Improving Compassion Measurement in the Workforce by Analyzing Users' Mouse-Cursor Movements

Completed Research

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Abstract

Compassion is often an important characteristic of effective employees in the workplace. To measure improvements in employee compassion, identify shortcomings, and even screen applicants, researchers and practitioners have sought reliable measures of compassion. Measuring compassion, however, can be very difficult because people are hesitant reporting a lack of compassion, due to their desire to be viewed favorably by others. We draw on the domain of human-computer interaction to help address this issue. Namely, we propose a theoretically-grounded methodology for helping differentiate between high and low compassion by monitoring users' mouse-cursor movements in specialized online surveys. We find that people with lower compassion show greater deviation in their mouse-movement trajectories when answering affirmatively that they are compassionate. Based on this finding, we suggest future research to use this deviation measure to help correct for bias in self-reported compassion levels both in a research and professional setting.

Keywords

Workplace compassion, mouse-cursor movements, graded-motor response analysis, response bias

Introduction

Compassion is defined as a sympathetic consciousness of others' distress together with a desire to alleviate it (Webster 2019). Compassion has always been deeply rooted into our social system and has been found to be crucial to the survival of any given species (Darwin 1871). Likewise, recent studies have shown compassion has been noted as a key contribution in a variety of fields, such as management (Simpson et al. 2014; Wang et al. 2018), healthcare, education, and the justice system (Strauss et al. 2016). Additionally, in workplaces that are fraught difficulties (Frost 1999; Frost 2003), compassion has been shown to alleviate grief caused by events both inside and outside of the workplace, thereby improving the connections employees feel with coworkers, their company, and the goals of that company (Lilius J. 2013). Compassionate acts have been seen to improve the overall image of an organization (Dutton 2012). Researchers and practitioners, therefore, have sought reliable instruments to measure improvements in employee compassion, identify compassion shortcomings, and even screen applicants for compassion in organizational positions (Josephs 2018).

Given the need to accurately measure compassion, Strauss et al. (2016) called for "the development of a measure of compassion, following good practice guidelines to identify items and to test its psychometric properties" (p. 26). However, attempts to measure compassion face a myriad of challenges. One challenge is that people are hesitant to report a lack of compassion due to their desire to be viewed favorably by others—a bias known as social-desirability bias (Fisher 1993). As a result, differentiating between people with low and high compassion is increasingly difficult.

We draw on the domain of human-computer interaction to help address this need. Namely, we explain how people with low compassion will show greater deviation in a specialized online survey when answering affirmatively that they have compassion. We support this hypothesis through the theoretical lens of the response-activation model, which helps explain how the decision conflict between answering affirmatively and answering truthfully will exhibit in people's mouse-cursor movements. We test our hypothesis in an experiment that utilizes a zero-sum game design to objectively measure compassion and then monitor people's mouse-cursor movements as they self-report their compassion. We find that people with lower compassion show greater deviation in their mouse-movement trajectories when answering affirmatively that they are compassionate. We propose that future research can use this deviation indicator of compassion to help adjust for bias, resulting in a more complete understanding of compassion in the workplace.

Background

When describing the effect of compassion in interpersonal relationships, Lilius et al. (2008) explained: "While compassionate interpersonal acts are rarely large or dramatic, they may become so in the minds of the recipients…smallness does not equate with significance…short moments can have large consequences" (p. 5). Short moments of compassion are particularly magnifying in the workplace. Compassion results in better leadership, helps managers connect with those they lead, and by doing so, helps them lead more effectively and successfully (Boyatzis and McKee 2005). Maitlis and Ozcelik (2004) explains that emotion interacts critically with rationality, rules, and politics in organizational decision making, making compassion ever-more important in a business setting where futures are based on decisions.

Given the importance of compassion in the workplace, both researchers and practitioners have sought measurements of compassion (Sinclair et al. 2017). Such measures would allow them to better understand antecedents of compassion, improvements in compassion, and shortcomings of compassion. However, developing a consistent measurement of compassion faces several challenges. Foremost, people are often hesitant to admit low levels of compassion, in an effort to appear favorably to others (Fisher 1993).

