The Illusion of the Illusion of Control

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Control

"A person's estimate that a given behavior will lead to certain outcomes."
—Bandura, 1977

▸ More definitions of control

The Illusion of Control

"…as an expectancy of a personal success probability inappropriately higher than the objective probability would warrant."
—Langer, 1975

My Question

Are people's estimates of control accurate?

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Are people's estimates of control accurate? Yes! But …

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Are people's estimates of control accurate? Yes! But …only if you ask them properly.

Main Results of My Work

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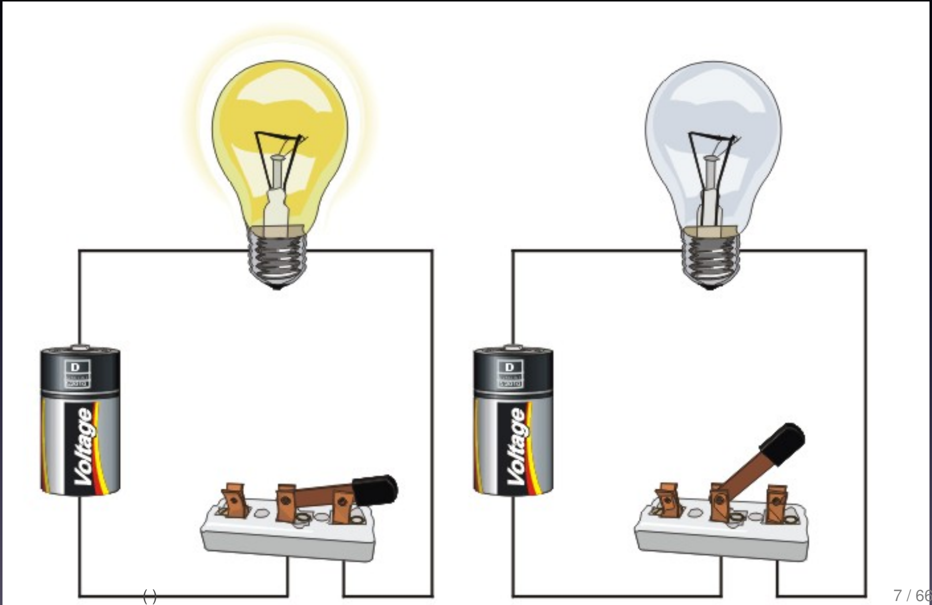
- People are really good at estimating contingency in a Bayesian manner
- People's view of control $\neq$ experimenters definition of control
- Mis-estimates of control and accurate estimates of contingency occur in non-dichotomous cases

Our Universe of Discourse



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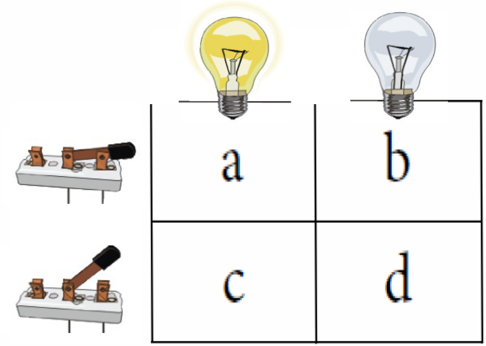

A Normative Measure of Control

	O_1	O_2	
I_1	a	b	$a + b$
I_2	c	d	$c + d$
	$a + c$	$b + d$	$a + b + c + d = N$

2×2 contingency matrix representing the joint frequencies of two binary input (I) and output (O) variables over N trials, along with row and column sums.

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	$a + c$	$b + d$	$a + b + c + d = N$

$$\Delta P = P(O_1|I_1) - P(O_1|I_2) = a/(a + b) - c/(c + d)$$

A Normative Process for Control

1. Find the % of successes with one action: $P(O_1|I_1)$
2. Find the % of successes with the other action: $P(O_1|I_2)$
3. Find the difference between these two numbers: ΔP

Keeping the Illusion of Control Under Control

Do people always over-estimate control?

