The Surprising Role of Self-Efficacy in Collective Problem Solving

Dorit Geifman
University of Haifa
dgeifman@univ.haifa.ac.il

Daphne R. Raban
University of Haifa
draban@univ.haifa.ac.il

Abstract

Self-efficacy is essential to learning but what happens when learning is done as a result of a collective process? What is the role of individual self-efficacy in collective problem solving? This research examines whether self-efficacy of traders in prediction markets, when configured as collective problem-solving platforms, affects market performance.

Prediction markets are collective-intelligence platforms that use a financial markets mechanism to combine knowledge and opinions of a group of people. In these markets, traders express their opinions or knowledge by buying and selling "stocks" related to questions or events. The collective outcome is derived from the final price of the stocks.

Self-efficacy, one's belief in his or her ability to act in a manner that leads to success, is known to affect personal performance in many domains. To date, its manifestation in computer-mediated collaborative environments and its effect on the collective outcome has not been studied.

In controlled experiments, 632 participants in 47 markets traded a solution to a complex problem, a naïve framing of the knapsack problem. The findings demonstrate that prediction markets form an effective collective problem-solving platform. They correctly aggregate individual knowledge and are resilient to traders' self-efficacy.

Keywords: collective problem-solving, self-efficacy, prediction markets, social influence.

Introduction

Collective problem-solving platforms are gaining acceptance as effective mechanisms for solving complex problems. A variety of aggregation mechanisms are available to compile individual knowledge, decisions, and creativity into a pooled intelligence artifact. Prediction markets are a genre of collective-intelligence platforms and are used for problem solving. They use financial markets as an underlying mechanism to aggregate dispersed information, predict future events, and combine knowledge and opinions of a large and distributed group of people. In such markets, stocks represent a statement to be evaluated or an event to be predicted. The price of the stocks traded reflects the market's opinion as to the probability of the occurrence of the event or the correctness of the statement. Prediction markets are deployed as public platforms on the Web as well as within organizations.

Self-efficacy, the belief in one's own ability to act in a manner that leads to success, affects individual performance by determining goal selection, course of action, and persistence (Bandura, 1997). Studies show that individuals that exhibit higher degrees of self-efficacy perform better at problem solving (Bouffard-Bouchard, 1990).

This paper presents a controlled experiment examining the effectiveness of prediction markets as a collective problem-solving platforms and the effect of traders' self-efficacy on the market.

Prediction Markets

Prediction markets have emerged as a new information aggregation and collective-intelligence platform (Wolfers & Zitzewitz, 2004). In prediction markets, stocks are created so that their final cash value is tied to the outcome of a particular statement or question. It may refer to an event (e.g. will a nuclear arms disarmament treaty be signed with Iran before the end of the year?), to a parameter (e.g. how many tons of salt are there in the Dead Sea?) or to an opinion (e.g. will an increase of budget deficit decrease unemployment?). Traders express their opinions regarding the probability of the event or the value of the parameter by buying or selling a certain amount of stocks at the current price. The market mechanism updates the market price, which is interpreted as the collective opinion of all traders. Figure 1 displays a typical prediction market trading interface.

Figure 1. A typical prediction market screen

Markets function best for close-ended questions but can also be used as a consensus setting mechanism for open-ended questions. In the public Internet sphere, prediction markets address a variety of topics ranging from sports and entertainment to scientific innovation and politics. Due to anti-gambling regulations most markets use play-money and social incentives. The promise of prediction markets as a collective-intelligence platform lies in the corporate environment, the public sector, and civic debate (Cowgill, Wolfers, & Zitzewitz, 2008; Polgreen, Nelson, & Neumann, 2007; Slamka, Jank, & Skiera, 2009). There, they are used for innovation management, business forecasting, problem solving, and elicitation of knowledge and opinion (Geifman, Raban, & Rafaeli, 2011).

