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3   **Towards a Process-level Understanding of Correspondence among Indirect Measures of Racial Threat**

4   **Stereotypes**

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33   **Towards a Process-level Understanding of Correspondence among Indirect Measures of Racial Threat**

34   **Stereotypes**

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37   **Abstract**

38   Previous research often reveals relatively poor correspondence among three prominent indirect

39   measures configured to assess racial stereotypes: the Weapon Identification Task (WIT), the First-Person

40   Shooter Task (FPST), and the Implicit Association Test (IAT). Importantly, these measures differ on a

41   variety of procedural dimensions (e.g., task instructions, stimulus presentation, response time limits),

42   which confounds explanations of low correspondence. In a fully within-participants design, N = 372

43   participants completed versions of the WIT, FPST, and IAT that were aligned on several procedural

44   dimensions. Process modeling revealed high correlations among measures for model parameters

45   reflecting controlled and automatic processes. However, model-based racial bias estimates correlated

46   only moderately between the WIT and FPST, and not at all with the IAT. Our findings suggest that all

47   three measures share some correspondence when procedurally aligned but each reflects a specific

48   aspect of racial threat stereotypes.

49

50   *Abstract:* 139 words

51   *Keywords:* weapon identification task, first person shooter task, implicit association test,

52   multinomial processing tree modeling, process model, racial bias

53   *Word count:* 9902 (excluding references [1946], footnotes [706], tables, and figures)

54   **Introduction**

55   Indirect measures[1] were initially developed to assess the influence of racial biases on behavior by

56   minimizing the influence of other mental processes that would otherwise constrain the expression of

57   bias (Gawronski et al., 2020). Measures such as the Weapon Identification Task (WIT; Payne, 2001), First-

58   Person Shooter Task (FPST; Correll et al., 2002), and the Implicit Association Test (IAT; Greenwald et al.,

59   1998) are often configured to assess racial bias operationalized as stereotypes (i.e., traits) associated

60   with different racial groups (e.g., Black men seen as threatening). However, previous research has

61   revealed relatively weak to no correlations between racial bias estimates assessed by different indirect

62   measures of racial bias[2] (Bar-Anan & Nosek, 2014; Cunningham et al., 2001; Glaser & Knowles, 2008; Ito

63   et al., 2015; Payne, 2005; Volpert-Esmond et al., 2020), which is surprising for measures that are

64   configured to assess a common construct.

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[1] The measures we examine in the present research are sometimes colloquially referred to as "implicit

measures" (Gawronski et al., 2020; Greenwald & Lai, 2020; Payne & Correll, 2020). However, the term

"implicit" is used inconsistently in (and beyond) the social cognitive literature to refer to characteristics

of the measurement instrument, outcome measure, behavioral response, or underlying mental

representation (Corneille & Hütter, 2020; Gawronski et al., 2020). Instead, here we adopt the term

"indirect" to refer to a measure that quantifies responses in terms of their latency or accuracy, and in

contrast to measures in which participants are directly asked to report a response (e.g., "How much do

you associate Black men with threat?").

[2] Bar-Anan and Vianello (2018) found relatively close correspondence across indirect measures of racial

bias by accounting for measurement error. However, Schimmack (2001) criticized this study for

unrealistic assumptions about method variance in their structural equation modeling approach.

65   Small correlations among conceptually analogous indirect measures may call into question the

66   validity of their racial bias estimates (Schimmack, 2021). Nevertheless, even when indirect measures are

67   configured to assess the same construct, a wide variety of procedural differences among those measures

68   remain, such as differences in stimuli, response time limits, number of trials, task instructions, and

69   stimuli presentation procedures. Task procedures necessarily determine which processes influence

70   responses (Gawronski et al., 2010), so procedural differences may attenuate correlations across

71   measures that otherwise assess the same construct. Thus, in the present research, we assess

72   correspondence across three indirect measures configured to assess threat stereotypes – the WIT, FPST,

73   and IAT– that are equated across several procedural dimensions. In doing so, we remove procedural

74   differences that otherwise confound comparisons across measures (i.e., stimuli material, response time

75   limit, number of trials) while retaining features that are inherent to each indirect measure (i.e., task

76   structure).

77   Moreover, responses on indirect measures of racial bias are traditionally operationalized in terms

78   of summary statistics (e.g., Bar-Anan & Nosek, 2014; Bar-Anan & Vianello, 2018; Cunningham et al.,

79   2001; Glaser & Knowles, 2008; Greenwald et al., 2003), which provide little insight into the cognitive

80   process(es) that contribute to responses (Calanchini, 2020). For example, similar performance across

81   indirect measures could be due to participants' cognitive control abilities in responding, their biased

82   mental representations, or both (Ito et al., 2015; Klauer et al., 2010; Payne, 2005). Consequently, in the

83   present research we apply the Process Dissociation Procedure (Payne, 2001) as a formal mathematical

84   modeling technique to disentangle the influence of controlled and automatic processes on performance

85   and investigate correspondence among those processes across indirect measures.

86   **Process modeling and indirect measures of racial threat stereotypes**

87   We are not the first to recognize that procedural differences across indirect measures affect

88   correspondence across racial bias estimates (e.g., Olson & Fazio, 2003), nor are we the first to use formal

89   mathematical modeling to assess correspondence across measures. Indeed, Ito and colleagues (2015)

90   investigated the contributions of two qualitatively distinct types of cognitive processes on the WIT, FPST,

91   and IAT. They found that estimates of controlled processing correlated moderately-to-strongly across

92   measures ($r = .29 - .61$) but estimates of racial bias based on automatic processing correlated weakly

93   across measures ($r = .02 - .16$).

94   To the extent that indirect measures of racial bias were developed to primarily assess

95   automatically activated mental representations (Fazio et al., 1995; Gawronski et al., 2020; Greenwald et

96   al., 1998), the small magnitude of correlations among racial bias estimates calls into question whether

97   these measures configured to assess threat stereotypes reflect a common construct. However, and

98   importantly, Ito and colleagues (2015) relied on the standard versions of each indirect measure as they

99   are typically configured. This approach certainly has ecological validity, in terms of correspondence with

100   how these measures are traditionally used by researchers. But as we review below, these three indirect

101   measures differ from one another on many dimensions – which in turn confounds any strong

102   interpretations of the small correlations in racial bias estimates between measures.

103   **Overview of standard versions of indirect measures of racial bias**

104   **Weapon Identification Task**

105   The WIT is a sequential priming paradigm developed by Payne (2001). Over a series of trials,

106   participants view a prime image (i.e., Black or White male face) quickly followed by a target image (i.e.,

107   gun or tool). On each trial, participants' task is to identify quickly and accurately the target while

108   disregarding the prime (Payne, 2001; Rivers, 2017).

109   **First-Person Shooter Task**

110   The FPST is a simplified videogame simulation developed by Correll et al. (2002). Over a series of

111   trials, participants view a naturalistic scene (e.g., a park) in which a person (i.e., Black or White man)

112   appears who is either armed (e.g., holding a gun) or unarmed (e.g., holding a cell phone). On each trial,

113   participants' task is to quickly and accurately decide whether to "shoot" or "don't shoot". Target persons

114   are presented as full body photographs with varying postures against different background scenes, with

115   changing target onset times and screen positions (Correll et al., 2002; 2007; 2015).

116   **Implicit Association Test**

117   The IAT is a dual-categorization task developed by Greenwald et al. (1998). Over a series of trials,

118   participants view two stimulus types – typically target groups (e.g., pictures of Black and White male

119   faces) and attributes (e.g., words referring to threat or safety) – presented one at a time. In some blocks

120   of trials, one target type shares a response key with one attribute type (e.g., Black/threat) and the other

121   target type shares a response key with the other attribute type (e.g., White/safety). However, in other

122   blocks of trials, the key pairings are reversed (e.g., Black/safety, White/threat). On each trial,

123   participants' task is to categorize the presented stimulus quickly and accurately.