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Bayesian Inference

$$p(H|D) = \frac{p(D|H)p(H)}{p(D)}$$

$p(H|D)$ is the posterior, the updated estimate of H
$p(H)$ is the prior, the assumed hypothesis before data is observed
$p(D|H)$ is called the likelihood and is the chance of data being observed if the hypothesis is true

Bayesian Inference

$$f(\theta|Data) = \frac{f(Data|\theta)f(\theta)}{f(Data)}$$

Bayesian Inference

$$f(\theta|Data) = \frac{f(Data|\theta)f(\theta)}{f(Data)}$$

$$Posterior \propto Likelihood \times Prior$$

Simulating the Illusion of Control

- Imagine we run 1000 experiments
- Each experiment has x subjects
- Each subject is perfectly Bayesian
- Subjects press a button for r rounds and observe the outcomes
- The button has a true probability of success, θ

Simulating the Illusion of Control

- The set of rounds per subject is a Binomial distribution:

$$f(Data|\theta) \sim Bin(r, \theta)$$

- The prior beliefs each subject has for θ can be modeled:

$$f(\theta) \sim Beta(\alpha, \beta)$$

- People's prior is usually ~ 45%

Simulation Results

% Success	Empirical mean θ	Simulated mean θ
90%	64.83%	65.19%
60%	47.00%	47.83%

Understanding Control: Study Aims

- Do people estimate control using ΔP as a normative model?
- How are estimates of the contingency between buttons and outcomes related to estimates of control?
- Do people process contingency information in a Bayesian manner?

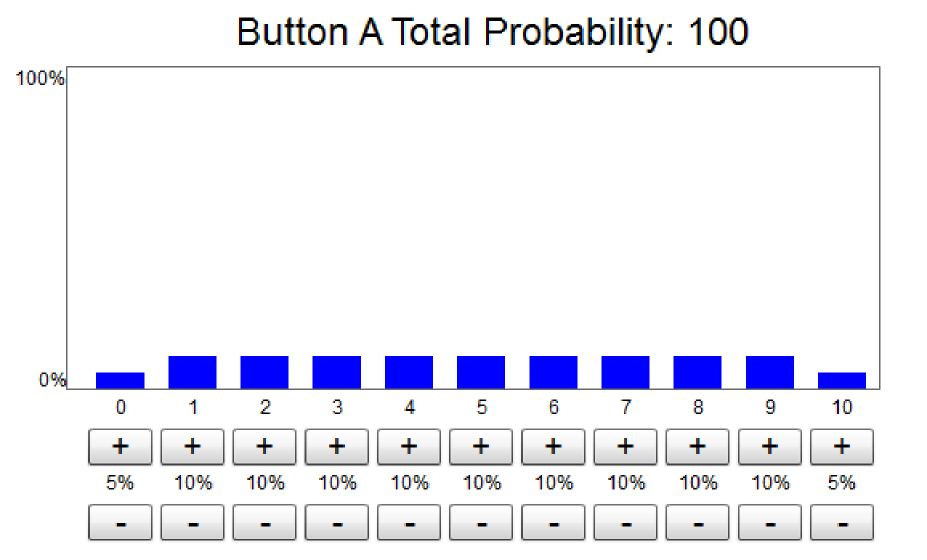
Design

- 165 participants paid $1.25 on MTurk
- Two-button event-onset design
- One active button, θ_a, one base-rate button, θ_b
- Each round, must press a button and observe if it lights up a bulb.
- 100 total rounds—each button must be pressed 50 times
- Every 10 rounds per button, contingency, $p(\theta_x)$, is elicited