Self-Efficacy

Self-efficacy theory suggests that cognitive and affective processes, which differ among individuals, play an important role in the acquisition, regulation, and retention of behavior patterns. These processes, which build on the personal cognitive and emotional state, combined with environmental stimuli and reinforcements, may strengthen or weaken effective behavior

(Bandura, 1997). A large body of research established that self-efficacy shapes the effective performance of individuals in a wide variety of areas such as learning and academic achievements (Bandura & Schunk, 1981; Chemers, Hu, & Garcia, 2001), organizational behavior (Bandura & Wood, 1989; Krueger & Dickson, 1994), coping with health conditions (Condiotte & Lichtenstein, 1981; O'Leary, 1985), attaining goals (Bandura & Wood, 1989; Locke, Frederick, Lee, & Bobko, 1984) and more.

In tasks that rely on cognitive skills, self-efficacy beliefs affect the individual's cognitive states as well as his or her thinking processes. People with high personal efficacy focus their attention on analyzing and finding solutions to problems, in contrast to persons with lower efficacy who are beset with doubts, tend to turn their attention inwardly, and become self-occupied (Bandura & Wood, 1989). Self-efficacious individuals are quicker to dispose of faulty thinking directions and are less inclined to reject good solutions prematurely (Bouffard-Bouchard, Parent, & Larivee, 1991). Bouffard-Bouchard (1990) demonstrated that differences in efficacy perceptions were related to the number of problems completed, the efficiency of problem-solving strategies, and the accuracy of self-evaluation of responses.

Research hypotheses

Collective problem-solving involves adaptive problem-solving, trial and error learning, and strategies of problem decomposition. It can benefit from the distributed access to a broad audience available through prediction markets as well as from aggregation and dissemination of information and continuous revision of the solution, which are built into the market mechanism, leading to the first hypothesis:

H1: A prediction market performs better than individuals in solving problems

In financial markets, the accumulation of various anomalies brought to the flourishing of the field of behavioral finance (Shiller, 2003). The similarity between prediction markets and financial markets leads to expect behavioral phenomena similar to those studied in the field of behavioral finance. Some studies in the field show that behavioral biases are evident in prediction markets (Cowgill et al., 2008; Gjerstad & Hall, 2005), while others demonstrate market resilience to cognitive biases (Forsythe, Rietz, & Ross, 1999; Forsythe, Nelson, Neumann, & Wright, 1992). Self-efficacy is a social-cognitive disposition and its collective effect on the outcome of prediction market has not been studied. We hypothesize that:

H2: Controlling for market-level knowledge, higher level of the combined self-efficacy of traders in the market positively influences the collective solution

Research Method

632 Participants grouped in 47 markets participated in a controlled experiment. They were asked to individually solve the following problem and then trade their solution in a marketplace to reach a collective solution:

> *A burglar broke into a house and filled his sacks with loot. Each sack weighs differently and contains a different worth of goods. But alas!! When trying to leave, the burglar could not carry all the sacks, as the burden was too heavy.*
> *Help the burglar choose the sacks he is able to carry while maximizing his profit.*

This seemingly simple riddle is a non-technical framing of the knapsack problem, which simulates complex combinatorial optimization problems. Certain heuristics may be applied to specific cases of the problem, but there is no known deterministic solution in polynomial computation time.

Participants traded on a commercial prediction markets platform (www.inklingmarkets.com), which was configured in alignment with the parameters of a burglar problem. Each stock represented a sack, and its continuous price changes reflected the opinion of traders regarding the probability of the sack to be part of the solution. Ideally, at market closing stocks of sacks that belonged to the solution were expected to reach the price of 100 and others to be nullified. Figure 2 presents the experiment's main screen.