124   **Similarities and differences among standard versions of indirect measures of racial bias**

125   All three of these measures – the WIT, FPST, and the IAT – have been used to assess racial bias

126   operationalized in terms of threat stereotypes. Moreover, all three measures share a common feature in

127   that they require participants to make a categorization decision (e.g., whether the stimulus is a gun or

128   tool). However, as Table 1 illustrates, these three measures diverge on several procedural

129   characteristics, including: the number of critical trials, the presence and length of the response time

130   limit, and stimulus material. Not only do these measures differ from one another on these procedural

131   dimensions, but versions of each measure have also been implemented with a variety of task

132   procedures. For example, the WIT has been used with additional neutral face outlines and has been

133   configured with as few as 80 and as many as 1100 critical trials (for a review, see Rivers, 2017). The FPST

134   exists in several different adaptations that present full body images of people holding the target object in

135   their hand (Correll et al., 2002; Payne & Correll, 2020), target objects superimposed on the forehead of a

136   face (Plant et al., 2005), and target objects presented on the left or right side of a face (Unkelbach et al.,

137   2008, 2009). Furthermore, IATs have been developed that implement response deadlines, different

138   numbers of trials, and different block structures (Calanchini et al., 2021; Meissner & Rothermund, 2013;

139   Sriram & Greenwald, 2009).

140   **Table 1**

141   *Procedural details of the WIT, FPST, and IAT in their originally published versions.*

	Weapon Identification Task (WIT; Payne, 2001)	First-person Shooter Task (FPST; Correll et al. 2002)	Implicit Association Test (IAT; Greenwald et al., 1998; Study 3)
response time limit	none (Study 1); 500 ms (Study 2)	850ms (Study 1 & 3); 630ms (Study 2)	none
number of practice trials	48 trials	no trials	150 trials
number of experimental trials	192 trials	80 trials	200 trials
stimulus material: target group / category	cropped face images of Black and White male faces as primes	full body image of Black and White men	first names judged to be more likely to belong to Black or White persons
stimulus material: target object / attribute	target images of weapons and tools	target weapon object or an innocuous object (e.g., a cell phone, a wallet) held by Black and White men	unpleasant and pleasant words as attributes
presentation order of stimulus material	sequential: prime face followed by target objects presented in the center of the screen	concurrent: person holding target object presented at a random position on screen	serial: target category or attribute stimuli presented in the center of the screen in a random order between target and attribute stimuli
instruction	identifying target object while ignoring face prime	"shoot" armed person, "don't shoot" unarmed person	correctly categorize the target category and attribute stimuli
analysis	correct response latencies, error rates, process dissociation procedure	correct response latencies, error rates, signal detection modeling	correct response latencies

142

143   Procedural differences necessarily introduce variance between measures, which in turn may

144   obscure relationships among estimates of racial bias (Fazio et al., 1995; Greenwald & Lai, 2020; Mekawi

145   & Bresin, 2015; Payne, 2005; Olson & Fazio, 2003; Volpert-Esmond et al., 2020). Differences in the

146   stimuli presentation traditionally used in each indirect measure provide a straightforward illustration of

147   this point. For example, the WIT typically presents the target object clearly visible in the center of the

148   screen without any distracting cues, and at approximately the same size as the face primes are

149   presented. In contrast, the FPST typically presents the target object held in the hand of a person who is

150   pictured in a variety of scenes and thus represents only a small feature in a larger context. The IAT differs

151   from both of these paradigms and typically does not use images of target objects but, instead,

152   represents attributes like words indicating safety versus danger (Ito et al., 2015). Stimuli that are

153   intended to reflect different operationalizations of the same construct (e.g., words versus pictures) can

154   nevertheless activate different sets (or subsets) of mental representations (Foroni & Bel-Bahar, 2010;

155   Rosch, 1975). Thus, low correspondence among these measures may reflect different kinds of stimuli

156   activating different subsets of threat stereotypes.

157   Though all three indirect measures differ on a variety of procedural dimensions, we propose that

158   task structure is the most crucial difference. The WIT presents stimuli sequentially and explicitly instructs

159   participants to respond to target objects and disregard face primes. The FPST presents stimuli

160   concurrently, and participants are instructed to "shoot" an armed person and "don't shoot" an unarmed

161   person.[3] The IAT presents stimuli serially, such that participants must attend and categorize both types

162   of stimuli. In the present research, we argue that task structure is the defining feature of each measure.

163   Thus, we aligned measures on procedural characteristics that have varied in previous research but held

164   constant what we view as the defining feature of each measure: task structure.

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[3] A recent version of the FPST also allows for a dynamic presentation of target stimuli by showing a video

clip of a person reaching into their pocket and pulling out the target object, resulting in a sequential

presentation of the person first and the target object second (Frenken et al., 2022).

165   **Indirect measures of racial bias reflect the contributions of multiple cognitive processes**

166   Despite procedural differences among the WIT, FPST, and IAT, they were all designed with the

167   same goal of assessing racial stereotypes by minimizing the contributions of other processes that would

168   constrain their expression. To be sure, compared to analogous direct measures (e.g., feeling

169   thermometers; questionnaires), these indirect measures minimize the contributions of motivations and

170   biases that would modify responses in a socially desirable direction. However, responses on indirect

171   measures do not solely reflect the contributions of stereotype information. Instead, multinomial

172   processing tree (MPT; Riefer & Batchelder, 1988) models can disentangle the joint contributions of

173   multiple cognitive processes to responses on indirect measures. MPT models are tailored to specific

174   experimental paradigms that provide frequency data (e.g., number of correct and incorrect responses),

175   and specify the number, nature, and composition of cognitive processes thought to be involved in the

176   paradigm (for reviews see Calanchini, 2020; Erdfelder et al., 2009; Hütter & Klauer, 2016).

177   In the present research, we applied the Process Dissociation Procedure (PDP; Payne, 2001) to all

178   three indirect measures of racial bias. The PDP is an MPT that has been applied to each of these

179   measures in previous research and provides a robust way to disentangle the contribution of controlled

180   and automatic processes on response behavior (Bishara & Payne, 2009; Payne, 2009; Ito et al., 2015).[4]

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[4] For full transparency, one of the original goals of the present research was to compare different MPT

models across the three indirect measures. A variety of other models, such as Lindsay and Jacoby's

(1994) Stroop model and Conrey et al.'s (2005) quad model, have been previously compared in the

context of indirect measures like the WIT (Bishara & Payne, 2009). We applied different MPT models to

the data from each indirect measure, and the PDP consistently provided best fit to all three measures.

Consequently, we focus on results from the PDP in the main text and report the results from the other

MPT models in the supplement.

181   Below we describe the structure and the logic of the PDP in the context of the WIT, which also apply to

182   the FPST and IAT.

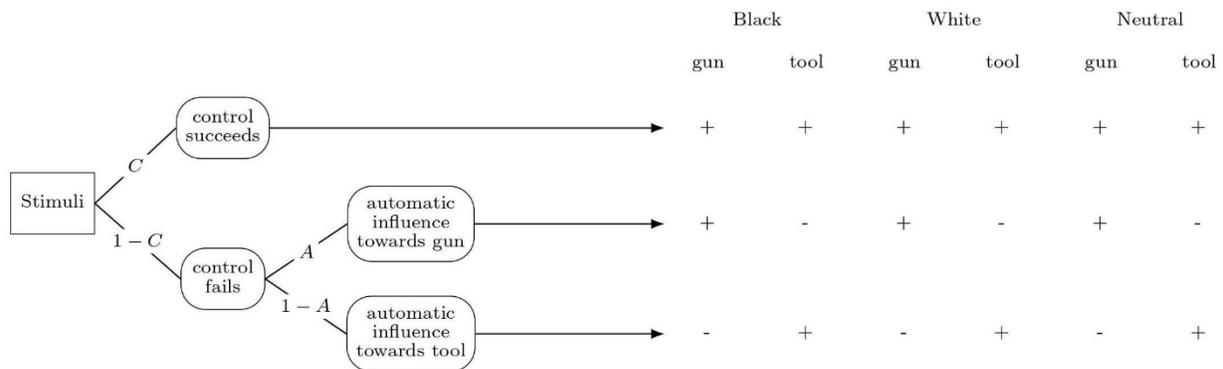183   **Process Dissociation Procedure**

184   The PDP (Jacoby, 1991; Payne, 2001) is depicted in Figure 1. This model consists of a Controlled

185   (*C*) and an Automatic (*A*) process parameter.[5] The Controlled process parameter represents any