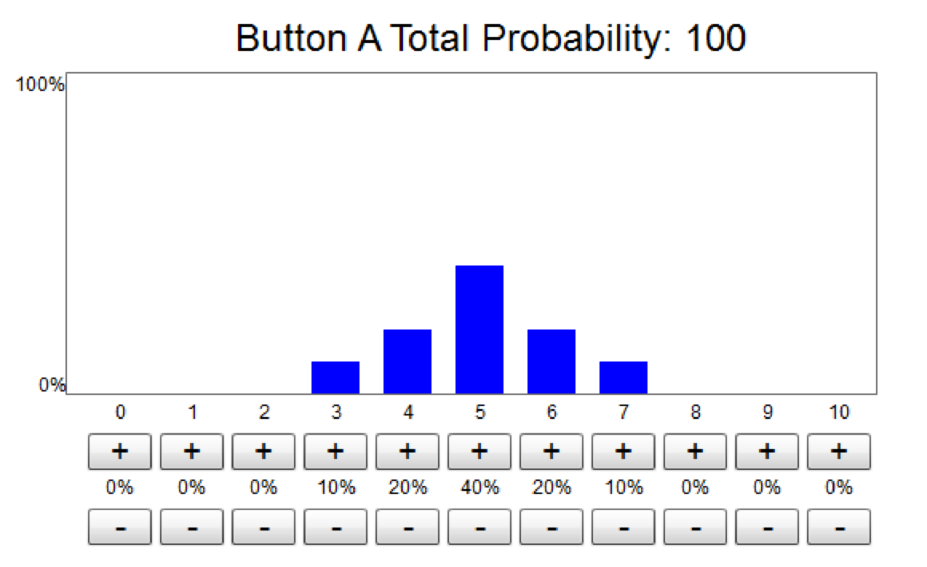
Elicitation

"We will ask you to estimate the likelihood that pushing Button A|B ten times in a row will produce 10 lit bulbs as well as estimating that pressing it ten times will result in 9,8,7,6,5,4,3,2,1 and 0 lit bulbs. These probabilities should reflect your own personal estimate of the number of times the light bulb would come on, given what you have observed."

Elicitation



Elicitation



Measures

- Participants estimated the number of successes in 100 future trials for each button
- Incentivized for accuracy—bonus of $0.50
- Asked for personal definition of control
- Then use that definition to estimate their control on scale (0–100)

Results: Control Estimates

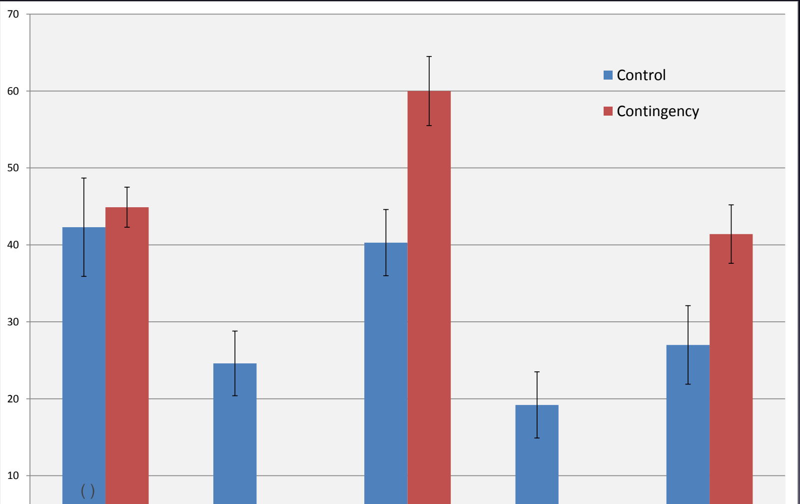
Condition	Active %	Base %	Control (ΔP)	Mean Estimated Control (SD)
1	100%	50%	50%	42.34% (35.93)
2	50%	50%	0%	24.64%* (26.13)
3	100%	20%	80%	40.25%* (25.76)
4	20%	20%	0%	19.21%* (22.96)
5	70%	20%	50%	26.97%* (27.68)

