Logistical Challenges When Measuring Attitudes

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Introduction

The perils of self-reporting are well-documented (e.g., Holmes 2009). They are in the forefront of every test user's mind when administering such measures. However, while they remain controversial, their utility is unquestionable. Self-report measures provide usable data, but how results are used remains an obvious issue for psychometricians and researchers alike. One of many problems of self-reporting test users need to be cognizant of, the focus of Study 2, is something referred to researchers as Cognitive Bias. Implicit Attitudes Testing is one way cognitive biases can be identified, so as to control for results.

Another element that affects self-reporting measurement is Social Desirability. This creates bias within the responder in real-time, there must be development of instruments which avoid this pitfall. Developments of these instruments remain in their initial stages. Research conducted by Jeffrey Holmes shows people can deceive an Implicit Attitude Test (2009). He explores how participants are altered by in-person pressures to respond to prompts in particular ways. He found that responses given were indistinguishable regardless of the level of purposeful bias, showing that the transparency of the measures used created results that were unusable given this kind of context.

Methods Study 1

Participants: 77 college age students, primarily under the age of 24, female, and White, were recruited for this study.

Materials: Greenwald, Nosek, and Banaji's Disability version of the Implicit Attitude Test (D-IAT) was used.

Procedure: Students were randomly assigned to one of three conditions, "Fake Good", "Fake Bad", "Control." During the first round of testing, all students saw the standard D-IAT with the original directions for how to complete it. During the second round of testing, which immediately followed the completion of the first round, including being notified of their results (e.g., "Your data suggest a moderate automatic preference for Abled Persons compared to Disabled Persons.") individuals in the "Fake Good" condition were asked to complete the D-IAT again, but this time to respond in a manner that would make them "look good." Individual's in the "Fake Bad" condition, were given similar changes in directions, but this time asked to "look bad." The individuals in the control condition received the same directions as they did during the first round of the D-IAT.

Results Study 1

	Trial 1	Trial 2
Fake Bad	.595 (.302)	.495 (.302)*
Fake Good	.734 (.412)	.488 (.344)*
Control	.456 (.439)	.343 (.340)*

Discussion Study 1

Regardless of the directions provided to the participants, their responses on the second trial became more favorable. The greatest gain in favorability was found in individuals who were instructed to "Fake Good."
Individuals who were told to "fake bad" actually performed very differently than they did the first time, giving an indication that they were trying to behave worse, and yet, their scores, if anything, improved.

Methods Study 2

Participants: Recruitment included of 69 ESU students by sending the survey link out to classes and clubs on campus.

Materials: Survey Monkey; 36 Item Bias Awareness Inventory

Procedure: We created a 36 item survey using 12 common cognitive biases. Students were asked to respond using a 4 point Likert Scale. We broke up the survey into 3 sections with 12 questions each.

- Section 1: participants were instructed: "choose the response that you feel is true for OTHER PEOPLE."
- Section 2: participants were instructed: "choose the response that you feel is true for YOU."
- Section 3: participants were given definitions of each biases and asked: "How often have you fallen victim to each bias?"

Results Study 2

Cognitive Bias	Description	stats	Cognitive Bias in Others	Cognitive Bias in Self	Awareness of Cognitive Bias
Blind Spot Bias	tendency to see others' biases; inability to see your own cognitive bias	Mean	3.26	1.85	2.36
		SD	.76	.81	.86
		95CI	3.44-3.08	2.04-1.65	2.53-2.18
Availability Heuristic	placing too much emphasis on information already have	Mean	1.77	1.39	2.20
		SD	.64	.78	.86
		95CI	1.92-1.62	1.57-1.20	2.25-1.95
Confirmation Bias	tendency to only pay attention to things that reinforce previous believes.	Mean	2.67	1.57	2.32
		SD	.67	.74	.85
		95CI	2.85-2.54	1.75-1.39	2.53-2.11
Overconfidence Bias	tendency to take larger risks because you are too confident in your ability.	Mean	2.13	1.69	2.03
		SD	.75	.78	.84
		95CI	3.02-2.66	1.88-1.51	2.24-1-83
Ostrich Effect	tendency avoid exposure to undesirable information.	Mean	3.28	2.05	1.78
		SD	.72	.81	.88
		95CI	3.45-3.10	2.21-1.82	1.99-1.57
Stereotyping Bias	tendency to exaggerate over generalized beliefs rejecting individuality	Mean	2.10	1.85	1.75
		SD	.78	.88	.75
		95	2.29-1.92	2.06-1.64	1.93-1.57
Bandwagon Effect	going along with something because of how many other people are doing it.	Mean	2.65	1.63	2.10
		SD	.78	.67	.95
		95CI	2.84-2.47	1.79-1.47	2.53-2.12

Discussion Study 2

In general, college students do not seem to be aware of commonly documented cognitive biases. Moreover, they tend to discount many of them in themselves. However, they do acknowledge that other people may have some cognitive biases, specifically that others are more apt to reject information that upsets them and to find it easier to find flaws in others than to identify their own flaws.

Discussion

Discussion: From what we know about self-reporting there can be a lot of errors made from those who take self-reporting questionnaires. Errors made by participants can manifest because of various biases that exist implicitly. We have identified social desirability as well as 12 common biases we have found to impact the results of self-reporting questionnaires and have shown these biases skew results. Further, when we prompted participants to respond in a particular way, they were unable to differentiate their own honest opinions from the opinions we forced upon them, showing that the influence of social desirability was not only present but also unavoidable.

We believe the next course of action in detecting bias would be to develop computer software which can analyze inflections in the voice such as response latency, readability and word count. We think that it is not only feasible, but appropriate in view of the pilot test of our Implicit Attitudes Test software providing 'technically statistical significant' results, indicating to us that we are on the right track (Green 2017). We believe it is time to develop this kind of software as soon as possible. This software should be able to detect, at minimum, response latency, readability, and word count. We are also looking into other aspects of speech to detect implicit attitudes such as pitch and number of pauses, as well as looking at the rhetoric through the lens of particular biases like Linguistic Intergroup Bias and Stereotypic Explanatory Bias. We think that in making use of this kind of software it is possible to pick up on elements of bias that have been historically overlooked. We believe there are far-reaching implications in detecting some these more minute elements of bias, which arguably cannot easily be interpersonally controlled. If we can garner a better understanding of these biases, we will be able to analyze results of research not only more accurately but also more usefully, making results more valid on the whole.