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Tolerance for Uncertainty and Patterns of Decision-Making in Complex Problem-Solving Strategies

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Abstract: Current studies of complex problem-solving do not commonly evaluate the regulatory role of such personality-based variables as tolerance for uncertainty, risk-readiness, and patterns for coping with decisional conflict. This research aims to establish the contribution of those traits into individual parameters of complex problem-solving strategies. The study was conducted on 53 healthy individuals 17 to 29 years old (M = 20.42; SD = 2.34). Our own computerized complex problem task "The Anthill" was developed for this research. We identified five measurable parameters of the participants' problem-solving strategies: preferred orientational level (POL); orientational level variability (OLV); class quotas' range (R); mean and median quotas shift (MS and MeS); and abrupt changes of strategy (AC). Psychodiagnostic methods included: new questionnaire of tolerance/intolerance for uncertainty; personal decision-making factors questionnaire; Melbourne Decision Making Questionnaire; Subjective Risk Intelligence Scale; Eysencks' Impulsiveness Scale. The study showed the role of tolerance for uncertainty, risk-readiness, negative attitude toward uncertainty, and decision-making styles in the regulation of complex problem-solving strategies. Specifically, procrastination, tolerance for uncertainty, and risk-readiness were significant predictors of individual strategy indicators, such as POL, OLV, and MeS. Thus, personality traits were shown to regulate resource allocation strategies and the required level of orientation in a complex problem.

Keywords: tolerance for uncertainty; complex problem-solving; decision-making strategy

1. Introduction

The term "complex problem" and the concept behind it became an essential part of scientific discourse during the 1980s. By that time, most researchers strongly agreed that human problem-solving capabilities could not be fully scientifically understood based on studies of simple problems only. Laboratory data obtained in such studies significantly lacked ecological validity because of several reasons. First, common tasks, used in laboratory experiments on thinking and decision-making, had little to do with problems that people faced and had to solve in real life. Second, it became more and more evident that problem-solving in real life was not only connected with the actualization of different mental processes (rational thinking) but also regulated by personality and psychological factors, such as motivation, self-esteem, personal involvement in the problem, etc., [1].

From the very beginning, several research traditions emerged in that field, that had little in common [1]. Among currently existing approaches toward complex problem-solving, the more prominent are Naturalistic Decision Making (NDM), Dynamic Decision Making (DDM), Implicit Learning in System Control, Expert Adaptive Decision Making, Complex Problem Solving (European tradition), and so forth [2,3]. Research approaches varied from field studies involving real-life situations in NDM to the development of simulation scenarios with more or less complex structure. It is possible to say that all the traditions used complex, dynamic situations to research problem-solving on a new level, unreachable by earlier approaches [2]. However (or, specifically, because of that pluralism of approaches), no universally accepted definition for the complex problem and complexity, in general, was established, thus making it still difficult to compare and integrate different branches of complex problem-solving studies.

Earlier attempts in that direction were mainly revolving around the identification of objective characteristics of the "complex problem" task. Campbell [4] conducted an extensive literature analysis and marked three main approaches to understanding the "complexity" of a task. According to him, complexity can be understood first in the context of the person's subjective experience; second, as a characteristic of the human-task interaction, and third, as the objective characteristic of the task itself. Campbell's position was consistent with the latter approach, and he suggested that complexity could and should be determined objectively. He identified four primary sources of complexity in the task: (1) The presence of many ways to achieve the goal; (2) the presence of many goals; (3) the presence of a contradiction between different goals; and (4) probabilistic relationship between the methods and the goals.

On the contrary, recent works usually attempt to describe complexity from the subjective experience approach. For example, Osman considered problem-solving as "the process by which people transform the unknown to the known" [5] (p. 52). In this case, complexity represented the level of subjective uncertainty. There can be different sources of uncertainty, such as characteristics of the problem itself (random fluctuations, probabilistic relationships between cause and effect, nonlinearity), or psychological factors (inaccurate representation of the problem's structure; biased assessment of probabilistic relationships, etc.,). Regardless of those sources, the subjective feeling of uncertainty can be considered the criterion of equivalence for various complex problems.

Dörner [6] pointed out that complex problems had one central requirement for the person, trying to solve those problems: the demand for the personal ability to tolerate uncertainty. In their 2017 article, Dörner and Funke [7] emphasized the role of mentalizing in eliminating the uncertainty. In this case, mentalizing was understood in the broader sense, including both discursive (reasoning) and non-discursive (creative, intuitive) thinking processes. According to those authors, complex problem-solving includes cognitive, emotional, and motivational aspects [7] (p. 6).

Among subjective factors influencing complex problem-solving effectiveness, cognitive abilities are the most researched ones [8,9]. Early studies found no correlation between psychometric intelligence and successful complex problem-solving [10]. The low ecological validity of standard intelligence tests was one of the probable explanations [11]. The requirements of complex problems and intelligence tests widely varied, indeed. Usually, complex problem-solving involves goal setting and planning processes actualization, active search, and information selection, hypothesizing, structuring and restructuring knowledge acquired in the process, and feedback-based action-management. Traditional intelligence tests cannot grasp most of these aspects. To explain human ability to use their cognitive abilities and skills, Dörner [6] proposed the term "operative intelligence." Thus, human interaction with complex dynamical systems should not be reduced to some generalized scheme, which could be solved by some universal algorithms or optimal strategies, such as Newell and Simon's general problem solver [12]. Problem-solving strategies and methods are only adequate for specific conditions of the task or situation. Thus, planning, goal setting, reflection, and self-reflection play an essential role in complex problems and should be taken into consideration.

Yet, the "classical" complex problems (such as LOHHAUSEN, MORO, etc., [6,13]) were often criticized for low reliability and weak foundation of the complex problem-solving success measurements. Various complex problems indeed approached performance assessment differently. Those assessments could include scores on a scale or a set of scales, genuine system properties understanding, finding the strategy that would be closest to the optimal one, etc. The diversity and heterogeneity of those tasks and measures made it hard to compare performance in different tasks in a meaningful way. These considerations served as one of the origins of the psychometric approach in complex problem-solving research [7]. This approach aimed to develop reliable diagnostic methods for complex problem-solving assessment [14]. The paradigm of minimal complex systems was proposed as an alternative to microworlds with many variables and connections between them [14,15]. Currently, within this approach, MicroDYN and MicroFIN scenarios are the most used as general models of a complex problem.

A recent meta-analysis [16], which included 60 studies from 1982 to 2014, showed that the correlations between successful complex problem-solving and intelligence varied from 0.339 to 0.585, depending on the type of the complex problem. The weakest correlation (0.339) was obtained for "classical" complex problem tasks (LOHHAUSEN, MORO, TAILORSHOP, etc.,) [6,13], while the strongest (0.585)—for minimal complex systems tasks (MicroDYN, MicroFIN, etc.,) [16].

As was already mentioned, Dörner [6] considered psychometric intelligence to be a poor predictor of success in complex problem-solving (supported by the correlations above). Comparing the "bad" and "good" "burgomasters" in the LOHHAUSEN simulation, he pointed out the following differences: "good" participants acted more comprehensively, considered more aspects of the system, tested hypotheses through questioning to clarify the causal relationships of the variables, generally organized, and structured their behavior better. On the opposite, "bad burgomasters" tended to switch from one problem to another when faced with obstacles, were more often distracted by current stimuli, and sometimes demonstrated "encapsulated" behavior, spending a lot of effort on solving insignificant problems. Thereby, the difference between the participants in this task was more about personality and less about pure intelligence or knowledge.