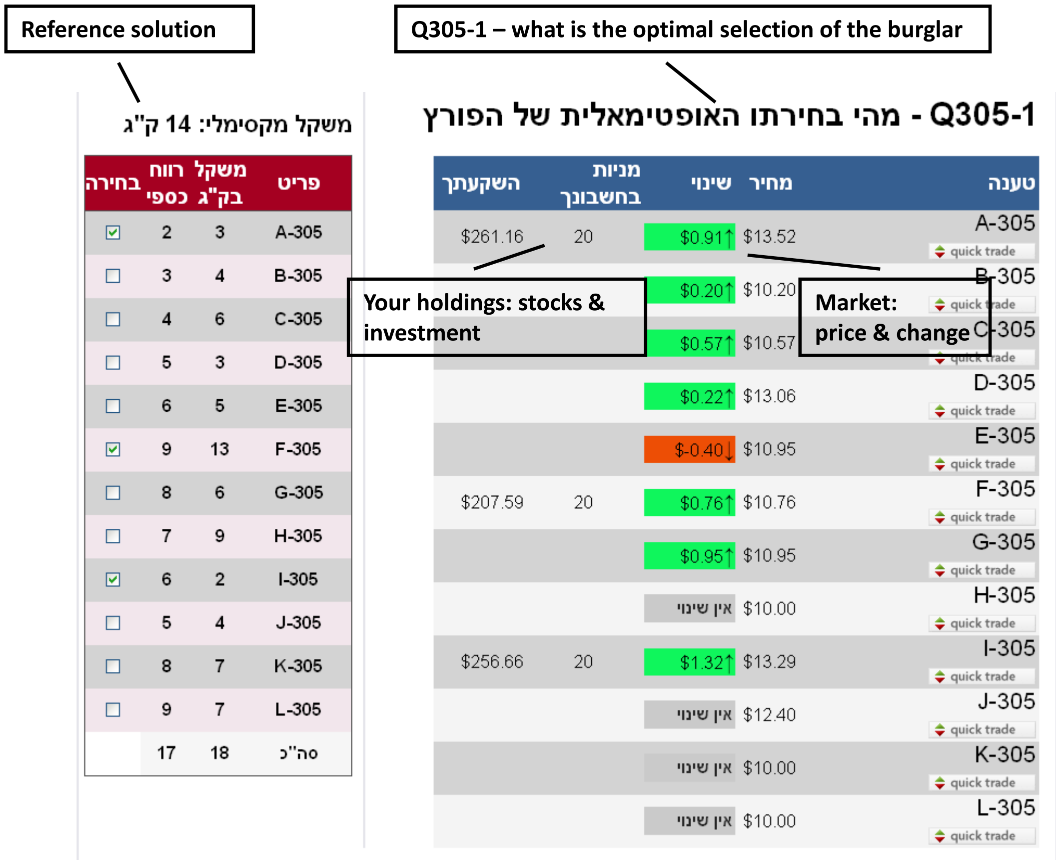

Figure 2. The problem and marketplace screen

Before trading, participants were given time to individually solve the problem without interruption. When time expired, they started to trade their solutions. During this time, participants could react to market price signals, change their original solutions, and revise their trading decisions. When the market closed the collective solution, as reflected by the final price of the stocks, was compared to the ideal price, which was known to the experimenter. The participant who earned the highest profits received a symbolic prize.

The main part of the experiment was preceded by a training stage and a questionnaire by which participants reported their perceived efficacy at the task. The questionnaire included 6 items that comprised the trader self-efficacy scale. The scale was designed according to guidelines of self-efficacy measurement (Bandura, 1986; Lee & Bobko, 1994) to capture self-efficacy at the different modalities and difficulty levels of the task and environment.

The variables analyzed were derived from the questionnaire and system logs and are described in Table 1.

Table 1. Analysis variables *(t = trader, m = market)

Variable	Description	Source
t_correct*	A binary indication of the correctness of the trader's individual solution	Experiment platform logs
t_SE	Trader's self-efficacy at the task. A 6 items, 0-5 Likert-type scale	Self-report
m_correct	A binary indication of the correctness of the market solution. True if the highest price ranking stocks represent all sacks that constitute a correct solution, False otherwise.	Market platform logs
m_accuracy	Complement of the Root Mean Squared Error (RMSE) of the final market price with respect to the ideal price	Market platform logs
m_knowledge	Initial knowledge in the market. The proportion of traders in the market who correctly identified the solution individually	Experiment platform log
m_SE	Mean t_SE for traders in the market	Calculated

Results

Figure 3 describes the distribution of participants by age and gender.