We draw on the domain of human-computer interaction—specifically the analysis of mouse-cursor movements—to help address the need for more accurate estimates of compassion. Mouse cursor tracking has long been used to gain real insight into human intention. Originally as a proxy for eye tracking in an HCI context to denote attention (Raghunath et al. 2012), mouse tracking is now used as a fine-grained measurement to denote hidden cognitive processes (Freeman et al. 2011). As a result, mouse-cursor tracking has been used in hundreds of studies to better understand the psychology and physiology of users, including being used to better understand decision conflict (Anderson et al. 2015), response difficulty (Horwitz et al. 2017), response certainty (Jenkins et al. 2015), dynamic cognitive competition (Freeman and Ambady 2011), and emotional reactions (Hibbeln et al. 2017), to name a few. Importantly, the analysis of mouse-movement trajectories can provide insight into self-reported biases. For example, Jenkins et al. (2017) found that when using mouse-movement deviation as a moderator to survey responses, the r-squared of using the survey response to predict an outcome more than doubled. We build on these studies to explain how the analysis of mouse-cursor movements can provide insight into the measurement of compassion.

Theory

To explain how mouse cursor-movements can provide insight into the measurement of compassion, we draw on the response activation model. The Response Activation Model (RAM) (Welsh and Elliott 2004) explains the neuro-physiological process that occurs when people move their hand (i.e., such as when moving a computer mouse) to a selected target (i.e., to answer a question about compassion). When considering moving the hand to a target, the brain begins to prime movements toward that target, often before the person has fully decided which target to move towards. To prime a movement response refers to transmitting nerve impulses to the hand and arm muscles to move towards the stimulus. However, the resulting movement is not only influenced by primed movements toward the ultimate intended target, rather it is influenced by primed movements to all targets that the user may have been considering moving to (Georgopoulos 1990; Song and Nakayama 2008). For example, when a person with lower compassion completes a questionnaire about compassion, the movement would be influenced by the social-desirable answer (i.e., I have compassion) and also the honest answer (i.e., I do not have compassion).

The parallel programming to competing targets is an automatic, subconscious process that allows the body to react more quickly to stimuli that a person may eventually decide to move towards. As a result of parallel stimulated movement to several targets, the hand deviates from directly answering the intended question toward the alterative primed responses (Welsh and Elliott 2004). For example, in the case of a compassion question, if one is intending to report high compassion, and the low compassion option catches his or her attention because it is more accurate, the hand will prime movements toward this answer in addition to the intended answer. Together, this results in the movement trajectory that deviates away from directly answering in the intended way. Ultimately, the brain will inhibit the competing priming, correct these departures, and reach the desired destination (Welsh and Elliott 2004). However, monitoring the movement of the computer mouse during this process offers a "continuous streams of output that can reveal ongoing dynamics of processing, potentially capturing the mind in motion with fine-grained temporal sensitivity" (Freeman et al. 2011, p. 1).

In summary, when people are misrepresenting their level of compassion, the option to report accurately and the option to report in a social-desirably way will both capture their attention. As a result of the brain processing responses to both targets that capture attention, the trajectory will show greater deviation towards the competing response. However, if people are reporting accurately, there will be less competing programming (Krapohl et al. 2009) and therefore less deviation towards the other competing answers. We therefore hypothesize:

Research Hypothesis: Lower compassion will cause greater mouse-movement deviation in the direction of disclosing low compassion.

Methodology

To test our hypothesis, we created an experiment that utilizes a zero-sum game design to objectively measure compassion. Afterwards, we had participants answer questions about whether they would help individuals (i.e., show compassion) as we unobtrusively measured their mouse-cursor movements. We utilized a graded-motor response analysis to analyze whether people with lower compassion (as objectively measured in the zero-sum game) showed greater deviation toward disclosing low compassion than people with higher compassion.

