Chapter 2
Can Artificial Traders Learn and Err Like Human Traders? A New Direction for Computational Intelligence in Behavioral Finance

Shu-Heng Chen, Kuo-Chuan Shih, and Chung-Ching Tai

Abstract The microstructure of markets involves not only human traders' learning and erring processes but also their heterogeneity. Much of this part has not been taken into account in the agent-based artificial markets, despite the fact that various computational intelligence tools have been applied to artificial-agent modeling. One possible reason for this little progress is due to the lack of good-quality data by which the learning and erring patterns of human traders can be easily archived and analyzed. In this chapter, we take a pioneering step in this direction by, first, conducting double auction market experiments and obtaining a dataset involving about 165 human traders. The controlled laboratory setting then enables us to anchor the observing trading behavior of human traders to a benchmark (a global optimum) and to develop a learning index by which the learning and erring patterns can be better studied, in particular, in light of traders' personal attributes, such as their cognitive capacity and personality. The behavior of artificial traders driven by genetic programming (GP) is also studied in parallel to human traders; however, how to represent the observed heterogeneity using GP remains a challenging issue.

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2.1 Introduction and Motivation

2.1.1 Learning About Human Traders' Learning

When human subjects are placed in the market for trading competition [50, 51, 55], we have to admit that, up to the present, we do not have a good theory or even well-archived empirical evidence which can help answer the very general question regarding *who learns what and when*? The traditional approach to handling this issue is very much in the line initiated by Arthur [4], which is to compare the patterns observed from human traders with those observed from artificial (machine-learning) agents and, based on the similarity of the pattern, to decide whether human-subject learning has been well captured by the proposed computational intelligence models, such as genetic algorithms [2, 3], reinforcement learning [20], and so on and so forth.

One, of course, can gain some insights from this *mirroring approach* [16] that is conditional on a carefully chosen similarity metric. However, saying that human traders behave like the artificial agents, driven by evolutionary computation or reinforcement learning, seems at best to be only a *first-order approximation* of many complex or complicated details that human traders may face in the real markets, but are nonetheless difficult model at this stage. Humans are emotional beings and have different personal traits, which can easily result in great deviations from the behavioral dynamics as predicted by computational intelligence, be they genetic algorithms or reinforcement learning.

We try to use Fig. 2.1 to elaborate on this point. As typically assumed in most textbooks on financial mathematics, a global optimum exists for a well-defined trading problem. For example, it can be an optimum trading strategy which advises traders with respect to both the market timing and pricing (bids or asks) decisions. Given the existence of the global optimum, presumably one can then define and measure errors that a trader made based on the observed deviations. Both artificial traders and human traders can make mistakes and mistakes may have their *patterns*.[1] These patterns can be further analyzed to understand the underlying mechanisms which cause these patterns. In addition, in response to the errors, both artificial traders and human traders are supposed to learn, and their learning may also have patterns.[2] The question is then whether one can use computational intelligence to construct artificial agents in a way that both patterns of errors and learning observed from human subjects can be well understood.

What will be claimed in this chapter is that studies devoted to these issues are still in their infancy stage. While studies devoted to the financial application of

[1] Various patterns of mistakes, also known as *behavioral biases*, have been long studied by psychologists and social scientists. See [5], Part II, for a review of various biases. Also see [34].

[2] Learning does not necessarily mean correction in a right direction; the well-known over-reaction or over-adjustment are typical examples of this pattern of learning [48]. Furthermore, learning may take a while to see its effect; this is known as slower learning or the inertial effect [12].

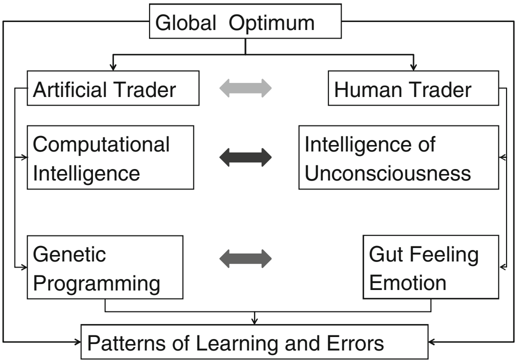

Fig. 2.1 Artificial traders and human traders

computational intelligence are piling-up research, most of them only have artificial traders or programmed traders as their main concern (the left part of Fig. 2.1). Few ever go further to see the possible connections to real human traders. Although the term "heuristics" is a psychology-oriented term and has lately also been widely used in computational intelligence,[3] the heuristics developed in the latter tend to be very much disentangled from the former.[4] It seems to us that the former belongs to a separate literature (the right part of Fig. 2.1) known as behavioral finance, psychological finance or, recently, neurofinance [5].

The tools and the languages used by intelligent finance and psychological finance are very different. For the former, the decision is made based on intensive search and data mining, such as genetic programming, whereas for the latter the decision is often made by very limited search in a very spontaneous and reflexive manner, such as gut feelings [32]. Needless to say, to build human-like artificial traders, it would be necessary to narrow the gap.[5] Hence, the first step is to have a thorough understanding of what kinds of patterns, both in learning and error-making, are neglected by the conventional financial applications of computational intelligence [18].

2.1.2 Research Framework

In this study, we bring a new direction by taking a first step in narrowing the gap. Instead of fitting a specific CI model to the observations of human traders, we propose a sensible measure, called the *learning index*, which takes into account some important details and hence sheds light on the exact cognitive orientation of human traders in the bazaar.

[3]See [33] for a simple historical review of the use of this term.

[4]For example, the recently published handbook on metaheuristics [31] has no single mention of psychology.

[5]Probably partially because of this gap, artificial traders cannot replace human traders [15].

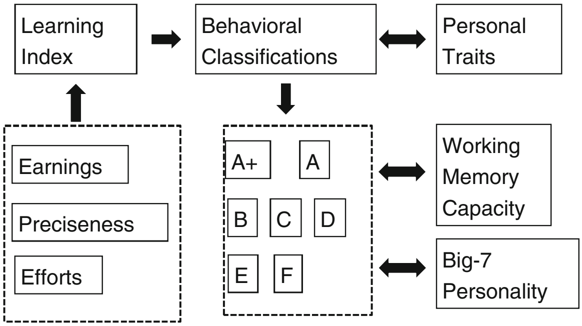

Fig. 2.2 Research framework

Our proposed learning index is based on three major elements related to the behavior of human traders. These three elements are *earning capacity*, *trading preciseness*, and *trading efforts*, as shown in the left block of Fig. 2.2. Each of the three will be motivated and detailed later; they together show the distinguishing feature of this learning index: not only can each element tell us whether the human agents have learned, but more importantly can inform us of the *quality* of their learning, which includes the degree, speed, and stability (fragility) of their learning. Hence, it gives us not just a one-shot end-result but more on the *process*, and, as we mention above, it is the process that matters in the applications of computational intelligence to modeling the human-trader behavior.

We then use the learning index to classify the performance of human subjects into distinctive groups, which basically range from inferior learning to superior learning. Hence, at the low end, such as Class "F" (middle block, Fig. 2.2), we have human subjects who have learned little or not at all, whereas, at the very top end such as "A+" or "A" (middle block, Fig. 2.2), we have subjects who have learned by heart. In the middle, we have subjects whose learning is not complete and their confidence about what they have learned has not been established either. For them, while the sky is not entirely clouded, shadows appear here and there.[6]

We then can proceed further to understand the causes of the observed heterogeneity among different subjects. The observed heterogeneities of human agents have not been represented by the standard applications of computational intelligence, and hence the causes of the observed heterogeneity have generally been neglected in the literature on artificial agents [18]. The study has not been picked up until very recently [19]. While human subjects can be heterogeneous in many dimensions, this chapter is limited to only two important ones: *cognitive capacity* and *personality*. These two dimensions are included because the literature indicates that they, by and large, can have an impact upon the decision-making quality [14, 46]. Hence, as a first step, we would like to examine their contribution to account for the observed heterogeneity in learning.

[6]Recently, there have been a number of studies focusing on the neurocognitive study of decision making under *uncertainty* or *ambiguity*, which may well serve as a neural foundation for the observed behavioral phenomena here [36, 54].

The proposed research framework with the three major components is summarized in Fig. 2.2. To illustrate the implementation of this framework, below we shall provide a concrete example based on the *double auction markets*. However, before we proceed further, let us wrap up this section by pointing out that each component of the proposed framework is flexible enough to make it adaptable to different applications. The essence is to meaningfully understand the learning and erring processes of human traders in a controlled (experimental) environment and hence to bridge the gap in learning and erring behavior between artificial traders and human traders, if the latter, to a quite large extent, cannot be replaced by the former [15].

The rest of this chapter is organized as follows. Section 2.2 describes the trading environment, a double auction market, based on which the laboratory experiments were designed. The global optimal trading strategy in this trading environment can be derived as a solution from a combinatorial optimization problem (integer programming). The solution can be read as an application of the economic theory of optimal procrastination. With this global optimum, Sect. 2.3 proposes the learning index which can help us observe the learning and erring patterns of both artificial traders and human traders. It can further help cluster different behavioral patterns, upon which the optimum-discovery capability of human traders can be observed. Section 2.4 applies the established learning index to sets of 165 and 168 human traders, respectively, and then associates the observed heterogeneities among these traders with their personal attributes, including cognitive capacity and personality. Section 2.5 presents the concluding remarks.

2.2 Trading Environment: The Double Auction Markets

In this study, both artificial traders and human traders are placed in a typical double auction market experiment [53]. In a double auction market, both buyers and sellers can submit bids and asks. This contrasts with only buyers shouting bids (as in an *English Auction*) or only sellers shouting asks (as in a *Dutch Auction*). There are several variations of DA markets. One example is the *clearinghouse* DA of the Santa Fe Token Exchange (SFTE) [50] on which this work is based.

