Self-appraised social problem solving abilities, emotional reactions and actual problem solving performance

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Abstract

Self-report measures of social problem solving abilities have yet to be associated with objective problem solving performance in any consistent manner. In the present study, we investigated the relation of social problem solving abilities — as measured by the Social Problem Solving Skills Inventory — Revised (SPSI-R [Maydeu-Olivares, A. & D’Zurilla, T. J. (1996). A factor analytic study of the Social Problem Solving Inventory: an integration of theory and data. \textit{Cognitive Therapy and Research}, 20, 115–133]) — to performance on a structured problem solving task. Unlike previous studies, we examined the relation of problem solving skills to performance curves observed in repeated trials, while controlling for affective reactions to each trial. Using hierarchical modeling techniques, a negative problem orientation was significantly predictive of performance and this effect was not mediated by negative affectivity. Results are discussed as they pertain to contemporary models of social problem solving. © 2000 Elsevier Science Ltd. All rights reserved.

1. Introduction

Social problem solving has been defined as the set of instrumental, cognitive-behavioral skills necessary for adaptation in everyday life (D’Zurilla & Nezu, 1982). Contemporary formulations categorize social problem solving abilities into two broad components that operate in the problem solving process. According to D’Zurilla and colleagues, these are

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defined as the problem orientation and the problem solving skills components (D'Zurilla & Nezu, 1990). The problem orientation component involves many beliefs and attitudes about the self and one's ability to handle problems encountered in everyday life and is comprised of a positive and a negative problem orientation. A positive problem orientation entails a set of beliefs, expectancies and abilities that serve to motivate an individual through problem solving and promote positive affects that can facilitate effective problem solving. A negative problem orientation renders an individual vulnerable to recurrent and prolonged experiences of negative affect that can inhibit or disrupt complex problem solving, as the individual harbors pessimistic appraisals of the self and expectancies. An individual with a high negative orientation often lacks motivation for complex problem solving.

The problem solving skills component encompasses cognitive-behavioral abilities in identifying problems, generating solutions, evaluating options, implementing a plan, monitoring progress and evaluating outcomes (D'Zurilla & Nezu, 1982, 1990). This can involve rational problem solving skills that are useful in everyday problem solving, but also includes inefficient strategies often observed in avoidant, impulsive and careless styles (D'Zurilla & Nezu, 1990).

Converging evidence indicates that self-appraised problem solving abilities are related to adjustment in a rather predictable fashion. Studies that have examined correlates of specific subscales of several problem solving measures have found that both problem orientation components are often uniquely predictive of depressive behavior, health complaints, anxiety, neuroticism and negative affect under general and stressful conditions (Dugas, Letarte, Rheaume, Freeston & Ladouceur, 1995; Elliott, Herrick, MacNair & Harkins, 1994; Elliott & Marmarosh, 1994; Elliott, Sherwin, Harkins & Marmarosh, 1995). Evidence indicates that these relations may be due in part to the mood-regulatory properties of the problem orientation component (Elliott, Shewchuk, Richeson, Pickelman & Franklin, 1996b) and to the positive expectancies associated with this component (Chang & D'Zurilla, 1996).

There are several unresolved and controversial issues that hinder our understanding of social problem solving abilities. Despite the rather clear association between self-appraised problem solving and adjustment across correlational studies, experimental research has found that effective and ineffective problem solvers do not differ in their spontaneous attempts to solve simulated problems in a social setting (Larson, Potenza, Wennstedt & Sailors, 1995). This discrepancy may be explained in part by a lack of multiple and precise measures of problem solving components in experimental situations and the possible lack of generalizability from experimental to field settings (D'Zurilla & Maydeu-Olivares, 1995). It is possible, for example, that those with more effective problem solving abilities benefit from experience and repeated trials so that differential performance curves may be observed over time. Nevertheless, research has yet to establish the mechanisms by which problem solving affects performance and behaviorally-based outcomes.

There is some evidence that self-appraised problem solving abilities are related to objective indices of performance over time. For example, elements of the problem orientation component have been significantly predictive of academic performance (e.g. course grade, grade point averages; Blankstein, Flett & Watson, 1992; Elliott, Godshall, Shrout & Witty, 1990). Other research indicates that problem solving skills are associated with academic performance (D'Zurilla & Nezu, 1990; D'Zurilla & Sheedy, 1992). Problem solving skills have
also been uniquely associated with indicators of behavioral self-care (e.g., pressure sores among persons with severe physical disabilities; Herrick, Elliott & Crow, 1994) and with behavioral patterns of undergraduates (Godshall & Elliott, 1997).