Procedure

We ran an experiment that contained two stages. The purpose of stage 1 was to collect an objective indicator of compassion. The purpose of stage 2 was to gather a self-reported measure of compassion while we monitored mouse-cursor movements in a specialized online survey. We then examined whether the objective measure of compassion in stage 1 is correlated with the amount of deviation when people responded affirmatively that they would have compassion in stage 2.

Phase 1: We created a zero-sum game to gather an objective indicator of compassion. In game theory and economic theory, a zero-sum game is a mathematical representation of a situation in which each participant's gain or loss of utility is exactly balanced by the losses or gains of the utility of the other participants. This game required participants to choose whether to act compassionately, at their own expense. Participants were instructed to play a computer game, similar to the game: Chutes and Ladders® (see Figure 1). Each participant played against three other study participants. The game required each participant to roll a dice and advance along a path. The first participant to reach the end, wins. However, unbeknownst to the participants, the other three participants in each game were computer bots and the game was rigged so that the human participant is guaranteed to win.

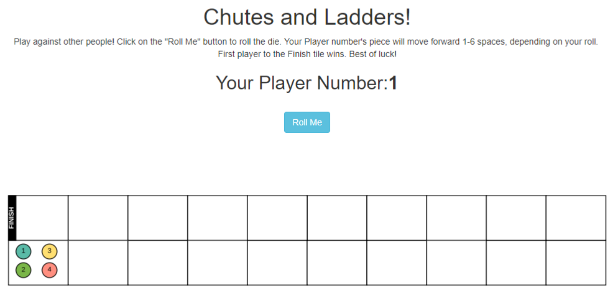

Figure 1: Game format

After participants play the game and "win", they were informed that at the conclusion of the study a long monotonous task must be completed between them and the other three players. However, because the individual "won," they will get to decide whether they want to help with the task, and if so, how much they will help. They may choose to help or choose to make the "losers" complete the task alone. They make this decision using a slider-bar to indicate the percentage of work they choose to do. The amount of work they choose to do, instead of making their co-players do that work, is our objective indicator of compassion. The higher the amount, the higher the compassion.

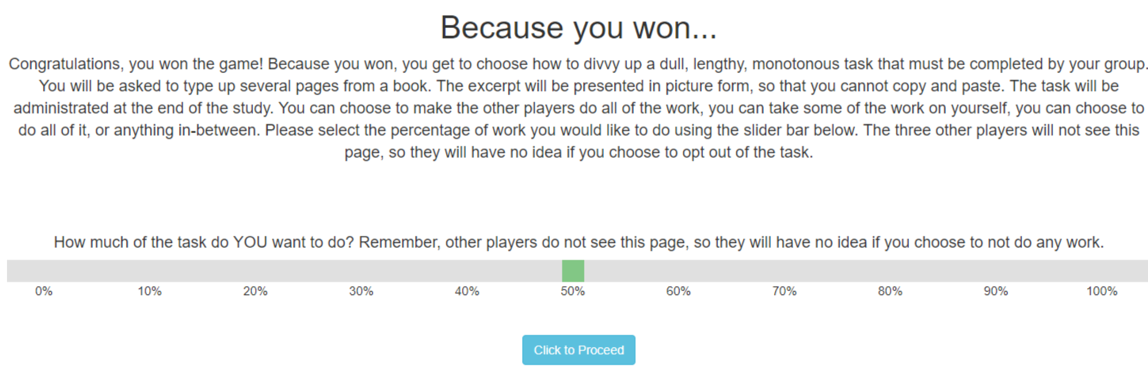

Figure 2: Slider page

Phase 2: After the game, participants were directed to a specialized online survey where they were shown a series of images of people who need varying degrees of help. They were then asked to self-report "If you had the means, would you help this person?" To answer, participants dragged an icon from the bottom of the screen to either the "Yes", "No", or "This person doesn't need help" boxes located respectively in the upper left-hand corner, right-hand corner, and top center region of the screen (see Figure 3). We recorded both the answer, and the mouse-movement trajectory (the x and y coordinate of each movement, as well as the timestamp of movement). To capture people's thought process per the response-activation model, participants were required to start moving the mouse up to trigger the showing of the pictures, and then continue moving the mouse until they answered (otherwise, they would see an error and be forwarded to the next image). This ensured that we would capture the response-activation behavior as participants were deciding how to answer.