Results: Contingency Estimates

Condition	Control (ΔP)	Est. Control	Est. Contingency
1	50%	42.34% (35.93)	44.91% (14.9)
2	0%	24.64%* (26.13)	4.18% (12.0)
3	80%	40.25%* (25.76)	59.86%* (27.3)
4	0%	19.21%* (22.96)	1.2% (11.4)
5	50%	26.97%* (27.68)	41.48%* (20.4)

Contingency to Control

Estimates of contingency and control are not correlated!*



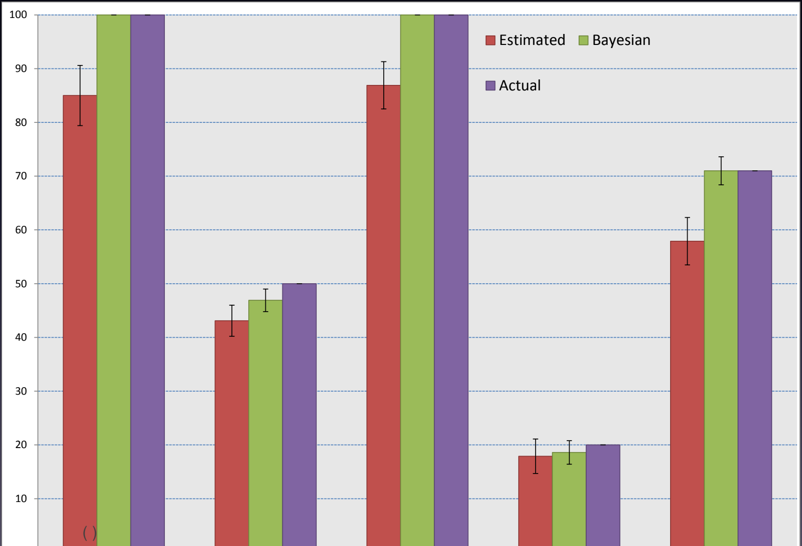
Sympathy for Participants

- We can compare estimates of contingency to observations
- Run a binomial test on each participant
- Non-significant results = *reasonable*
- Out of 165, 110 (66%) were reasonable for both buttons
- Most people are quite accurate!

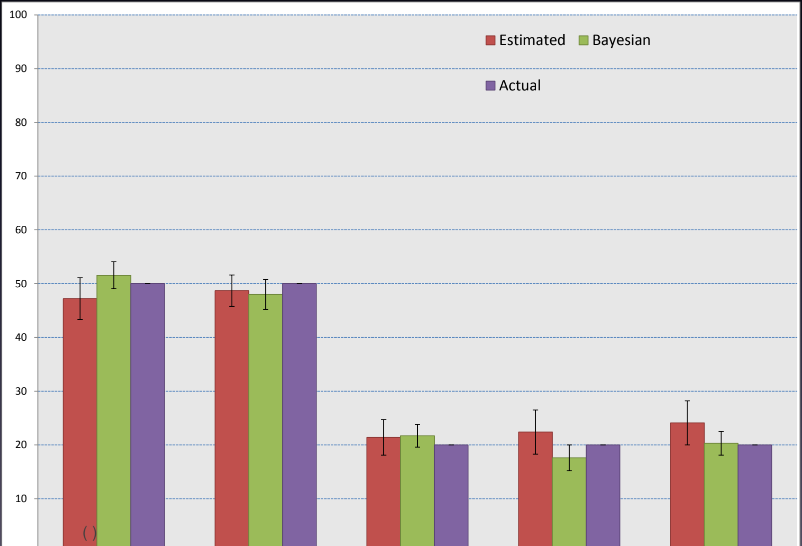
How Bayesian were participants?