On the SFTE platform, time is *discretized* into alternating *bid/ask* (BA) and *buy/sell* (BS) steps. Initially, the DA market opens with a BA step in which all traders are allowed to simultaneously post bids and asks for one token only. After the clearinghouse informs the traders of each others' bids and asks, the holders of the *highest bid* and *lowest ask* are matched and enter a BS step. During the BS step, the two matched traders carry out the transaction using the *mid-point* between the *highest bid* and the *lowest ask* as the transaction price. Once the transaction is cleared, the market enters a BA stage for the next auction round. The DA market operations are a series of alternating BA and BS steps.

The specific market architecture employed in this study has four buyers and four sellers. They are numbered from Buyer 1 to Buyer 4 and Seller 1 to Seller 4,

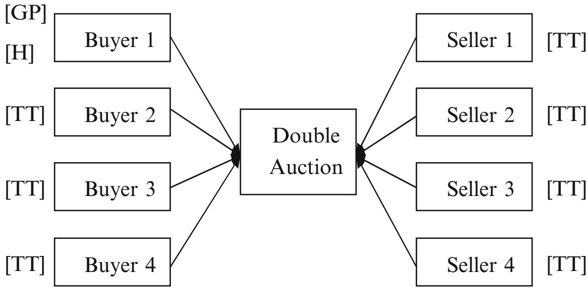

Fig. 2.3 Composition of market participants

Table 2.1 The token value table

	Token 1	Token 2	Token 3	Token 4
Buyer 1	10,518	10,073	6,984	6,593
Buyer 2	10,519	10,072	6,981	6,593
Buyer 3	10,516	10,071	6,985	6,589
Buyer 4	10,521	10,071	6,987	6,590
Seller 1	622	1,013	4,102	4,547
Seller 2	622	1,010	4,101	4,548
Seller 3	618	1,014	4,100	4,545
Seller 4	619	1,016	4,100	4,550

accordingly, as shown in Fig. 2.3. The commodity traded in this market is called the *token*. Buyers value these tokens and their *maximum willingness to pay* (the *reservation price* of buyers) for each token is specified in the *token-value table*. The willingness to pay is nonincreasing with the number of tokens already owned. For example, in Table 2.1, for Buyer 1, the maximum willingness to pay for the first token is 10,518, followed by 10,073 for the second, 6,984 for the third, and 6,593 for the fourth. On the other hand, sellers would like to provide these tokens and the *minimum acceptable price* (the *reservation price* of the seller) for each token is also specified in the token-value table. As the opposite of the maximum willingness to pay, the minimum acceptable price is nondecreasing with the number of tokens already sold. Let us use Seller 1 in Table 2.1 as an example. The minimum acceptable price starts with 622 for the first token, then 1,013 for the second, 4,102 for the third, and 4,547 for the fourth.

This structure of the token-value table is generated in light of the familiar behavior of marginal utility and marginal cost and hence it fits well with the law of demand and supply. If we pool all of the maximum willingness to pay and the minimum acceptable price together, and arrange them in descending order and ascending order separately, we can then draw a downward-sloping demand schedule and upward-sloping supply schedule, as shown in Fig. 2.4.

The artificial traders and human traders, placed in this market environment, will play the role of Buyer 1 (Fig. 2.3). The trading behavior of the artificial traders and the human traders is the focus of this study. The artificial traders will be programmed

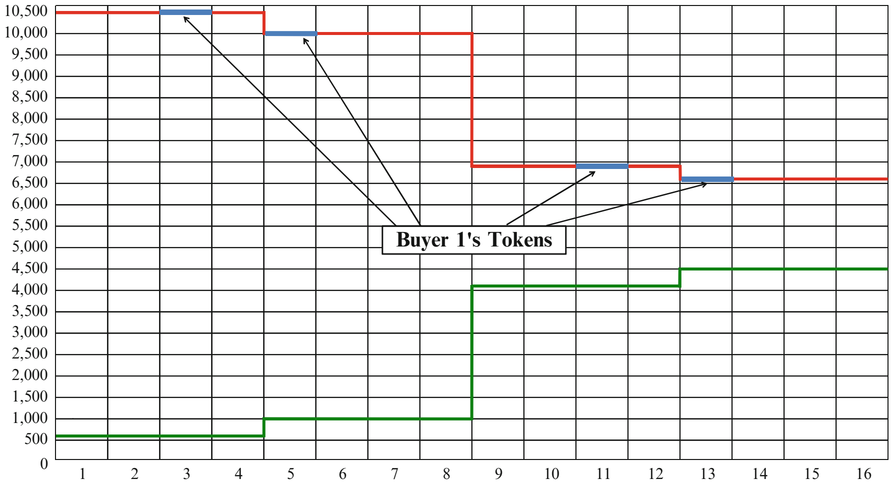

Fig. 2.4 The demand–supply schedule: the demand and supply schedule given above is drawn by arranging a list of all reservation prices in descending order for buyers' reservation prices and in ascending order for sellers' reservation prices

by *genetic programming*.[7] We also assume that all other market participants, i.e., the opponents of the artificial or human traders, are *truth tellers* (Fig. 2.3). Being a truth teller, the trader simply bids or asks at his current reservation price (along the demand and supply curves).

2.2.1 Benchmark: Market Timing and Bids

The institutional assumption of a discrete-time double auction in the form of SFTE coupled with the behavioral assumption of truth telling enables us to represent the given environment as a solvable *combinatorial optimization problem* (see the Appendix) [56]. Solving this optimization problem will give Buyer 1 the best *market timing* and the *most favorable bids*, which together leads to the highest trading profits for Buyer 1. The solvability of this problem allows us to keep a *benchmark* upon which our further analysis of learning and erring is based (Figs. 2.1 and 2.2).

For Buyer 1, the unique optimal trading strategy for the constrained combinatorial optimization is derived and presented in the left panel of Table 2.2. The panel has three columns, and the leftmost one is simply the number of trading steps, and, by following SFTE, there are a total of 25 trading steps for each market experiment.

[7] Chen [17] argues that genetic programming equips economists with a tool to model the chance-discovering agent, which is an essential element of modern economic theory.

Table 2.2 Trading schedule by optimization (*left panel*) and by the GP trader (*right panel*)

Optimization			GP simulation		
Step	Bidding time and bid	Match or not	Step	Bidding time and bid	Match or not
1	−1		1	−1	
2	−1		2	618	
3	−1		3	619	
4	−1		4	622	
5	−1		5	622	
6	−1		6	1,010	
7	6,988	Yes	7	1,013	
8	6,988	Yes	8	1,014	
9	−1		9	1,016	
10	−1		10	4,100	
11	−1		11	4,100	
12	−1		12	4,101	
13	−1		13	4,102	
14	−1		14	4,545	Yes
15	4,548	Yes	15	4,545	
16	4,550	Yes	16	4,547	Yes
17	−1		17	4,547	
18	−1		18	4,548	Yes
19	−1		19	4,548	
20	−1		20	4,550	Yes
21	−1		21	−1	
22	−1		22	−1	
23	−1		23	−1	
24	−1		24	−1	
25	−1		25	−1	

All trades have to be finished within these 25 steps. Normally, this is more than what an optimal trading strategy needs. The question is when to get into the market and how much to bid (ask), and the answers are shown in the 2nd column. Hence we can see that in this specific market, the optimal time to enter the market is at steps 7, 8, 15, and 16 with bids of 6,988, 6,988, 4,548, and 4,550, respectively. In this way, Buyer 1 can earn a maximum profit of 17,067. The symbol "−1" also showing in many rows of the table is not a value to bid, but a sign indicating "Pass," i.e., not entering the market. The third column then shows whether a deal is made given the offers (bids) and the asks from the sellers. Being an optimal trading strategy, this means that all bids are successfully matched, as the sign "Yes" indicates.

The intuition behind this optimum solution is the economic theory of *optimal procrastination*, which basically means that the trader attempts to delay his participation in the market transaction so as to avoid early competition and become a *monopsonist* in the later stage. Once getting there, he will then fully exercise the monopsony power by bidding with *third-degree price discrimination*. However, procrastination may also cause the agent to miss some good offers; therefore, there is an opportunity cost for procrastination and the agent will try to optimize the procrastination time by balancing his monopsony profits against these costs. Procrastinating in *two* stages gives the balance. As shown in Fig. 2.4, there is a sharp fall in the market demand curve accompanied by the sharp rise in the supply curve, which suggests dividing the sequence of trading actions into two, one before the change and one after the change.

2.2.2 Deviations: A Case of the GP Trader

The benchmark is an optimal strategy. In that sense, it becomes a rest state; additional efforts for searching or learning are not necessary. Therefore, as a benchmark, it helps us not only evaluate the earning performance of GP, but also enables us to see how much energy is being devoted to searching and learning. The second kind of deviation, deviation from *effort minimization*, can be equally, if not more, important than the first kind of deviation, deviation from *profit maximization*, even though in the machine learning literature we often only consider the first kind rather than the second.

Let us illustrate the second kind of deviation using one example from GP, as shown in Table 2.2.[8] This specific trading strategy found by GP generates the following trading behavior. We notice that, compared to the benchmark, GP traded at a different time schedule and made deals in periods 14, 16, 18 and 20 with lower bids (from 4,445 to 4,550). Not surprisingly, in this way, it also ended up with a lower profit of 15,978, rather than the maximum one of 17,067.

In light of the benchmark, we can see that the GP trader also learned to delay trading (as clearly shown in Table 2.2), but it did not procrastinate in the optimal way, i.e., in two stages; instead, it did so in one stage only. In addition to that, the GP trader had a total of 19 visits to the market, which is four times higher than the minimum effort required by the benchmark, i.e., four visits only. Hence, in sum, the GP traders deviate from the benchmark in *earnings*, *trading schedule* (market timing and bids), and *trading frequency*. The interpretation of these deviations for artificial traders, like GP, can be very different from that for human traders. All kinds of feelings related to uncertainty, such as gut feelings, fast and frugal heuristics, greed, fear, regret aversion, risk aversion, fatigue, and overconfidence, good or bad, may cause human traders to deviate from the benchmark in all three above-mentioned dimensions, and probably, in very different manner, too [52].