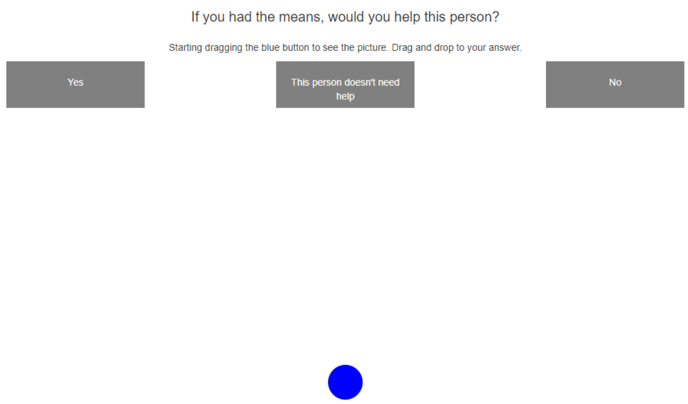

Figure 3: Mouse-cursor tracking survey

Participants

We recruited participants from Amazon's Mechanical Turk to complete the experiment. Participants were paid $2 for approximately a 10-minute task (equating to approximately a $12 per hour rate). To help ensure high quality, participants were required to have a Mechanical Turk Master's Certification, and several attention tests were used throughout the study to screen for poor data. We had 134 valid participants in the study. Each participant was shown 25 separate scenarios and responded whether they would help the subject or not.

Mouse-Movement Data

While participants answered the 25 scenarios, we captured their x- and y-positions and timestamp for each movement through JavaScript installed in the website. The JavaScript capture the mousemove events and sent them to our server for processing.

To ensure accuracy and quality, we first time-normalized the data on the server. Time-normalized data provides information regarding the overall shape of the trajectories, which can be used as a comparison for different people and different situations (Dale et al. 2007). The reason that time-normalization is important in this process is that recorded trajectories sometimes have different durations and even sampling rates. This means that people naturally respond to questions differently. For example, some users are faster than others in responding. Consider a response from one person that lasts 800 milliseconds and a response from another person, who naturally moves slower, that lasts 1,600 milliseconds. If you try to compare the trajectories at 800 milliseconds for each response, you may not be comparing the same part of the trajectory-one respondent is finishing the movement while the other is still in the middle of the movement.

To address these limitations, we divided up the x,y coordinate pairs into 101 equal segments using linear interpolation. Each segment has an average x, y coordinate computed based on the x,y coordinate pairs in that segment. By doing this, one can compare movement of any particular segment by running a statistical analysis on the average x or y coordinate in that particular segment (Jenkins et al. 2019). For example, for two groups of people, we can compare the 50th (out of 101) spot in their trajectory and see if they are equal.

Because each person responded to 25 different scenarios, and each scenario has the 101-time normalized buckets, we averaged each bucket across the 25 different scenarios for each participant. This resulted in a single set of 101 buckets for participants. We only included instances where the person indicated affirmatively that they would be compassionate, so that other answers would not bias the trajectories.

Analysis

To analyze whether lower compassion will cause greater mouse-movement deviation in the direction of disclosing low compassion in this specialized online survey, we analyzed the 101 x-positions in a graded motor-response analysis. The graded motor-response analysis is a technique used to test whether two mouse-movement trajectories are different (Dale et al. 2007). The graded motor response analysis works by checking whether the x-position in each bucket is significant different in two trajectories using an appropriate analysis (e.g., regression, t-test, etc.)

To avoid alpha slippage from running 101 tests when comparing the entire trajectory, overall trajectories are only deemed significantly different if eight segments in a row are significantly different from each other. This cutoff was determined through bootstrapping simulations to provide a conservative criterion that accounts for alpha slippage (Dale et al. 2007). This equates to a critical value of .05^8, or p < 0.000000000039, to conclude that two trajectories are different from each other.