We believe there are several testable possibilities that might explain how social problem solving abilities might influence performance. First, the problem orientation component might mediate the relation between problem solving skills and performance. An individual with a positive problem orientation should be sufficiently motivated to solve complex problems and would thus employ problem solving strategies as necessary to meet task demands; individuals with a negative orientation would lack such motivation and thus would not apply their problem solving skills. Alternatively, the problem orientation component serves to regulate mood under general and stressful conditions (Elliott et al., 1995, 1996b). Those with a negative orientation might experience more negative moods which in turn reduce flexibility, distort available and pertinent information, interfere with retrieval and/or storage of information and impair the implementation of solutions (Heppner & Krauskopf, 1987). A person with a positive orientation would be more likely to experience positive affects which can facilitate problem solving and information processing (Isen, Daubman & Nowicki, 1987). It is also possible that effective problem solving skills would influence performance, regardless of the problem orientation component, as implied in the Herrick et al. (1994) and Godshall and Elliott (1997) studies. Finally, as D’Zurilla and Maydeu-Olivares (1995) imply, it is possible that research designs to date have been insensitive to the ways in which problem orientation and problem solving skills components operate to influence rates of change in performance over time. Problem solving processes may be best studied with multiple and repeated measures of performance under uniform conditions and with statistical techniques sensitive to covarying relationships and variability in performance trajectories.

We examined these possibilities in the present study. Specifically, we examined the relation of self-appraised problem solving abilities to emotional reactions to a standardized task that required participants to solve problems over repeated administrations. Thus, we were able to assess successful performance over repeated trials so that individual performance curves could be computed and analyzed. In this manner, we were able to test the presumed associations between social problem solving abilities, affect and objective performance in a problem solving task over time.

2. Method

2.1. Participants

The sample consisted of 131 undergraduates (50 men, 81 women, mean age = 19.72, S.D. = 4.06) enrolled in introductory psychology courses at a metropolitan university. Participants were recruited from sign-up sheets on a department bulletin board and from a list of students who filled out an initial screening questionnaire for the department. Participants received research participation credits following completion of their session.
2.2. Measures

2.2.1. The Social Problem Solving Inventory — Revised (SPSI-R; D’Zurilla, Nezu & Maydeu-Olivares, in press)

The SPSI-R is a 52-item self-report measure of social problem solving abilities (Maydeu-Olivares & D’Zurilla, 1996). The SPSI-R is based on a five-dimensional model of problem solving and provides five scales. Two of the scales measure problem orientation dimensions: positive problem orientation (PO) and negative problem orientation (NO). The remaining three scales are considered problem solving skills scales. These include rational problem solving (RP), impulsivity/carelessness style (IC) and avoidance style (AS).

The Positive Problem Orientation scale (PO) assesses a general cognitive set which includes the tendency to view problems as challenges rather than threats and to be optimistic regarding the existence of a solution and one’s ability to detect and implement effective solutions. The Negative Problem Orientation scale (NO) assesses a cognitive-emotional set that hinders effective problem solving.

The Rational Problem Solving scale (RP) assesses the tendency to systematically and deliberately employ effective problem solving techniques including defining the problem, generating alternatives, evaluating alternatives and implementing solutions and evaluating outcomes. The Impulsivity/Carelessness Style scale (IC) measures the tendency to solve problems in an impulsive, incomplete and haphazard manner. The Avoidance Style scale (AS) assesses dysfunctional patterns of problem solving characterized by putting the problem off and waiting for problems to solve themselves.

Internal consistency estimates for the scales with college students range from alphas of 0.76 for PO to 0.92 for RP and test–retest (3 weeks) reliability ranges from 0.72 for PO to 0.88 for NO for the same sample (D’Zurilla et al., in press). Criterion-referenced validity is evidenced by significant correlations with relevant scales on the Problem Solving Inventory (PSI; Heppner, 1988) and with other theoretically related constructs as stress, somatic symptoms, anxiety, depression, hopelessness and suicidality (Chang & D’Zurilla, 1996; D’Zurilla et al., in press). The SPSI-R scales have been predictably associated with self-esteem, life satisfaction, extraversion, social adjustment and social skills (D’Zurilla et al., in press; Sadowski and Kelly, 1993.

