the app via their computers. This setup allowed experimenters to monitor the actual usage of the app over the four weeks of training. The app comprised a comprehensive library of 200 games (fifty 1-step games, fifty 2-step games, fifty 3-step games, and fifty 4-step-games) from which the games played were extracted. The assignment of payoffs in the three rows and columns was randomly allocated by the app at the start of each trial, ensuring participants never encountered the situation of repeatedly playing the same game.

At the conclusion of the four-week training period, participants were invited to take part in a new experimental session (Re-assessment phase), which essentially replicated the Assessment phase. This phase included three 1-step, three 2-step, three four 3-step, and three 4-step games, albeit with different payoffs than those presented in the previous sessions. The goal of the Re-assessment phase was to assess participants' learning in terms of the proportion of optimal choices and the accuracy of their beliefs.

NEN participants recruited in Prolific were incentivized throughout all stages of the experiment. In each experimental session, they had the opportunity to earn an amount ranging from a minimum of 2,10 pounds to a maximum of 6 pounds, depending on the outcome of their choices and the accuracy of their beliefs. Specifically, at the end of each experimental session, a round was randomly selected, and the participant received an amount depending on the outcome of the interaction (up to a maximum of 2 pounds) and the accuracy of their beliefs (up to a maximum of 2 pounds), in addition to a show-up fee of 2 pounds. Belief elicitation was incentivized with a quadratic scoring rule defined as follows: let y_g^i represent the stated belief of player i in game g, where y_g^i is a probability distribution over the three actions ("I", "II", and "III") of player j (the counterpart). The probability distribution is expressed as $y_g^i = (y_{g,"I"}^i\ y_{g,"II"}^i\ y_{g,"III"}^i)$, with the constraint that $y_g^i \in \Delta^2 = \{y_g^i \in \Re^3 | \sum_{C \in \{\text{"I", "II", and "III"}\}} y_{g,c}^i = 1\}$. The action chosen by player j (the counterpart) is denoted as $x_g^j = (x_{g,"I"}^j\ x_{g,"II"}^j\ x_{g,"III"}^j)$, where x_g^j equals 1 for the chosen action and zero otherwise. The payoff v_g of player i is calculated using the following quadratic scoring rule $v_g = A - c\left[(y_{g,"I"}^i - x_{g,"I"}^j)^2 + (y_{g,"II"}^i - x_{g,"II"}^j)^2 + (y_{g,"III"}^i - x_{g,"III"}^j)^2\right]$, where A and c are constants (A =1 Pound and c = 0.5 Pounds). Prior to the experiment, participants were provided with a clear explanation of the quadrating scoring rule along with several examples. Expert negotiators were not remunerated but voluntarily participated in the experiment as part of a project funded by Intesa Sanpaolo Innovation Center S.p.A., aimed at enhancing negotiation skills within the human resources of their Business Unit.

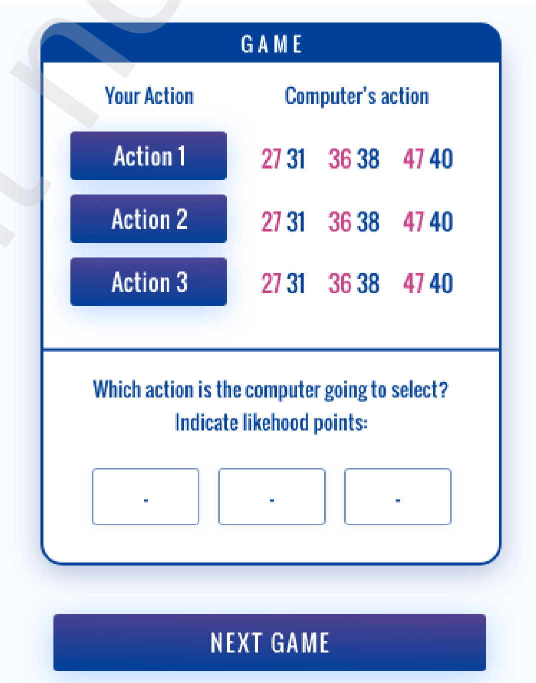

Figure 3. Graphic representation of how the choice task and belief elicitation were presented to the participants in the app. In each trial, the participants had to both select their own action as row player and declare the probability (expressed with values from 0 to 100) with which they believed the counterpart (the computer) would select each of the three possible columns. Participants were free to indicate the probabilities first or select their own action, but they could not proceed to the next trial until they had completed all fields (choosing the action and entering beliefs about the three possible actions of the counterpart). Once these fields were completed, participants could move on to the next trial by validating their selections with the "next game" button.

2.2 The games

In the Assessment and Re-assessment phases (as well as in the three parts of the Training phase), we utilized 12 two-person 3x3 one-shot games presented in matrix form, each featuring a unique pure strategy Nash equilibrium. These games were categorized into four classes based on their structure and complexity: 1-step, 2-step, 3-step, and 4-step. Across each class, we manipulated the magnitude and location of payoffs while maintaining constant the structural properties described below:

1-step games: In these games, participants possess a "strictly dominant" strategy, ensuring a higher payoff than any other strategy (i.e., the "dominated" strategies), regardless of the opponent's actions. The optimal solution can be identified through a single step of strategic thinking—eliminating the dominated strategies—by solely considering their own payoffs, without assessing the counterpart's incentives.

2-step games: Here, the opponent holds a "strictly dominant" strategy. The participant must identify the opponent's dominant strategy and respond accordingly to its expected action. Solving this type of game requires two steps of strategic thinking (or two steps of iterated elimination of dominated strategies) and the formation of first-order beliefs regarding the expected action of the counterpart.

3-step games: The solution requires three steps of strategic thinking. Initially, participants must recognize that they have a "dominated" strategy, i.e., a strategy paying less than any other available strategy, regardless of the opponent's potential actions. Then, they should realize that the opponent is aware that the participant will not choose the dominated strategy. This comes from the fact that the computer acts as a rational, profit maximizing agent. Therefore, the opponent would choose the best action for itself (i.e., the dominant action) between the two remaining actions. Ultimately, participants should predict the agent's action and respond accordingly, resulting in three steps of strategic thinking (and 3 steps of iterative elimination of dominated strategies).