Alternatively put, the learning and erring behavior of human traders should be studied in the context of both cognitive psychology and personality psychology [30, 43–45]. Unless these psychological attributes have been incorporated into the design of artificial agents, one could hardly expect the same deviation patterns

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[8] The details of the GP run in this chapter can be found in [22].

between humans and machines.[9] Therefore, in the following, we will propose a measure of learning or a learning index which not only allows us to examine the end-results (earnings), but also enables us to trace some *psychological details* of the learning process of human subjects.

2.3 Leaning Index

2.3.1 The Three Criteria

What is proposed in this section is a learning index (LI) built upon the three above-mentioned possible deviations, namely, earnings, the trading schedule (market timing and bids), and trading frequency. The basic idea is to assign credits to the three above-mentioned criteria in such a way that in the end very different behavioral patterns can be easily distinguished. This is summarized in Table 2.3.

Here, very much in the spirit of the widely used *balanced scorecard* [40], we assign credits for each strategy or action that either fulfills or partially fulfills the target (given by the benchmark). Hence, X_1 points are given to the action if it leads to the maximum profit, and X_2 if it fails to do so. Obviously, $X_1 > X_2$. As we have learned from Table 2.2, if the action fails to fulfill the target return, it must then fail to follow the target trading schedule in terms of either market timing or bidding. Hence, a partial credit of Y points will be given for each single successful match. From Table 2.2, we know that these are a total of four units to trade; therefore, the trader will be assigned $4 \times Y$ points if the entire trading schedule is matched. Otherwise, it could be $3 \times Y$, $2 \times Y, \dots,$ all the way down to zero if there is no single match.

It is possible that the trader can still gain the maximum profits while not following the target trading schedule, because not all trades will be successful or effective, as we have seen from the GP trader in Table 2.2. Therefore, in considering that each offer, regardless of being successful or not, involves a cost, broadly known as the

Table 2.3 Credit assignment rule

	Criterion	Credits assigned	Range
1	Target earning	X_1 points if achieved X_2 points if not achieved X_3 points if surpassed	X_2, X_1, X_3
2	Trading schedule	Y for every single match	$0, Y, 2Y, 3Y, 4Y$
3	Trading frequency	Z for each entering to the market	$21Z, 20Z, \dots, 0$

[9]The fundamental pursuit here is: when a mistake is made, what are the differences between that made by an artificial agent and that made by human agents?

transaction cost,[10] we "credit" each additional unnecessary entrance to the market with Z points and $Z < 0$. Since a single market experiment lasts for 25 steps and 4 steps are necessary for finishing all possible trades, the trader can be "credited" with $21 \times Z$ as a maximum for his transaction cost.

2.3.1.1 Greed and Gambling

This gives the basic structure of the learning index. One thing which enables us to make a further distinction is the case where the trader may earn a profit which is higher than the benchmark. This subtle situation can occur when there is a piece of luck on which the benchmark does not rely on. This kind of luck occurs when a deal can be made with two or more identical offers, say, two identical bids, and then a lottery will be applied to decide who has the right to buy.

For example, according to the benchmark, the second token shall be bid in step 8 at a price of 6,988 (Table 2.2), which is one dollar higher than what Buyer 4 will bid at that moment (Table 2.1). Hence, if instead of 6,988 Buyer 1 bids more *greedily* also with 6,987, he may still get the deal with a 50% chance. If he has that luck, he may even earn an additional profit of 0.5, up to a total of 17,067.5. Nevertheless, if it is Buyer 3 who has the luck and not him, then he will lose the good price, 1,016, offered by Seller 4, and the next available quote for him will be a much higher 4,100, offered by Seller 3 or 4 (Fig. 2.4 and Table 2.1), which can cause him a dramatic drop in profits, from the target 17,067 to 16,622. Since our benchmark will not take this risky action, it may, therefore, lose to a trader who would like to bet on this luck.

This delicate design enables us to observe human traders' exploration of profit opportunities and their reevaluation of these opportunities after being aware of the underlying risk. We call this process "route to a gambler," and we wish to examine how traders' personalities may have an effect on the choice of this route and how this route has affected traders' total performance. To achieve this goal, a credit of X_3 will be assigned to the *gambler* ($X_3 > X_2$) if he did conclude a successful deal (Table 2.3). In this way, we can easily identify the occurrence of the gambler's route during the trader's learning process.

2.3.2 *Illustrations*

The proposed learning index is illustrated with three cases, one GP trader and two human traders. Before we do so, we need to set the values of the credit parameters appearing in Table 2.2. There is no unique way to set these values. Many possible sets of values should work fine as long as they help us easily separate agents with

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[10] It does not have to be narrowly limited to the pecuniary costs associated with trading, such as broker fees or the Tobin tax. It can cost personal health as well [6].

Table 2.4 Parameter setting for the credit assignment

Parameter	Value
X_1	1,000
X_2	0
X_3	2,000
Y	100
Z	−1

very different leaning and erring patterns. In a sense, these sets of values serve the role of separating the hyperplane, such as the support vector machine. With this understanding, we, therefore, arbitrarily choose one set of values, as given in Table 2.4, and will fix this setting throughout the rest of the chapter.

2.3.2.1 Artificial Trader

We begin with a very simple demonstration and apply the learning index to the GP trader introduced in Table 2.2. First, this GP trader did not earn the target profit; hence, his earning performance is credit zero ($X_2 = 0$). Second, he failed to follow the target trading schedule from the first token to the last token; hence, the credit assigned to his trading schedule is also zero ($0 \times Y = 0$). Finally, as to the transaction frequency, he also failed to use the necessary trading times: he used 15 more times. His credits earned in this part become -15 ($15 \times Z = -15$). As a total, the learning index of this GP trader is, therefore, -15 ($= X_2 + (0 \times Y) + (15 \times Z)$).

2.3.2.2 Human Traders

Human-subject experiments in double auction markets were conducted at the Experimental Economics Laboratory (EEL), National Chengchi University, from May to July 2010. Each student played the role of Buyer 1 as shown in Fig. 2.4. The DA experiments were repeated 30 times for each subject, and as a whole could be finished in 1 h. In addition to the DA experiment, they were also paid to run two additional psychological tests, namely, the *working memory test* (Sect. 2.4.2.1) and *personality test*. The experimental results, including their DA market performance as well as psychological tests, are all well archived in the Experimental Subject Database (ESD). From this database, we successfully retrieved a set of 165 subjects with the working memory test and 168 subjects with the personality test.[11] In the following, our illustration will be based on two representative subjects, namely, Subjects 1331 and 1129.

[11] In fact, there are a total of 185 subjects attending the double auction experiments, but for some of them the data are incomplete. Hence, for the WMC test the valid sample has 165 subjects, and for the personality test the valid sample has 168 subjects. There are 151 subjects appearing in both samples.

1331	Period																													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Index	-5	99	2098	2098	-4	2096	196	1196	1297	1397	1299	1398	1399	1398	1398	-6	1398	1293	1398	1398	1400	1398	1400	1397	1398	1297	1399	1298	1398	1398
Step 1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 2	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 3	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 4	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 5	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 6	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	6988	-1	-1	-1	-1	-1	-1
Step 7	-1	6988	6988	6988	-1	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	-1	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988
Step 8	-1	6986	6987	6987	6987	6987	6987	6988	6988	6988	6988	6988	6988	6988	6988	-1	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988
Step 9	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 10	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 11	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 12	-1	-1	-1	-1	-1	-1	4548	-1	-1	4548	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 13	-1	-1	-1	-1	4545	4545	4548	4545	-1	4548	-1	4548	-1	4548	4548	4548	4548	4548	4548	4548	-1	4548	-1	4548	4548	4548	-1	-1	4548	4548
Step 14	4545	-1	-1	-1	4545	4545	4548	4547	4547	4548	-1	4548	4548	4548	4548	4550	4548	4548	4548	4548	-1	4548	-1	4548	4548	4548	4548	4548	4548	4548
Step 15	4545	4547	-1	-1	4547	4545	4548	4547	4548	4548	4548	4548	4548	4548	4548	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 16	4547	4748	4548	4548	4548	4548	4548	4548	4548	4550	4548	4550	4550	4550	4550	4548	4550	4548	4550	4550	4550	4550	4550	4550	4550	4548	4550	4548	4550	4550
Step 17	4547	4749	4548	4548	4548	4548	4550	4548	455	-1	4550	-1	-1	-1	-1	4548	-1	4548	-1	-1	-1	-1	-1	-1	-1	4550	-1	4550	-1	-1
Step 18	4748	-1	4550	4550	4550	4550	-1	4550	4550	-1	-1	-1	-1	-1	-1	4548	-1	4548	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 19	4548	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	4548	-1	4548	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 20	4550	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	4550	-1	4548	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 21	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	4550	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 22	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 23	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 24	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 25	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Profit	15878	16322.5	17067.5	17067.5	16521.5	17067.5	16521.5	17067	17067	17067	17067	17067	17067	17067	17067	15975	17067	17067	17067	17067	17067	17067	17067	17067	17067	17067	17067	17067	17067	17067

Fig. 2.5 The learning and erring process of Subject 1331

Figure 2.5 gives the trading process of Subject 1331. As said, the DA experiments were repeated 30 times (periods). For each period, bids and asks were made and matched 25 times (steps). Hence, basically, what is demonstrated in Fig. 2.5 is a 25-by-30 table. Each column vector then indicates how the subject bid and made deals during the respective period. At the very top of the table, the "Index" row (the 2nd row) gives the sum of the credits assigned for each of the three criteria.