2.2.2. The Short Category Test, Booklet Format (SCT-B; Wetzel & Boll, 1987)

The SCT-B is a measure of concept formation and hypothesis testing. The SCT-B (like other versions of the Halstead Category Test; Reitan & Davison, 1974) requires a respondent to (1) develop hypotheses and organizing principles in response to a demanding situation, (2) evaluate these hypotheses based on positive and negative feedback from the examiner and (3) adjust these hypotheses in a dynamic way based on the feedback (Bertram, Abeles & Snyder, 1990). In this sense, effective performance is optimized by flexibility in problem solving and a certain degree of facility with problem solving strategies.

Each of the five subtests consists of a booklet of 20 cards depicting geometric shapes, lines, colors and figures. The cards in each subtest are arranged according to an underlying principle that the participant must discern from the feedback given by the examiner. The examiner gives feedback only by responding ‘right’ and ‘wrong’ after the person’s response to each card. The
instrument gives a total error score for the sum of all five subtests and there are means and standard deviations available for younger (<45 years) and older adults (>45 years). Higher correct subscale scores represent better performance. In the present study, data from the first administration were not used for analysis, as this is primarily an instructional ‘trial’ during which the respondent is oriented to the task. Responses to the remaining four subtests were used to examine our hypotheses concerning social problem solving abilities and performance over time.

Split half reliability estimates for the SCT-B were found to be 0.81 (Summers & Boll, 1987). Test–retest reliability information is not available on this version of the original Category Test because of potential practice effects. The validity of the SCT-B is supported through high correlations with the original, longer Category Test. In addition, the utility of the SCT-B for discriminating brain-damaged patients from non-brain-injured individuals has been successfully demonstrated (Wetzel & Boll, 1987). In the present study, the SCT-B was used to assess problem solving performance.

2.2.3. Positive and negative affect

An abbreviated version of the Affect Intensity Questionnaire (AIQ; Harkins, Gramling & Elliott, 1990; Elliott et al., 1995) was used to measure state positive and negative affect. Four items measuring negative affectivity were frustrated, angry, depressed and distressed. The measure of positive affect were the four items from the Positive and Negative Affect Schedule (Watson, Clark & Tellegen, 1988) with the highest loadings on the positive affect factor. These items were included enthusiastic, interested, determined and excited. Participants were asked to rate each of these terms as they reflect how they are feeling at that moment. Each of these eight items had a visual analog scale with “very slightly or not at all” at one end and “very much” at the other end. The responses were then measured from a range of 0–150 mm and summed to attain separate scores of positive and negative affect.

2.3. Procedure

Participants completed the SPSI-R as part of a group screening procedure for research credit in an undergraduate psychology class. Individual sessions were then scheduled two to five weeks later with each participant for administration of the SCT-B. Upon arrival to the session, participants were briefed and informed consent was obtained. A trained assistant then administered the SCT-B. This administration followed standard protocol with the following exception: state affect was assessed before the first subtest and following each of the five subtests. The administrators included the second author and three trained assistants. Participants were told to rate how they are feeling “at this time” for each administration of the measure of affect. Following assessment, participants were debriefed about the nature of the study.

2.3.1. Statistical analyses

The principal research questions in this study were addressed by using the Multilevel Modeling features of LISREL 8 (Jöreskog, Sörbom, du Toit & du Toit, 1999) to examine the time-ordered performance measures that were obtained from participants under four different
experimental conditions. Multilevel modeling procedures provide opportunity to investigate curves reflecting the change in participant-specific performance over measurement occasions, the level of between participant variation in the parameters defining the individual change curves and the extent to which such variation could be predicted by hypothesized individual differences in social problem solving abilities. Conceptually, the longitudinal or time-ordered (i.e. repeated) observations of performance represent a hierarchical or nested data structure where time-ordered measures of performance are level 1 data units that are nested within individual participants who represent level 2 data units.

In the level 1 model, the repeated measures of the performance task were used to estimate participant-specific trajectories of performance as a linear function of time. These performance trajectories are defined by a unique set of participant-specific intercept and slope parameters that describe the *intraindividual* or *within-person* relationship between task performance and time. (HLM; Bryk, Raudenbush & Congdon, 1996) This model can be specified using conventional HLM notation as

\[ Y_{ij} = \pi_{0j} + \pi_{1j}(\text{Time})_j + r_{ij}, \]

where \( Y_{ij} \) is the measure of performance for participant \( i \) at time \( j \), \( \pi_{0j} \) is an intercept parameter that represents an estimate of a participant’s true initial performance (i.e. performance at time = 0 where time is coded 0, 1, 2, 3), \( \pi_{1j} \) is a slope parameter that represents the linear rate of change in performance for participant \( i \) during a unit of time and \( r_{ij} \) is the within participant residual (i.e. random error for participant \( i \) at the \( j \)th measurement occasion). The residual term represents the deviation between \( Y_{ij} \) and the true level of performance for a participant at a measurement occasion and is assumed, for our analysis, to be normally distributed and uncorrelated across both participants and measurement occasions.

