Embodied decision making:

Measuring choice preferences dynamically during risky decision making

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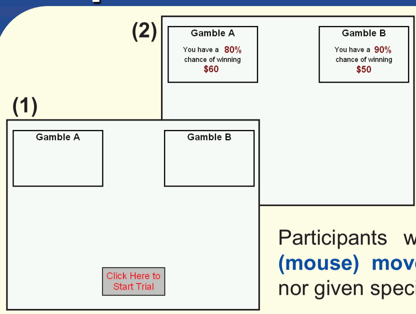
Background

Process-tracing techniques such as mouse- and eye-tracking have become popular for drawing inferences about the information acquisition process in decision-making—but not necessarily the dynamic mapping of that information onto a response (utilization). Rather, even these very studies continue to treat responses discretely. In contrast, we propose that closer examination of the **time course of the *response* process can yield new insights**.

The current work draws upon a growing body of research in cognitive science focusing on "action dynamics" (Dale, Kehoe, & Spivey, 2007; McKinstry, Dale, & Spivey, 2008; Spivey & Dale, 2006). This research has shown quite clearly that **mental processing dynamics can be revealed in the associated continuous motor response**.

Experimental Design



Participants **began each trial at the screen bottom-center (1)**, where a click made gamble **stimuli appear upper-left and upper-right (2)**. Clicking within the box of their chosen gamble ended the trial.

Participants were not aware **the response (mouse) movements were being recorded**, nor given special instructions about responding.

Stimuli were **43 pairs of gambles**, each with one nonzero outcome in the range **$40 – $90** with a win probability in the range **60% – 90%**. The **average difference in EV was $7**, with a range of $0 – $20. A **between-subjects loss condition was created by attaching negative signs to all outcomes**. Pairs were randomized across trials, and left-right order was counterbalanced.

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Analyses

Response dynamics are visualized by **tracing the response trajectories during a trial.** Greater curvature suggests greater competitive "pull" from the non-chosen option (Spivey & Dale, 2006).

Stimulus risk was operationalized using gamble variance. **Risky choices in gains, and safe choices in losses showed greater attraction, from the non-chosen gamble.** This effect was quantified by t-tests comparing X-coordinates at each of 101 time-normalized steps.

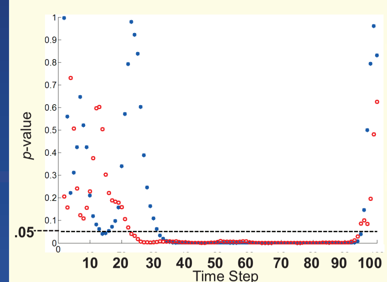

Figure 3. Significance tests for **differences between Risky and Safe** response trajectories. **Gains** differed from time steps 32 – 95 and **Losses** differed from time steps 22 – 94.

These continuous data allow for the calculation of derivatives such as velocity (left) and acceleration (right), showing **quantitative differences between choice of risky and safe gains, and differences between gains and losses**.

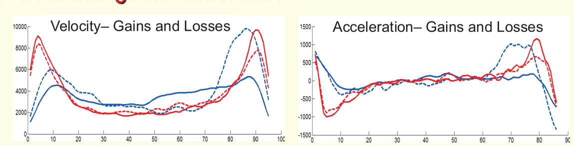

Figure 4. Derivatives of response trajectories. (Left) Velocity of trajectories calculated as average pixel distance per time step across a moving window of 7 time steps. (Right) Acceleration of trajectories calculated as the change in average pixel distance per time step across a moving window of 14 steps.

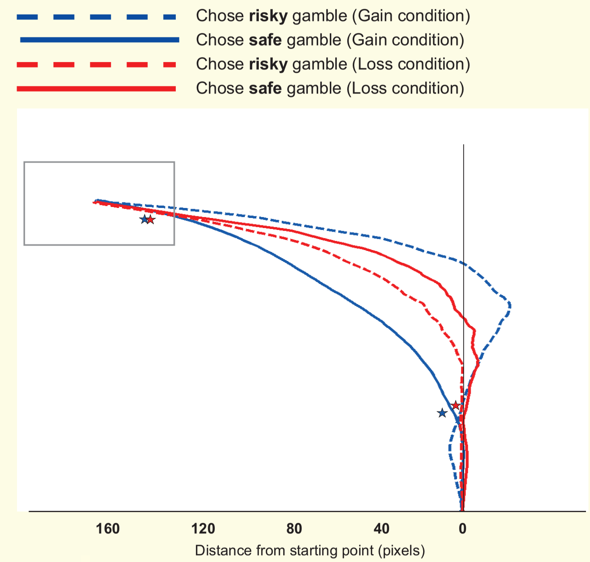

Figure 5. **All response trajectories were horizontally reflected to align onto a common (i.e., left) response box for ease of comparison.** Plot is time-normalized to 101 time steps, plotted as offset (in pixels) from trial initiation point. Placement of response box is approximate. Stars estimate the point at which significant differences begin and end as noted in *Figure 3.* Axis units are in pixels, where the response initiation point = (0,0)

Conclusions

- Response dynamics suggest ability to measure online preference formation
- Unlike some traditional measures, response dynamics can show online preference reversals
- Demonstrates converging evidence with prospect theory's risk-aversion in gains and risk-seeking in losses
- Deriving corresponding predictions for specific models/strategies will allow for formal assessment

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