4-step games: The solution requires four steps of strategic thinking. Initially, participants must recognize that the counterpart has a "dominated" strategy. Participants should believe that the opponent will never select that action and eliminate that possibility from the set of possible actions of the counterpart. After eliminating this action, the players have the opportunity to exclude one of their own options which is also dominated. At this point, the counterpart, understanding that "rational" participants will never choose the now-dominated option, will choose the best action for itself (i.e., the dominant action). Ultimately, participants should best respond to this dominant action of the counterpart resulting from the iterative elimination of dominated strategies.

An example of the four game types is illustrated in Figure 4. The comprehensive list of games can be found in Section A.1 of the Supplementary Material.

1-step

	i	ii	iii
I	42 , 73	68 , 81	18 , 19
II	33 , 82	48 , 29	27 , 57
III	81 , 38	75 , 46	$\underline{37}$, $\underline{68}$

2-step

	i	ii	iii
I	82 , 68	33 , 47	41 , 76
II	67 , 40	79 , 33	53 , 50
III	17 , 19	57 , 29	$\underline{65}$, $\underline{40}$

3-step

	i	ii	iii
I	39 , 90	57 , 86	36 , 28
II	83 , 11	65 , 70	50 , 79
III	11 , 50	40 , 43	$\underline{69}$, $\underline{61}$

4-step

	i	ii	iii
I	34 , 91	96 , 43	68 , 62
II	85 , 44	39 , 18	36 , 48
III	43 , 41	25 , 53	$\underline{72}$, $\underline{55}$

Figure 4. Examples of the four classes of games (1-step, 2-step, 3-step, 4-step). Participants acted as row players, while the computer acted as the column player. The equilibrium solution of the game is indicated by underlined payoffs. Dominant and dominated strategies are highlighted with green and orange backgrounds, respectively. In 1-step games, the participant possesses a strictly dominant strategy (Action III). The column player optimizes their payoff by choosing Action iii. For 2-step games, the opponent has a strictly dominant strategy (Action iii), and the row player responds optimally by choosing Action III. In 3-step games, three steps of iterated elimination of dominated strategies are needed. The row players eliminate their own dominated strategy (Action I) and respond optimally (Action III) to the opponent's dominant action (Action

ii), derived by excluding the row player's dominated strategy from the set of possible actions. In 4-step games, four steps of iterated elimination of dominated strategies are required. The row player eliminates the opponent's dominated strategy (Action ii), then eliminates their resulting dominated strategy (Action I). Subsequently, the row players respond optimally to the resulting dominant strategy of the counterpart (Action III).

3. Results

3.1 Analysis of the Assessment phase

Not all participants completed all three phases of the experiment. Out of the 69 expert negotiators who took part in the Assessment phase, 38 completed the entire training phase and participated in the Re-assessment phase. Those who did not complete the full training phase were excluded from the subsequent Re-assessment phase. Similarly, out of the 200 participants recruited through Prolific, 130 completed the entire training phase and participated in the Re-assessment phase, while 70 were excluded from the Re-assessment phase for either not completing the training phase or simply not showing up during this final phase of the experiment (33 of whom belonged to the training condition and 37 to the no-training condition).

We first test whether there is a significant difference in the rate of equilibrium choices and in the accuracy of beliefs observed in the Assessment phase, between participants who completed all phases of the experiment and those excluded from the reassessment phase. If no difference is detected, we can pool data for the Assessment phase. We conducted a Wilcoxon rank-sum test for both NEN and EN participants, and in both cases, there is no difference between the two groups when comparing the proportion of equilibrium responses (EN participants: Wilcoxon rank-sum test, $W = 559$, p-value = 0.72; NEN participants: Wilcoxon rank-sum test, $W = 5170$, p-value = 0.103) and also when comparing the accuracy of the beliefs (EN participants: Wilcoxon rank-sum test, $W = 718$, p-value = 0.121; NEN participants: Wilcoxon rank-sum test, $W = 4353$, p-value = 0.61). Based on these results, to compare the initial strategic abilities of the two groups (EN and NEN participants) measured during the assessment phase, we considered the entire sample of participants. It is important to note that the results remain unchanged even when considering only the participants who completed all phases of the experiment (see Section A.2.1 of the Supplementary Material). Comparing the proportion of choices consistent with the equilibrium and the accuracy of beliefs, the results show a significant difference between EN and NEN subjects (Choices: Wilcoxon rank-sum test, $W = 10036$, p-value < 0.001; Beliefs: Wilcoxon rank-sum test, $W = 9617$, p-value < 0.001). In particular, EN participants more frequently choose the action consistent with the equilibrium (Mean EN = 0.45; Mean NEN = 0.31) and have, on average, more accurate beliefs regarding the action the counterpart will take (Mean EN = 0.47; Mean NEN = 0.36).

There are two different hypotheses that can explain these differences. The first is that EN participants may have superior computational abilities compared to the NEN participants. The second hypothesis is that they analyze the strategic structure of the game more carefully before responding. Some insight can be derived from the analysis of the response times of the two groups. If EN participants think more carefully about the possible actions of the counterpart, their response times should be longer than those of NEN participants. This hypothesis is confirmed by the data (Wilcoxon rank-sum test, $W = 12211$, p-value < 0.001). EN participants take, on average, more than twice the time to make their decisions compared to NEN participants (Mean EN = 97650 ms.; Mean NEN = 38648 ms.). The average response times are generally quite long, indicating that both groups invested effort and attention in the task before making their decisions.