For example, this number in the 31st column (the last trading period) is 1,398, which can be broken down into 1,000 (X_1), 400 ($4 \times Y$), and -2 ($2 \times Z$). The reasons for these assigned credits are clear. The subject did earn the target profit (1,000 credits); in addition, the trading schedules of all four tokens (bidding time and bids) were exactly the same as the benchmark strategy (400 credits). Nevertheless, he also made two unnecessary early bids for the last two tokens; by the third criterion, he lost two points (-2). Therefore, his learning index (LI) over the three criteria is 1,398 points. This performance, compared to his initial value, -5 in period 1 and 98 in period 2, shows a significant improvement.

We, however, would like to draw readers' attention to two stylized patterns of human learning and erring. First, while many subjects are able to show significant improvement made over time, *their learning curve is not monotonically increasing and may fluctuate significantly*, which leads to our next point. The fluctuating pattern of their performance can be attributed to either *accidents* or *a lack of confidence* in what they learned. In the case of Subject 1331, we can see the relevance of these two possibilities. The sudden drop from a peak of "1,398" in period 15 to "-6" in period 16 could be hypothesized as an accident due to an absent mind (forgot to bid in Steps 7 and 8). In addition, in periods 21 and 23, the subject already had a full score; however, he was constantly trying something else nearby and that cost him some additional points. This indicates that some degree of uncertainty or confusion

1129	Period																													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Index	-6	88	-13	188	188	188	87	87	87	188	288	87	2288	2288	288	2288	2288	2288	288	288	1388	1388	1388	1388	1388	1388	288	1388	1388	1388
Step 1	10518	4550	4549	4545	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 2	10525	4550	4549	4545	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 3	10080	4550	4549	4545	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 4	10517	4550	4549	4545	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 5	10518	4550	4549	4545	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 6	7000	4550	4549	4545	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 7	10584	4550	4549	4545	4545	4545	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988	69988	6988	6988	6988
Step 8	-1	4550	4549	4545	4545	4545	6986	6987	6987	6987	6987	6987	6987	6987	6987	6987	6987	6987	6987	6987	6988	6988	6988	6988	6988	6988	6988	6988	6988	6988
Step 9	-1	4550	4549	4545	4545	4545	4545	6988	6987	4550	6987	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 10	-1	4550	4549	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 11	-1	4550	4549	4545	4545	4545	4545	4545	4545	4550	4548	4548	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 12	-1	4550	4549	4545	4545	4545	4545	4545	4545	4550	4548	4545	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 13	-1	4550	4549	4545	4545	4545	4545	4545	4545	4550	4548	4545	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 14	-1	4550	4549	4547	4547	4547	4547	4545	4545	4550	4548	4545	4548	4548	4547	4548	4548	4548	4547	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 15	-1	4550	4549	4548	4548	4548	4550	4545	4545	4550	4548	4547	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548	4548
Step 16	-1	4550	4549	4550	4550	4550	4548	4547	4548	4550	4550	4548	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550	4550
Step 17	-1	-1	4550	-1	-1	-1	4550	4550	4550	-1	-1	4550	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 18	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 19	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 20	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 21	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 22	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 23	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 24	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Step 25	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Profit	11464	15973	15975	15978	15978	15978	16521	16072	15526	17066.5	15526	16522	17067.5	17067.5	16522	17067.5	17067.5	17067.5	16522	16522	17067	17067	17067	17067	17067	17067	-14433	17067	17067	17067

Fig. 2.6 The learning and erring process of Subject 1129

remains, even though he was very close to having a full grasp of the underlying environment and incessantly earned the highest profit from period 17 to the end (see the last row).

What is particularly interesting is the gambler's route as we have discussed in Sect. 2.3.1.1. Subject 1331 at a very early stage had already found the route for the risky higher profit. His learning index in periods 3, 4, and 6 of 2,096 or 2,098 shows his success in trading the second unit at a noncompetitive bid. This noncompetitive bid caused him to lose the deal in period 7, and he seemed to learn the risk associated with this lower bid with this loss, and decided to walk away from this gambler's route and never came back. This pattern clearly shows that when he recognized the risk and decided not to take the risk, period 7 was the critical point.

Figure 2.6 shows another example of discovering the gambler's route. Subject 1129 also found the gambler's route in period 13, when he tried to bid at an equal level to the bid of Buyer 4 with 6,987. He succeeded by "stealing" the deal and earned a higher profit. By the same greedy strategy, he also succeeded four times in the next five periods (periods 14–19). He did fail in period 15, but that single failure did not prevent him from walking on this gambler's route. Then the two consecutive losses in periods 20 and 21 finally made him realize that his luck was simply not as good as he expected. So, he also walked away from the gambler's route and never came back.

This pattern of "walking away from the gambler's route" is intriguing because human traders were not supplied with the information on the chance of getting the deal when the two bids were equal. They had to calculate the risk solely based on their experience. They may thus behave like the expected-profit maximizer except that, without being given the underlying probability, their profit expectations have to be formed through experience. The judgment of risk or risk preference is obviously different among traders. For Subject 1331, it took only one failure before he walked away, but, for Subject 1129, it took failures on three occasions.

Table 2.5 Learning and erring patterns represented by different plateaus

Plateau	Index	Points	Target earning	Description
A+	$X_3 + \alpha Y + \beta Z$	1,975–2,400	Higher	Lucky gambler
A	$X_1 + 4Y$	1,400	Y	Global optimizer
B	$X_1 + 4Y + \beta Z$	1,375–1,399	Y	First-order ε-global optimizer
C	$X_1 + 3Y + \beta Z$	1,275–1,300	Y	Second-order ε-global optimizer
D	$X_1 + 2Y + \beta Z$	1,175–1,200	Y	Third-order ε-global optimizer
	$X_1 + Y + \beta Z$	1,075–1,100		
	$X_1 + \beta Z$	975–1,000		
F	$X_2 + 3Y + \beta Z$	275–300	N	Non-optimizer
	$X_2 + 2Y + \beta Z$	175–200		
	$X_2 + 1Y + \beta Z$	75–100		
	$X_2 + \beta Z$	-25 to 0		

$\alpha \in \{1,2,3,4\}$, and $\beta \in \{0,1,2,\ldots,25\}$. Points given in the third column "points" are the results from the index formula (second column) using the parameters specified in Table 2.4

2.3.3 Plateaus

The credit assignment rule specified in Sect. 2.3.1 allows us to easily separate several different kinds of behavior, as is now summarized in Table 2.5, and which can be read as a sequence of plateaus arranged in descending order. Basically, we have classified traders into four distinct groups, namely, lucky gamblers (Class A+), optimizers (Class A), near optimizers (Classes B, C, and D), and non-optimizers (Class F).

Traders belonging to Class A+ have been described in Sect. 2.3.1.1. Traders belonging to the other four highest classes, Classes A, B, C, D, are those who are able to achieve target returns. However, what distinguishes Class A from other classes is that the traders belonging to the former are exactly on the trading schedule (market timing and bids), whereas the traders belonging to the latter are not. This can happen when the human trader misplaced an aggressive lower bid, which caused him to miss an early trade and fall out of the target trading schedule accordingly. Every such single miss can be interpreted as if human traders were still testing other possibilities of generating a higher profit by exploring around a small (ε) neighborhood of a global optimum. Hence, Classes B, C, and D can be pictured as traders who are in the small neighborhood of the global optimum with different radii, from a smaller one to a larger one. In the parlance of economics, if Class A is equivalent to rational traders, then Classes B, C, and D can be analogous to near-rational traders.

In contrast to the above four classes, Class F traders are traders who are still distant from the global optimum due to various errors (bidding, timing, etc.).

Despite the noticeable distance, some agents were able to figure out part of the structure of the trading game; they, therefore, made one, or two, or three deals in line with the trading schedule. However, since all of them are still in the early or the middle stage of learning, they are qualitatively separated from the global optimizers.

2.3.4 Learned or Not and When?

Based on the two illustrations in Sect. 2.3.2, can we use the learning index to decide whether the subject has actually learned the optimum strategy, and, if so, when? This issue is more subtle than what one might think. Using the examples above, can we consider a subject with a score of 1,400 to be the one who has learned? The answer is *yes*, if he could have repeatedly achieved this score, but what happens if he did not? The idea to be discussed below is to allow for a kind of deviation which we shall call an *accident* and to develop an *accident-tolerance criterion* for determining whether the agent has learned.

By that, we intend to consider the case where the subject seemed to learn the benchmark strategy, but his learning index was not consistently high as 1,400 and might occasionally have fallen down to a lower level (Fig. 2.5). These falls may occur for various reasons. First, the subject was tired, absent-minded, and made operational mistakes. Second, the subject was not sure that he had already found the benchmark strategy and attempted to explore further before realizing that nothing was there. Falls of these kinds can then be tolerated as long as they do not occur *frequently*. Hence, a subject is considered to have learned the benchmark strategy if he can stay on the high plateau long enough to make any fall look like an accident.

The discussion above motivates the development of the accident-tolerance criterion. What we propose is a $Q-q$ rule, where Q refers to the *length of window* denoting the most recent Q periods. Among the most recent Q periods, the subject is either on a high plateau or not: q_1 is the number of the periods that he stayed on a high plateau, and q_2 is the number of periods that he did not. Obviously, $Q = q_1 + q_2$. Now, consider the ratio $q = q_2/Q$. If the error is an accident, then q must be low enough to justify it being so. The question is how low. The answer may further depend on the subject's most recent Q location. Is it a global optimum or an epsilon-global optimum? Intuitively, q can be higher if the subject has already been in the global optimum, and lower if the subject has not. Quantitatively speaking, q should be an inverse function of ε (the radius of the neighborhood of the global optimum).

To implement this $Q-q$ rule, we have to parameterize it. What we suggest in this study is the following. We only consider Classes A and B (Table 2.5) as the high plateau, i.e., we take the first-order near-optimum as the threshold for the applicability of the $Q-q$ rule. Higher-order near-optima will make it difficult for us to distinguish accidental errors from true errors, which in turn will make it harder to catch the first crossing time that the subject learns the optimum. Other parameters are specified in Fig. 2.7 to satisfy a q as a monotone decreasing function of the radius of a neighborhood of the global optimum.