Among non-cognitive variables, the most studied ones are motivation and the process of goal setting [17–19]. Recent studies in MicroDYN scenarios showed the contribution of the "Big Five" personality traits in complex problem-solving [20], however, with only relatively small effect sizes. To our knowledge, personality traits related to attitudes toward uncertainty were not previously researched in the context of complex problem-solving.

Dörner suggested that the ability to cope with uncertainty was a significant predictor of complex problem-solving success [6]. Thus, in the current study, we found it necessary to focus on personality traits known to contribute to decision-making under uncertainty. Iowa Gambling Task-based studies [21] showed tolerance for uncertainty to regulate risk propensity during the initial stages of decision-making, influencing exploratory learning. Intolerance for uncertainty, on the other hand, was shown to regulate risk propensity after a failed trial. According to the authors, intolerance for uncertainty, thus, potentially constrained learning under uncertainty through risk aversion [21].

Among other personality traits, mediating decision-making under uncertainty, psychologists mention impulsiveness [22], intuition [23], risk-readiness, and rationality [24]. Janis and Mann [25] argued that strategies to cope with decisional conflict (arising in uncertain situations) also influenced decision-making significantly. Our previous study showed that people with different forecasting strategies had a significant difference in their intolerance for uncertainty levels [26]. Other studies showed that tolerance/intolerance for uncertainty traits ratio and levels of personal risk-readiness formed stable latent profiles, explaining personal attitude toward uncertain situations [24].

It is worth noticing that our interest in the current research revolved around the connection of those personality traits with human activity while interacting with a complex dynamic system. Thus, we wanted to know whether the personality traits mentioned above can predict the parameters of such activity and were not deliberately focusing on success or failure in complex problem-solving.

For minimal complex systems such as MicroDYN and MicroFIN, two basic strategies of interaction with complex systems were described [17,18], with different research behavior patterns aimed to test hypotheses. The first basic strategy requires systematically changing only one exogenous variable at a time to observe cause-and-effect relationships for that variable. This strategy is called VOTAT (Vary One Thing at a Time). The opposite strategy is the unsystematic change of all exogenous variables (CA, Change All). The combination of those strategies in exploratory behavior usually referred to as Heterogenous Testing (HT). Individuals using the VOTAT strategy generally perform better in minimal complex systems [17,18]. In recent works PULSE strategy also was described for minimal complex systems with eigendynamic [27].

At the same time, "classical" complex problems have no general theoretical framework that allows the identification and classification of problem-solving strategies. However, it is possible to point out two approaches to the analysis of complex problem-solving strategies. These are: by the analysis of aloud reasoning protocols and questions from the participants to the researcher (as done in Dörner's studies), or by allowing the participants to gather information about the task and its structure by themselves. Both ways had their advantages and disadvantages.

The first way allowed the researcher to analyze the individual dynamics of the decision-making, such as choosing the goal, characteristics of hypotheses, and methods of testing them. However, the use of quantitative methods was limited because of the difficulties in the individual protocol comparison.

The second way allowed quantitative evaluation of the participant's activity, fixated by the computerized task's log files, and further statistical analysis. For example, in the FIRECHIEF scenario, used by Cañas et al. [28], the log-files analysis led to the identification of three distinguishable strategies with different ratios of assumed basic "quenching" and "control" strategies in them. In the later study using the same simulation [29], different quantitative parameters were used, such as the distribution of the resources (tractors and helicopters) in different moments. Based on those logs, the authors identified such parameters of problem-solving strategies as strategical planning, tactical planning, strategy flexibility, etc. However, the log-files analysis has weaknesses as well. For instance, it is not able to identify internal psychological mechanisms, mediating seemingly similar decisions.

The studies of decision-making strategies in sequential choice problems [21,26] demonstrated tolerance/intolerance for uncertainty and risk-readiness' contribution to the participant's' activity regulation. On this basis, we suggested that those (and some related) variables could be involved in the regulation of activity when solving complex problems as well.

Thus, we assumed the following general hypotheses:

1. In complex problem-solving, tolerance/intolerance for uncertainty and rationality are associated with a preference for a certain level of awareness of the state of the system.
2. The willingness to vary this level of awareness during the interaction with the system is associated with uncertainty coping strategies use (specifically, buck-passing and procrastination levels) and personal risk-readiness.
3. The general variability of actions while interacting with a complex system and the tendency to experiment with the variables are associated with intuition, problem-solving self-efficacy, tolerance for uncertainty, and risk-readiness.
4. The tendency to perform significant abrupt changes in decisions and actions while interacting with the complex system is associated with impulsiveness.

To test those hypotheses and with the chosen approach to use a "classical" complex problem, we needed to create a suitable task allowing us to record the parameters of the subject's activity of interest in the log files in the first place. Especially for this study, we developed a computerized Java-based task called "The Anthill." The participants were asked to manage a simplified model of an anthill. The management process included decision-making about resource distribution to ensure the survival of the anthill. There were two resources in the task: the ants and the food. The ants could be distributed freely by the player between three classes with different roles and functionality—the scouts, the workers, and the soldiers. The task is described in detail in Section 2.2.1 of this article.

We chose the quantitative (log-files-based approach) to identify general strategies indicators (such as variability of actions, depth of orientation) and their connections with the participants' personal specifics. That was the reason to introduce the scouts as a possible ant-class for the player to spend resources on. Scouts helped the participants to gather information about the riskiness and potentials gains of certain decisions and actions. Based on scouts and other variables-related decisions, made by the participants, several parameters were identified during the log-files analysis, further explained in Section 2.2.1 of this article.

2. Materials and Methods

2.1. Participants

The voluntary participants for the research were recruited via advertising in the students' groups (2–5-year students of clinical psychology major, Sechenov University). The final sample consisted of 53 participants, aged 17–29 (M = 20.42; SD = 2.34), among them 49 were female. All the participants received additional academic credit for an ongoing psychological discipline regardless of their success in the task.

2.2. Methods and Measures

2.2.1. "The Anthill" Computer-Based Complex Problem Task

"The Anthill" is a Java-based task, that was specifically designed for the research purposes for this and the following studies. The basic instruction stated the following: "In this game, you will be controlling an "anthill" for 15 consecutive turns. Please, keep in mind that "the Anthill" is not a model of a real anthill, so any knowledge about the real-life ants and anthills will be of no use for you in this task." For the more detailed description with interface screenshots and instructions, see Appendix A.

There were five key parameters, observable for the participants, and guiding the decisions: (1) the total number of ants (population); (2) the food supply; (3) health; (4) mood, and (5) loyalty of the ants. The participants were given the following instruction: "try to manage the anthill well for the 15 turns in this simulation. If one of the key parameters reaches zero, the game is over, and you lose". The internal structure of the task (as required for a complex problem) was unclear for the participants. Thus, they did not know which parameters of the model influenced the key parameters and how. For the structure of the connections between the parameters, see Figure 1.