A level 2 model also was specified to examine the *between* participant variability in the parameters defining the performance curve for each participant. Conceptually, we hypothesized that the variation in the *within* participant growth curves (i.e. the variability of level 1 parameters \( \pi_{0j} \) and \( \pi_{1j} \)) could be modeled at level 2 as a function of fixed and random effects that included a set of social problem solving characteristics hypothesized to vary between participants. In other words, the coefficients describing the level 1 performance trajectories become the outcome variables in the level 2 model. Using HLM notation, the model reflecting the hypothesized level 2 relationships can be expressed as

\[ \pi_{0j} = \beta_{00} + \beta_{01}(\text{NO}) + \beta_{02}(\text{PO}) + \beta_{03}(\text{AS}) + \beta_{04}(\text{IC}) + \beta_{05}(\text{RP}) + u_{0j} \]

and

\[ \pi_{1j} = \beta_{10} + \beta_{11}(\text{NO}) + \beta_{12}(\text{PO}) + \beta_{13}(\text{AS}) + \beta_{14}(\text{IC}) + \beta_{15}(\text{RP}) + u_{1j}, \]

where \( \pi_{0j} \) and \( \pi_{1j} \) are now dependent variables; \( \beta_{00} \) is the level 2 estimate of the population mean of participants’ values at a fixed time point, \( \beta_{10} \) is the population mean of the participants’ rates of change; \( \beta \)'s are the effects of problem solving variables measured at the participant level (i.e. on the initial status and rate of change parameters; and \( u_{0j} \) and \( u_{1j} \) are residual terms representing the random effects or the variability left unexplained by the participant level variables.
As suggested above, our main interest in this study concerned the cross-level analyses that enable us to examine the variability in individual performance curve parameters as a function of individual differences in social problem solving abilities. However, before evaluating substantively focused models we specified a series of unconditional or null models that did not include hypothesized level 2 (i.e. between-participant) predictors of the variation in the level 1 parameters estimates. Although generally not of particular theoretical interest, unconditional models provide baseline estimates that are useful in evaluating the relative explanatory contributions of various hypothesized models.

To summarize, our examination of the patterns and correlates of changes occurring in the performance of a task that was observed under different experimental conditions first involved the estimation of parameters that defined performance curves for individual participants. We then examined problem solving abilities as predictors of the variation in performance curve parameters. In using a multilevel modeling approach, we assumed that observed levels of performance reflected ongoing change processes that could be represented by continuous time-dependent curves at the individual participant level. Furthermore, we also assumed that there would be sufficient variation in these curves that could be modeled as a function of systematic individual differences in variables that describe the participants’ problem solving characteristics.

A defining characteristic of the multilevel modeling approach used in this study and one that is shared with similar techniques such as hierarchical linear modeling (Bryk & Raudenbush, 1992), mixed linear models (Goldstein, 1986) or random coefficient models (de Leeuw & Kreft, 1986; Kreft & de Leeuw, 1998) is the hierarchical or nested arrangement of the data structure. As stated previously, repeated individual observations in our analyses provided level 1 data units assumed to be nested within each individual participant or level 2 unit. A principal advantage of a multilevel modeling approach as opposed to a more traditional repeated measures design lies in its ability to make use of data from both levels of the data structure to simultaneously examine the relationships that occur both within and between hierarchically arranged data units. By linking both levels of data, it is possible to identify systematic patterns of change and correlates of change that would be difficult to discern when examining mean change levels associated with aggregate level data. Another major advantage of using an HLM approach as opposed to ANOVA/MANOVA designs — especially with longitudinal data — is that it provides statistically efficient solutions for data which include missing or nonsynchronous observations (Bryk & Raudenbush, 1987; Tate & Hokanson, 1993; see also Francis, Fletcher, Stuebing, Davidson and Thompson (1991), for a comparison of HLM with more traditional repeated measures designs). The statistical and conceptual bases for HLM modeling of longitudinal data have been discussed in considerable detail (Bryk & Raudenbush, 1992; Goldstein, 1986; Goldstein, Healy & Rasbash, 1994; Willett, 1988).