	Button A Modal %			Button B Modal %		
	Est.	Bayes	Act.	Est.	Bayes	Act.
1	85	100	100	47.2	51.56	50
2	43.1	46.9	50	48.7	48.0	50
3	86.9	100	100	21.4	21.7	20
4	17.9	18.6	20	22.4	17.6	20
5	57.9	71.0	71	24.1	20.3	20

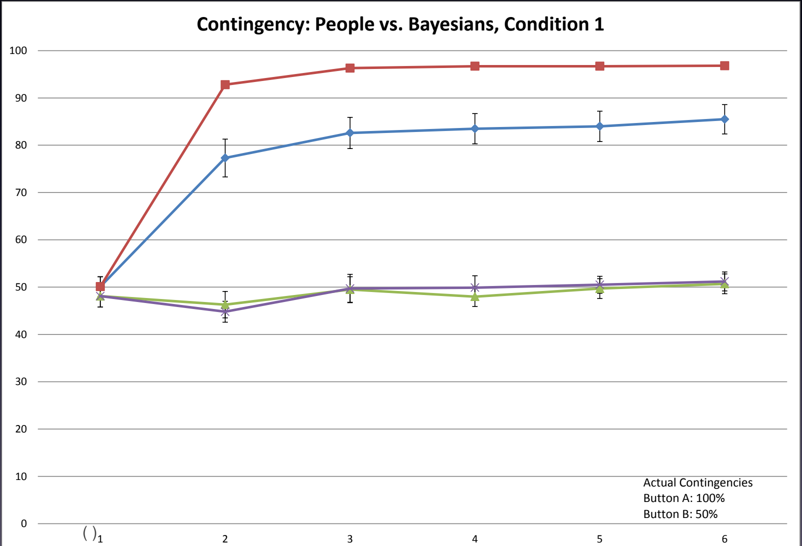
Button A: Participants vs. Bayesians



Button B: Participants vs. Bayesians



Bayesian comparison



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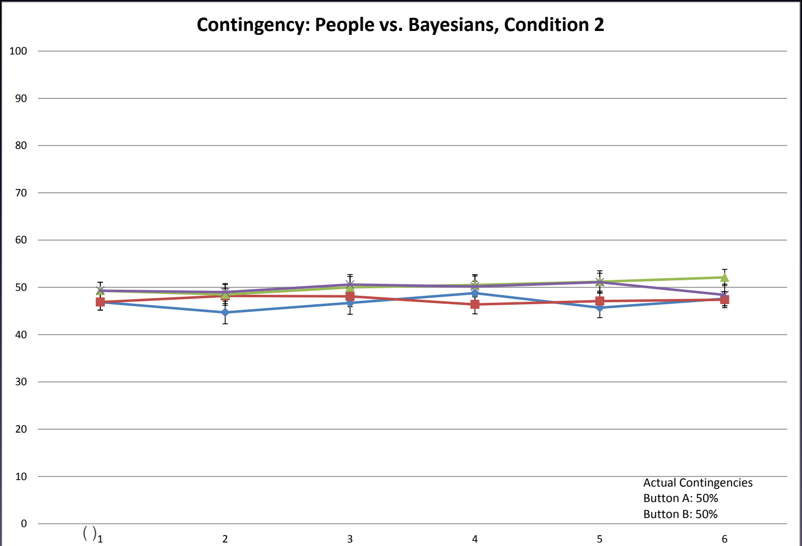