Following this procedure, we examined each bucket to determine whether the objective level of compassion (see stage 1 of the experiment) was significantly correlated with the x-position in each of the 101 buckets using a regression. A negative coefficient in the regression indicates that higher compassion resulted in more directly answering "yes" that the participants would help. Vice versa, a positive coefficient means that the trajectory for a person with less compassion is deviating more towards answering "no". The results are shown in Table 1.

Bucket	**Estimate**	**Std.Error**	**t-value**	**p-value**
x_1_avg_value	(0.0634)	0.1731	(0.3663)	0.7147
x_2_avg_value	(1.0655)	1.1279	(0.9446)	0.3466
x_3_avg_value	(3.3860)	1.5144	(2.2359)	0.0270
x_4_avg_value	(7.3691)	2.5218	(2.9221)	0.0041
x_5_avg_value	(7.8631)	3.2586	(2.4131)	0.0172
x_6_avg_value	(8.8828)	3.6499	(2.4337)	0.0163
x_7_avg_value	(9.0790)	3.8741	(2.3435)	0.0206
x_8_avg_value	(9.2411)	4.1653	(2.2186)	0.0282
x_9_avg_value	(8.7356)	4.1866	(2.0866)	0.0389
x_10_avg_value	(6.4488)	4.3457	(1.4840)	0.1402
x_11_avg_value	(5.5423)	4.6946	(1.1806)	0.2399
x_12_avg_value	(5.5984)	4.7560	(1.1771)	0.2413
x_13_avg_value	(5.2960)	5.0376	(1.0513)	0.2950
x_14_avg_value	(6.4219)	5.1781	(1.2402)	0.2171
x_15_avg_value	(7.8298)	5.4359	(1.4404)	0.1521
x_16_avg_value	(8.8686)	5.8524	(1.5154)	0.1321
x_17_avg_value	(10.1090)	6.4353	(1.5709)	0.1186
x_18_avg_value	(10.1496)	6.6374	(1.5292)	0.1286
x_19_avg_value	(9.7490)	7.0024	(1.3922)	0.1662
x_20_avg_value	(10.3212)	7.1249	(1.4486)	0.1498
x_21_avg_value	(11.1969)	7.1231	(1.5719)	0.1184
x_22_avg_value	(10.0342)	(10.0342)	(1.3686)	0.1735
x_23_avg_value	(11.0764)	7.3100	(1.5152)	0.1321
x_24_avg_value	(11.1910)	7.4517	(1.5018)	0.1355
x_25_avg_value	(11.0176)	7.4836	(1.4722)	0.1433
x_26_avg_value	(10.7368)	7.4035	(1.4502)	0.1494
x_27_avg_value	(11.4737)	7.6266	(1.5044)	0.1349
x_28_avg_value	(11.9835)	7.6711	(1.5622)	0.1206
x_29_avg_value	(12.6044)	7.7520	(1.6260)	0.1063
x_30_avg_value	(12.6959)	7.9823	(1.5905)	0.1141
x_31_avg_value	(14.5848)	7.9941	(1.8244)	0.0703
x_32_avg_value	(14.5028)	8.1605	(1.7772)	0.0778
x_33_avg_value	(13.3163)	8.3768	(1.5897)	0.1143
x_34_avg_value	(13.2497)	8.5632	(1.5473)	0.1242
x_35_avg_value	(13.1976)	8.8754	(1.4870)	0.1394
x_36_avg_value	(13.9145)	8.9560	(1.5536)	0.1227
x_37_avg_value	(6.7100)	9.3269	(0.7194)	0.4732
x_38_avg_value	(7.5269)	9.4336	(0.7979)	0.4264
x_39_avg_value	(9.1355)	9.3078	(0.9815)	0.3281
x_40_avg_value	(8.7503)	9.2537	(0.9456)	0.3461
x_41_avg_value	(11.3236)	9.2132	(1.2291)	0.2212
x_42_avg_value	(14.4020)	8.8761	(1.6226)	0.1071
x_43_avg_value	(18.3081)	8.7636	(2.0891)	0.0386
x_44_avg_value	(19.9684)	8.6378	(2.3117)	0.0223
x_45_avg_value	(21.0571)	8.8378	(2.3826)	0.0186
x_46_avg_value	(22.3907)	8.8519	(2.5295)	0.0126
x_47_avg_value	(23.2043)	8.8010	(2.6366)	0.0094
x_48_avg_value	(23.4773)	8.9272	(2.6299)	0.0096
x_49_avg_value	(23.3110)	9.2412	(2.5225)	0.0096
x_50_avg_value	(24.8435)	9.5415	(2.6037)	0.0103
x_51_avg_value	(25.5429)	9.8820	(2.5848)	0.0108
x_52_avg_value	(24.2945)	9.9064	(2.4524)	0.0155
x_53_avg_value	(21.8809)	10.0128	(2.1853)	0.0306
x_54_avg_value	(21.4891)	9.9884	(2.1514)	0.0333
x_55_avg_value	(21.0029)	9.9459	(2.1117)	0.0366
x_56_avg_value	(19.9813)	9.7321	(2.0531)	0.0420
x_57_avg_value	(18.9152)	9.6878	(1.9525)	0.0530
x_58_avg_value	(21.1083)	9.7852	(2.1572)	0.0328
x_59_avg_value	(21.2518)	9.6799	(2.1954)	0.0299
x_60_avg_value	(20.7537)	9.8295	(2.1114)	0.0366