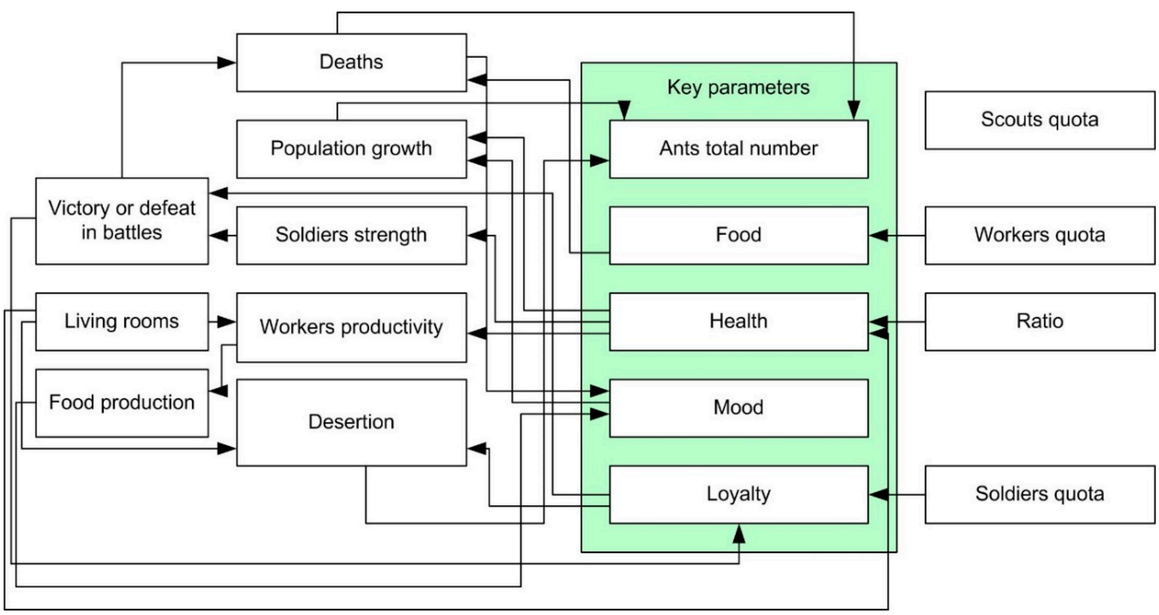

Figure 1. The structure of variables relationships in "The Anthill" complex problem.

As mentioned in the instruction, the decline of key parameters to zero meant a loss in the simulation. Those parameters were settled in the complex system of relationships with other variables:

1. The ants' population (total number of ants) depended on the natural growth (each turn), mortality rates, and the number of escaped ants (desertion rate). Those indicators, in turn, depended on a few others. The population growth rate was determined by the population on the previous turn multiplied by a coefficient that depended on the health and mood of the ants. The mortality rate increased because of the lack of food, but also by losses in battles with enemy ants. Deserting ants number depended on the loyalty and the lack of spare room in the anthill.
2. Food supply depended on the chosen diet for the ants (ratio) and player's success in the tactical phase when workers were sent to gather food. The workers' ability to get more food depended on their productivity, which was directly proportional to the health indicator. The success in gathering food also relied on the number of soldiers accompanying workers.
3. The health indicator increased with a rich diet but fell if the anthill became too crowded. Thus, the living space in the anthill should constantly exceed the number of ants by a certain percentage. Health significantly influenced the productivity of the workers and the soldiers' strength.
4. The mood indicator depended on the amount of food gathered this turn (positively) and the number of dead ants (negatively). The health indicator also had a small effect on the mood.
5. The loyalty indicator was positively related to the soldiers' quota in the anthill and depended on the results of the battles (increased with victories and decreased with defeats). At the same time, higher loyalty increased the chances to win the fight while low loyalty decreased those chances.

The scouts' quota on each turn did not impact any key parameter directly. However, the use of scouts was essential for decision tactics, as more scouts were able to determine better the number of soldiers and workers needed to gather food successfully. Indirectly this affected all the indicators. However, the excessive use of scouts was not a necessary winning condition. The pilot testing of the task with several volunteers showed that even the minimum number of scouts was enough to manage the anthill successfully. Overall, the pilot testing concluded that there is no single winning strategy in this task.

As a result of the log-files analysis, five parameters of the participants' strategies were identified for the "The Anthill" task.

1. *Preferred orientational level (POL)* indicated the importance of accurate representation of the in-game situation for the participant. It was calculated as the average share of the scouts throughout the game:
$$\begin{gathered} POL = \overline{Q}sc, \\ Qsc = \{Qsc_1, \ldots Qsc_n\}, Qsc_i = \frac{Nsc_i}{N_i}, \end{gathered} \tag{1}$$
where Qsc_i was the share of the scouts on the i-th turn, Nsc_i was the number of the scouts on the i-th turn, N_i was the total number of ants on the i-th turn.
2. *Orientational level variability (OLV)* represented how different the participant's orientational level could get throughout the game. It was calculated as the standard deviation of the share of the scouts:
$$\text{OLV} = \sigma(\text{Qsc}). \tag{2}$$

We suggested that the key indicators' dynamics during the session required the player to adapt their strategies to changing conditions. Specifically, it included resource allocation policies. The participant's willingness to experiment and change their orientation level reflected the flexibility or rigidity of the orientational component of their strategy. Higher OLV meant flexibility, while lower OLV scores meant rigidity of the orientational level.

There were two main reasons for the participants to change their decision-making strategies regularly while performing the "The Anthill" task. Opaque connections between the variables determined the first reason. The only way to open up those connections for the player was to try different entries and thoroughly control the results. The second reason for experimenting with strategies underlaid the structure of the game. The goals were conflicting, which was reflected in the dynamics of the key parameters. Basically, everything could not go well in the Anthill at the same time. To succeed and survive for 15 turns, the participant had to change input variables at least occasionally. The question here was—how the player changes those variables?—and it was how dynamic control manifested itself in the task from turn to turn.

We evaluated three quantitative indicators related to dynamic control as well:

3. *Ants class quotas' range (R)* was the measurement of strategy variability. It was established by the minimum and maximum ratios of different classes of ants. The formula for this parameter was:

$$R = \sqrt{(\max(Qsc) - \min(Qsc))^2 + (\max(Qso) - \min(Qso))^2 + (\max(Qwo) - \min(Qwo))^2}, \quad (3)$$

where Qsc was the quota of the scouts, Qso was the quota of the soldiers, Qwo was the quota of workers

4. *Mean* and *Median quotas shift* (*MS* and *MeS*, respectively) reflected the participant's tendency to experiment with exogenous variables from turn to turn and was the measurement for the participants' caution in the game:

$$\begin{gathered} MS = \overline{\Delta Q}, MeS = Me(\Delta Q), \\ \Delta Q = \{dQ_1, \ldots dQ_{n-1}\}, \\ dQ_i = \sqrt{(Qsc_{i+1} - Qsc_i)^2 + (Qso_{i+1} - Qso_i)^2 + (Qwo_{i+1} - Qwo_i)^2}. \end{gathered} \quad (4)$$

We used both the mean and the median as a quantitative assessment here because of the differences in the number of turns our participants made during their games and the sensitivity of the mean scores to outliers in small samples.

5. *Abrupt changes of strategy (AC)* manifested themselves through single pronounced changes in the distribution of ants between classes in single turns. The quantitative measure for those changes was the difference between the mean and the median shifts from turn to turn, as seen in the formula:

$$AC = |\text{MS-MeS}|. \quad (5)$$

With fewer such changes and with them being more pronounced, the higher was the AC parameter.