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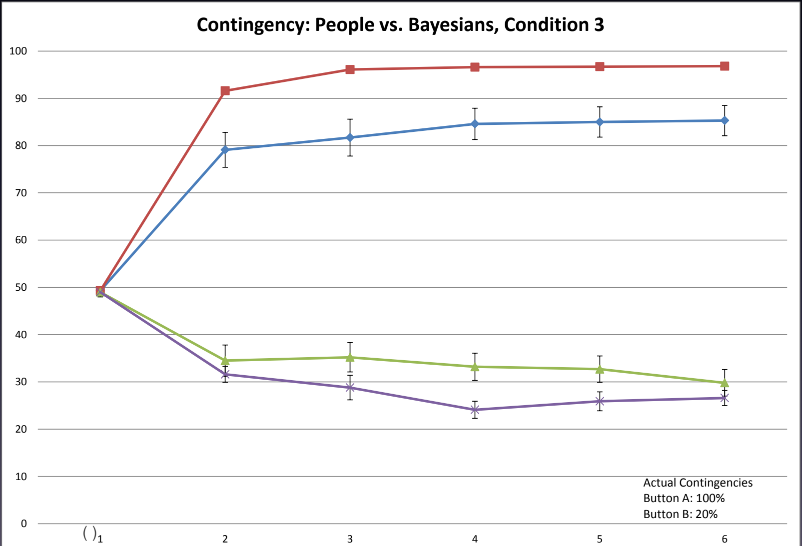

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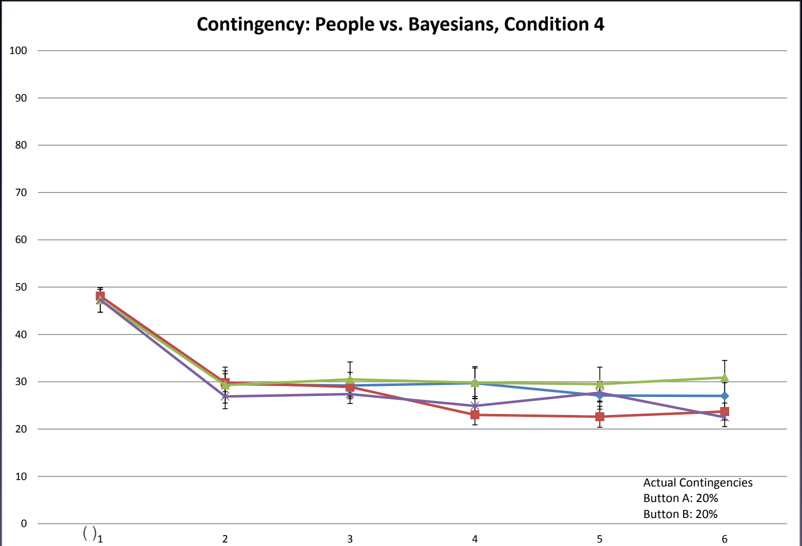

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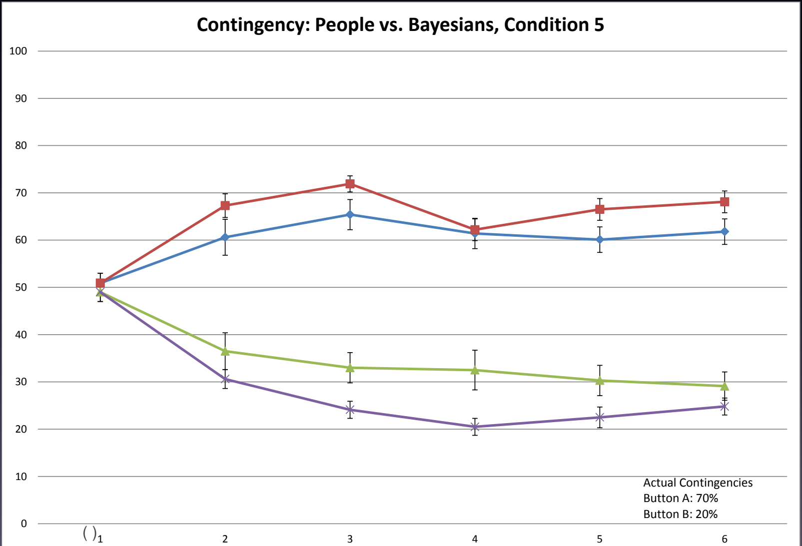

Study Conclusions

- Similar patterns of control estimates to previous studies
- Estimates of contingency are generally accurate
- Estimates of control are not correlated to estimates of contingency
- Estimates of contingency are processed in a Bayesian-like manner

Understanding Control Redux: Study Aims

- Perhaps results in previous study were due to the forced sampling and elicitation?
- Relaxing these requirements should lead to:
  1. Less sampling, leading to more regressive estimates
  2. Less elicitation leading to less accurate contingency estimates
- How would people respond to ΔP?