The next question we want to answer is whether the difference between EN and NEN participants depends on the strategic complexity of the game type or if it is an independent and generalized effect across different strategic environments. Our hypothesis is that the difference between the two groups increases with the increasing of the complexity of the strategic environment and the number of iterative steps required to identify the optimal response. In this regard, we compare the frequency of equilibrium choices between the two groups in the four game types by running a two-way repeated-measure ANOVA and considering a possible interaction (within-subject factor: *Game type* (1-step, 2-step, 3-step and 4-step); between-subject factor: *Group* (EN – NEN participants)). Results indicates a significant effect of the *Game type* ($F(1, 267) = 42.4$, $p < 0.001$) a significant effect of the *Group* ($F(3, 801) = 176.18$, $p < 0.001$) and a significant interaction (*Game type* Group* (3, 801) = 12.86, $p < 0.001$. Pairwise comparisons show that for participants in the EN group, there is a significantly higher proportion of equilibrium choices in step-1 and step-2 games compared to step-3 and step-4 games (1-step - 3-step: $p < 0.001$; 1-step - 4-step: $p < 0.001$; 2-step - 3-step: $p < 0.001$; 2-step - 4-step: $p < 0.001$). On the other hand, for participants in the NEN group, except for step-3 and step-4 games, there is a significant decrease in equilibrium responses as the strategic complexity of the game increases. The full list of pairwise comparisons is reported in Section A.2.2, SM.

As shown in Figure 5, NEN participants select more often the equilibrium response in simple games (1-step) that do not require considering the counterpart's incentives to identify the optimal option. However, the opposite is observed when considering more complex games (2-step, 3-step and 4-

step) that require forming accurate beliefs about the counterpart's behavior to identify the optimal strategy. These results can be explained by the fact that NEN participants more frequently use, compared to EN participants, a rather common decision heuristic based on selecting the option with the highest average payoff (see Polonio et al., 2015). This heuristic ensures the selection of the optimal response exclusively in 1-step games.

The results concerning choices are replicated in the analysis of beliefs, with the only difference being that in this case, the interaction is not significant. Indeed, a two-way repeated-measure ANOVA using the average accuracy of beliefs about the counterpart's choice as the dependent variable shows a significant effect of Game type ($F(1, 267) = 158.082$, $p < 0.001$), a significant effect of Group ($F(3, 801) = 32.01$, $p < 0.001$), and no significant interaction (Game type* Group $(3, 801) = 2.138$, $p = 0.094$).

As can be inferred from Figure 6, the accuracy of beliefs for both groups is higher for the 2-step game class, than for any other game class. These findings are consistent with prior research indicating that individuals often attribute simple decision-making strategies to their counterparts. They face challenges in acknowledging that counterparts also develop beliefs about their actions, striving to respond optimally based on their anticipation of others' behavior. (Costa-Gomes & Weizsäcker, 2008; Polonio & Coricelli 2019). In our specific case, 2-step games correspond to situations where the counterpart (the computer) has a dominant choice, and participants find it relatively straightforward to predict that the counterpart will choose that option. However, participants exhibit much less accurate beliefs in 1-step games since, to respond correctly in these games, they should anticipate that the counterpart will select the optimal response to their dominant option. This requires considering a counterpart that thinks about what they will do in that particular game.

Accurate beliefs in 2-step games paired with non-equilibrium choices (as observed for NEN subjects) clearly indicate a general inconsistency between choices and beliefs (i.e., choices are not optimal responses to personal beliefs). This outcome is extensively documented in the literature for players employing simple decision rules, such as the heuristic of selecting the option with the highest average payoff. Specifically, participants employing this simple decision rule tend to attribute the same decision strategy to their counterpart, resulting in a choice behavior that is not optimal according to their belief statements (Costa-Gomes & Weizsäcker, 2008; Polonio & Coricelli, 2019).

In summary, our findings indicate a consistent distinction between the two groups concerning the proportion of optimal choices and the accuracy of beliefs. However, it is important to note that this difference, especially regarding participants' choices, is contingent upon the specific type of game under consideration. Moreover, both groups appear far from exhibiting optimal decision-making behavior and accurate beliefs in games that require more than one step of reasoning. In these games, the rate of optimal choices for both groups falls below 0.6 (EN: step-1 = 0.64; step-2 = 0.53; step-3 = 0.31; step-4 = 0.31; NEN: step-1 = 0.70; step-2 = 0.25; step-3 = 0.12; step-4 = 0.14).

In the next paragraph, we will examine whether training with the app has been able to enhance the participants' decision-making skills in different types of games and whether there is a difference in the level of learning achieved by the two groups of participants (EN and NEN participants).

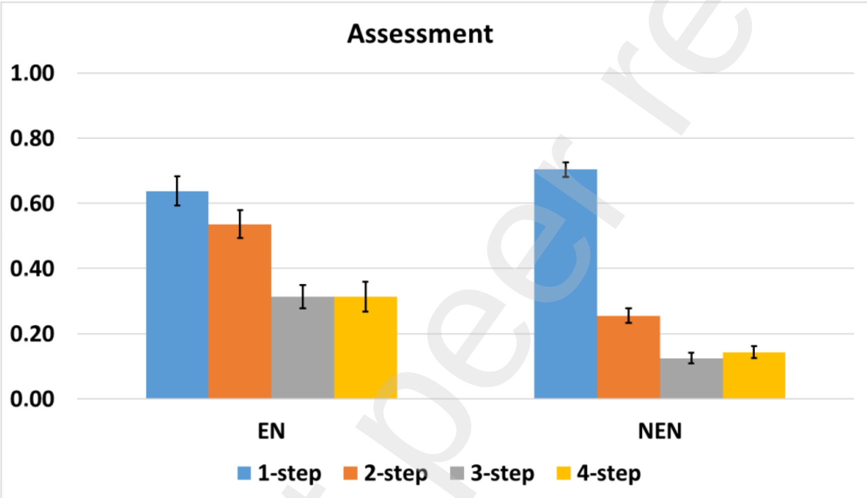

Figure 5. Proportion of responses consistent with the equilibrium for the two groups of participants (EN and NEN participants) in the four types of games (1-step, 2-step, 3-step, 4-step). Data refer to the Assessment phase.