x_61_avg_value	(18.8967)	9.1158	(2.0730)	0.0401
x_62_avg_value	(17.4418)	8.9375	(1.9515)	0.0531
x_63_avg_value	(14.5393)	9.1336	(1.5918)	0.1138
x_64_avg_value	(11.8463)	9.0255	(1.3125)	0.1916
x_65_avg_value	(11.4282)	9.1757	(1.2455)	0.2152
x_66_avg_value	(11.2002)	9.2868	(1.2060)	0.2300
x_67_avg_value	(10.8415)	9.2425	(1.1730)	0.2429
x_68_avg_value	(8.7114)	9.4078	(0.9260)	0.3561
x_69_avg_value	(7.2518)	9.5888	(0.7563)	0.4508
x_70_avg_value	(7.4066)	9.3920	(0.7886)	0.4318
x_71_avg_value	(6.8158)	9.5192	(0.7160)	0.4753
x_72_avg_value	(4.8852)	9.7493	(0.5011)	0.6171
x_73_avg_value	(4.7114)	9.6497	(0.4882)	0.6262
x_74_avg_value	(3.3748)	9.5468	(0.3535)	0.7243
x_75_avg_value	(2.4111)	9.5805	(0.2517)	0.8017
sx_76_avg_value	(8.4752)	4.0868	(2.0738)	0.0400
x_77_avg_value	(2.4168)	9.5049	(0.2543)	0.7997
x_78_avg_value	(7.2325)	8.3525	(0.8659)	0.3881
x_79_avg_value	(6.2327)	8.2869	(0.7521)	0.4533
x_80_avg_value	(5.5454)	8.2254	(0.6742)	0.5014
x_81_avg_value	(6.4833)	8.0322	(0.8072)	0.4210
x_82_avg_value	(7.1352)	8.0572	(0.8856)	0.3775
x_83_avg_value	(8.1675)	8.0470	(1.0150)	0.3120
x_84_avg_value	(9.4643)	7.7194	(1.2260)	0.2224
x_85_avg_value	(8.4721)	7.6652	(1.1053)	0.2711
x_86_avg_value	(7.2990)	7.5668	(0.9646)	0.3365
x_87_avg_value	(7.0990)	7.3177	(0.9701)	0.3338
x_88_avg_value	(5.4149)	7.2164	(0.7504)	0.4544
x_89_avg_value	(3.4330)	7.0196	(0.4891)	0.6256
x_90_avg_value	(2.2392)	6.8926	(0.3249)	0.7458
x_91_avg_value	(0.8101)	6.6795	(0.1213)	0.9037
x_92_avg_value	(0.1279)	6.3288	(0.0202)	0.9839
x_93_avg_value	1.7362	6.0967	0.2848	0.7763
x_94_avg_value	2.6511	5.7064	0.4646	0.6430
x_95_avg_value	3.9333	5.4922	0.7162	0.4752
x_96_avg_value	5.2224	5.3710	0.9723	0.3327
x_97_avg_value	5.1763	5.1941	0.9966	0.3208
x_98_avg_value	6.7021	5.1936	1.2904	0.1992
x_99_avg_value	7.0888	5.4514	1.3004	0.1957
x_100_avg_value	6.6153	5.4706	1.2093	0.2287
x_101_avg_value	6.1776	5.5156	1.1200	0.2647