186   process(es) that result(s) in a correct response, which include but are not limited to general accuracy in

187   responding based on successful target discrimination, and conflict monitoring/resolution when

188   automatic processes would produce a response that conflicts with the correct response (Klauer & Voss,

189   2008; Laukenmann et al., 2023). The Automatic process parameter represents response tendencies

190   towards a "gun" versus "tool" response, which may include the influence of threat stereotypes by prime

191   faces, handedness, guessing, and recoding (Klauer & Voss, 2008; Meissner & Rothermund, 2013). Vitally,

192   in the PDP, Controlled processing dominates automaticity, such that the influence of Automatic

193   processing is irrelevant whenever the Controlled process succeeds. However, and importantly, the PDP is

194   agnostic about the temporal order of processing. For example, Automatic processing might be activated

195   very quickly after stimulus onset, but if Controlled processing successfully intervenes at any time before

196   a response is made then it will override the response tendency that would be produced by Automatic

197   processing (Klauer & Voss, 2008; Laukenmann et al., 2023). Thus, the equations of the PDP are specified

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[5] We use the terms Controlled and Automatic to refer to the PDP's parameters in correspondence with

the terminology of Payne (2001). However, we expressly refrain from assuming that the processes

assessed by either parameter possess features of controllability (e.g., conscious, intentional, resource-

dependent, slow) or automaticity (e.g., unconscious, unintentional, efficient, fast) as articulated in

traditional dual-process perspectives of cognition (e.g., Metcalfe & Mischel, 1999; Shiffrin & Schneider,

1977).

198   such that the success of the Controlled process (*C*) will always produce the correct response (+). The

199   Automatic process can only produce a response in the absence of influence from the Controlled process

200   (1 – *C*), with the probability (*A*) representing a "gun" response and with the counter-probability (1 – *A*)

201   representing a "tool" response. When the target stimulus is a gun, (*A*) produces a correct response (+),

202   and (1 – *A*) produces an incorrect response (–). In contrast, when the target stimulus is a tool, (*A*)

203   produces an incorrect response (–), and (1 – *A*) produces a correct response (+).

204

205

206   **Figure 1.** Multinomial processing trees of the process dissociation procedure (PDP). Branches lead to

207   correct (+) and incorrect (–) responses. *C* = Controlled process parameter, *A* = Automatic process

208   parameter.

209   **The present research**

210   The aim of the present research is to investigate correspondence across three indirect measures

211   of racial bias – the WIT, FPST, and IAT – configured to assess racial threat stereotypes. Importantly, we

212   retain each measure's traditional structure (i.e., sequential, concurrent, serial, respectively) but align

213   them on all other procedural dimensions. Specifically, we used the same stimuli, response time window,

214   and number of trials in all three measures. In doing so, we can investigate the extent to which the small

215   correlations among racial bias estimates identified in previous research (Glaser & Knowles, 2008; Ito et

216   al., 2015; Payne, 2005) reflect procedural artifacts versus meaningful differences among measures.

217   In the present research, we relied on a fully within-participants design such that each participant

218   completed all three measures. We investigated correspondence among responses in two main ways.

219   First, we examined summary statistics of performance in terms of differences in response accuracy and

220   latency between critical trials. Next, to provide more theoretically precise insight than can be revealed by

221   summary statistics, we applied the PDP to participants' responses on each indirect measure. Replicating

222   previous research, we expect parameters that reflect controlled processes to correlate moderately-to-

223   strongly between indirect measures (Ito et al., 2015). Additionally, and in contrast to previous research,

224   we expect parameters that reflect automatic processes and racial bias to correlate moderately-to-

225   strongly between measures because we have aligned stimuli across them.

226   All data, preregistration, analytic code and supplementary material are available at

227   https://osf.io/2whze/.

228   **Methods**

229   **Participants**

230   We recruited 547 undergraduate students at a large, public Southern California university to

231   participate for partial course credit. As required by the Institutional Review Board at the university

232   where the study took place, we excluded participants from analysis who chose to reject data inclusion at

233   the end of the study (44 rejected inclusion). We excluded participants whose error rate was >50% for any

234   task (9 WIT; 2 FPST; 5 IAT; 1 in at least two tasks) to account for random responding. We also excluded

235   participants if they missed trials (i.e., trials with no response, a too fast response <100ms, or a too slow

236   response >1700ms) at a rate 1.5 times the interquartile range above the median (i.e., Tukey's criterion)

237   for any task (43 WIT; 26 FPST; 6 IAT; 46 in at least two tasks) to account for inattentive responding.

238   Because we collected these data online, we adopted relatively conservative inclusion criteria to ensure

239   data quality. In total, we excluded 26.0% of participants who agreed to be included in data analysis.

240   The final sample comprised 372 participants (age: M_{age} = 19.6, SD_{age} = 2.3; gender: 225 female,

241   141 male, 5 other, 1 unreported; race: 33 White, 11 Black, 130 Asian, 146 Latino, 48 other, 4

242   unreported). A post-hoc power analysis for a repeated measurement ANOVA with a sample size of N =

243   372, and a Type-1 error level of α = .05 (Faul et al., 2007) afforded a test power of at least 1-β > .49 to

244   detect small effects (f = .1 or η_p^2 = .01 in the underlying population, cf. Cohen, 1992). If effects are at

245   least of medium size (f = .25 or η_p^2 = .06 in the underlying population, cf. Cohen, 1992), the power

246   increases to 1-β > .99 under otherwise identical conditions. A post-hoc power analysis for a bivariate

247   correlation and a two-tailed Type-1 error level of α = .05 afforded a test power of at least 1-β = .49 to

248   detect a small correlation (r = .10) and increased to a test power of at least 1-β > .97 to detect a

249   correlation of r =. 20 given identical conditions. Overall, our study is sufficiently powered.

250   **Procedure**

251   We collected data online using the software lab.js (Henninger et al., 2022). After providing

252   consent, participants completed the three indirect measures in random order. Then, participants

253   completed a basic demographic questionnaire (age, gender, ethnicity) and were asked what they

254   thought the study was about. Participants were thanked and debriefed at the end. The response keys D

255   and L were counterbalanced between participants across all measures, and the response keys

256   corresponding to gun and tool targets were held constant within participants.

257   ***Weapon Identification Task***. Participants completed an adapted version of the WIT (Payne, 2001;

258   Rivers, 2017). Participants were instructed to identify as quickly and accurately as possible a target

259   object (i.e., gun, tool) preceded by a face image as prime. In addition to the Black and White male faces,

260   the adapted WIT also included an outline of a face as a neutral prime (Rivers, 2017).[6] In each trial,

261   participants were presented with a fixation cross (500 ms), a face prime (200 ms), a target object (200

262   ms), a pattern mask (500 ms),[7] and a feedback screen (1000 ms), each presented in the center of the

263   screen. On practice trials, participants received the following feedback: 'correct!', 'false!', 'too slow!'.

264   Slow responses were operationalized as responses made 700 ms or more after target object onset. On

265   experimental trials, participants only received feedback if their response was too slow. Participants'

266   response latency was recorded, even if it exceeded the 700 ms limit. Participants first completed 20

267   practice trials containing only neutral face outlines as primes, half of which were paired with a gun target

268   and half of which were paired with a tool target. Next, participants completed 240 experimental trials

269   with 80 trials for each prime race by target object combination in random order. Participants had two

270   self-paced breaks after 80 and 160 trials.