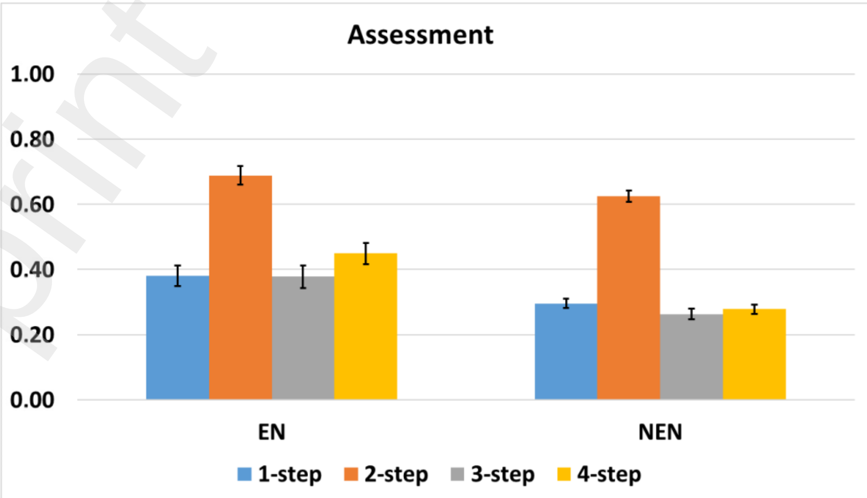

Figure 6. Average proportion of beliefs aligning with the actions of the rational and profit-maximizing counterpart for both participant groups (EN and NEN participants) across the four game types (1-step, 2-step, 3-step, 4-step). The data pertain to the Assessment phase.

3.2 Evidence of learning, choice task

When assessing learning for the two groups, we must consider only those participants who have completed all phases of the experiment. Overall, we have 38 EN participants and 130 NEN participants. The NEN participants are 63 participants belonging in the control condition who did not undergo training with the app (NEN no-training) and 67 participants who underwent training (NEN training).

First, we conducted a series of random effects logistic models on choice data to examine the presence of a learning effect contingent on the group (EN, NEN training, NEN no-training), comparing the Assessment and Re-assessment phases (a summary of the models is reported in Section A.2.3, SM). The trial-by-trial equilibrium responses (0: choice inconsistent with Nash equilibrium; 1: choice consistent with Nash equilibrium) were used as the binary dependent variable, with phase (Assessment; Re-assessment) and game type (1-step, 2-step, 3-step, 4-step) and their interactions as independent factors. The intercept was allowed to vary across participants, with random effects at the participant level to address intra-subject correlations from repeated assessments. Omnibus results for participants in the EN group indicate a significant main effect of the *phase* ($\chi2(1, N = 38) = 77.45$, $p < 0.001$), a significant main effect of the *game type* ($\chi2(3, N= 38) = 61.60$, $p < 0.001$) and no interaction ($\chi2(3, N= 38) = 2.65$, $p = 0.45$). When considering the NEN training group, we find a significant main effect of the *phase* ($\chi2(1, N = 69) = 67.20$, $p < 0.001$) a significant effect of the *game type* ($\chi2(3, N = 67) = 257.13$, $p < 0.001$), and a significant interaction ($\chi2(3, N = 69) = 28.75$, $p < 0.001$). The effect of *phase* is not significant for participants in the NEN no-training group ($\chi2(1, N = 63) = 2.81$, $p = 0.09$), while there is a significant effect of *game type* ($\chi2(3, N = 63) = 250.44$, $p < 0.001$) and a significant interaction ($\chi2(3, N = 63) = 18.50$, $p < 0.001$).

Figure 7 provides a clear description of the learning in the four classes of games for the three groups.