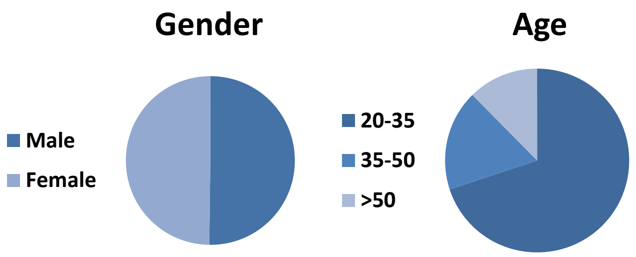

Figure 3. Participants' age and gender

Individually, 21% of the traders succeeded to solve the burglar problem. Collectively, 40% of the markets correctly identified the solution when measured by the m_correct flag (see Table 1). This confirms hypothesis H1 and demonstrates that prediction markets form an effective collective problem-solving instrument.

The trader self-efficacy scale (t_SE) demonstrated high reliability (Cronbach $\alpha = 0.935$). Factor analysis of the 6 items of the scale established its unidimentionality by producing one factor explaining 75% of the variance with all loadings above 0.85.

The inter-correlations presented in Table 2 demonstrate that knowledge is positively correlated with market accuracy and so is self-efficacy, but to a lesser extent. A positive correlation is also evident between individual knowledge and self-efficacy.

Table 2. Market-level inter-correlations

	accuracy	knowledge	m_SE
knowledge	.628**		
m_SE	.329*	.339*	
Mean	–.611	.22	2.53
SD	.135	.162	.403

*p < 0.05, **p < 0.00

Hierarchical regression was applied to determine the marginal contribution of market-level self-efficacy to the initial knowledge in predicting the accuracy of the market. Knowledge was introduced first to the model, followed by m_SE. With all variables in the equation, the model was significant at $F_{(2, 44)} = 15.27$, $p < 0.001$ and the adjusted R^2 indicated that the model predicts 38% of variability in market accuracy. It is, however, evident from Table 3 that market-level self-efficacy does not contribute to the model.

Table 3. Market-level analysis hierarchical regression

Step	Variable	R^2 change	F change	β
1	knowledge	.394	29.317	.584**
2	m_SE	.015	1.132	.131

**$P < 0.001$

These findings reject hypothesis H2 and demonstrate resilience of prediction markets to individual self-efficacy bias.

Discussion

Crowdsourcing for solutions to scientific, business and other problems has become common and is supported by many commercial platforms, e.g. Innocentive (www.innocentive.com) and NineSigma (www.ninesigma.com). By providing access a large body of independent and diverse individual problem solvers Crowdsourcing platform facilitate original solution to complex problems. These platforms, however, do not provide collaboration, coordination, or aggregation mechanisms that enable collective problem solving. The current research demonstrated that while the probability of reaching a solution by individuals was 21%, solving a problem by means of prediction markets increased this probability to 40%. The research suggests that by adding an aggregation mechanism to crowdsourcing platforms, the process of problem-solving can significantly improve.

Self-efficacy is a personal disposition that is mainly affected by the experience of personal mastery, but also influenced by affective and social aspects such as vicarious experience, i.e. looking at others performing a task, and verbal persuasion. Group processes are often subject to social influences. Social influence in groups is explained by the theories of normative and informational influence. Normative influence theory focuses on the position of the individual in the group, emphasizing motives such as seeking social rewards and interpersonal relations. Informational influence theory emphasizes the task dimension and the drive of the individual to reach an accurate outcome. In prediction markets, the potential of normative influence is low as persistent social structures are not created. Informational influence, however, does exist as the changing market price provides traders with cues about the opinions of other traders to which they can, and do, relate (Guarnaschelli, Kwasnica, & Plott, 2003). Kaplan and Miller (1987) show that informational influences are predominant in groups that deal with intellective issues on a regular basis. The present research demonstrated that in prediction markets, the information that traders introduce to the market plays a major role in the accuracy of the collective outcome. This is in line with the efficient markets theory (Fama, 1970). The research further showed that self-efficacy, which involves a social perspective, did not affect the outcome of the market beyond the influence of the initial knowledge in the market. This finding rejects hypothesis H2 and suggest that prediction markets are resilient to informational influences.

To conclude, this research demonstrated that prediction markets are effective collective problem-solving mechanisms. These findings call for further research on the influences of self-efficacy on collective performance in other open collaboration environments, where social structures are more cohesive.

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