3. Results

To ensure normality of the distribution of variables without dramatically reducing the total N, persons with ages > 45 were deleted from the sample. Those with a total negative affectivity score > 1600 at baseline were also deleted. The following means were observed on the SPSI-R scales: Positive Problem Orientation, 11.98 (S.D. = 3.95), Negative Problem Orientation, 14.93
(S.D. = 8.62), Rational Problem Solving skills, 44.75 (S.D. = 15.2), Avoidant Style, 9.19 (S.D. = 4.83) and Impulsive/Careless Style, 12.13 (S.D. = 6.84). Positive affectivity scores were also collected, but preliminary analyses indicated that there was a high degree of collinearity with negative affectivity, which created convergence problems when both variables were specified in later equations. In light of prior evidence that negative affectivity can mediate the relation of social problem solving abilities to an outcome measure (Elliott et al., 1995, study 4) and the statistical problems posed by collinearity, positive affectivity were dropped from further analyses. Means and standard deviations for negative affectivity and performance variables are presented in Tables 1 and 2.

3.1. Unconditional models

3.1.1. Random intercept model

Before addressing hypotheses concerning problem solving variables, we first estimated a fully unconditional or random intercept model. As the functional equivalent to a one-way random effects ANOVA, this model was used to partition the total observed variability in performance into between-participant and within-participant components (Bryk & Raudenbush, 1992). This decomposition of variance provided baseline estimates that were useful for evaluating the explanatory contributions of other more substantively oriented specifications.

The equations defining the random intercept model at both level 1 and level 2 included only intercepts and residual terms (see Table 3). At level 1, observed performance was modeled as a function of a participant-specific intercept parameter (i.e. \( \pi_{0j} \)) and a random residual term (i.e. \( r_{ij} \)). Because the equation was specified without covariates or predictors, each level 1 intercept provided an estimate of the average performance (i.e. number of correct responses) for a participant over the four measurement occasions. At level 2, the estimates of the level 1 intercepts were modeled as a function of the grand mean of performance for all participants over time (i.e. \( b_{00} = 12.37 \)) and a random residual term (i.e. \( u_{0j} \)). The variance of the level 1 residuals (i.e. \( \sigma^2 = 21.87 \)) provided an estimate of the within-participant variability and the variance of the level 2 residuals (i.e. \( \tau_{00} = 4.46 \)) provided an estimate of the between-participant variability.

The ratio of between-participant variance to the total variance (i.e. \( \tau_{00}/\tau_{00}+\sigma^2 \)) is defined as the intra-class correlation (ICC). Generally, the value of the ICC is interpreted as the degree of within group or in our case, within-participant homogeneity or consistency. From another

<table>
<thead>
<tr>
<th></th>
<th>Negative affect</th>
<th>Total correct solutions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>Time 1</td>
<td>50.97</td>
<td>46.60</td>
</tr>
<tr>
<td>Time 2</td>
<td>82.68</td>
<td>84.10</td>
</tr>
<tr>
<td>Time 3</td>
<td>77.44</td>
<td>82.03</td>
</tr>
<tr>
<td>Time 4</td>
<td>76.51</td>
<td>79.23</td>
</tr>
</tbody>
</table>

Table 1
Means and standard deviations for negative affect and performance variables (N = 126)
perspective, the ICC indicates the proportion of variance in the outcome that resides between participants and therefore is available for modeling as a function of hypothesized constructs. The ICC value computed from our random intercept model variance estimates (4.46/4.46 + 21.87) indicates that only 16.73% of the variability in task performance was available to be modeled as a function of between participant differences.

3.1.2. Random-coefficient regression model

The second model was specified as a simple linear growth model by including the measurement occasion variable (i.e. time) as a level 1 covariate (see Table 4). This model did not include any level 2 predictors and therefore also can be considered an unconditional model. The level 1 estimates for the initial status parameter (intercept) were modeled at level 2 as a function of the average intercept over all participants, \( \beta_{00} \) and a residual, \( u_{0j} \). Similarly, the estimates for the rate of change parameter (slope) were modeled at level 2 in terms of the overall average slope across all participants, \( \beta_{10} \) and a residual \( u_{ij} \). The estimate for \( \beta_{00} \) indicates that on average, participants in this study made 9.88 correct responses at the first

Table 2
Correlations of variables used in multilevel analyses. *\( p < 0.05 \). \( N = 126 \). TC1–TC4 are the total correct responses at each observation, PO is positive problem orientation, NO negative problem orientation, RP rational problem solving, IC impulsive/careless style, AS avoidant style and NA1–NA4 the negative affect at time 1–4

