Delay discounting (DD) is the decline in the present value of a reward with delay to its receipt (Odum, 2011). DD is typically measured using questionnaires in which participants choose between smaller-immediate and larger-delayed hypothetical outcomes (e.g., Rachlin et al., 1991).

There are several questionnaires available to measure DD and, for the most part, they produce systematic data (see Figure 1a). Nonetheless, each DD questionnaire produces nonsystematic data in a subset of participants (see Figure 1b. & 1c.). Nonsystematic data occur when participants choose that, for them, the value of the larger-later reward increases with delay duration (Johnson & Bickel, 2008). In most published studies, nonsystematic data are excluded from analysis; this is a limit to the validity of the DD task.

Our research was conducted to evaluate the prevalence of nonsystematic data when DD is assessed with three frequently used tasks.

Figure 1. Panel (a.) Line graph of a typical systematic data pattern. (b & c.) Line graphs of two types of nonsystematic delay-discounting data. The X axis represents the delays to the delivery of the larger-later reward, and the Y axis represents the subjective value of that reward.

II. Methods

Participants (N = 180) were undergraduate students (18 ≥ years old) attending USU. Compensation was course/extra credit.

After providing consent, participants were assigned to 1 of 3 groups, which differed in the DD task they completed. The tasks were completed on Qualtrics *

1.) Rachlin, Rainieri, & Cross (1991)
   • List of 30 choices between immediate and delayed amounts (Figure 2e.)
2.) Du , Green, & Myerson (2002)
   • Titrating scale: the amount of the immediate reward changes depending on the participant's choice (Figure 2b.)
3.) Johnson, Herrmann, & Johnson (2015)
   • Visual Analog Scale (VAS): slider scale (Figure 2c.)

In all 3 tasks, indifference points were obtained at the same delays ranging from 1 week to 25 years; and there was a constant larger later magnitude of $1000.

Figure 2. The three delay discounting tasks as they appeared online. Panel (a.) shows the Rachlin et al., (b.) the Du et al. (2002), and (c.) the Johnson et al. (2015) tasks.

III. Results

Of the 180 participants, 155 completed a DD task in full. Twenty-nine participants' data were flagged as nonsystematic according to the Johnson & Bickel (2008) criteria. Across all tasks, 19% of participants provided nonsystematic data.

Table 1 shows the number of participants who provided systematic and nonsystematic data. The difference in frequencies of nonsystematic data across tasks was statistically significant using a chi-squared analysis, $X^2 (2, n = 155) = 7.65, p < .05$. The effect size was moderate ($V = .22$).

Although the Rachlin et al. (1991) task produced a nominally lower rate of nonsystematic data than the Du et al. (2002) task, 11 participants failed to complete the task correctly; thus the Du et al. task produced the highest proportion of useable data (86%).

Calculation of each tasks completion time revealed that the Rachlin et al. (1991), and Du et al. (2002) procedures shared a median time of 9 minutes. The Johnson et al. (2015) task had a median completion time of 5 minutes.

Table 1. Frequencies of data classified as systematic and nonsystematic by task type.

<table>
<thead>
<tr>
<th>Task</th>
<th>Systematic</th>
<th>Nonsystematic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rachlin et al.</td>
<td>41</td>
<td>5</td>
</tr>
<tr>
<td>Du et al.</td>
<td>49</td>
<td>8</td>
</tr>
<tr>
<td>Johnson et al.</td>
<td>36</td>
<td>16</td>
</tr>
</tbody>
</table>

Future research should aim to understand why nonsystematic data occur. This will help in further refinement of DD tasks. Optimizing DD tasks is important because rates of DD consistently differentiate between addicted populations and matched non-addicted controls. -

IV. Conclusions

The DD task affected the likelihood of a participant producing nonsystematic data. The VAS produced the highest rates of nonsystematic data and the Rachlin et al. (1991) and Du et al. (2002) tasks produced the lowest rates. The Du et al. task proved to be the most useful because all participants completed that task correctly, and did so in about 9 minutes.

Future research should aim to understand why nonsystematic data occur. This will help in further refinement of DD tasks. Optimizing DD tasks is important because rates of DD consistently differentiate between addicted populations and matched non-addicted controls. -

References

*Note: All DD tasks are part of a larger study investigating delayed and probabilistic rewards. The Psychological record, 52, 479-490.


Optimizing Delay Discounting Procedures

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Figure 1a: Systematic Discounting Data

Figure 1b: Unsystematic Discounting Data

Figure 1c: Nonsystematic Discounting Data