Design

- Similar to the previous study—two button event-onset
- 138 participants through MTurk, paid \$0.75 and incentive of \$0.50 for accuracy
- No Bayesian elicitation and subjects could sample as much (or little) as desired

Results

Actual Control	BIOC Control	BIOC ΔP	Control	Est. ΔP
50%	42.34%	44.91%	63.6%*	48.8%
0%	24.64%*	4.18%	34.7%*	2.2%
80%	40.25%*	59.86%*	68.4%	84.1%
0%	19.21%*	1.2%	17.3%*	1.2%
50%	26.97%*	41.48%*	28.3%*	45.6%

Introducing ΔP

One way to measure the amount of control that people have in this situation with the light bulbs is to measure the percentage of times the light bulb comes on when you press Button A and when you press Button B. The difference between these two percentages is the amount of control your choice of which button to press has on the light bulb. For example, from your answers, you would expect Button A to light the light bulb up X% of the time and Button B to work Y% of the time. Thus, according to this measure of control, you would expect to have $(X - Y)\%$ control over making the light bulb light up.
Do you agree with this definition of control? Please use the following scale below to indicate how strongly you agree with this suggested definition of control. (1–7 scale)

Responses to ΔP

Scale from 1=Strongly Disagree, 4=Neither Agree nor Disagree, 7=Strongly Agree

Condition	Mean Agreement with ΔP (SD)	% Favoring ΔP (N)
1	4.5 (2.0)	17.9% (5)
2	4.9 (1.3)	19.4% (7)
3	4.4 (2.2)	18.1% (4)
4	5.3 (1.4)	42.3% (11)
5	3.9 (1.8)	26.0% (6)

Conclusion

- People did sample less: M=66.5 (SD=68.5)
- ΔP is not embraced as a normative measure by participants
- People were still quite accurate, but not regressive
- Lack of a formal elicitation mechanism did not appear to affect accuracy

Study: Non-Dichotomous Control

- Many of the outcomes of our efforts are not on/off

Study: Non-Dichotomous Control

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- Stocks

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- Manufacturing output

Study: Non-Dichotomous Control

- Many of the outcomes of our efforts are not on/off
- Stocks
- Manufacturing output
- Performance measures

Extending ΔP

$$\Delta P = P(O_1|I_1) - P(O_1|I_2)$$

- How can we adapt ΔP for non-dichotomous situations?
- O_1 represents success
- We need to define a new threshold of success

Extending ΔP

$$\Delta P = P(O_1|I_1) - P(O_1|I_2)$$

- Imagine we are evaluating two widget producing machines, A and B.
- I_1 is machine A, I_2 is machine B
- O is the number of widgets produced
- Define success as 100 or more widgets produced

Extending ΔP

$$\Delta P = P(O \geq 100|A) - P(O \geq 100|B)$$

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Extending ΔP

$$Extended\,\Delta P = P(O \geq 100|A) - P(O \geq 100|B)$$

- If A and B have the exact same probability distribution then ΔP is 0
- Suppose they have different parameters or different families?
- How can we calculate this?

Extending ΔP

$$Extended\,\Delta P = -F_A(x) - F_B(x) \text{ where } F_X(x) = P(X \leq x)$$

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$$Extended\Delta P = -F_A(100) - F_B(100) \text{ where } F_X(100) = P(X \leq 100)$$

Study Aims

- Is this extension an accurate measure of control?
- Demonstrate that people will show the same pattern of control estimates as previous studies

Design

- 99 participants recruited on MTurk and paid $1.00
- Assume the role of a factory manager testing two widget-making machines
- Each machine needs to be tested 50 times

Measures

- Estimate the average number of widgets produced by each machine in 100 runs
- “How much control of widget production did your choice of Machine A vs. B give you?”
- “If your goal was to produce 600 or more widgets, how much control did your choice of Machine A vs. B give you in achieving your goal?”