<table>
<thead>
<tr>
<th></th>
<th>NA4</th>
<th>NA3</th>
<th>NA2</th>
<th>NA1</th>
<th>AS</th>
<th>IC</th>
<th>RP</th>
<th>NO</th>
<th>PO</th>
<th>TC4</th>
<th>TC3</th>
<th>TC2</th>
</tr>
</thead>
<tbody>
<tr>
<td>TC1</td>
<td>0.03</td>
<td>–0.09</td>
<td>–0.23*</td>
<td>–0.10</td>
<td>–0.09</td>
<td>0.02</td>
<td>–0.10</td>
<td>–0.09</td>
<td>0.03</td>
<td>0.19*</td>
<td>0.05</td>
<td>0.40*</td>
</tr>
<tr>
<td>TC2</td>
<td>–0.09</td>
<td>–0.39*</td>
<td>–0.04</td>
<td>0.04</td>
<td>0.07</td>
<td>0.10</td>
<td>–0.09</td>
<td>0.01</td>
<td>–0.01</td>
<td>0.33*</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>TC3</td>
<td>–0.18*</td>
<td>0.03</td>
<td>–0.04</td>
<td>–0.00</td>
<td>0.08</td>
<td>0.16</td>
<td>0.03</td>
<td>–0.12</td>
<td>0.12</td>
<td>0.62*</td>
<td>–</td>
<td>0.62*</td>
</tr>
<tr>
<td>TC4</td>
<td>–0.11</td>
<td>–0.14</td>
<td>–0.03</td>
<td>–0.07</td>
<td>0.00</td>
<td>0.11</td>
<td>–0.06</td>
<td>–0.16</td>
<td>0.05</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>PO</td>
<td>–0.14</td>
<td>–0.09</td>
<td>–0.21*</td>
<td>–0.15</td>
<td>–0.41*</td>
<td>–0.22*</td>
<td>0.64*</td>
<td>–0.43*</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>NO</td>
<td>0.24*</td>
<td>0.15</td>
<td>0.29*</td>
<td>0.17</td>
<td>0.62*</td>
<td>0.44*</td>
<td>–0.14</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>RP</td>
<td>–0.03</td>
<td>0.00</td>
<td>–0.06</td>
<td>–0.14</td>
<td>0.18*</td>
<td>–0.41*</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>IC</td>
<td>0.02</td>
<td>0.09</td>
<td>0.18*</td>
<td>0.11</td>
<td>0.01</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<td>–</td>
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<td>–</td>
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<tr>
<td>AS</td>
<td>0.22*</td>
<td>0.11</td>
<td>0.21*</td>
<td>0.14</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<td>–</td>
</tr>
<tr>
<td>NA1</td>
<td>0.30*</td>
<td>0.33*</td>
<td>0.45*</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<td>–</td>
</tr>
<tr>
<td>NA2</td>
<td>0.44*</td>
<td>0.40*</td>
<td>–</td>
<td>–</td>
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<td>–</td>
<td>–</td>
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<tr>
<td>NA3</td>
<td>0.58*</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<td>NA4</td>
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</table>

Table 3
Fully unconditional one-way random effects ANOVA model (level 1: \( Y_{ij} = \pi_{0j} + r_{ij} \), level 2: \( \pi_{0j} = \beta_{00} + u_{0j} \)) \( N = 126 \)

<table>
<thead>
<tr>
<th>Fixed effects</th>
<th>Coefficient</th>
<th>S.E.</th>
<th>( z )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average initial performance, ( \beta_{00} )</td>
<td>12.37</td>
<td>0.23</td>
<td>54.06</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Random effects*</td>
<td>Variance component</td>
<td>4.46</td>
<td>0.16</td>
<td>28.14</td>
</tr>
<tr>
<td>Initial performance, ( u_{0j} )</td>
<td>21.87</td>
<td>0.07</td>
<td>300.69</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Level 1 Error, ( \sigma^2 )</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

* \( r_{ij} \sim N(0, \sigma^2) \), \( u_{0j} \sim N(0, \tau_{00}) \).
measurement occasion and the estimate for $\beta_{10}$ indicates that participants averaged 1.66 additional correct responses on each successive measurement occasion. More importantly, however, is the information provided by the statistically significant estimates of variance which indicate that adequate variation existing in both the intercept and slope parameters to warrant additional modeling efforts. The difference between the within-participant variance estimates for the fully unconditional model and the unconditional random coefficients model (expressed as a percentage of within-participant variance from the fully unconditional model) indicated that a sizeable percentage (31%) of what had been error or random variation was accounted for by including the linear effect of time as a predictor of performance.