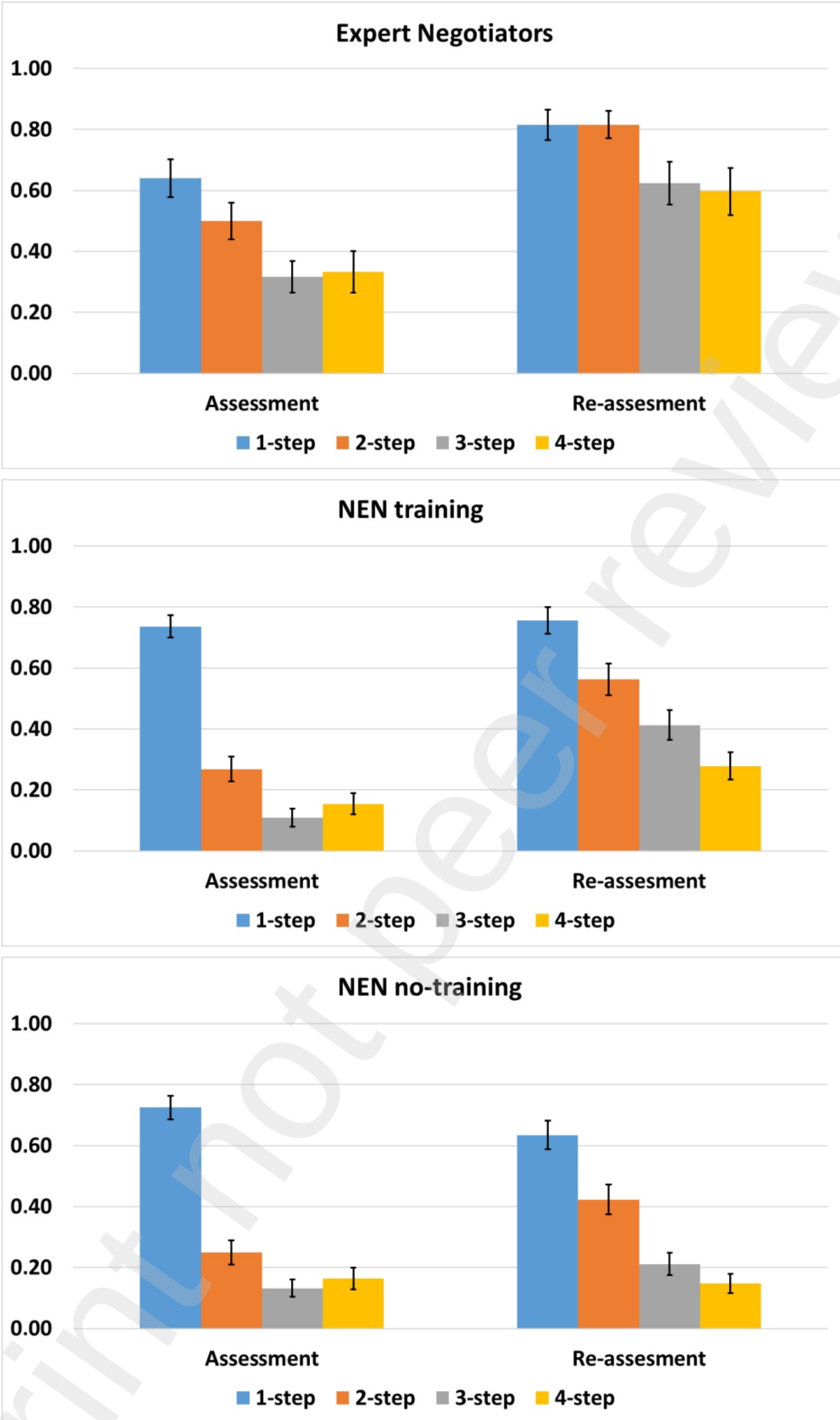

Figure 7. Proportion of choices consistent with the Nash equilibrium across phases (Assessment, Re-assessment) and game types for the three groups (EN, NEN training, NEN no-training). The error bars report between-subject standard errors of the mean.

Expert negotiators show a significant improvement in all four types of games. In 1-step games, they move from an initial average proportion of equilibrium choices of 0.64 to a proportion of 0.82. The same proportion is achieved in 2-step games with a 32% increase in equilibrium responses

(Assessment = 0.50, Re-assessment = 0.82). The initial proportion of equilibrium choices in 3-step and 4-step games does not differ from random choices (Assessment 3-step = 0.32; Assessment 4-step = 0.33), but after the training phase, they choose the equilibrium action on average almost two-thirds of the time (Re-assessment 3-step = 0.62; Re-assessment 4-step = 0.60).

The observed learning for NEN participants is less pronounced than that of EN participants, and it occurs less and less as the complexity of the strategic environment increases. NEN participants already exhibited a high proportion of equilibrium choices in 1-step games. This is probably due to the initial heuristic primarily used by these players, which involves selecting the option with the highest average payoff without considering the counterpart's choice behavior (Polonio et al. 2015). By construction, this heuristic is always consistent with equilibrium choice in 1-step games and never in other types of games. For this reason, in the Assessment phase, both NEN training and NEN no-training participants show a relatively high proportion of equilibrium choices in 1-step games (0.74 and 0.72, respectively), which persists in the Re-assessment phase for NEN training participants (1-step = 0.76). As mentioned before, this heuristic is less effective in the remaining types of games, resulting in a consistently low proportion of equilibrium choices in the Assessment phase for both NEN training (Assessment 2-step = 0.27; Assessment 3-step = 0.11; Assessment 4-step = 0.15) and the NEN no-training (Assessment 2-step = 0.25; Assessment 3-step = 0.13; Assessment 4-step = 0.16). In the Re-assessment phase, the increase in equilibrium choices for participants in the NEN training group is closely linked to the complexity of the game type. They achieve a proportion of equilibrium responses of 0.56 in 2-step games, 0.41 in 3-step games, and only 0.28 in 4-step games. Participants in the NEN no-training group show an increase in equilibrium choices only in 2-step games. This increase can be attributed to practice with the choice task and a change in the type of choice heuristic. The increase in equilibrium responses in 2-step games (Assessment 2-step = 0.25; Re-assessment 2-step = 0.42) is accompanied by a decrease in 1-step games (Assessment 1-step = 0.72; Re-assessment 1-step = 0.63), indicating that these participants struggle to adapt their choice strategy to the type of game they face.

3.3 Evidence of learning, belief elicitation task

We expect to replicate the findings from the choice task in the belief elicitation task. To investigate this, we employed a mixed-effects linear model analysis for the three participant groups, utilizing the proportion of correct beliefs as the dependent variable. The independent variables included *phase* and *game type*, and we incorporated random effects at the participant level. Our analysis revealed significant main effects of phase ($\chi2(1, N = 38) = 208.77$, $p < 0.001$) and game type ($\chi2(3, N= 38) = 56.06$, $p < 0.001$), as well as a significant interaction ($\chi2(3, N= 38) = 19.52$, $p < 0.001$) for participants in the EN group. Similarly, participants in the NEN training group exhibited significant main effects of phase ($\chi2(1, N = 69) = 118.97$, $p < 0.001$) and game type ($\chi2(3, N = 67) = 242.01$, $p < 0.001$), along with a significant interaction ($\chi2(3, N = 69) = 18.95$, $p < 0.001$). The NEN no-training group also demonstrated significant effects of phase ($\chi2(1, N = 63) = 6.72$, $p = 0.009$) and game type ($\chi2(3, N = 63) = 297.05$, $p < 0.001$), with a significant interaction ($\chi2(3, N = 63) = 16.32$, $p < 0.001$). A summary of the models is reported in Section A.2.4 (SM).

The results from the belief elicitation task replicate those obtained in the choice task, with the only difference being that in this case, a significant increase in the proportion of beliefs consistent with Nash equilibrium is observed even for participants in the NEN no-training group. This increase, as evident from Figure 8, is of modest magnitude (less than 5%, on average) compared to the increase observed for the EN (30% on average) and NEN training (17% on average) conditions and can be attributed to repeated practice with the task at hand.