Conditions

Condition	Machine A Mean (SD)	Machine B Mean (SD)	Control ($X \geq 600$)
1	500 (100)	500 (100)	0%
2	700 (100)	500 (100)	68.3%

Results: Estimates of Control

Machine A Est. Mean (SD)	Machine B Est. Mean (SD)	Est. Control	Est. Control ($X \geq 600$)
511.6 (96.14)	497.5 (79.19)	23.9% (27.8)	33.67%* (30.78)
671.9 (107.9)	475.9 (86.33)	39.0% (32.8)	61.0% (30.78)

Results: Estimates of Means

- If we compare the difference in means:
- (Machine A estimate - Machine B estimate) - (Machine A actual mean - Machine B actual mean) = 0
- This comparison is not significantly different from 0 (M=2.22, SD=69.7)

Non-dichotomous Conclusion

- Participants' estimates of outcomes are accurate
- Estimates of control are not accurate—Different definition of control?
- Does extended ΔP work?

Causes of Control?

- Thompson et al. (1998) suggested the control heuristic
- Estimates of control are affected by perceptions of:
  - Intentionality
  - Connection
- This doesn't explain the uncoupling of contingency and control

Attribute Substitution?

- Perhaps people are answering a different question when their estimate of control is elicited?
- Kahneman & Frederick (2002) propose a new explanation for the representativeness heuristic
- When asked a question, people *substitute* difficult attributes with easier attributes
- "How much control did your choice of button A or button B have on the light bulb lighting up?"

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- When asked a question, people *substitute* difficult attributes with easier attributes
- "How much control did your choice of button A or button B have on the light bulb lighting up?"
- "How much success did you have in making the light bulb light up?"

Implications & Future Research

- Taylor & Brown (1988) argue that positive illusions are adaptive
- Base their argument on “depressive realism” (e.g. Abramson & Alloy, 1981)
- Dykman et al. (1989) show that depressed estimates are in fact, just depressed
- Perhaps the adaptive benefits of the illusion of control are due to possessing a belief of at least some control?

Implications & Future Research

- Overconfidence shows a similar pattern of results to control estimation
- Emerson's definition of power = ΔP
- Correspondence bias: perhaps people partition judgements into controllable and not controllable?

Implications & Future Research

- More (statistical) work on what factors affect estimates of control
- Better understanding of people’s definitions of control
- More realistic experiments
    - Control in ethical decision-making

Main Results of My Work

- People under-estimate control when it high
- Perfectly normative information processors will also mis-estimate contingency
- People are really good at estimating contingency in a Bayesian manner
- People's view of control $\neq$ experimenters definition of control
- Mis-estimates of control and accurate estimates of contingency occur in non-dichotomous cases

Summation

- These results indicate that people do not consistently over-estimate their control
- If we ask them nicely, they give us the “correct” answers
- Thus, my evidence suggests that the illusion of control is an illusion

Thank You!

Special thanks to my persevering advisor, Don Moore

More Definitions of Control

- "The concept of control may be defined in terms of perceptions of contingencies. If a person perceives a contingency between his behaviors and an outcome …outcome is considered controllable." —Glass and Carver, 1980
- "The accumulation of action-outcome episodes that accrue based on an individual's actions in a set of objective control conditions which are interpreted according to his or her subjective control beliefs." —Skinner, 1985
- Base Rate: "The subjective probability with which the current situation will lead to a future outcome without action" —Heckhausen, 1977
- Actual control: "The measure of actual control that subjects are given is directly tied to the amount of change the environment allows the subjects to effect" —Chanowitz and Langer, 1980

The End!