Based on identified strategy measurements, we transformed our general hypotheses into empirical hypotheses to test in the current study:

1. Higher preferred orientational level (POV) as the desire for complete knowledge about the situation positively correlates with personality traits rationality and intolerance for uncertainty and negatively correlates with tolerance for uncertainty (related to general hypothesis 1).
2. Higher orientational level variability (OLV) positively correlates with non-productive patterns for coping with decisional conflict: buck-passing and procrastination (those two reflect the general unwillingness to change the usual behavioral patterns in uncertain situations) and negatively with personal risk-readiness (related to general hypothesis 2).
3. The class quotas' range (R) as a measure of the overall strategy's variability, positively correlates with the subjective risk-intelligence scales—imaginative capability and problem-solving self-efficacy and thinking styles intuitive ability and intuitive engagement (related to general hypothesis 3).
4. Mean and median quotas shift (MS and MeS) reflecting the willingness to experiment with strategies positively correlate with tolerance for uncertainty and risk-readiness (related to general hypothesis 3).

5. Abrupt changes of strategy (AC) parameter positively correlates with impulsiveness and hypervigilance, as a pattern for coping with decisional conflict (related to general hypothesis 4).

2.2.2. Psychodiagnostic Methods

Several psychodiagnostic questionnaires were used to obtain data about the participant's personality traits related to decision-making and problem-solving.

1. Personal Decision-Making Factors Questionnaire (LFR-21) developed by Kornilova [30]. It consisted of 21 yes-or-no statements divided into two scales: (1) rationality, as the inclination for a broader orientation in the situation of decision-making, and (2) personal risk-readiness, as the willingness and ability to make choices in uncertain situations.
2. New questionnaire of tolerance/intolerance for uncertainty (NTN) developed by Kornilova [30]. It consisted of 33 statements, evaluated with a seven-point Likert scale (from "completely disagree" to "completely agree"). The questionnaire included three scales: (1) Tolerance for uncertainty, as the personal acceptance of novelty, complexity, inconsistency in problem-solving and decision-making conditions; the willingness to act in new and unusual ways; (2) intolerance for uncertainty, as the desire for clarity, orderliness; avoidance of uncertainty, reliance on rules and principles; a tendency to see opinions, values, and methods of action as either right or wrong; (3) interpersonal intolerance for uncertainty, as the desire for control in interpersonal relationships, for clarity, and the discomfort in relationships, that were lacking that clarity.
3. Eysencks' Impulsiveness Scale (seventh version, I7) [31] in Russian short adaptation by Kornilova and Dolnikova [32]. It consisted of 28 yes-or-no questions with three sub-scales: (1) Impulsiveness, as the decrease in self-control and the tendency to act under the spur of the moment; (2) venturesomeness, as the search for strong emotions, thrills, and (3) empathy, as the ability to empathize with others, feel their emotions as your own.
4. Russian version of Epstein's Faith in Intuition scale from the Rational Experiential Inventory (REI) [33,34] with two sub-scales: (1) experiential (intuitive) ability, as the ability to report one's intuitive impressions and feelings, and (2) experiential (intuitive) engagement, as the willingness to make decisions depending on intuition and feelings.
5. Melbourne decision-making questionnaire (MDMQ), in Russian adaptation by Kornilova [35,36]. The Russian version retained the original's 22-statement structure with four scales: (1) Vigilance, as the productive uncertainty coping strategy, the desire to carefully consider possible alternatives for the decision-making; and three unproductive copings; (2) buck-passing, as the desire to abandon independent decision-making; (3) procrastination, as the desire to delay decision-making; and (4) hypervigilance, as the tendency to decide impulsively, the desire to get rid of the uncertain situation without intellectual orientation in it.
6. The Subjective Risk Intelligence Scale (SRIS) [37] in Russian adaptation by Pavlova. The Russian variant included three scales from the original four-scale version of this questionnaire: (1) Imaginative capability, as the personal ability to explore the unknown, generate unusual, new, widely useful ideas; (2) problem-solving self-efficacy, as the self-confidence while dealing with problem-solving and decision-making, and (3) negative attitude toward uncertainty, as the acceptance or avoidance of risk in decision-making and problem-solving.

2.3. Statistical Methods

For group comparison and correlational analysis, non-parametric methods were chosen because of sample-sizes and non-normal data distribution. Thus, Mann–Whitney U test and Spearman's rank correlation coefficient (rho) were used for further calculations, multiple linear regression.

All calculations were made in IBM SPSS Statistics version 22.

2.4. Procedure

The study consisted of two stages. During the first, the participants were asked to fill out pen-and-paper variants of the psychodiagnostic questionnaires listed in Section 2.2.2. In the second stage, the "Anthill" task was introduced. Each participant received a printed instruction, explaining the rules, and describing the game interface. After the participants got acquainted with the instruction, they were asked if the instructions were clear. Additional oral explanations were provided by the researcher if needed. Then the participant was able to start interacting with the task. The first stage was conducted with a group of participants in the same room under supervision with no ability to communicate or look in each other's questionnaires. The second stage was organized individually for each participant using PC stations with the same configuration (which had no significant impact on the task rather than providing general stability for the program).

3. Results

3.1. Game Success Frequencies in Our Sample

Game success statistics are shown in Table 1. Of the 53 participants, only 23 were able to reach the final 15th turn of the simulation.

Table 1. The amount of turn made by the participants until the end of the simulation.

Turns	4	5	6	7	8	9	10	11	12	13	14	15
Frequency	1	6	2	1	3	3	4	1	1	6	2	23

According to the results from Table 1, the participants were divided into "successful" ($N = 23$, those, who completed all 15 turns) and "unsuccessful" ($N = 30$, those, who lost the game before the 15th turn) subgroup, using the Mann-Whitney U test. No significant differences were found for any personality traits or strategical parameters.

We also calculated descriptive statistics for strategies' parameters and personality questionnaires scores in our sample, see Appendix B.

3.2. Relationships between Complex Problem-Solving Strategies and Personality Metrics

We used correlational analysis to evaluate the relationships between complex problem-solving strategies' parameters, evaluated in the "The Anthill" task, and personality traits, measured by psychodiagnostic questionnaires. Since the distributions of the most measurements were different from normal, we used the Spearman's rank correlation coefficient. See Table 2 for significant correlations. See Appendix C for the full correlations.

Table 2. Significant correlations between complex problem-solving strategies' parameters and psychological variables.

	POL	**OLV**	**MeS**	**R**
Venturesomeness		0.296		
Buck Passing		−0.293		
Tolerance for Uncertainty	−0.275			
Intuitive Ability				0.292
Negative Attitude Towards Uncertainty		−0.274	−0.309	

All significant with $p < 0.05$.

As seen in Table 2, four out of five strategy parameters showed significant correlations with personality traits.

The multiplicity of relationships of some parameters allowed us to use regression analysis to assess the overall effect of personality traits on the parameters of complex problem-solving strategies.

3.3. Regression Analysis of the Effects of Psychodiagnostic Indicators on Indicators of Strategies

To evaluate the magnitude of the effects of the personality variables and to reveal the general variance explained by them, we conducted a stepwise linear regression. As a result, we managed to obtain three regression models, where the preferred orientation level (POL), the orientational level variability (OLV), and the median quotas shift (MeS) appeared as dependent variables. Parameters and coefficients for the models are shown in Tables 3–5.

Table 3. Regression model parameters for the preferred orientation level (POL).

	Unstandardized Coefficients		**Standardized Coefficients**	**Tolerance**	**Sig.**
Model	B	Standard Error	Beta		
Constant	−0.036	0.13		−0.28	0.781
Tolerance for uncertainty	−0.342	0.127	−0.347	−2.693	0.009

POL as dependent; Adj R-Square = 0.104.