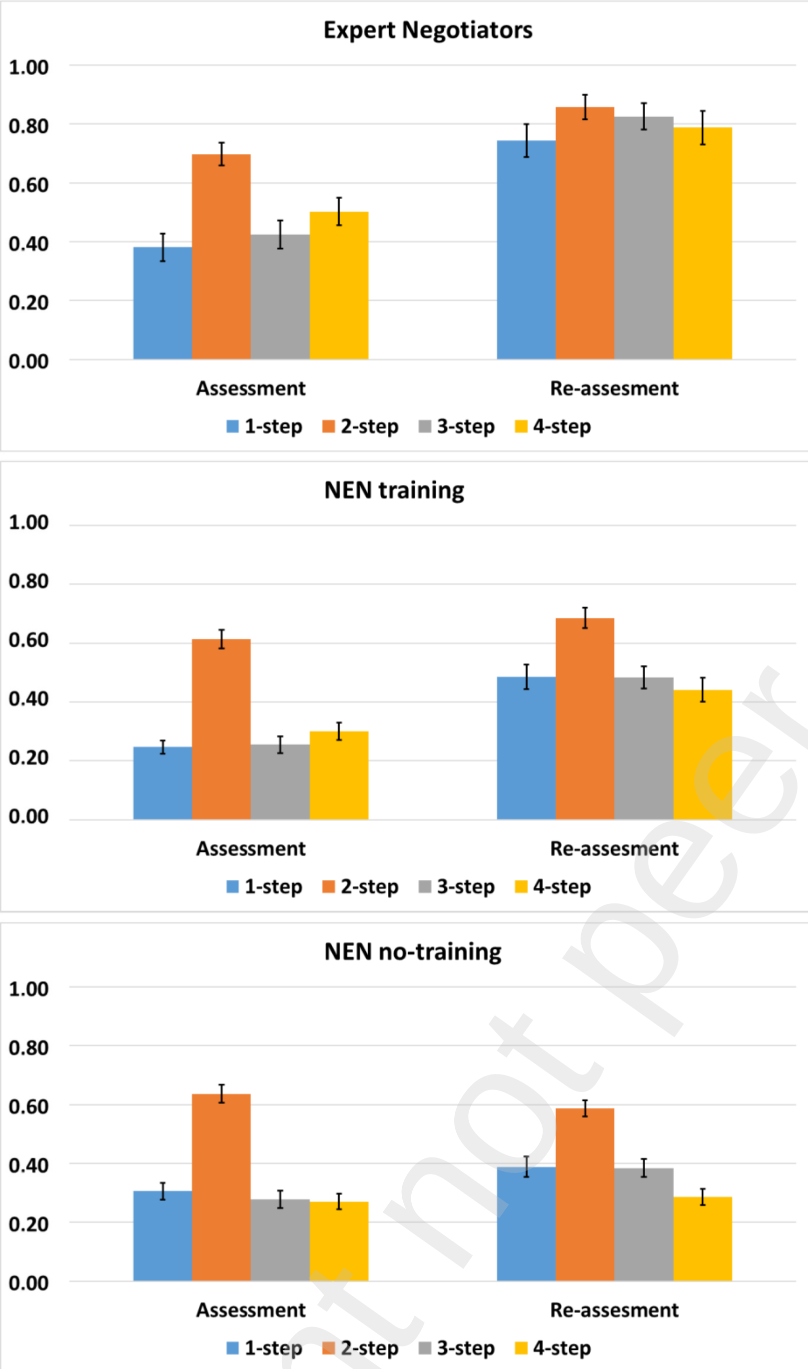

Figure 8. Mean proportion of beliefs consistent with the Nash equilibrium during the two phases (Assessment, Re-assessment) and game types for the three groups (EN, NEN training, NEN no-training). Error bars indicate between-subject standard errors of the mean.

3.4 Difference between groups after training

As shown in Figures 7 and 8, the accuracy in choices and beliefs for participants who underwent the training phase (EN and NEN training) appears to be substantially higher than that of NEN participants who did not (NEN no-training). To validate this observation, we performed a Kruskal-Wallis test, incorporating the *Group* (EN, NEN training, and NEN no-training) as a between-subject factor. The results show a significant effect both for the proportion of choices at equilibrium (Kruskal-Wallis chi-squared = 33.66, df = 2, $p < 0.001$) and for the average proportion of beliefs consistent with equilibrium (Kruskal-Wallis chi-squared = 49.39, df = 2, $p < 0.001$). Pairwise comparisons adjusted for multiple testing (Holm method) indicate a significant difference between all groups in terms of choices consistent with equilibrium (EN – NEN training: $p = 0.001$; EN – NEN no-training: $p < 0.001$; NEN training – NEN no-training: $p = 0.001$) and also in terms of beliefs consistent with the selected action of the counterpart (EN – NEN training: $p < 0.001$; EN – NEN no-training: $p < 0.001$; NEN training – NEN no-training: $p = 0.006$).

In the next section, we will delve into a detailed characterization of the participants' behavior in the three groups. This involves assessing their relative level of strategic thinking using the Cognitive Hierarchy (CH) model and examining how it evolves following the app training.

3.5 Learning in the framework of the CH model

To characterize participants' behavior in the three groups, we computed their relative levels of strategic thinking, as estimated by the CH model.[1] The CH model assumes a Poisson distribution, denoted as $f(k)$, for the frequency distribution of players' hierarchical steps of strategic thinking. This distribution is characterized by a single parameter τ, representing both the mean and variance. A higher τ indicates a greater level of strategic sophistication within a population (within each group in our case). To validate the findings from the previous section, we compared the τ parameter across phases and treatments to explore changes in strategic sophistication resulting from the app training. Interestingly, during the Assessment phase, participants in the three groups exhibited a uniform initial level of strategic sophistication between level-0 and level-1 (EN: $\tau = 0.45$; NEN training: $\tau = 0.62$; NEN no-training: $\tau = 0.61$). This means that participants struggled to provide an optimal response even in simple games where they had a dominant choice. Such a low level of this parameter for all three groups underscores the general inability of individuals to exhibit high levels of strategic sophistication in complex decision-making environments, as those presented in this study. However, the analysis of results related to the re-assessment phase shows a substantial

[1] It is important to note that, since in our experiment the players were aware that the counterpart was an algorithm consistently making rational choices aimed at maximizing gains, assuming that the counterpart (i.e., the participant) would also always choose rationally with the goal of winning as much as possible, any deviations from equilibrium by the participants cannot be explained by assuming that they had different beliefs about the sophistication level of the counterpart (i.e. the algorithm). Instead, these deviations can be exclusively attributed to their limitations in strategic thinking abilities.

increase in the level of strategic sophistication for participants who underwent app training. The group comprising EN participants reaches a level of strategic sophistication between level-3 and level-4 ($\tau = 3.43$), meaning that these players learned, on average, to solve games that require 3 and in some cases 4 steps of iterated elimination of dominated strategies to be solved. There is a significant increase in the level of strategic sophistication for NEN training participants as well, transitioning from an initial τ of 0.62 to a post-training τ of 2.23. They thus attain a level of strategic sophistication higher than level-2, enabling them to solve games that require 2 steps of iterated elimination of dominated strategies. Participants in the NEN no-training condition, on the other hand, do not exhibit any increase in their level of strategic sophistication, moving from a τ of 0.61 to a τ of 0.59. These results suggest that, although participants in the NEN no-training condition improve in terms of the average proportion of equilibrium responses, this increase is likely due to the use of more efficient heuristics rather than a genuine enhancement of their strategic sophistication.