Criteria \ Period	–6	–5	–4	–3	–2	–1	Current period
LI = 1400							
1400 > LI ≥ 1395							
1400 > LI ≥ 1390							
1400 > LI ≥ 1380							
1400 > LI ≥ 1375							

Fig. 2.7 Accident-tolerance criteria for deciding whether the subject has learned

As suggested in the figure, it is sufficient to consider that the subject has learned the optimum strategy if he had the highest score (1,400) twice over the last three periods ($q = 1/3$). In other words, if he has been really good on two occasions, then missing once is accepted as an accident. In a similar vein, we also consider a subject to have learned if his score is between 1,395 and 1,400 three times over the last four periods ($q = 1/4$), or between 1,390 and 1,400 four times over the last five periods ($q = 1/5$), or between 1,380 and 1,400 five times over the last six periods ($q = 1/6$), or between 1,375 and 1,400 six times over the last seven periods ($q = 1/7$).

2.4 Heterogeneity in Learning

2.4.1 Time Required to Learn and the Aftermath

The learning index (Table 2.3) and the accident-tolerance criteria (Fig. 2.7) are now applied to the 165 subjects (Sect. 2.3.2.2). The results are shown in Fig. 2.8. To maintain brevity, we only show those subjects who have learned, at least once, in the sense of the accident-tolerance criteria. In other words, one of the five possibilities, as shown in Fig. 2.7, must apply for the subject at least once during the 30-period experiment; if that never happens, the subject simply did not learn the optimum and the code is not shown in this figure. In this way, the learning dynamics of 29 subjects (17.5% of the 165 subjects) are presented in Fig. 2.8. Their code is listed in the first column of the figure from the bottom to the top, based on the time used to learn the optimum; the lower, the faster.

Each row then denotes the state of each subject in each of the 30 periods of the experiment, from the left to the right. The blank cell means that the subject has not learned or learned but "forgot" in that respective period. The blue-colored cell means that one of the accident-tolerance criteria (Fig. 2.7) applies to the respective agent in the respective period. The first blue-colored cell in each row refers to the earliest time that the subject learned the optimum, and all other blue-colored cells following this leading one indicated that the subject stayed on the optimum strategy after having learned it.

As we can read from the bottom to the top, some subjects were able to learn the optimum strategy in the very early periods, like Subject 1531, who had already

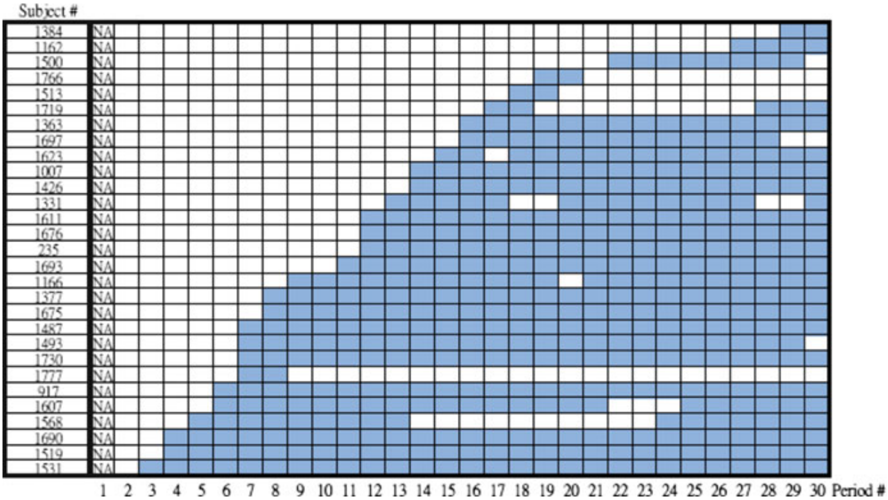

Fig. 2.8 Subjects who have learned the global optimal trading strategy: when it was the first time that the human traders learned the optimum trading strategy, and, after they learned it, whether they stayed on the optimal state. Out of 165 human traders, only 29 have learned the optimum before the expiration of the entire experiment. Their code is listed in the first column of the figure from the *bottom* to the *top*, based on the time used to learn the optimum; the lower, the faster. Each *row* then indicates the state of each subject in each of the 30 periods of the experiment, from the *left* to the *right*. A *blank cell* means that the subject has not learned or has learned but "forgot" during that respective period. The first *blue-colored* cell in each row indicates the earliest time that the subject learned the optimum, and all other *blue-colored* cells following this leading one indicate that the subject stayed on the optimum trading strategy after having learned it

done so in period 3; some needed a longer time to do so, like Subject 1384, who did not learn the optimum strategy until period 29. In addition to the minimum time required to learn the optimum, the aftermath of reaching the global optimum is also heterogeneous among agents. Once after being blue-colored, most subjects remain blue-colored, such as Subjects 1531, 1519, and 1690 (Fig. 2.8). There are a few, such as 1568 and 1607, who detoured from the optimum strategy to have further explorations, but were able to return in a later period. Only a very few, such as 1777, failed to come back again before the expiration of the experiment. Hence, in general, the global optimum is quite *stable* for most subjects: once they learn it, they will constantly keep it.

2.4.2 Cognitive Capacity

Our double auction experiment shows once again the heterogeneity of the learning dynamics among human traders. One of the most ambitious plans under the integration of agent-based computational economics and finance and experimental economics is to examine and model the great heterogeneity of human subjects as manifested in their learning dynamics.[12] There are two fundamental issues arising in this research direction. First, under the parsimony principle, how many attributes are needed for representing, up to a substantial degree, each human trader so that their heterogeneity in the learning dynamics can be replicated through artificial agents? Second, for each attribute and the assigned value, should we consider a different computational intelligence algorithm or the same algorithm but with different parameter values?

In this chapter, our focus is on the first issue and starts from a very fundamental level, namely, the psychological attribute of human traders.[13] By that, we mean differentiating human traders by either their *cognitive attributes* or *personality attributes*. The key measurement of the former is *working memory capacity*, whereas the key measurement of the latter is a Chinese version of *Big Five*. In this section, we shall focus on the former and provide details of the latter in a separate section (Sect. 2.4.3).

2.4.2.1 Working Memory Capacity

Cognitive capacity is a general concept used in psychology to describe a human's cognitive flexibility, verbal learning capacity, learning strategies, intellectual ability, etc. [13]. Although cognitive capacity is a very general concept and can be measured from different aspects with different tests, concrete concepts such as the intelligence quotient (IQ) and working memory capacity are considered to be highly representative of this notion. We adopt working memory capacity as a measure of cognitive capacity because working memory capacity is not simply a measurement of the capacity of short-term memory, but a "conceptual ragbag for everything that is needed for successful reasoning, decision making, and action planning" (p. 167, [47]). It has been shown that WMC is highly correlated with general intelligence [26, 39] and performance in other cognitive domains, such as sentence comprehension [27] and reasoning [41]. Recently, working memory capacity has been regarded as an important economic variable in both experimental economics and agent-based computational economics.[14]

In this study, human traders involved in the double auction experiments are requested to take a working memory test. The test version is based on [42] and is composed of five parts, which are backward digit span (BDG), memory updating (MU), operation span (OS), sentence span (SS), and spatial short-term

[12] For those readers who are unfamiliar with this development, some backgrounds are available from [19, 20].

[13] While the conversation between psychology and economics has a long history and a rapidly growing literature, it was only very recently that economists started to take into account psychological attributes in their economic modeling and analysis.

[14] A survey is available from [21].

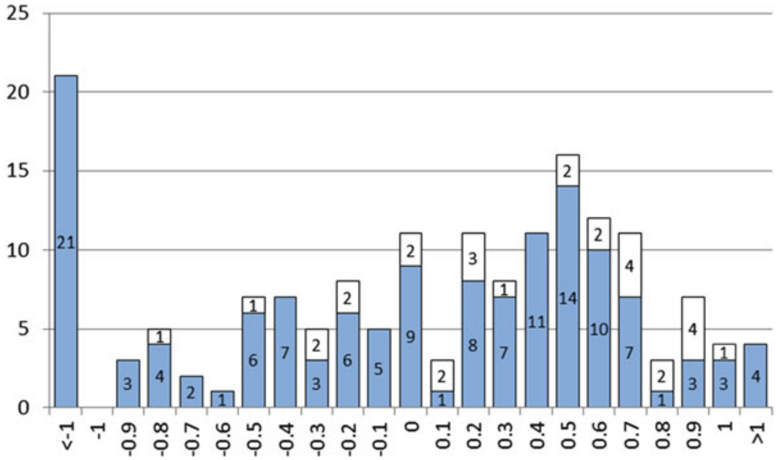

Fig. 2.9 Score distribution of the working memory test

memory (SSTM). They basically ask the subjects to undertake some tasks, such as memorizing series of numbers and letters and performing very basic arithmetical operations. By following the conventional procedure in psychological tests, the scores for each task are normalized using the mean and the standard deviation of the subject pool. The five standardized scores for the five tasks will then be averaged to arrive at the WMC of a specific subject. The histogram of the normalized WMC is depicted in Fig. 2.9. The histogram starts with the leftmost cluster "WMC < -1" (21 subjects in this cluster) and ends at the rightmost cluster "WMC > 1" (4 subjects). In between, there are 20 clusters, each with a range of 0.1, dividing the distribution equally into 20 equal intervals, from $[-1, -0.9)$, $[-0.9, 0.8)$, ..., all the way up to $[0.9, 1]$.

2.4.2.2 Optimum-Discovery Capability

To have a general picture of how WMC may actually impact the capability to discover the pattern or to learn the optimum strategy, we also indicate, within each WMC cluster, the number of human traders who were able to discover and learn the optimum and place it on a higher layer (blank-colored) to be separated from the number of those who did not on a lower layer (blue-colored).