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[6] We included neutral face primes to provide enough degrees of freedom for the MPT model comparison

that we initially planned for this project (see Footnote 4). We still use responses to neutral faces as

reference category to investigate differences in response tendency for different face races compared to

a neutral face outline.

[7] In a first wave of preliminary data collection (N = 42), we imposed a response time limit of 500 ms after

target onset (with a pattern mask shown for 300 ms) which resulted in a substantially higher error rate

for the WIT (M = 33.9%) compared to the FPST (M = 13.8%) and the IAT (M = 12.6%). To improve

comparability between indirect measures, we aim to have similar error rates for participants across

measures and thus adjusted the response time limit to 700 ms for the WIT. This preliminary data was not

included in further analysis.

271   ***First-Person Shooter Task***. Participants completed an adapted version of the FPST (Correll et al.,

272   2002, 2014; Unkelbach et al., 2008). Participants were instructed to "shoot" or "don't shoot" as quickly

273   and accurately as possible an image of a Black male face, a White male face, or the outline of a face as a

274   neutral image, that was paired with either a gun ("armed") or tool ("unarmed") target object. The target

275   object was displayed on either the left or right side of the face with its handle pointing towards the face.

276   In each trial, participants were presented with a fixation cross (500 ms), a face image and target object

277   presented simultaneously at one of nine random positions on the screen (700 ms), and a feedback

278   screen (1000 ms). On practice trials, participants received the following feedback: 'correct!', 'false!', 'too

279   slow!'. Slow responses were operationalized as response made 700 ms or more after the onset of the

280   target object with the face image. On experimental trials, participants only received feedback if their

281   response was too slow. Participants first completed 20 practice trials containing only neutral face

282   outlines as face images, half of which were paired with a gun target and half of which were paired with a

283   tool target. Next, participants completed 240 experimental trials with 80 trials for each face race by

284   target object combination in random order. Participants had two self-paced breaks after 80 and 160

285   trials.

286   ***Implicit Association Test***. Participants completed an adapted version of the IAT (Greenwald et al.,

287   1998). Participants were instructed to categorize as quickly and accurately as possible target objects (a

288   gun or a tool) and face images (a Black male face, a White male face, or a neutral face outline). In each

289   trial, participants were presented with a fixation cross (500 ms), a target object or face image (700 ms),

290   and a feedback screen (1000 ms), each presented in the center of the screen. On practice trials,

291   participants received the following feedback: 'correct!', 'false!', 'too slow!'. Slow responses were

292   operationalized as responses made 700 ms or more after the onset of the target object or face image. On

293   experimental trials, participants only received feedback if their response was too slow. In each trial, key

294   assignments for the categories (target objects: "gun"/"tool"; race categories: "Black"/"White"/"neutral")

295   were continuously displayed on the left or right lower corner on screen. In total, the IAT consisted of 13

296   blocks, seven practice blocks with 20 trials and six experimental blocks with 40 trials each. The first

297   practice block consisted of learning the assignment of the target objects *gun* and *tool* to the left or right

298   response key. Next, each of the three combinations of face image category pairings (Black versus White

299   male faces; Black male faces versus neutral outline; White male faces versus neutral outline) were

300   presented in a grouping of four blocks. These four blocks each consisted of a practice block in which

301   participants learned the assignment of the race categories to the left and right response keys, an

302   experimental block combining target objects and face images, a practice block with reversed assignment

303   of the race categories to the response keys, and an experimental block combining target objects and face

304   images with reversed key assignment for the face images. The order of key pairings for target objects

305   with race categories was randomized within each race category pairing. The four blocks of each race

306   category pairing were presented in a random order for each participant.

307   **Materials**

308   Each indirect measure included the same stimulus material taken from Rivers (2017) and Phills et

309   al. (2011) and were displayed with a 300 × 300-pixel resolution. Face primes consisted of 24 Black male

310   faces, 24 White male faces, and one neutral image of the outline of a face. Target objects consisted of 5

311   drawings of guns and of 5 tools presented horizontally.

312   **Results**

313   **Data pre-processing**

314   Prior to all analyses, we excluded trials with latencies <100 ms and >1700 ms, resulting in

315   exclusion of 1.05% of trials. The indirect measures were presented in random order for each participant

316   to rule out order effects. We first analyzed error rates, correct response times, and PDP parameters from

317   the three indirect measures. In a second exploratory set of analyses, we investigated whether the order

318   in which participants completed the measures affected PDP parameters.

319   **Error rates analysis[8]**

320   Figure 2 shows the error rates of all three indirect measures by race and target. A 3 (task) × 3

321   (race) × 2 (target) mixed analysis of variance (ANOVA) with Greenhouse-Geyser correction on the error

322   rates yielded a main effect of measure $F(1.68, 622.45) = 60.75$, $p < .001$, $\eta_p^2 = .141$, which indicates that

323   error rates varied across measures. To investigate these differences, we used paired t-test comparisons.

324   The WIT had a significantly higher error rate ($M = 14.0\%$, $SD = 9.4$) than the FPST ($M = 11.1\%$, $SD = 6.9$),

325   $t(371) = 6.37$, $p < .001$, $d_z = 0.25$, and the IAT ($M = 9.7\%$, $SD = 5.2$), $t(371) = 9.92$, $p < .001$, $d_z = 0.38$. The

326   FPST had a significantly higher error rate than the IAT, $t(371) = 5.01$, $p < .001$, $d_z = 0.17$.

327   The ANOVA also yielded the expected race × target interaction, $F(1.96, 726.08) = 63.08$, $p < .001$,

328   $\eta_p^2 = .145$, indicating that error rates for each target type varied as a function of race. A three-way

329   interaction also emerged, $F(3.71, 1374.92) = 3.53$, $p = .009$, $\eta_p^2 = .009$, indicating that the racial bias effect

330   varied across measures. Nevertheless, analyzing each measure separately, the race by target interaction

331   remained significant for all three measures: WIT $F(1.86, 690.93) = 26.53$, $p < .001$, $\eta_p^2 = .067$, FPST $F(1.98,$

332   $735.68) = 17.56$, $p < .001$, $\eta_p^2 = .045$, and IAT $F(1.98, 735.79) = 38.13$, $p < .001$, $\eta_p^2 = .093$.

---

[8] We report means, standard deviations and further statistical analysis of error rates and correct

response times in the supplement.
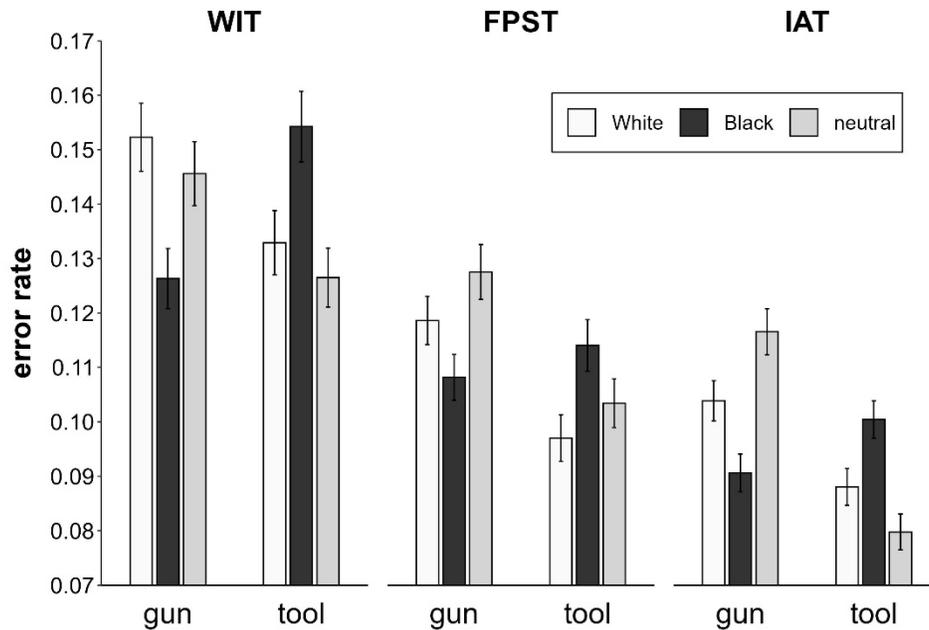
333

334   **Figure 2.** Error rates of the three indirect measures by race and target. WIT = Weapon Identification