Table 4. Regression model parameters for the orientational level variability (OLV).

	Unstandardized Coefficients		**Standardized Coefficients**	**Tolerance**	**Sig.**
Model	B	Standard Error	Beta		
Constant	0.037	0.132		0.28	0.78
Procrastination	−0.299	0.129	−0.303	−2.318	0.024

OLV as dependent; Adj R-Square = 0.075.

Table 5. Regression model parameters for the median quotas shift (MeS)

	Unstandardized Coefficients		**Standardized Coefficients**	**Tolerance**	**Sig.**
Model	B	Standard Error	Beta		
Constant	0.014	0.13		0.108	0.915
Procrastination	−0.388	0.135	−0.389	−2.862	0.006
Risk Readiness	−0.296	0.138	−0.291	−2.144	0.037

MeS as dependent; Adj R-Square = 0.145.

4. Discussion

In three out of five empirical hypotheses (numbered 1, 2, and 4), we expected to find relationships between the parameters of complex problem-solving strategies and the scales of the LFR-21 questionnaire—rationality and personal risk-readiness. According to the authors of the questionnaire, those scales describe the personal properties of self-regulation in decision-making and actions under uncertainty [30]. It means that risk-readiness and rationality here are more than personal dispositions, but somewhat generalized characteristics of how people can find their way out of uncertain situations.

By assuming the connection between risk-readiness, rationality, and complex problem-solving strategies, we, thus, hold the idea that those uncertainty-dealing general personal characteristic would manifest in choosing and varying the preferred levels of orientation, as well as when varying the distribution of resources in the "The Anthill" task (as a representation of a complex problem in our study). We were unable to confirm those assumptions.

We did not find evidence that risk-readiness and rationality are directly included in complex problem-solving, at least at the planning level. More likely, those two traits characterize the style of action in uncertain situations. The same applies to the imaginative capability and problem-solving self-efficacy, measured by the Subjective Risk Intelligence Scale [37]. Additional research is needed to clarify this new assumption. It will also require the inclusion of new parameters of complex problem-solving strategies.

According to our data, the preferred orientational level in the task negatively correlated with tolerance for uncertainty ($r = -0.291$ at $p < 0.05$). Those, who are more tolerant toward incompleteness and inconsistency of the information at their disposal, and prefer new and complex tasks, require less information (or less accurate information) while trying to solve a complex problem. On the other hand, we did not find any significant connection between intolerance for uncertainty or rationality with the POL parameter, which means that both the first empirical and general hypotheses can only be accepted partially.

The second empirical hypothesis of our study (matching the second general hypothesis) is also partially accepted. Of the two unproductive copings (buck-passing and procrastination), only the buck-passing showed correlations with the flexibility of the orientation level (higher OLV) with r = −0.293 at $p < 0.05$. Buck-passing is described as a refusal to make decisions independently [35,36]. As a pattern for coping with decisional conflict in complex problem-solving, it can manifest itself as a refusal to change some parameters of the strategy, the desire to act "in a usual way," consistently with previous turns. Additionally, we found significant correlations between higher orientational level variability and the negative attitude toward uncertainty (r = −0.274 at $p < 0.05$), as well as with venturesomeness (r = 0.296 at $p < 0.05$). Like the buck-passing, the negative attitude toward uncertainty is associated with the rejection of attempts to change one's research behavior in uncertain situations when the effect of this change is unknown and unpredictable [37]. The assessment of that effect would appear as a separate task, which apparently would probably make the situation even more subjectively uncertain. On the contrary, the venturesomeness manifests itself as a desire to try something new, to look for new experience and thrills; it pushes a person to experiment—in case of "The Anthill" task—with resource distribution throughout the game. Risk-readiness, on the contrary, did not demonstrate a significant correlation with orientational level variability.

The third empirical hypothesis is partially accepted, as well. The class quotas' range parameter reflects the boundaries of the search area for a successful strategy. It shows to what extent a participant is ready to experiment with input variables in complex problem-solving. In a situation of an opaque task with a high degree of uncertainty, this activity cannot be regulated only by discursive reasoning. Hypothesizing and verifying those hypotheses in the absence of sufficient information is primarily based on conjecture and intuition. We found a significant correlation between the class quotas' range and intuitive ability (r = 0.292 at $p < 0.05$), but no correlation with intuitive engagement was found. No significant correlations were found between the class quotas' range with the imaginative capability and problem-solving self-efficacy as well.

The fourth empirical hypothesis was not confirmed. It was built on the assumption that the mean and median shifts in quotas distribution would reflect the degree of the participant's caution. In a situation of consistent decision-making, cautious people would perform minimal modifications of their previous decisions. However, there are no relationships with risk-readiness and tolerance for uncertainty, which, among other things, reflect the personal willingness to unexpected consequences of their decisions and actions. Nevertheless, a negative correlation was found between median quotas shift and negative attitude toward uncertainty (r = −0.309 at $p < 0.05$), which fits well with our interpretation of the general class quotas' range parameter. A wide range of changes in input variables reflects the willingness of the participant to experiment, and any pronounced change in input leads to a significant difference in output, which in turn adds new information that needs to be taken into account when making decisions. New information in an opaque situation with many hidden variables and relationships increases subjective uncertainty, rather than clarifying the situation.

For the abrupt changes of strategy indicator, no correlations were found. The fifth empirical hypothesis and the fourth general hypothesis are not accepted.

Regression analysis revealed the predictors of three complex problem-solving strategies' parameters. Procrastination demonstrated a statistically significant effect on the orientational level variability and the median quotas shift. Both reflect a person's willingness to experiment with input variables in the process of solving the problem. Postponing decision-making, as a way of coping with uncertainty in complex problem-solving, can manifest itself as a decrease in the variability of the strategy in general, or between single turns.

Additionally, risk-readiness had a negative effect on the median quotas shift. That result was somewhat unexpected for us, as risk-readiness is generally associated with the ability to make decisions and act under uncertainty. We expected that higher risk-readiness would lead to bigger shifts in resource distribution from turn to turn.

However, another interpretation is possible, since procrastination is the second predictor of the variability of shifts. Risk-readiness, in this case, can enhance the effect of procrastination, since the rejection to choose includes the adoption of the consequences of this rejection as well, which seems to be easier for people with higher risk-readiness. Still, this requires further research on larger and more balanced sample.

For the preferred orientational level, the only significant predictor was tolerance for uncertainty. We explained the correlation of these indicators at the beginning of this section.

For all three regression models, the percentage of explained variance was not remarkably high (no more than 15 percent). Nevertheless, we were able to show some contribution of personality factors to the regulation of complex problem-solving strategies.

Thus, some of our initial assumptions about the relationships between personality traits and parameters of people's activity when interacting with a complex dynamic system were confirmed. A decrease in tolerance for uncertainty was associated with a desire for more comprehensive information about the system's state. The use of buck-passing and procrastination as coping strategies reduces the variability of the preferred level of awareness in the progression of the game. Intuitive ability is associated with a greater tendency to experiment with variables.

Limitations. In the current study, the sample was small and unbalanced by gender (female participants prevailed) and age. Those characteristics limit the possibility of generalizing the obtained results.

There is no generally accepted conceptualization of the strategy concerning complex problem-solving, just as there is no generally accepted formalized model of this process. Therefore, it is rather difficult to evaluate the extent to which the parameters of strategies that we have identified describe human activity in complex problem-solving. The analysis of those strategies did not consider the influence of feedback on the participants' actions, which limits our abilities to understand their activity fully. Refinement of the script to include feedback display in log-file at each turn would allow us to monitor how the participants change their actions accordingly. In the current state of the program, this information is exceedingly difficult to work with, as it requires step-by-step reproduction of the participants' actions following the log-file.