By just eye-browsing Fig. 2.9, we can see that most human traders who were able to discover the pattern have a positive WMC (23 out of 29), and for those subjects who have a WMC below -0.5, only one, out of 32, is able to do so. Therefore, there is evidence indicating a positive influence of WMC on the pattern discovering capability. To present the result in a more precise manner, we also average the WMC of the performing group (29 subjects) and compare it with that of the nonperforming

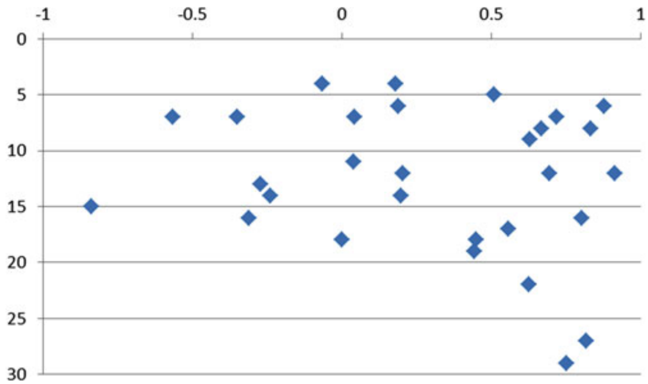

Fig. 2.10 First time and WMC

group (136 subjects). It is found that the mean WMC is 0.28036 for the performing group, but only −0.12648 for the nonperforming group; the whole population average is −0.05004.

Despite the positive statistics between WMC and the optimum-discovery capability, it is also interesting to notice the existence of some "outliers." Specifically, the four subjects belonging to the highest cluster of WMC (>1) and the three out of four in the next highest cluster ([0.9,1]) all failed to discover the global optimum. We shall come back to this point later in Sect. 2.4.2.4.

2.4.2.3 Time Required to Discover

To have a further look at the effect of cognitive capacity, we examine, within the performing group, whether the trader with a *higher* WMC tends to discover or learn the optimum *faster*. To do so, Fig. 2.10 gives the $X-Y$ plot of the pairs between WMC and the discovering time for each trader belonging to the performing group. Subject 1531, the trader who used the minimal time to discover the optimum, spent only three periods to "touch down" and stay on the optimum strategy almost for the entire duration (Fig. 2.8); yet, his WMC is only in the middle, 0.2475, and not particularly high.[15] In fact, the whole $X-Y$ plot of Fig. 2.10 shows that there is no significant relationship between WMC and discovering time, except for the following interesting finding. After 15 periods, most low WMC traders were no longer able to learn the optimum; more working time for them is to no avail.

[15]From Fig. 2.7, for a trader who is identified as a case of learning the optimum in period 3, his learning index must be in plateau A in the first three periods. Actually, Subject 1531 started performing the optimal strategy in period 2 until the end of the experiment except for one period obviously due to a typo. Subject 1531 seems to thoroughly understand the market features in period 1, and then performs the optimum strategy seamlessly in period 2.

Table 2.6 Working memory capacity and staying frequencies in the high and low plateaus

Class (plateau)	Frequencies	Cardinality	Mean WMC
A–D	15	38	0.31396
	20	30	0.33392
	25	18	0.24462
F	30	121	−0.17702
	10	139	−0.11911

However, this "bottleneck" does not exist for the high WMC traders. In fact, the nine subjects who discovered the optimum after period 15 all have positive WMC, except one.

The bottleneck observed in Fig. 2.10 can be regarded as a cognitive trap. The depth of the trap might be different for traders with different WMC. For traders with lower WMC, this trap might be too deep to jump out; hence, if these traders do not initially stand in a favorable position outside the trap, a longer learning time may help them a little. That is why we see that very few can walk out of this trap in the entire second half of the experiment. The attempt to associate the *energy* required to climb the hill with *cognitive capacity* is first made in [24]. Here, we also have some observations similar to this psychological analogy of the numerical trap.[16]

2.4.2.4 Target Return

The purpose of this section is to see whether cognitive capacity may have effects on the learning behavior of human traders. To do this, we separate human traders into different groups, for example, those who learned the optimum and those who did not, and then examine whether the WMCs of these two groups are different. We can also consider other grouping possibilities. One of them is to differentiate subjects by the frequencies according to which they stayed in different plateaus. Hence, we can differentiate those frequently visiting a high plateau from those frequently visiting a low plateau. For both, we may further differentiate them by *degree*, such as normal frequency or high frequency. We exemplify this kind of grouping in Table 2.6.

[16] This chapter and [24] are both under the umbrella of a 3-year NSC research project. Hence, they both share some similar features. What distinguishes [24] from this chapter is that the former explicitly constructs traders' learning paths in a numerical landscape. The question is then to address whether the observed learning behavior of traders can also be understood as an output of a numerical search algorithm. In other words, they inquire whether there is a connection between *behavioral search* and *numerical search*. However, the trading environment here makes it hard to derive this geometrical representation; therefore, the use of a learning index becomes another way to see how this trap might actually also exist. Despite this difference, the implication of these two studies is the same: *we need to equip artificial agents with different CI tools so that their search behavior can be meaningfully connected to the cognitive capacity of human traders, or, more directly, we need to reflect upon the cognitive capacity of different CI tools* [19].

The upper panel of Table 2.6 denotes the group of traders who are frequently classified into the high plateau, namely, Classes A, B, C, and D. In other words, they are the traders who frequently meet the target return. By different frequencies, we further consider three types of traders: those who were classified into this high plateau at least 15 times, at least 20 times, and at least 25 times, abbreviated as "15," "20," and "25" in the second column of the table. Similarly, the lower panel refers to the traders who are frequently classified into the low plateau (Class F) and who failed to earn the target return. The two subgroups "30" and "10" refer to the types of traders who were classified into this low plateau all the time (30 times) and at least 10 times, respectively.

These five groups are not exclusive to each other. In fact, group "25" is obviously a subset of group "20," which in turn is also a subset of group "15." As we can see from the 3rd column of Table 2.6, there are 38 subjects belonging to group "15," but only 30 of them belong to group "20" and 18 belong to group "25." Similarly, group "30" is also a subset of group "10." There are 139 subjects belonging to the former, whereas only 121 out of these 139 belong to the latter. These five groups provide us with another opportunity to see the effect of cognitive capacity on trading performance.

First of all, very similar to our earlier analysis of the optimum-discovering capability, we find that traders frequently classified to F tend to have a lower WMC than those who were frequently classified to a high plateau. As one can see from the fourth column of Table 2.6, the former has an average of negative normalized WMC, whereas the latter has a positive average. Both the student t-test and Wilcoxon rank sum test show that the difference in WMC between these two classes, "F" and "A–D", is significant. Second, if we further isolate group "30" (those who failed to make the target return from the beginning to the end), then it has a particularly lower WMC (-0.17702), which is lower than that of group "10" (-0.11911). Third, however, if we do the same thing for the high plateau and isolated group "25," we shall be surprised by the result that this elitist group (traders who can make the target return 25 out of 30 times) does not have a higher WMC (0.24462) than its super sets, "15" (0.31396) and "20" (0.33392). This later evidence is very intriguing, because this finding accompanied by our early observations of the outliers in the "optimum-discovery" section (Sect. 2.4.2.2) together lend support to the hypothesis of *a diminishing marginal contribution of cognitive capacity* in the psychological literature.[17]

[17] As the psychological literature points out, high intelligence does not always contribute to high performance—the significance of intelligence in performance is more salient when the problems are more complex [25]. In addition, it appears that intelligence exhibits a decreasing marginal contribution in terms of performances [29, 37]. In the setting of an agent-based double auction market, Chen et al. [23] have replicated this diminishing marginal contribution of cognitive capacity. In that article, autonomous traders are modeled by genetic programming with different population size. The population size is manipulated as a proxy variable for working memory capacity. They then found that, while the trading performance between agents with small

2.4.3 Personality Traits

The second possible contributing factor for the observed heterogeneity among human traders in their learning behavior is personality. In personality psychology, there are many competing paradigms, but the personality trait is now the most widely accepted theory. Although there have been many studies regarding traits, they never seem to agree on the number of basic traits. Nevertheless, the *five-factor model* developed by Gordon Allport (1897–1967) is probably the most popular one. The five personality factors, also known as *Big Five*, are *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*. A convenient acronym is "OCEAN." Using the Big Five model, labor economists have already started to explore the relevance of personality to economics [14]. Big Five has also been applied to economic experiments [9–11, 35], while a lot of other measures are simultaneously used. Recently, there is even a trend to combine both cognitive and noncognitive factors to account for economic behavior [1, 24].

In this study, we applied a variant of Big Five to measure the personality trait of human traders, which we shall call Big Seven. The Big Seven was originally developed by Kuo-Shu Yang, a Fellow of Academia Sinica. Yang considered that Big Five may not be straightforwardly applied to Chinese due to their different cultural background; he, therefore, revised the Big Five model and made it the Big Seven model. The seven factors are *smartness*, *conscientiousness*, *agreeableness*, *trustworthiness*, *extraversion*, *chivalry*, and *optimism*.[18] A test accompanying this Big Seven model is also developed. The test is organized into seven major categories. For each category, there are 15–20 short descriptions (adjectives) of personality. As a total, there are 131 descriptions. For each description, the subject is required to rate himself on a scale from 1 (unsuitable) to 6 (suitable). Hence, "1," if he thinks that the adjective does not at all describe their personality, and "6," if he thinks that the adjective perfectly describes his personality. After filling in all 131 entries, his personality score will be calculated based on the loading (weight) of each entry.

The basic personality statistics of all 168 subjects are summarized in Table 2.7. The first two rows give the number of queries (each query is associated with an adjective) and the range of score. The third, fourth, and fifth rows give the mean of these scores over the whole group of 168 subjects, over the performing subgroup (those who were able to discover or learn the optimum) and over the non-performing subgroup (those who did not), respectively.

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population size and agents with a large one is significantly different, this difference between agents with a *large* one and agents with a *larger* one is negligible.