335   Task, FPST = First-Person Shooter Task, IAT = Implicit Association Task. Error bars represent one standard
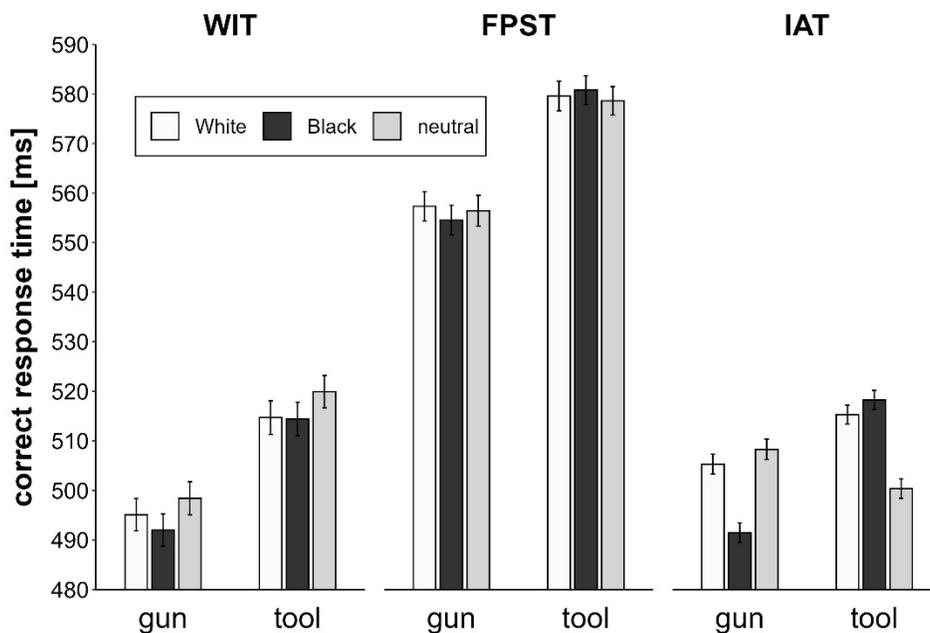
336   error.

337   To investigate correspondence between racial bias estimates, we analyzed the correlations

338   between summary statistics of accuracy as proxies for racial bias. To do so, we operationalized racial bias

339   as the difference between errors for gun and tool targets for each face type. Specifically, we calculated

340   Black versus White accuracy bias as: ((errors(tool|Black) – errors (gun|Black)) – ((errors (tool|White) –

341   errors (gun|White)). Conceptually replicating previous research, accuracy-based racial bias estimates

342   correlated significantly between the WIT and FPST (r = .18, p < .001), but not between the WIT and IAT (r

343   = .06, p = .27) or between the FPST and IAT (r = .02, p = .77).

344   **Correct response time analysis**

345   Figure 3 shows the correct response times (RT) of all three indirect measures by race and target.

346   A 3 (task) × 3 (race) × 2 (target) mixed analysis of variance (ANOVA) with Greenhouse-Geyser correction

347   on the correct RTs yielded a main effect of measure $F(1.59, 591.06)$ = 426.02, p <.001, η_p^2 = .535, which

348   indicates that correct RTs varied across measures. To investigate these differences, we used paired *t*-test

349   comparisons. The FPST had significantly slower mean correct RTs (*M* = 567.8ms, *SD* = 182.7) than the

350   WIT (*M* = 505.9ms, *SD* = 168.8), $t(371)$ = -22.84, *p* <.001, d_z = -1.01, and the IAT (*M* = 506.4ms, *SD* =

351   105.4), $t(371)$ = -61.41, *p* <.001, d_z = -1.13. However, mean correct RTs for the WIT and IAT were similar,

352    $t(371)$ = 0.26, *p* <.001, d_z = 0.01.

353   The ANOVA also yielded the expected race × target interaction, $F(1.99, 736.93)$ = 34.07, *p* <.001,

354   η_p^2 = .084, indicating that correct RTs for each target type varied as a function of race. A three-way

355   interaction also emerged, $F(2.90, 1445.95)$ = 25.33, *p* <.001, η_p^2 = .064, indicating that the racial bias

356   effect varied across measures. Analyzing each measure separately showed that the race by target

357   interaction is only significant for the IAT: WIT $F(1.99, 738.36)$ = 0.57, *p* = .565, η_p^2 = .002, FPST $F(2.00,$

358    $740.76)$ = 1.25, *p* = .286, η_p^2 = .003, and IAT $F(1.99, 737.35)$ = 101.70, *p* <.001, η_p^2 = .215.

359

360   **Figure 3.** Correct response times of the three indirect measures by race and target. WIT = Weapon

361   Identification Task, FPST = First-Person Shooter Task, IAT = Implicit Association Task. Error bars represent

362   one standard error.

363   To investigate correspondence between racial bias estimates, we analyzed the correlations

364   between summary statistics of correct RTs as proxies for racial bias. Similarly to above, we

365   operationalized racial bias as the difference between correct RTs for gun and tool targets for each face

366   type, i.e.,: ((RT(tool|Black) – RT (gun|Black)) – ((RT (tool|White) – RT (gun|White)). Correct RT-based

367   racial bias estimates correlated significantly between the WIT and FPST (r = .15, p = .004), but not

368   between the WIT and IAT (r = .02, p = .63) or between the FPST and IAT (r = .01, p = .80).

369   **Multinomial processing tree estimation**

370   ***Modeling procedure***. We used the hierarchical, latent-trait MPT modeling approach of Klauer

371   (2010) as a framework for all analyses. To assess goodness-of-fit, we used Bayesian posterior predictive

372   *p*-values corresponding to the test statistics T_1 and T_2 (Klauer, 2010; Klauer et al., 2015). A *p* >.05 reflects

373   no credible difference between observed and predicted frequencies and can be interpreted as evidence

374   that model assumptions are in line with the observed data (Klauer, 2010; Klauer et al., 2015).

375   We used the R package TreeBUGS (Heck et al., 2018) to fit the hierarchical latent-trait MPT with

376   default priors. We used the Markov Chain Monte Carlo algorithm for three independent estimation

377   chains with 1,000,000 iterations each, of which 250,000 were removed as a burn-in period. Every 500th

378   iteration was retained to compute summary statistics.

379   ***Joint modeling across indirect measures***. We conducted a joint MPT-model estimation which

380   applied the PDP to each indirect measure (PDP-joint model). This approach allows us to estimate PDP

381   parameters and their correlations within and between measures in one modeling step. We specified one

382   Controlled parameter for each measure and three Automatic parameters for each race condition within

383   each measure.