The obtained correlations need to be checked on larger samples. A larger sample would also open the possibility for the use of multivariate statistical methods. That would allow us to identify stable patterns of the ratio of fixed indicators of strategies and give a more general description of strategies.

Further research requires the construction of conceptual models of human activity in complex problem-solving. It will probably make it possible to operationalize the concept of strategy concerning complex problem-solving in the future.

5. Conclusions

Our study results showed that complex problem-solving strategies' parameters are related to several personality factors involved in the decision-making processes. Specifically, such personality traits as venturesomeness, intuitive ability, tolerance for uncertainty, negative attitude toward uncertainty, and buck-passing (as an uncertainty coping pattern) were found related to complex problem-solving strategies.

Copying strategy procrastination, tolerance for uncertainty, and risk-readiness can be considered as predictors of individual parameters of complex problem-solving strategies.

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Appendix A

"The Anthill" interface consists of several successively presented windows, with controls through which the participants make their decisions. The initial window is shown in Figure A1.

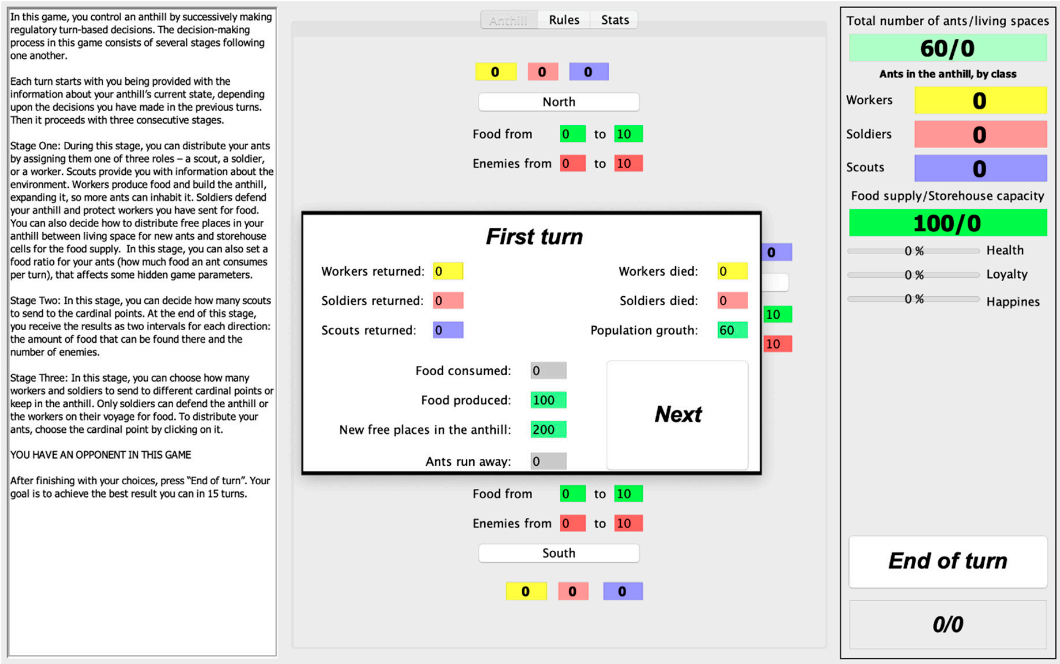

Figure A1. "The Anthill" starting window.

Each turn begins with the feedback in the central dialog box. The feedback consists of the main results of the previous turn, including the information on the increase and decrease in the ant's population, the amount of food obtained and consumed, and the increase in the number of spaces in the anthill. This dialog box is presented in Figure A2.

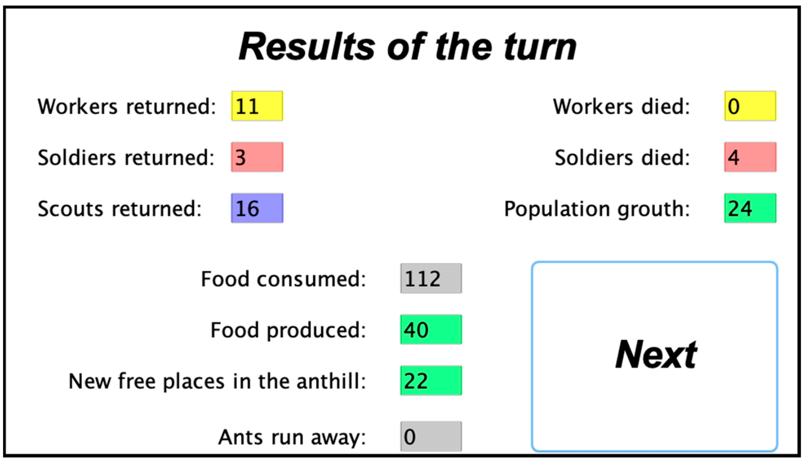

Figure A2. The feedback window.

After getting acquainted with the feedback information, the participants can click the "Next" button to get to another dialog box, this time with controls. In this screen, the participants are asked to distribute the resources at their disposal, namely, assign classes to the ants, determine their ratio, and allocate free places in the anthill (see Figure A3).

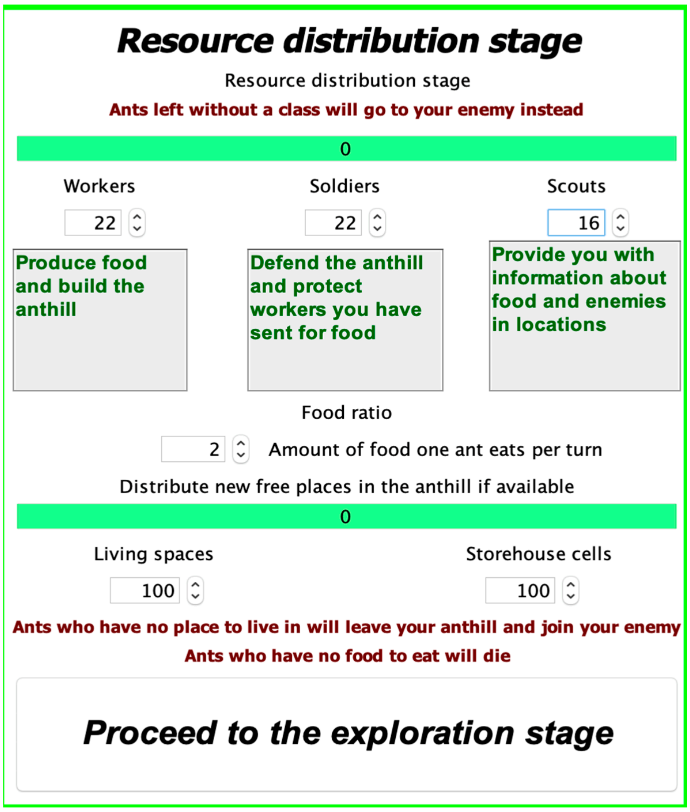

Figure A3. The resource distribution window.

The next window allows the participants to distribute their scouts to cardinal directions (see Figure A4).