Table 1. Graded Motor Response Analysis (significance level of <.05 highlighted in dark gray, significance level of < .1 highlighted in light gray)

Supporting our hypothesis, the trajectories were significantly different because greater than eight slots were significantly different from x-position 43 to x-position 56 (14 slots, $p < .05$). In addition, at a p-value of < .1, 20 slots were significantly different from each other (x-position 43 to x-position 62). The beginning of the trajectory x-position 3 to x-position 9 is also nearing significance with 7 consecutive spots. In both cases, and with the majority of the trajectory, people with more objective compassion answered more directly than people with less objective compassion (see Figure 4).

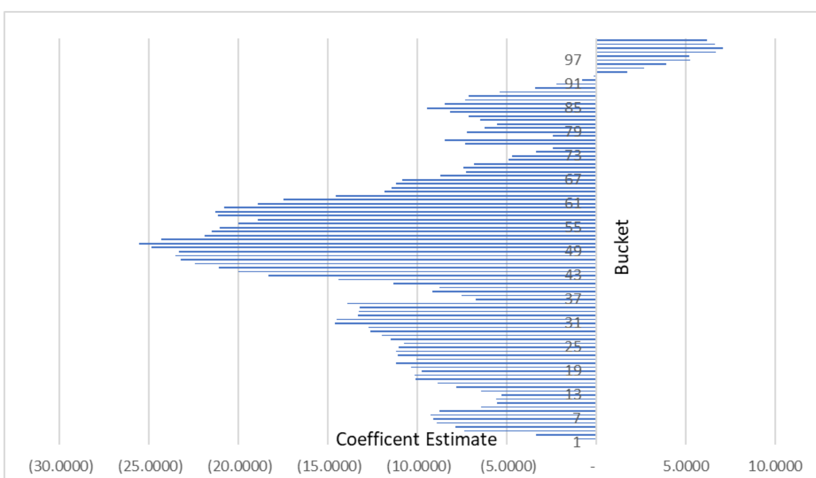

Figure 4. Coefficient Estimate Values for Compassion on X Position (a negative estimate denotes a more direct answer for high compassion, a positive estimate denotes a less direct answer for high compassion)

Discussion

This paper examined whether objective compassion influences how people respond to self-report questions on compassion. Supporting our hypothesis, we found that lower compassion is correlated with greater mouse-movement deviation in the direction of disclosing low compassion in a specialized online survey (when answering affirmatively that they have compassion). These findings represent an initial step in correcting for biased answers in self-reported compassion levels. Below, we discuss theoretical and practical implications of this research, along with limitations and future research opportunities within each section.

Implications for Research

This paper explains how objective compassion influences people's mouse-movement trajectories when answering questions about compassion. Building on literature on response bias (Jenkins et al. 2017), we suggest that potential bias may influence how people answer self-reported questions. In our study, we theoretically explained through the response activation model that when you have lower compassion, the answer that discloses lower compassion catches attention resulting in the brain programming movements toward that answer. The resulting movement is therefore biased—deviates towards—the opposite response. In an empirical study, we found support of this hypothesis, as lower compassion resulted in greater deviation towards disclosing lower compassion (even though the person answered that she / he has higher compassion).