384   The Rubin-Gelman statistic was smaller than $\hat{R}$ < 1.05 for all parameter estimates, indicating

385   acceptable convergence of estimation chains. The PDP-joint model fit the data well, *p(T_1) = .08, p(T_2) =*

386   *.45.* We report Controlled and Automatic process parameter estimates, racial bias estimates quantified

387 **Table 2**

388 *Mean parameter estimates and intercorrelations for PDP-joint model.*

Parameter	Mean	95%-BCI	1	2	3	4	5	6	7	8	9	10	11	12	13	14
WIT																
1. C	.75	[.73 – .77]														
2. A_B	.54	[.53 – .56]	-.13													
3. A_W	.46	[.44 – .48]	-.06	.15												
4. A_N	.46	[.44 – .48]	-.04	**.43**	**.51**											
5. ΔA_{BW}	.08	[.05 – .12]	-.03	**.61**	**-.69**	-.16										
FPST																
6. C	.80	[.78 – .81]	**.56**	-.18	-.12	-.05	-.03									
7. A_B	.51	[.48 – .53]	-.13	**.65**	**.31**	**.56**	**.22**	-.09								
8. A_W	.43	[.41 – .46]	-.10	**.54**	**.62**	**.71**	-.10	**-.21**	**.64**							
9. A_N	.44	[.41 – .46]	**-.18**	**.46**	**.51**	**.70**	-.07	-.08	**.65**	**.76**						
10. ΔA_{BW}	.07	[.05 – .10]	-.03	.10	**-.37**	-.19	**.38**	.14	**.39**	**-.44**	-.15					
IAT																
11. C	.82	[.81 – .83]	**.52**	-.08	.08	.02	-.12	**.65**	-.10	-.08	.02	-.02				
12. A_B	.53	[.51 – .55]	.18	**.38**	**.40**	**.46**	-.04	.24	**.47**	**.43**	**.39**	.03	.20			
13. A_W	.46	[.43 – .48]	-.13	**.34**	**.56**	**.47**	-.20	-.16	**.44**	**.50**	**.43**	-.09	-.02	.36		
14. A_N	.41	[.38 – .43]	-.10	**.46**	**.51**	**.56**	-.07	**-.23**	**.56**	**.64**	**.63**	-.10	.05	.32	**.55**	
15. ΔA_{BW}	.08	[.05 – .11]	**.26**	-.02	-.22	-.08	.16	**.34**	-.05	-.14	-.10	.11	.18	.44	**-.65**	-.26

389 *Note.* Correlations are calculated on the probit scale. Correlations in bold indicate that the 95% BCI of the correlation coefficient does not contain

390 zero. BCI = Bayesian Credibility Interval. *C* = Controlled process parameter, *A* = Automatic process parameter, *B* = Black, *W* = White, *N* = neutral.

391 Racial bias estimate: $\Delta A_{BW} = A_B - A_W$.

392   as the difference between Automatic process parameters for Black versus White targets, and their

393   correlations in Table 2.

394   Bayesian hierarchical latent-trait MPT models provide posterior distributions of their parameter

395   estimates. We can use these posterior estimates to calculate differences between parameters and

396   correlations which have not already been estimated by the MPT modeling procedure. In addition, we can

397   estimate Bayes factors for parameter differences and their correlations using the Savage-Dickey density

398   ratio test (Wagenmakers et al., 2010), which compares the posterior and prior density at null value of the

399   null hypothesis (i.e., 0 to indicate no differences and zero correlations). Bayes factors quantify the

400   likelihood of one hypothesis versus another, so in this context BF_{10} quantifies the likelihood of the

401   alternative hypothesis compared to the null hypothesis. Following Jeffreys' (1961) Bayes factor

402   interpretation scale, $BF_{10} = 3 - 10$ reflects moderate, $BF_{10} = 10 - 30$ reflects strong, $BF_{10} = 30 - 100$

403   reflects very strong, and $BF_{10} > 100$ reflects extreme evidence for the alternative hypothesis. Conversely,

404    $BF_{10} = 0.10 - 0.33$ reflects moderate, $BF_{10} = 0.03 - 0.10$ reflects strong, $BF_{10} = 0.01 - 0.03$ reflects very

405   strong, and $BF_{10} < 0.01$ reflects extreme evidence for the null hypothesis. In the following, we provide

406   Bayes factors when we investigate parameter differences and their correlations.

407   ***Racial bias estimates across indirect measures.*** The racial bias estimate for Black versus White

408   male faces in the PDP is reflected in the difference between Automatic process parameters for Black

409   versus White faces: $\Delta A_{BW} = A_B - A_W$. We operationalize racial bias in this way analogously to how racial

410   bias has been quantified before (e.g., Payne, 2005; Ito et al., 2015). We report mean values, their 95%

411   Bayesian Confidence Intervals (BCIs), and Bayes factors comparing the alternative hypothesis of a

412   credible difference ($\Delta A_{BW} \neq 0$) to the null hypothesis of no difference ($\Delta A_{BW} = 0$) using a weakly

413   informative prior for the difference between normally distributed variables $N(0,2)$.[9]

414   Positive ΔA_{BW} values (Table 2) with 95% BCIs that do not contain zero emerged for all three

415   indirect measures, with Bayes factors suggesting extreme evidence for the alternative hypothesis of a

416   credible difference: WIT (ΔA_{BW} = .08 [.05 − .11], $BF_{10} > 100$), FPST (ΔA_{BW} = .07 [.05 − .10], $BF_{10} > 100$), and

417   IAT (ΔA_{BW} = .08 [.05 − .11], $BF_{10} > 100$). Thus, all three indirect measures indicate that threatening objects

418   (i.e., guns) are credibly associated more strongly with Black than White male faces.

419   To get a better understanding of the nature of racial bias in these indirect measures, we used

420   Automatic process parameters estimated from the face outline stimuli (A_N) as a neutral reference against

421   which to interpret participants' response tendency towards guns versus tools. For the WIT, the response

422   tendency to respond "gun" was credibly higher for Black than neutral faces ($\Delta A_{BN} = A_B - A_N$ = .08 [.05 −

423   .11], $BF_{10} > 100$), but not different from neutral for White faces ($\Delta A_{WN} = A_W - A_N$ = -.001 [-.03 − .03], BF_{10} =

424   0.02). The same pattern emerged for the FPST, such that the response tendency to respond "gun" was

425   credibly higher for Black than neutral faces (ΔA_{BN} = .07 [.04 − .10], $BF_{10} > 100$), but not different from

426   neutral for White faces (ΔA_{WN} = -.004 [-.03 − .02], BF_{10} = 0.02). The IAT demonstrated a different pattern

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[9] We conducted the Savage-Dickey ratio test for MPT parameters on the probit scale to ensure normal

distribution of parameters. The default prior distribution of parameters in latent-trait MPT models in

TreeBUGS is a multivariate normal distribution (inverse-Wishart) reflecting a weakly informative prior

which also allows for correlations between parameters. However, to approximate the role of this weakly

informative prior distribution we choose N(0,2) as a weakly informative prior for parameter differences

based on the assumption that the difference between two weakly informative normally distributed

parameter priors with N(0,1) results in N(0,2) for their difference: N(0,1) − N(0,1).

427   of results, such that the response tendency to respond "gun" was credibly higher for both Black (ΔA_{BN} =

428   .13 [.10 − .16], BF_{10} > 100) and White faces (ΔA_{WN} = .05 [.02 − .08], BF_{10} = 4.42) than for neutral. Taken

429   together, in all three measures Black faces are more strongly associated with threat than is the neutral

430   face outline. However, only in the IAT White faces are more strongly associated with threat than is the

431   neutral face outline.

432   To further investigate racial bias in the IAT against the baseline of the neutral face outline, we

433   exploratorily estimated a PDP model specified with Automatic process parameters for each IAT block

434   combination of face-image category pairings (i.e., Black versus White male faces; Black male faces

435   versus neutral outline; White male faces versus neutral outline) and target type (object versus face).[10]

436   This model specification positions us to compare two different operationalizations of racial bias. The first

437   operationalization reflects how IAT bias is traditionally conceptualized and is based on the difference

438   between Automatic process parameters for the IAT block directly contrasting Black and White faces. We

439   found a credible racial bias estimate larger than zero for both target types (objects: ΔA_{BW} = .14 [.07 −

440   .20], BF_{10} > 100; faces: ΔA_{BW} = .12 [.06 − .19], BF_{10} = 18.92). The second operationalization conceptualizes

441   bias against a neutral standard and is based on the difference between Automatic process parameters

442   for the two IAT blocks directly contrasting the Black or White face with the neutral face outline (i.e., the

443   difference between the Automatic process parameters of the Black faces from the Black versus neutral

444   IAT block and of the White faces from the White versus neutral IAT block). We found a racial bias

445   estimate that was not credibly different from zero for either target type (objects: ΔA_{BW} = .01 [-.04 − .06],

446   BF_{10} = 0.03; faces: ΔA_{BW} = .08 [-.01 − .16], BF_{10} = 0.23). This exploratory analysis indicates that racial bias

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[10] We report the full model estimation with model fit, parameter estimates, racial bias estimates, and

correlations in the supplement (Table S9).