4. Conclusions

In this study, we examined and compared the strategic sophistication abilities of expert negotiators and participants not primarily engaged in negotiation within their professional domains. Following an initial phase to assess their level of strategic thinking, participants were provided with targeted training aimed at enhancing their strategic skills using a specially designed app. The goal of this paper was two-fold: first, testing whether our training app is an effective tool to boost strategic sophistication; second, inspecting whether expert negotiators learn to adapt their strategies to new strategic settings better than non-experts.

Our app focused on improving decision-making and belief formation skills related to the expected behavior of counterparts in interactive decision-making contexts. Users engaged with a profit maximizer algorithm that made optimal decisions in strategically interactive contexts of varying complexity. The app, developed to enhance strategic abilities across different competence levels, allowed users to learn through feedback on decision outcomes, the accuracy of beliefs about counterparts' actions, and observations of counterparts' actual choices. Users could also monitor their learning through score analysis and belief accuracy in different gaming sessions.

The results unveiled an initial inability to respond optimally in games requiring the evaluation of the counterpart's incentives and the formation of accurate beliefs about their expected behavior, both among expert negotiators and individuals inexperienced in negotiation. However, following training, expert negotiators demonstrated a significant increase in strategic abilities, making optimal decisions and holding accurate beliefs even in highly complex games. Non expert participants also exhibited improved strategic skills, although they did not consistently achieve optimal solutions in highly complex games. Conversely, the control group (non-experts without app training) showed limited improvement.

To further support these results, we estimate the relative levels of strategic thinking of the three groups using the Cognitive Hierarchy model. The Cognitive Hierarchy model findings provided further evidence that app training significantly enhanced participants' strategic thinking abilities. Both EN and NEN training groups exhibited different but significant increases in their levels of strategic sophistication. EN participants increased from a τ parameter of 0.45 to 3.43, while NEN training participants increased from 0.62 to 2.23. In contrast, the NEN no-training group showed no improvement (from 0.61 to 0.59).

These findings underscore the effectiveness of targeted app training in enhancing general strategic decision-making skills, highlighting its potential application in various contexts, including negotiation and interactive decision-making environments.

How do we explain a higher learning for expert negotiators? In the study we conducted, participants engaged in games with complete information. At the start of the experiment, they received explicit information about the counterpart's rationality, the counterpart's beliefs regarding the player's rationality, the counterpart's objectives, and the counterpart's beliefs about the player's objectives. However, these initial pieces of information proved insufficient to determine a high proportion of optimal choices and the formation of accurate beliefs regarding the expected behavior of the counterpart, even for expert negotiators. Our findings indicate that both expert negotiators and non-experts frequently make suboptimal decisions, even in simple games where they have a dominant strategy (36% for EN participants; 27% for NEN participants). This percentage of suboptimal choices increases drastically when considering more complex games. Nonetheless, a crucial skill for negotiators is to deepen their understanding of their opponents as negotiations progress. Negotiators must continually update their beliefs and adjust the probability distribution established regarding their opponent's type. This iterative process highlights the ongoing refinement of strategic considerations in response to the evolving dynamics of the negotiation. We believe that negotiators exploit years of practice (and probably a natural propensity) to adapt fast to the new interactive setting. This gives them an advantage on non-experts and explains the difference in performance after training.

In conclusion, our results support the hypothesis that expert negotiators are more adept than other individuals in implementing this continuous process of revising the strategic elements of an interaction.

A limitation of this study that is important to mention concerns the absence of indices on the cognitive abilities and intelligence of the participants. For this reason, we cannot exclude that the two groups may differ in terms of intelligence or in some specific type of cognitive ability. However, the estimation of the initial level of sophistication for the two groups, conducted under the framework of the CH model, revealed no differences. This suggests that the substantial difference observed in the re-assessment phase may be attributed to the unique ability of the negotiator group to comprehend and adapt to the feedback received on the observed algorithm's behavior.