Further, our study sets a foundation for future research to correct for biased in self-report responses of compassion. Namely, our results suggest that low objective compassion is correlated with mouse-cursor deviation when a person positively answers they have compassion. We do not use this measure of deviation to correct for bias in this paper. However, future research could potentially use this measure of deviation to create more accurate representations of compassion. One suggestion is to use the measure of deviation (e.g., an aggregation of coefficient estimates or x-position values) as a moderator in structural models between compassion and other variables. Jenkins et al. (2017) found that using mouse-movement statistics as moderators can help correct for bias and, in their study, nearly doubled the r-squared of the model. We suggest future research to likewise use our measure of deviation to improve estimates of compassion.

Further, our study sets a foundation for future research to measure bias on a variety of question types. Our study was limited to a specialized survey where people dragged a button to the upper corners of the page to answer the question. While this type of question format is atypical, this was done similarly in previous research on mouse-movement trajectory analysis (Freeman and Ambady 2011) to maximize one's ability to understand how compassion influences the trajectory. The results of the question format allowed us to capture the mind in motion with fine precision for this initial study of how compassion influences movements. However, our theory has applications to a much broader set of question types. Future research should examine how well our results apply to "normal" radio-button questions.

Our research can potentially also be applied to different compassion measures to improve compassion estimates in a research context. In our study, we had participants report of whether they would help a person in need in a variety of contexts as an indicator of compassion. However, there are many other instruments of compassion that measure the construct on a variety of dimensions (Papadopoulos and Ali 2016). Our theory suggest that deviation will be correlated with lower compassion with these instruments as well. We suggest future research to confirm this hypothesis.

Finally, we demonstrate that the computer mouse can be used as a fine-grained sensor in research to measure psychological constructs. As discussed in our literature review section, many studies have used the computer mouse as a fine-grained sensor to measure various psychological phenomenon (see Freeman et al. 2011 for summary of articles). We extend this research to suggest that the computer mouse may also be used as a sensor to understand compassion and self-report bias.

Implications for Practice

Compassion plays an important role in organizations. Effective management, team work, and customer relations are all impacted by employees' compassion. Measuring compassion, however, is very difficult, because people often are hesitant disclosing their true level of compassion, particularly when compassion is low. To help future research create more accurate estimates of compassion, we found that people with low compassion show more mouse-movement deviation toward disclosing low compassion, compared to people with higher compassion. This result creates a foundation for future research to correct for bias in self-report compassion measures and thereby improve estimates of compassion on two levels.

First, on an organizational level, companies can measure the organizational health as it relates to compassion. By mass deploying a questionnaire on compassion, measuring mouse-cursor movements through JavaScript, aggregating the answers and the amount of deviation, and using the amount of deviation to moderate the self-reported compassion, companies can gain a more accurate estimate of the level of compassion in their organizations, even if people are hesitant to disclose compassion. Using this measure, companies can identify shortcoming in compassion and measure improvement overtime.

Second, organizations can use our measure of compassion for employee screening. Using standardized compassion measures, our measure of deviation can potentially be used to identify when the self-reported measure might be suspicious. For example, an answer that a candidate has high compassion might be flagged if the answer was given with lots of deviation toward the answers of low-compassion. It is important to note, that deviation does not mean that someone is being deceptive about the answer. Rather, it indicates that there might be data-quality issues, and that one should consider asking follow-up questions about compassion, which may confirm or disconfirm the self-reported compassion. The benefit of our finding that deviation is correlated with lower compassion is that it helps focus additional questioning to those people who are more likely to benefit from such questioning.

Conclusion

Compassion plays an important role in effective organizations. Measuring compassion is important to identify shortcomings and improvements in the workplace. Measures of compassion, however, are fraught by bias, as people are hesitant to disclose low compassion. We draw on the science of mouse-cursor tracking to help create a foundation for improving estimates of compassion. Based on the response-activation model, we find that people with lower compassion are correlated with a greater deviation toward disclosing lower compassion, than people with higher compassion, although they all affirmatively answer they have compassion. Based on this finding, we suggest future research to validate this approach for correcting bias in self-reported compassion levels using this measure of mouse-movement deviation.

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