447   in the IAT is driven by directly contrasting Black and White race categories (i.e., Black versus White IAT

448   blocks). However, when contrasting either Black or White race categories against the neutral face

449   outline, Black and White faces were similarly strongly associated with threat. Taken together, racial bias

450   only emerges in IAT blocks in which Black and White race categories are directly contrasted, and not in

451   blocks in which either race category is contrasted against the neutral face outline.

452   ***Parameter and racial bias correlations across tasks.*** In the PDP-joint model, Controlled process

453   parameters correlated strongly ($r = .52 - .65$) among indirect measures, indicating that processes that

454   contribute to overall accuracy across measures correspond highly within participants. Automatic process

455   parameters correlated moderately to strongly within measures (WIT: $r = .15 - .51$; FPST: $r = .64 - .76$;

456   IAT: $r = .32 - .55$) and moderately to strongly between WIT and FPST ($r = .31 - .71$), WIT and IAT ($r = .34 -$

457     $.56$), and FPST and IAT ($r = .39 - .64$). This pattern of results indicates that participants' response

458   tendency towards "gun" over "tool" corresponded highly within and across indirect measures.

459   Racial bias estimates (i.e., $\Delta A_{BW} = A_B - A_W$) correlated moderately between the WIT and FPST ($r =$

460     $.38$ [.09. $- .66$]), but not between the IAT and WIT ($r = .16$ [-.19. $- .49$]) or between the IAT and FPST ($r =$

461     $.11$ [-.29 $- .49$]). To quantify the evidence for the correlations, we also computed Bayes factors (BF_{10})

462   comparing the alternative hypothesis ($|r| > 0$) against the null hypothesis ($r = 0$) using an uninformative

463   prior (i.e., a uniform distribution ranging from -1 to 1) for correlations (Guan et al., 2020). Bayes factors

464   indicate moderate evidence for a correlation of racial bias estimates between the WIT and FPST ($BF_{10} =$

465   4.00), but moderate evidence for the null hypothesis for the correlation of racial bias estimates between

466   the IAT and WIT ($BF_{10} = 0.33$) and the IAT and FPST ($BF_{10} = 0.32$).This pattern of results indicates good

467   correspondence between the WIT and FPST in racial bias estimates, but no correspondence in racial bias

468   estimates between the IAT and the other two measures.

469   **Exploring the influence of indirect measure order on PDP parameters**

470   ***Modeling procedure***. We counterbalanced the order in which participants completed indirect

471   measures to minimize the influence of order effects on our primary analyses. Nevertheless, task order

472   may have influenced participants' responses in important ways. With a consent form, three indirect

473   measures, a demographics survey, and debriefing, our study took up to one hour for participants to

474   complete. Thus, one possibility is that participants experienced fatigue on measures they completed

475   later relative to measures they completed earlier in the testing session. Another possibility is that

476   completing the IAT changed participants' responses on measures that came after it. On the WIT and

477   FPST, participants can ignore the face images altogether and make correct responses solely by attending

478   to weapons and harmless objects. In contrast, on the IAT participants must categorize the face images of

479   Black and White men on 50% of trials. Consequently, the IAT uniquely relies on racial categories, and

480   such category salience may carry over to influence participants' responses on subsequent tasks.

481   To investigate the influence of the order in which participants completed the indirect measures

482   on process parameters, we exploratorily estimated two additional PDP-joint models that included

483   measure order as a factorial covariate. The first model (indirect measure order model) estimated a

484   separate PDP parameter for each indirect measure depending on whether it was completed first,

485   second, or third. If participants experienced fatigue – in the form of depleted executive function and/or

486   reduced motivation – as they completed the study, we might expect for Controlled process parameters

487   to be lower on later tasks compared to earlier tasks; however we might expect for Automatic process

488   parameters and/or racial bias estimates (quantified as the difference between Automatic process

489   parameters for Black versus White targets) to be unaffected by potential fatigue effects (Govorun &

490   Payne, 2006).

491   The second model (IAT position model) estimated a separate PDP parameter for each indirect

492   measure depending on whether the IAT was completed first, second, or third. When participants

493   complete the IAT, they are directly instructed to categorize Black and White male faces. In contrast,

494   racial categories are incidental to participants' responses on the WIT and FPST, in which they are

495   instructed to discern whether objects are weapons or tools. Consequently, the IAT may function as a

496   race category salience manipulation, which could boost correspondence of racial bias estimates between

497   the IAT and other measures that participants complete subsequently (Olson & Fazio, 2003). If completing

498   the IAT increases racial category salience, we might expect for racial bias estimates (quantified as the

499   difference between Automatic process parameters for Black versus White targets) to be higher on WITs

500   and FPSTs completed after versus before the IAT. Furthermore – and extending beyond the predictions

501   of the indirect measure order model – we might expect for racial bias estimate correlations among tasks

502   to be stronger when participants completed the IAT first compared to later in the study.

503   We used the same Bayesian hierarchical latent-trait estimation approach here as we did with the

504   PDP-joint model reported above. For both models, the Rubin-Gelman statistic was smaller than $\hat{R} < 1.05$

505   for all parameter estimates, indicating acceptable convergence of estimation chains. Both models fit the

506   data well: indirect measure position model $p(T_1) =. 085$, $p(T_2) = .452$; IAT position model $p(T_1) = .495$,

507    $p(T_2) = .323$.

508   ***Influence of indirect measure position on PDP parameters***. In the indirect measure order model

509   (Table 3), Controlled process parameters were lower for measures that participants completed later in

510   the study. For all three measures, Bayes factors indicate at least strong evidence (all $BF_{10} > 24.40$) that

511   Controlled process parameters are higher for measures completed first versus second or third. For the

512   WIT and FPST the drop happened between the first and second measure, such that Controlled process

513   parameters did not differ between measures completed second versus third. In contrast, for the IAT the

514   drop happened between the second and third measure, such that Controlled process parameters did not

515   differ between measures completed first versus second.

516   Our model produced a total of 27 parameters representing Automatic processes and 3 racial bias

517   estimates. Of those 27 Automatic process parameters, Bayes factors associated with 22 of them (all BF_{10}

518   < 0.22) indicate moderate to strong evidence for the null hypothesis (i.e., that estimates do not vary as a

519   function of measure position). The Bayes factors associated with the remaining 5 tests (BF_{10} between

520   0.34 – 2.94) were equivocal, providing no clear evidence for either the alternative or null hypothesis.

521   Bayes factors for all racial bias estimates (all $BF_{10} < 0.09$) indicate strong evidence for the null hypothesis.

522 **Table 3**

523 *Mean parameter estimates by indirect measure position and Bayes factor for influence of indirect measure position.*