References

- Agranov, M., Potamites, E., Schotter, A., & Tergiman, C. (2012). Beliefs and endogenous cognitive levels: An experimental study. *Games and Economic Behavior*, *75*(2), 449-463.
- Alaoui, L., & Penta, A. (2016). Endogenous depth of reasoning. *The Review of Economic Studies*, *83*(4), 1297-1333.
- Alaoui, L., & Penta, A. (2022). Cost-benefit analysis in reasoning. *Journal of Political Economy*, *130*(4), 881-925.
- Babcock, L., & Loewenstein, G. (1997). Explaining bargaining impasse: The role of self-serving biases. *Journal of Economic Perspectives*, *11*(1), 109-126.
- Brañas-Garza, P., García-Muñoz, T., & González, R. H. (2012). Cognitive effort in the beauty contest game. *Journal of Economic Behavior & Organization*, *83*(2), 254-260.
- Burnham, T. C., Cesarini, D., Johannesson, M., Lichtenstein, P., & Wallace, B. (2009). Higher cognitive ability is associated with lower entries in a p-beauty contest. *Journal of Economic Behavior & Organization*, *72*(1), 171-175.
- Camerer, C. F., Ho, T.-H., & Chong, J.-K. (2004). A Cognitive Hierarchy Model of Games. *The Quarterly Journal of Economics*, *119*(3), 861–898.
- Carpenter, J., Graham, M., & Wolf, J. (2013). Cognitive ability and strategic sophistication. *Games and Economic Behavior*, *80*, 115-130.
- Chong, J.-K., Ho, T.-H., & Camerer, C. (2016). A generalized cognitive hierarchy model of games. *Games and Economic Behavior*, *99*, 257–274.
- Costa-Gomes, M. A., & Weizsäcker, G. (2008). Stated beliefs and play in normal-form games. *The Review of Economic Studies*, *75*(3), 729-762.
- Crawford, V. P. (2003). Lying for strategic advantage: Rational and boundedly rational misrepresentation of intentions. *American Economic Review*, *93*(1), 133–149.
- Druckman, D., Broome, B. J., & Korper, S. H. (1972). Negotiation under different decision rules: An experimental investigation. *Journal of Conflict Resolution*, *16*(3), 363-380.
- Fehr, D., & Huck, S. (2016). Who knows it is a game? On strategic awareness and cognitive ability. *Experimental Economics*, *19*, 713-726.
- Gill, D., & Prowse, V. (2016). Cognitive ability, character skills, and learning to play equilibrium: A level-k analysis. *Journal of Political Economy*, 124(6), 1619-1676.
- Goleman, D. (1996). Emotional intelligence. Why it can matter more than IQ. *Learning*, *24*(6), 49-50.
- Goodie, A. S., Doshi, P., & Young, D. L. (2012). Levels of theory-of-mind reasoning in competitive games. *Journal of Behavioral Decision Making*, *25*(1), 95-108.
- Grosskopf, B., & Nagel, R. (2008). The two-person beauty contest. *Games and Economic Behavior*, *62*(1), 93-99.
- Hanaki, N., Koriyama, Y., Sutan, A., & Willinger, M. (2019). The strategic environment effect in beauty contest games. *Games and Economic Behavior*, *113*, 587-610.
- Kiss, H. J., Rodriguez-Lara, I., & Rosa-García, A. (2016). Think twice before running! Bank runs

and cognitive abilities. *Journal of Behavioral and Experimental Economics*, *64*, 12-19.

- Knoepfle, D. T., Wang, J. T. Y., & Camerer, C. F. (2009). Studying learning in games using eye-tracking. *Journal of the European Economic Association*, *7*(2-3), 388-398.
- Loewenstein, J., & Thompson, L. L. (2006). Learning to negotiate: Novice and experienced negotiators. *Negotiation theory and research*, 77-97.
- Marchiori, D., Di Guida, S., & Polonio, L. (2021). Plasticity of strategic sophistication in interactive decision-making. *Journal of Economic Theory*, *196*, 105291.
- Nash Jr, J. F. (1950). Equilibrium points in n-person games. *Proceedings of the national academy of sciences*, *36*(1), 48-49.
- Polonio, L., & Coricelli, G. (2019). Testing the level of consistency between choices and beliefs in games using eye-tracking. *Games and Economic Behavior*, *113*, 566-586.
- Polonio, L., Di Guida, S., & Coricelli, G. (2015). Strategic sophistication and attention in games: An eye-tracking study. *Games and Economic Behavior*, 94, 80-96.
- Proto, E., Rustichini, A., & Sofianos, A. (2019). Intelligence, personality, and gains from cooperation in repeated interactions. *Journal of Political Economy*, *127*(3), 1351-1390.
- Pruitt, D. G. (1983). Strategic choice in negotiation. *American Behavioral Scientist*, *27*(2), 167-194.
- Pruitt, D. G., & Carnevale, P. J. (1993). *Negotiation in social conflict*. Thomson Brooks/Cole Publishing Co.
- Selten, R., Abbink, K., Buchta, J., & Sadrieh, A. (2003). How to play (3×3)-games: A strategy method experiment. *Games and Economic Behavior*, 45(1), 19-37.
- Thompson, L. (1990). An examination of naive and experienced negotiators. *Journal of Personality and social Psychology*, *59*(1), 82.
- Thompson, L., Wang, J., & Gunia, B. (2010). Negotiation. *Annual Review of Psychology, 61*, 491-515.
- Verbrugge, R., Meijering, B., Wierda, S., Van Rijn, H., & Taatgen, N. (2018). Stepwise training supports strategic second-order theory of mind in turn-taking games. *Judgement and Decision Making*, *13*(1), 79–98.
- Zonca, J., Coricelli, G., & Polonio, L. (2019). Does exposure to alternative decision rules change gaze patterns and behavioral strategies in games? *Journal of the Economic Science Association*, 5(1), 14-25.
- Zonca, J., Coricelli, G., & Polonio, L. (2020). Gaze patterns disclose the link between cognitive reflection and sophistication in strategic interaction. *Judgment and Decision making*, *15*(2), 230-245.
- Zonca, J., Vostroknutov, A., Coricelli, G., & Polonio, L. (2021). Timing of social feedback shapes observational learning in strategic interaction. *Scientific Reports*, *11*(1), 21972.

Acknowledgments

The research was conducted under a cooperative agreement between the IMT School for Advanced Studies Lucca and Intesa Sanpaolo Innovation Center S.p.A. and Intesa Sanpaolo S.p.A.

Founding

The authors declare that this study received funding from Intesa Sanpaolo Innovation Center S.p.A. The funder was not involved in the study design, collection, analysis, interpretation of data, and the writing of this article or the decision to submit it for publication.

Title:

Enhancing Strategic Sophistication: A Novel Approach for Expert Negotiators and Non-Experts

List of authors:

Luca Polonio
Department of Economics, Management and Statistics, University of Milano Bicocca.

Francesco Di Gruttola
IMT School for Advanced Studies Lucca

Sibilla Di Guida
IMT School for Advanced Studies Lucca

Francesca Maggi
Intesa Sanpaolo Innovation Center Torino

Marzio Alessi
Intesa Sanpaolo Innovation Center Torino

Salvatore Crescenzi
Intesa Sanpaolo Torino

Paolo Andrea Prandoni
Intesa Sanpaolo Torino

Davide Pietro Giuseppe Caironi
Intesa Sanpaolo Torino

Emiliano Ricciardi
IMT School for Advanced Studies Lucca

Davide Marchiori
Department of Marketing and Management, University of Southern Denmark