<table>
<thead>
<tr>
<th>Fixed effects</th>
<th>Coefficient</th>
<th>S.E.</th>
<th>z</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average initial performance, $\beta_{00}$</td>
<td>9.88</td>
<td>0.36</td>
<td>27.65</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Average rate of change in performance, $\beta_{10}$</td>
<td>1.66</td>
<td>0.19</td>
<td>8.67</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Random effects</td>
<td>Variance component</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial performance, $u_{0i}$</td>
<td>12.67</td>
<td>3.08</td>
<td>4.11</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Rate of change in performance, $u_{1i}$</td>
<td>1.28</td>
<td>0.61</td>
<td>2.11</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td>Level 1 error, $\sigma^2$</td>
<td>15.16</td>
<td>1.35</td>
<td>11.22</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Table 5

Final model including social problem solving abilities as predictors of performance curve parameters (level 1: $Y_{ij} = \pi_{0j} + \pi_{1j} (time)_i + r_{ij}$, level 2: $\pi_{0j} = \beta_{00} + u_{0j}$, $\pi_{1j} = \beta_{10} + \beta_{11} (NO)_i + \beta_{21} (PO)_i + \beta_{31} (RP)_i + \beta_{41} (IC)_i + \beta_{51} (AS)_i + u_{1j}$)\(^a\)

<table>
<thead>
<tr>
<th>Fixed effects</th>
<th>Coefficient</th>
<th>S.E.</th>
<th>z</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial status, $\beta_{00}$</td>
<td>9.81</td>
<td>0.45</td>
<td>21.69</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Rate of change in performance, $\beta_{10}$</td>
<td>1.68</td>
<td>0.19</td>
<td>8.75</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>NO, $\beta_{11}$</td>
<td>-0.05</td>
<td>0.02</td>
<td>-2.55</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td>PO, $\beta_{21}$</td>
<td>0.01</td>
<td>0.05</td>
<td>0.32</td>
<td>ns</td>
</tr>
<tr>
<td>RP, $\beta_{31}$</td>
<td>0.00</td>
<td>0.01</td>
<td>0.18</td>
<td>ns</td>
</tr>
<tr>
<td>IC, $\beta_{41}$</td>
<td>0.04</td>
<td>0.02</td>
<td>1.67</td>
<td>ns</td>
</tr>
<tr>
<td>AS, $\beta_{51}$</td>
<td>0.04</td>
<td>0.03</td>
<td>1.28</td>
<td>ns</td>
</tr>
<tr>
<td>Random effects</td>
<td>Variance Component</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial performance, $u_{0ij}$</td>
<td>13.37</td>
<td>3.12</td>
<td>4.28</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Rate of change in performance, $u_{1ij}$</td>
<td>1.30</td>
<td>0.59</td>
<td>2.19</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td>Level 1 Error, $\sigma^2$</td>
<td>14.73</td>
<td>1.31</td>
<td>11.22</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

\(^a\)The estimated coefficients for the non-random time-varying covariate (negative affectivity) are not included as they did not significantly contribute to the equation and inclusion would have encumbered the tabular presentation. NA means negative affectivity, PO positive problem orientation, NO negative problem orientation, RP rational problem solving, IC impulsive/careless problem solving and AS avoidant problem solving.
3.1.3. Final model

A final model was estimated to examine the variation in the level 1 rate-of-change parameters \((\pi_{11})\) as a function of problem solving abilities that were measured at the between participant level (see Table 5 for estimates obtained for this model). The final model also included negative affect as a nonrandom level-1 covariate that varied over time for each participant (i.e. a time varying covariate). The results obtained for this analysis indicated that the negative affect had a negligible effect on the performance at each measurement equation. Additionally, the high correlation \((-0.82)\) between the rate of growth and the initial status parameters indicated a near linear dependency. As such, only the variability in the rate of change parameter \((\pi_{1j})\) across participants was examined as a function of participant level problem solving measures at level 2. The results indicated that of the five problem solving variables in the model, only negative orientation had a statistically significant effect \((\beta_{11} = -0.05, p < 0.05)\) on the participants’ rate of change parameters. This negative coefficient indicates that participants who had a higher negative orientation made fewer correct responses over successive trials.

This variability in performance parameters was examined after controlling for negative affectivity as a non-random time-varying covariate. Specifically, the use of negative affectivity as a time-varying covariate permitted us to investigate the variance in the rate at which performance changed over time, independent of affect.