[18] There is no official translation of the seven factors. An attempt to do so on our own is not easy, in particular if one wants to describe the whole of 15–20 adjectives using a single word, such as conscientiousness. What we do here is to follow OCEAN closely and to use the same name if the factor in Big Seven shares very much in common with one of the Big Five. Examples are conscientiousness, agreeableness, and extraversion.

Table 2.7 Big-7 personality and discovery of the optimum

	S	C	A	T	E	Ch	O
# of queries	20	20	20	20	20	20	15
Range of score	20−120	20−120	20−120	20−120	20−120	20−120	15−90
Avg. (whole)	84.58	71.52	79.50	86.39	76.79	68.11	54.83
Avg. (performing)	86.43	71.90	78.93	90.78	79.00	70.56	56.87
Avg. (nonperforming)	84.15	71.43	79.63	85.36	76.27	67.54	54.35
Difference	2.28	0.47	−0.69	5.42	2.72	3.01	2.52

The first row is the initial of each of the Big Seven: smartness (S), conscientiousness (C), agreeableness (A), trustworthiness (T), extraversion (E), chivalry (Ch), and optimism (O)

Our analysis starts with a quick look at how the performing group and non-performing group differ in their Big Seven. For this purpose, the sixth column of Table 2.7 gives the differences between the two groups in these seven items. By looking at their relative magnitudes, among the seven, trustworthiness stands out, as the most salient one to distinguish the two groups, followed by chivalry, extraversion, optimism, and smartness. The two with rather small magnitudes are agreeableness and conscientiousness. These results are not well expected. First of all, conscientiousness, which has been constantly identified as a factor to predict economic behavior, is not founded here,[19] while our finding is consistent with this literature by singling out the extraversion as one of the top three. Second, the most salient one found in our dataset is trustworthiness.[20] This is the one which has never been mentioned in a separate study [24], which also examines the role of Big Seven in traders' performance.[21]

Like what we do for cognitive capacity (Fig. 2.9), we also plot the histogram of the Big-Seven personality score in Fig. 2.11, and, at the top of each bar, we indicate the number of the human traders who were able to discover the optimum. To make it easier to see the relationship between the seven factors and the capability to discover, we further rescale the presentation in terms of percentages. Hence, each cluster of each factor has a total of 100%, which is then divided by the size (share) of the blank-colored area (the performing one) and the blue-colored area (the nonperforming one). In this way, we can easily compare the relative size across different clusters.

By eye-browsing the seven histograms, one may find it difficult to see any visualizable pattern between personality factors and optimum-discovering capability except for the factor trustworthiness. In the case of trustworthiness, one can

[19]Conscientiousness is found to be a good predictor of job performance, mortality, divorce, educational attainment, car accidents, and credit score [1, 7, 8, 24, 38, 49].

[20]In fact, both our student t-test and Wilcoxon rank sum test only find this factor statistically significantly different between the performing group and the non-performing group.

[21]However, this study differs from [24] in using a different performance measure. See also footnote 16.

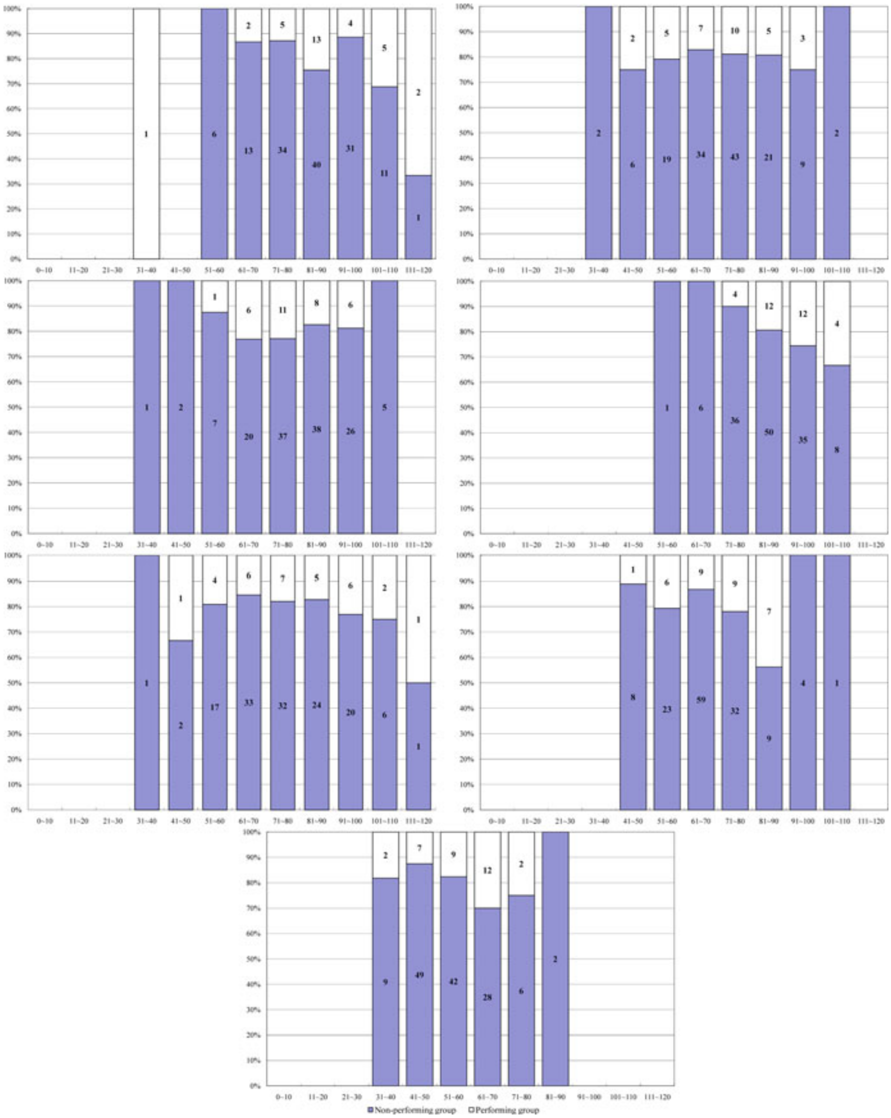

Fig. 2.11 Big-7 and learning performance: the seven figures, from the first row to the fourth row and from the *left* to the *right*, refer to the personality factor, smartness (*1st row, left*), conscientiousness (*1st row, right*), agreeableness (*2nd row, left*), trustworthiness (*2nd row, right*), extraversion (*3rd row, left*), chivalry (*3rd row, right*), and optimism (*4th row*), respectively

see that the percentage of performing human traders increases with the score of trustworthiness. This finding is consistent with the one revealed in Table 2.7. However, it is hard to argue why trustworthiness may help discover the optimum and it becomes even harder when other seemingly natural ones, such as conscientiousness, extraversion, and even smartness, all fail to play a role.[22] This may in fact indicate the potential problem in this self-reported evaluation.

Let us use Subject 917 to illustrate this problem. This smartness factor of this subject is self-reportedly between 30 and 40, i.e., the lowest one of the whole sample of 168 subjects. Nevertheless, he is one of the 32 subjects who were able to discover the optimum, and, therefore, behaves as an "outlier" in the sense of the only performing trader with a very low score in smartness. On the other hand, his WMC score is 0.8756, which is among the top 10%. So, in contrast to his WMC score, his self-reported smartness seems to be too much understated.

2.5 Concluding Remarks

The chapter, distinguished from most financial applications of computational intelligence in economics, is concerned with the issue of how computational intelligence can help build artificial traders who are capable of mimicking human traders' learning and erring behavior [18]. This research area is just in its very beginning stage, but it is important in the following two ways.

Firstly, there is no clear evidence indicating that human traders (human heuristics) can be or have been substantially replaced by robots (machine heuristics). While both cognitive psychology and computational intelligence have *heuristics* as their research interest, they seem to have been developed at different levels, in different directions, and have been applied to different domains. When coming to competition, what often surprises us is that, even in a simple situation like the double auction market, there is no clear evidence that heuristics developed by machines can outperform those coming out of humans.

Take our double auction experiments as an example. It is highly interesting to see how human traders actually learned, consciously or unconsciously, the *two-stage* procrastination strategy, particularly when a large number of runs of GP could only find the *one-stage* procrastination strategy. The one-stage procrastination has a simple heuristic behind it: hold everything till the end of a trade. This simplicity can be easily picked up by human traders with good intuition. Hence, one may

[22] Among the seven factors, Chen et al. [24] find conscientiousness, extraversion, and agreeableness to be influential, at least in some contexts. In their analysis, they attempt to justify each of these three. Among the three, conscientiousness is probably the easiest one to justify, given the already lengthily archived documents (see footnote 2.4.3). They then go further to justify the other two by using [28] to argue that extraverted subjects are more sensitive to potential rewarding stimuli through the mesolimbic dopamine, which may in turn help them more easily find the more profitable trading arrangements. In addition, for agreeableness, they argue that subjects with a higher degree of agreeableness can resist time pressure and may be able to think for a longer time before making decisions.

say that GP simply replicates human traders' heuristics or "rules of thumb." Hence, the heuristic developed by GP is consistent with the heuristics developed by many human traders.

Nonetheless, the two-stage procrastination bidding is less straightforward. GP succeeded in learning this strategy in only a few runs; most runs were trapped in a local optimum. However, as we can see from our human-trader experiments, some human traders could actually learn this strategy, while most of them also failed. Among the successful ones, some could even touch down in a few minutes. Evidently, for them, they did not learn this by solving a hard combinatoric optimization; instead, they learned it as a heuristic.

However, why were some people able to see this pattern, whereas others failed to do so? If we assume that some have a good representation of the problem, by that representation the problem becomes easier, but others do not "see" this pattern. Then, is this difference mainly due to chances, which are very much random, or can this difference be attributed to some more fundamental causes?