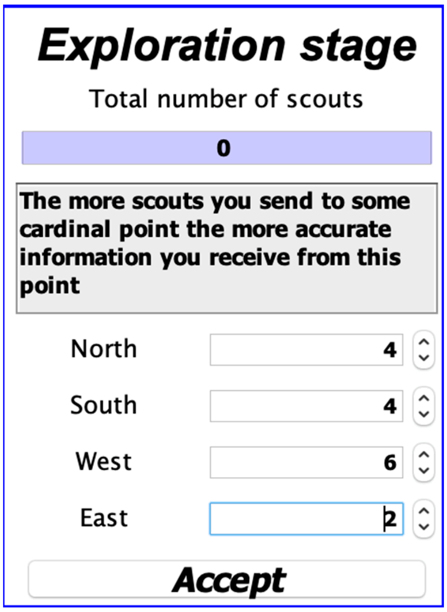

Figure A4. Scouts distribution window.

After the scouts were sent out to the cardinal points, the main window appears (see Figure A5).

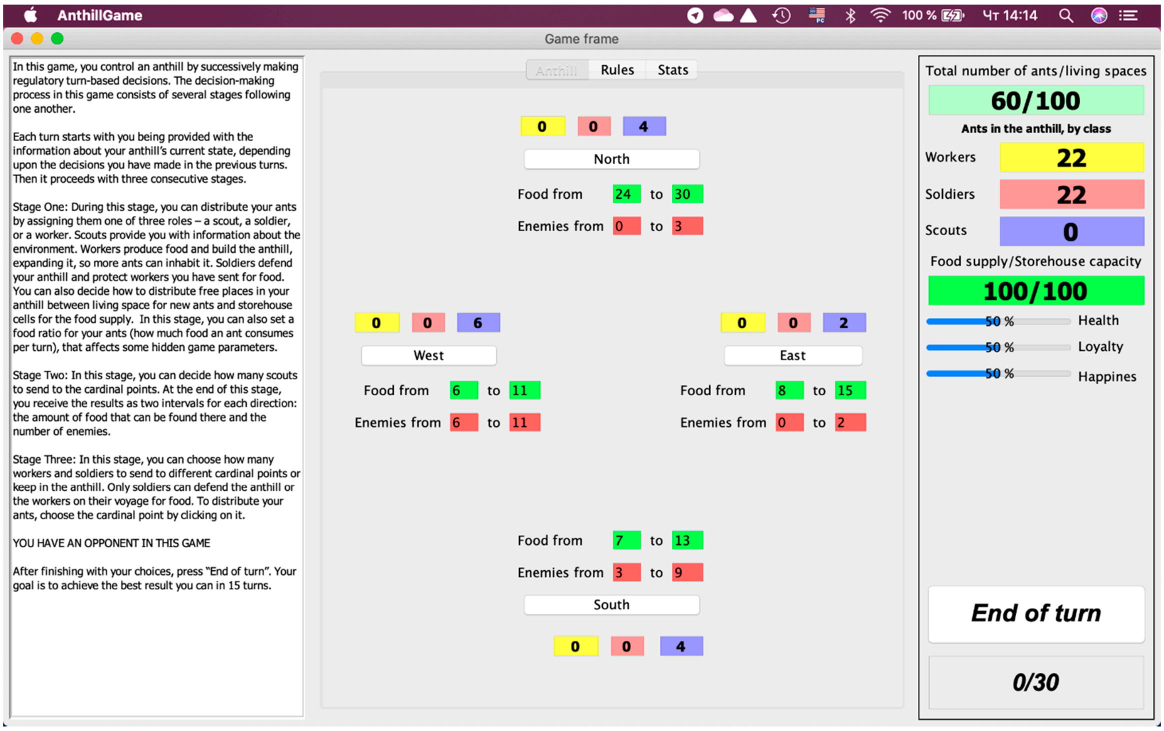

Figure A5. The main screen of "The Anthill" task.

The main screen is divided into three parts: A memo on the left, which briefly describes the basic rules and opportunities the player has; indicators of health, loyalty, mood, number of ants, food reserves, and number of places on the right; the middle part of the screen reflects the state of the cardinal points after scouting.

For each side of the world, two ranges are shown, reflecting the possible amount of food and the possible number of opponent ants. Those ranges were narrower if more scouts were sent in the corresponding direction previously. The ranges do not depend on the total number of scouts, but on their share among all ants—this is due to the need to equalize the complexity of the solutions for any total number of ants. The exact amounts of food enemies are always within the range but can be at any point. The amounts of food and enemy ants at each side of the world are calculated independently and randomly each turn. The total number of enemies and the total amount of food on the field is determined as a function of the total number of player's ants to adapt the conditions to the player's capabilities. Further, these two values are randomly distributed around the four sides of the world. The lack of distribution patterns was considered as a necessary condition that encourages the player to make informed decisions every move.

At this stage, the player can decide which part(s) of the world and in what quantity to send workers and soldiers. When the participant clicks the button with the name of the side of the world, a dialog box opens (see Figure A6).

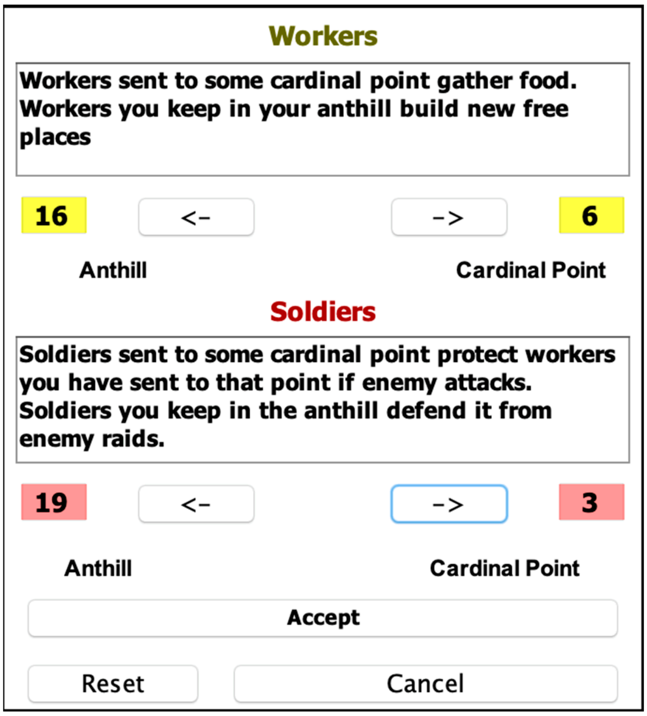

Figure A6. A window for sending workers and soldiers to the cardinal points.

It is up to the participant to send ants to all sides of the world, to some of them, or to none. The outcomes on each side of the world depend on the number of enemies, and the number of ants sent, as well as the state of several variables. The outcome of the battles is determined by considering the indicators of loyalty and strength of the soldiers. The higher those indicators, the better the ants fight, taking fewer losses. After the distribution of the ants to the cardinal points, all information about the distribution is given on the main screen (see Figure A7).