4. Discussion

Our results indicate that objective problem solving performance is not necessarily a function of instrumental, cognitive-behavioral skills in generating, evaluating and implementing rational solutions. It appears that the disposition to harbor pessimism about the self and one’s ability to perform adversely affects objective problem solving performance in a structured task. This effect does not seem to be mediated by negative affect. Analysis of performance curves revealed that a higher negative problem orientation was associated with a steady increase in errors over trials; a lower negative orientation was associated with improved performance over trials.

To a great extent, models of problem solving in the extant cognitive psychology literature (e.g. Frederiksen, 1984; Gick, 1986) emphasize the value of the same cognitive-behavioral strategies espoused in models of social problem solving (e.g. D’Zurilla & Nezu, 1982; D’Zurilla & Nezu, 1990). However, only the applied models recognize the role of emotional reactions, pessimistic self-appraisals and the regulation of these in the problem solving process. To date we have yet to understand how such abilities (and the apparent lack thereof) influence problem solving performance. Other research has demonstrated that negative mood expectancies might interact with distress to predict performance (Catanzaro, 1996). Yet the present study suggests that the relation of negative problem orientation to problem solving performance is independent of distressed mood.

One possible interpretation for this effect may stem from the presumed information processing properties associated with effective problem solving abilities. Persons who have a negative appraisal of their problem solving abilities likely have difficulty encoding new information and they may be cognitively inflexible under times of stress and challenge. A
person with a high negative orientation will have more pessimistic — if not erroneous and/or irrational — views of the problems they face and their abilities to cope (Heppner & Krauskopf, 1987). The problem orientation component encompasses the ways in which problems and abilities are perceived and interpreted (Nezu & Perri, 1989). A higher negative orientation might short-circuit problem solving by distorting information about the problem at hand, as the person is preoccupied about their inability to handle the situation, their emotional reactions and the likelihood of failure (Nezu, 1987; Nezu & Perri, 1989). These mechanisms parallel those observed among test-anxious persons (Sarason, 1984). The steady increase in errors evident in performance curves is consistent with the observation that a negative orientation is reinforced as minor problems are unresolved and exacerbate over time, increasing the sense of ineffectiveness and decreasing motivation for effortful problem solving (Nezu, 1987, p. 130).

A negative orientation, then, might impede motivation and the attainment of meaningful, goal-directed behavior in routine situations. Thus, undergraduates with a negative orientation might lack motivation to engage in problem solving required in the pursuit of a college education. This could explain in part why the problem orientation has been associated with grade point averages in some studies (e.g. Elliott et al., 1990). Future research could examine the relation of problem orientation to indices of job performance over time. Persons with a negative orientation are more susceptible to occupational burnout (Elliott, Shewchuk, Hagglund, Rybarczyk & Harkins, 1996a) and the subsequent impairments in cognitive flexibility and motivation could result in problems with job performance.

Alternatively, the relation of the negative orientation variable to performance trajectories might be an artifact of the laboratory situation in which problem solving performance was examined in our study. In laboratory conditions, individuals operate in rather structured environments and attend to tasks that are made artificially salient. These conditions may not be representative or reflective of real-life problem solving situations that may be of considerable personal importance and yet have fairly ambiguous, unstructured outcomes (D’Zurilla & Maydeu-Olivares, 1995). In the present study, then, individuals may have been confronted with a fairly complex task of no real personal importance or consequence, which in turn may have heightened the role of regulating mechanisms of the problem orientation component. In other words, the Short Category Test used to assess problem solving performance may have been “...disembedded from an individual’s ordinary experience” (Sternberg, Wagner, Williams & Horvath, 1995, p. 912). The SCT-B may have evaluated what is best described as academic knowledge and not the ‘tacit’ knowledge required in effective everyday problem solving (Sternberg et al., 1995). Negative emotional reactions may be more salient in everyday problem situations and the mediating role of affect absent in our study may be more likely to occur under naturalistic conditions.

In summary, our study indicates that a negative problem orientation can be associated with problem solving performance and this relationship may be best understood in terms of repeated trials and subsequent performance curves. Moreover, this relationship was not mediated by negative affect. However, it is unclear how these results might generalize to real-life problem solving situations. This is a shortcoming of most studies of self-appraised problem solving abilities and problem solving performance under laboratory conditions (D’Zurilla & Maydeu-Olivares, 1995). It is possible, for example, that the undergraduates in our study may
have lacked sufficient motivation for working diligently on the problem solving task used in study, which could have primed more negative cognitions — related to a negative problem orientation — about the problem solving stimulus. The present study provides an important step toward establishing a link between social problem solving abilities and objective performance and how the dynamics of this relationship may be effectively examined using a multilevel modeling approach.

References