To answer this question, this chapter proposes a new research framework. The new research framework includes the design of a novel learning index in light of a separation hyperplane. Through this index, one can better capture the state of human traders' learning dynamics and then develop various performance measures upon it. This performance measure, which encapsulates human traders' heterogeneity in learning dynamics, can be further analyzed in light of the basic attributes of human traders, such as their cognitive capacity and personality traits. This chapter, to the best of our knowledge, is one of the pioneering studies devoted to the inquires about whether cognitive capacity and personality have influences on traders' performance and their heuristic development in a laboratory setting.

Very similar to the earlier study [24], we once again confirm the significance of cognitive capacity to the heuristic development of human traders. However, we do not find a particularly insightful connection between personality and learning dynamics; in particular, the factor conscientiousness plays no role in the heuristic formation, a result different from that of the earlier study.

Secondly, tremendous analyses of heuristic biases of human traders are conducted in the area of psychology, cognitive neuroscience, and behavioral finance, but this literature, at this point, receives little interdisciplinary collaboration with the computational intelligence society. We believe that narrowing this gap may help us build more human-like artificial traders. Hence, carefully studying human heuristics with computational intelligence may lead us to explore a rich class of fast and frugal heuristics [32].

An emotional and neurocognitive study of financial decision making may benefit from the analysis provided in this chapter. It enables us to stand in the front line to see interesting behavior patterns which can be further explored from the aspects of psychological analysis, and also enables us too see how such advanced analysis can enrich the current literature on behavioral economics.

Acknowledgements The authors are grateful to Professor Kuo-Shu Yang for his generous permission for using his developed Chinese version of the Big-Five personality test. We are also grateful to Professor Li-Jen Weng and Professor Lei-Xieng Yang for their advice and guidance on the psychological tests implemented in this study. NSC research grants no. 98-2410-H-004-045-MY3, no. 99-2811-H-004-014, and no. 100-2410-H-029-001 are also gratefully acknowledged.

Appendix: Double Auction as a Combinatorial Optimization Problem

In order to set the benchmark, we have to determine the best bidding strategy for Buyer 1. However, to determine the best timing and bidding values in a discrete-time double auction is a combinatorial optimization problem and is NP-hard. To tackle this problem, one should first notice that the discrete-time double auction is in fact an integer programming problem constrained by various rules and market regulations, such as that a buyer should always bid from his/her highest token to the lowest token and he/she can only bid once in each step. Second, to solve this integer programming problem, Xia et al. [56] have shown the superiority of the branch-and-bound method. We therefore use the branch-and-bound method to find the optimal bidding strategy for Buyer 1 in our markets. We will first demonstrate the rules of bidding and matching, and the exact models of integer programming will then be given as well.

In the SFTE auction, there are *nb* buyers and *ns* sellers in the market. The bidding/asking rules as well as the transaction mechanism are as follows:

1. Each trader has *nt* ordered tokens. Starting from the first token, traders have to bid/ask based on the ordered token values.
2. The auction lasts *np* steps. In each step, every buyer and seller can choose to bid/ask or remain silent.
3. Only those who bid/ask in the market have chances to make transactions, and only those who make transactions earn profits. Staying silent will not pay.
4. The bidder with the highest bid price in a step is the current buyer, while the seller with the lowest ask price in that step is the current seller.
5. Only the current buyer and the current seller have the chance to complete a transaction, depending on whether the bid price is higher than the ask price.
6. The transaction price is the average of the current buyer's bid price and the current seller's ask price.
7. Once a trader is involved in a transaction, he/she naturally uses up one token and has to continue trading based on the next token value.
8. If a trader uses up all *nt* tokens, he/she is expelled from the market and can only return to the market when the market starts over again.
9. In our human experiments as well as GP simulations, all traders except human subjects or GP traders are truth tellers, who always truthfully use their token values as the bids or asks and will never keep silent in the market.

Table 2.8 Parameters and variables

b	Index for buyers
s	Index for sellers
j	Index for steps
k	Index for tokens
$btv_{b,k}$	Value of token k for buyer b
$stv_{s,k}$	Value of token k for seller s
bm	A very big number
nb	Number of buyers
ns	Number of sellers
np	Number of steps
nt	Number of tokens
$BT_{b,k,j}$	Whether buyer b's token k is bidded in the market in step j [0,1]
$AT_{s,k,j}$	Whether seller s's token k is asked in the market in step j [0,1]
$B_{b,j}$	Buyer b's bid in step j
$A_{s,j}$	Seller s's ask in step j
$CB_{b,j}$	Whether buyer b's bid is the highest bid in step j [0,1]
$CS_{s,j}$	Whether seller s's ask is the lowest ask in step j [0,1]
$\overline{B}_j$	The highest bid in step j
$\underline{A}_j$	The lowest ask in step j
$T^B_{b,k,j}$	Whether buyer b's token k reaches a transaction in step j [0,1]
$T^S_{s,k,j}$	Whether seller s's token k reaches a transaction in step j [0,1]
T_j	Whether a transaction is made in step j [0,1]
P_j	The transaction price in step j

Our goal is to find the best bidding strategy, which maximizes Buyer 1's profit in the face of truth telling opponents. Since this is an integer programming problem, we can describe the problem with the objective function (2.1) and constraints ((2.2)–(2.21)). Notice that the constraints are proposed here to directly or indirectly enforce the rules and mechanisms developed above. Notations used in the objective function and the constraints are summarized in Table 2.8.

Objective Function

$$\max \ \sum_{j}^{np}\sum_{k}^{nt}[(btv_{1,k}-P_j)\times T^B_{1,k,j}] \tag{2.1}$$

Constraint for Rule 1

$$\forall b,\ BT_{b,1,1}=1 \ \| \ \forall s,\ AT_{s,1,1}=1 \tag{2.2}$$

Constraint for Rule 2

$$\forall b,j,\ \sum_{k}^{nt}BT_{b,k,j}\leq 1 \ \| \ \forall s,j,\ \sum_{k}^{nt}AT_{s,k,j}\leq 1 \tag{2.3}$$

Constraints for Rule 3

$$\forall b, j, k,\ T^B_{b,k,j} \leq BT_{b,k,j} \ \parallel\ \forall s, j, k,\ T^S_{s,k,j} \leq AT_{s,k,j} \tag{2.4}$$

$$\forall b, j,\ CB_{b,j} \geq \sum_{k}^{nt} T^B_{b,k,j} \ \parallel\ \forall s, j,\ CS_j \geq \sum_{k}^{nt} T^S_{s,k,j} \tag{2.5}$$

Constraints for Rule 4

$$\forall j,\ \overline{B}_j = \sum_{b}^{nb} (CB_{b,j} \times B_{b,j}) \ \parallel\ \forall j,\ \underline{A}_j = \sum_{s}^{ns} (CS_{s,j} \times A_{s,j}) \tag{2.6}$$

$$\forall b, j,\ \overline{B}_j \geq B_{b,j} \ \parallel\ \forall s, j,\ \underline{A}_j \leq A_{s,j} \tag{2.7}$$

$$\forall j,\ \sum_{b}^{nb} CB_{b,j} = 1 \ \parallel\ \forall j,\ \sum_{s}^{ns} CS_{s,j} = 1 \tag{2.8}$$

Constraints for Rule 5

$$\forall j,\ \sum_{b}^{nb} \sum_{k}^{nt} T^B_{b,k,j} \leq 1 \ \parallel\ \forall j,\ \sum_{s}^{ns} \sum_{k}^{nt} T^S_{s,k,j} \leq 1 \tag{2.9}$$

$$\forall j,\ \sum_{b}^{nb} \sum_{k}^{nt} T^B_{b,k,j} = \sum_{s}^{ns} \sum_{k}^{nt} T^S_{s,k,j} \tag{2.10}$$

$$\forall j,\ (\overline{B}_j - \underline{A}_j) \times T_j \geq 0 \tag{2.11}$$

$$\forall j,\ \sum_{b}^{nb} \sum_{k}^{nt} T^B_{b,k,j} = T_j \tag{2.12}$$

Constraints for Rule 6

$$\forall j,\ (\overline{B}_j - \underline{A}_j) < T_j \times bm \tag{2.13}$$

$$\forall j,\ 2 \times P_j = (\overline{B}_j + \underline{A}_j) \tag{2.14}$$

Constraints for Rule 7

$$\forall b, k,\ \sum_{j}^{np} T^B_{b,k,j} \leq 1 \ \parallel\ \forall s, k,\ \sum_{j}^{np} T^S_{s,k,j} \leq 1 \tag{2.15}$$

$$\forall b, j \in 2 \ldots np,\ BT_{b,1,j} = BT_{b,1,j-1} - T^{B}_{b,1,j-1} \ \ \|$$
$$\forall s, j \in 2 \ldots np,\ AT_{s,1,j} = AT_{s,1,j-1} - T^{S}_{s,1,j-1} \tag{2.16}$$

$$\forall b, k \in 2 \ldots nt, j \in 2 \ldots np,\ BT_{b,k,j} = BT_{s,k,j-1} + T^{B}_{s,k-1,j-1} \ \ \|$$
$$\forall s, k \in 2 \ldots nt, j \in 2 \ldots np,\ AT_{s,k,j} = AT_{s,k,j-1} + T^{S}_{s,k-1,j-1} \tag{2.17}$$

Constraints for Rule 8

$$\forall b,\ \sum_{j}^{np}\sum_{k}^{nt} T^{B}_{b,k,j} \leq nt \ \ \| \ \ \forall s,\ \sum_{j}^{np}\sum_{k}^{nt} T^{S}_{s,k,j} \leq nt \tag{2.18}$$

$$\forall s,\ \sum_{j}^{np} T^{S}_{s,nt+1,j} = 0 \tag{2.19}$$

Constraints for Rule 9

$$\forall b \in 2 \ldots 4, j,\ B_{b,j} = \sum_{k}^{nt} (BT_{b,k,j} \times btv_{b,k}) \tag{2.20}$$

$$\forall s, j,\ A_{s,j} = \sum_{k}^{nt} (AT_{s,k,j} \times stv_{s,k}) \tag{2.21}$$

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