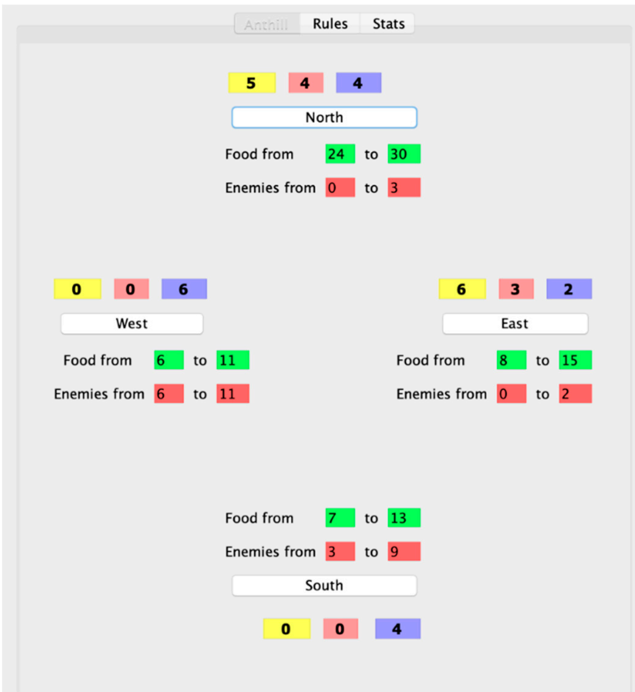

Figure A7. The main screen with ants distributed to the cardinal points.

Next, after the click on the "Complete the move" button in the lower right corner of the screen, the program performs the calculations, and the next simulation turn starts.

Depending on how well the player acted previously, enemy ants can raid the player's anthill after the turn (there is no prior notice that this can happen apart from the note "you have an opponent in this game" in the memo section on the main screen). The outcome of the raid depends on the balance of power of the parties. If the opponent wins, the player loses part of the food supply of the anthill.

All decisions made by the participant are recorded in the program log.

Appendix B

Table A1. Descriptive statistics for the parameters of the strategies.

	M	SD
Preferred orientational level (POL)	0.217	0.113
Orientational level variability (OLV)	0.085	0.063
Mean quotas shift (MS)	0.132	0.074
Median quotas shift (MeS)	0.104	0.070
Ants class quotas′ range (R)	0.509	0.291
Abrupt changes of strategy (AC)	0.028	0.039

Table A2. Descriptive statistics for the personality measurements.

Questionnaire	Scales	M	SD
LFR-21	Rationality	3.55	3.841
	Risk-readiness	0.53	4.131
NTN	Tolerance for uncertainty	61.21	7.986
	Intolerance for uncertainty	57.40	10.976
	Interpersonal intolerance for uncertainty	35.91	6.831
I7	Impulsiveness	3.98	2.197
	Venturesomeness	5.45	2.374
	Empathy	7.02	1.670
REI	Intuitive ability	29.43	5.394
	Intuitive engagement	30.26	6.442
MDMQ	Vigilance	15.00	2.130
	Buck-passing	11.06	3.243
	Procrastination	8.89	2.998
	Hypervigilance	9.66	2.534
SRIS	Imaginative capability	19.00	3.942
	Problem-solving self-efficacy	20.64	3.888
	Negative attitude toward uncertainty	21.66	6.983

Appendix C

Table A3. Correlations between psychodiagnostics questionnaires scales.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Rationality																
2. Risk-Readiness	−0.357 **															
3. Tolerance for uncertainty	−0.192	0.297 *														
4. Intolerance for Uncertainty	0.485 **	−0.172	−0.119													
5. Interpersonal Intolerance for Uncertainty	0.273 *	−0.443 **	−0.037	0.413 **												
6. Impulsiveness	−0.442 **	0.067	0.134	−0.205	0.246											
7. Venturesomeness	−0.034	0.263	0.293 *	−0.162	−0.271	−0.226										
8. Empathy	0.137	−0.122	0.104	0.131	0.247	−0.094	0.113									
9. Intuitive Ability	0.121	0.178	0.186	0.031	0.050	0.114	0.321 *	−0.032								
10. Intuitive Engagement	−0.091	0.172	0.127	0.019	0.053	0.288 *	0.185	−0.101	0.632 **							
11. Vigilance	0.603 **	−0.215	0.065	0.250	0.268	−0.221	−0.055	0.372 **	0.239	0.089						
12. Buck-Passing	0.163	−0.535 **	−0.165	0.101	0.528 **	0.114	−0.317 *	0.172	−0.167	−0.095	0.062					
13. Procrastination	0.009	−0.373 **	0.038	−0.024	0.473 **	0.277 *	−0.300 *	0.276 *	−0.049	0.035	0.090	0.802 **				
14. Hypervigilance	0.033	−0.406 **	−0.067	0.255	0.461 **	0.295 *	−0.339 *	0.073	−0.143	−0.083	0.016	0.592 **	0.577 **			
15. Imaginative Capability	0.224	0.095	0.500 **	0.153	−0.045	−0.203	0.321 *	−0.058	0.254	−0.030	0.262	−0.131	−0.106	−0.023		
16. Problem-Solving Self-Efficacy	0.133	0.194	0.348 *	0.101	−0.159	−0.098	0.410 **	−0.100	0.388 **	0.126	0.123	−0.332 *	−0.290 *	−0.241	0.614 **	
17. Negative Attitude Toward Uncertainty	0.054	−0.507 **	−0.119	0.113	0.639 **	0.349 *	−0.246	0.324 *	−0.117	0.016	0.130	0.612 **	0.625 **	0.535 **	−0.307 *	−0.423 **

Note: **—significant with $p < 0.01$; *—significant with $p < 0.05$.

Table A4. Correlations between complex problem-solving strategies' parameters.

	POL	OLV	MS	MeS	R
Preferred Orientational Level (POL)					
Orientational Level Variability (OLV)	0.045				
Mean Quotas Shift (MS)	−0.020	0.685 **			
Median Quotas Shift (MeS)	−0.046	0.400 **	0.774 **		
Ants Class Quotas' Range (R)	−0.126	0.852 **	0.809 **	0.454 **	
Abrupt Changes of Strategy (AC)	−0.028	0.439 **	0.409 **	−0.156	0.564 **

Note: **—significant with $p < 0.01$.

Table A5. Correlations between psychodiagnostics questionnaires scales and complex problem-solving strategies' parameters.

	POL	OLV	MS	MeS	R	AC
Rationality	0.064	0.105	0.080	0.093	0.068	0.000
Risk-Readiness	0.019	0.041	0.073	0.032	−0.023	0.175
Tolerance for Uncertainty	−0.275 *	0.047	−0.008	−0.029	0.054	0.087
Intolerance for Uncertainty	0.130	0.053	0.159	0.056	0.128	0.178
Interpersonal Intolerance for Uncertainty	0.066	−0.080	−0.088	−0.235	−0.024	0.141
Impulsiveness	−0.082	−0.247	−0.144	−0.025	−0.184	−0.198
Venturesomeness	−0.182	0.296 *	0.238	0.251	0.217	0.121
Empathy	−0.018	−0.114	0.087	0.071	0.026	0.056
Intuitive Ability	−0.108	0.243	0.173	0.148	0.292 *	0.206
Intuitive Engagement	−0.076	0.002	−0.203	−0.146	−0.048	0.018
Vigilance	−0.133	−0.018	−0.026	0.006	−0.007	−0.060
Buck-Passing	0.116	−0.293 *	−0.219	−0.235	−0.209	0.038
Procrastination	0.056	−0.222	−0.221	−0.241	−0.124	0.024
Hypervigilance	0.217	−0.056	−0.017	−0.112	0.034	0.048
Imaginative Capability	0.052	0.206	0.139	0.108	0.209	0.110
Problem-Solving Self-Efficacy	−0.241	0.160	0.067	0.141	0.170	0.066
Negative Attitude Toward Uncertainty	0.064	−0.274 *	−0.223	−0.309 *	−0.192	0.051

Note: * significant with $p < 0.05$.

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