| | position of indirect measure | | | | | | Bayes factor (BF_{10}) of measure position influence | | |
| | 1st position | | 2nd position | | 3rd position | | $1^{st} - 2^{nd}$ | $1^{st} - 3^{rd}$ | $2^{nd} - 3^{rd}$ |
Parameter	Mean	95%-BCI	Mean	95%-BCI	Mean	95%-BCI			
WIT	N = 123		N = 135		N = 114				
1. C	.89	[.82 – .97]	.68	[.61 – .75]	.67	[.60 – .75]	**32.13**	**24.40**	*0.09*
2. A_B	.55	[.47 – .63]	.53	[.45 – .60]	.55	[.48 – .63]	*0.08*	*0.08*	*0.09*
3. A_W	.43	[.35 – .51]	.49	[.42 – .57]	.46	[.38 – .53]	0.13	*0.09*	*0.09*
4. A_N	.53	[.46 – .60]	.43	[.37 – .50]	.41	[.35 – .48]	0.34	0.49	*0.07*
5. ΔA_{BW}	0.12	[0.01 – 0.23]	0.03	[-0.07 – 0.14]	0.10	[-0.01 – 0.20]	*0.09*	*0.06*	*0.07*
FPST	N = 115		N = 126		N = 111				
6. C	.94	[.89 – >.99]	.77	[.72 – .82]	.69	[.64 – .74]	**>100.00**	**>100.00**	0.35
7. A_B	.54	[.45 – .62]	.50	[.43 – .57]	.49	[.42 – .56]	*0.10*	*0.10*	*0.08*
8. A_W	.48	[.40 – .56]	.44	[.37 – .51]	.39	[.32 – .46]	*0.10*	0.19	0.11
9. A_N	.56	[.48 – .64]	.37	[.30 – .45]	.39	[.31 – .46]	2.94	2.44	*0.08*
10. ΔA_{BW}	0.06	[-0.05 – 0.17]	0.06	[-0.04 – 0.15]	0.10	[0.02 – 0.19]	*0.06*	*0.06*	*0.06*
IAT	N = 134		N = 111		N = 127				
11. C	.89	[.85 – .93]	.87	[.82 – .92]	.70	[.66 – .75]	0.11	**>100.00**	**>100.00**
12. A_B	.58	[51. – .66]	.50	[.42 – .58]	.52	[.45 – .58]	0.19	0.14	*0.08*
13. A_W	.53	[.46 – .61]	.44	[.37 – .52]	.39	[.32 – .46]	0.22	1.26	0.12
14. A_N	.38	[.31 – .46]	.45	[.37 – .52]	.39	[.32 – .46]	0.14	*0.08*	0.13
15. ΔA_{BW}	0.05	[-0.05 – 0.15]	0.06	[-0.05 – 0.16]	0.12	[0.03 – 0.22]	*0.06*	*0.09*	*0.06*

524 *Note.* BCI = Bayesian Credibility Interval. *C* = Controlled process parameter, *A* = Automatic process parameter, *B* = Black, *W* = White, *N* = neutral.
525 Racial bias estimate: $\Delta A_{BW} = A_B - A_W$. Bayes factors are quantifying the evidence of the alternative hypothesis, that is a difference ($\Delta \neq 0$) to no
526 difference ($\Delta = 0$) by indirect measure position. Bayes factors (BF_{10}) >10, indicating at least strong evidence for the alternative hypothesis, are in
527 bold. Bayes factors (BF_{10}) <.10, indicating at least strong evidence for the null hypothesis, are in italics.
528

529   Taken together, this model suggests that Automatic process parameters and racial bias estimates

530   did not vary as a function of measure position.

531   Overall, this pattern of results shows that participants' Controlled process parameters decreased

532   over the course of the experiment, which suggests fatigue or decreasing motivation effects. In contrast,

533   Automatic process parameters and racial bias estimates did not vary as a function of measure position,

534   which indicates that response bias and racial bias is not influenced by fatigue or motivation effects.

535   ***Variation in racial bias estimates and their correlations as a function of IAT position.*** In the IAT

536   position model (Table 4) racial bias estimates were similar for the WIT and FPST independent of when

537   participants completed the IAT (all $BF_{10} < 0.17$). Similarly, racial bias estimates for the IAT did not vary as

538   a function of when participants completed it (all $BF_{10} < 0.08$).

539   To investigate the influence of IAT position on racial bias correlations among indirect measures,

540   we transformed correlation estimates using Fisher's z-transformation and tested their difference against

541   zero with a weakly informative prior $N(0,2)$. The size of racial bias correlations between WIT and FPST

542   (IAT-first: $r = .41$ [.06 - .68]; IAT-second: $r = .34$ [-.01 - .65]; IAT-third: $r = .36$ [.03 - .65]) did not vary as a

543   function of when participants completed the IAT (all $BF_{10} < .09$). Similarly, the position in which

544   participants completed the IAT had no influence (all $BF_{10} < 0.07$) on the correlation of racial bias

545   estimates between the IAT and either the WIT (IAT-first: $r = .13$ [-.25 - .49]; IAT-second: $r = .15$ [-.24 -

546   .51]; IAT-third: $r = .17$ [-.18 - .52]) or the FPST (IAT-first: $r = .14$ [-.28 - .52]; IAT-second: $r = .13$ [-.30 - .53];

547   IAT-third: $r = .17$ [-.25 - .55]).

548   Taken together, these results indicate that IAT position does not influence the size of racial bias
549   estimates or their correlations across indirect measures.

550 **Table 4.**

551 *Mean parameter estimates by IAT position and Bayes factor for influence of IAT position.*

	position of IAT						Bayes factor (BF$_{10}$) of IAT position influence		
	1st position (N = 134)		*2nd position (N = 111)*		*3rd position (N = 127)*		*1st – 2nd*	*1st – 3rd*	*2nd – 3rd*
Parameter	*Mean*	*95%-BCI*	*Mean*	*95%-BCI*	*Mean*	*95%-BCI*			
WIT									
1. C	.70	[.62 – .79]	.73	[.64 – .83]	.81	[.72 – .90]	0.13	0.38	0.22
2. A$_B$	.64	[.56 – .71]	.52	[.44 – .60]	.47	[.39 – .55]	0.34	1.79	0.11
3. A$_W$	.51	[.43 – .59]	.43	[.34 – .51]	.43	[.35 – .52]	0.19	0.17	*0.09*
4. A$_N$	.53	[.46 – .60]	.43	[.37 – .50]	.41	[.35 – .48]	*0.08*	0.38	0.61
5. ΔA$_{BW}$	0.12	[0.01 – 0.23]	0.09	[-0.02 – 0.21]	0.04	[-0.08 – 0.15]	*0.06*	*0.09*	*0.07*
FPST									
6. C	.74	[.68 – .81]	.79	[.72 – .86]	.86	[.80 – .93]	0.13	0.92	0.24
7. A$_B$	.53	[.46 – .60]	.51	[.43 – .59]	.48	[.41 – .56]	*0.08*	*0.10*	*0.09*
8. A$_W$	.44	[.37 – .52]	.38	[.30 – .45]	.48	[.40 – .56]	0.15	*0.09*	0.26
9. A$_N$	.41	[.33 – .49]	.42	[.34 – .51]	.47	[.39 – .55]	*0.01*	0.12	0.12
10. ΔA$_{BW}$	0.08	[-0.01 – 0.17]	0.14	[0.04 – 0.23]	0.06	[-0.09 – 0.11]	*0.07*	*0.08*	0.17
IAT									
11. C	.90	[.85 – .95]	.85	[.79 – .91]	.71	[.66 – .76]	0.20	**>100.00**	4.55
12. A$_B$	.60	[.52. – .67]	.49	[.41 – .57]	.51	[.44 – .58]	0.33	0.21	*0.08*
13. A$_W$	.55	[.48 – .62]	.44	[.36 – .51]	.39	[.32 – .46]	0.34	2.10	0.11
14. A$_N$	.40	[.32 – .48]	.43	[.35 – .51]	.39	[.31 – .46]	*0.10*	*0.09*	0.11
15. ΔA$_{BW}$	0.05	[-0.05 – 0.15]	0.05	[-0.05 – 0.16]	0.12	[0.03 – 0.22]	*0.06*	*0.08*	*0.08*

552 *Note.* BCI = Bayesian Credibility Interval. *C* = Controlled process parameter, *A* = Automatic process parameter, *B* = Black, *W* = White, *N* = neutral.

553 Racial bias estimate: ΔA$_{BW}$ = A$_B$ – A$_W$. Bayes factors are quantifying the evidence of the alternative hypothesis, that is a difference (Δ ≠ 0) to no

554 difference (Δ = 0) by indirect measure position. Bayes factors (BF$_{10}$) >10, indicating at least strong evidence for the alternative hypothesis, are in

555 bold. Bayes factors (BF$_{10}$) <.10, indicating at least strong evidence for the null hypothesis, are in italics.

General Discussion

In the present research, we investigated correspondence among three indirect measures of racial bias: the Weapon Identification Task (WIT), the First-Person Shooter Task (FPST) and the Implicit Association Test (IAT). Previous research showing small or null correlations among these measures is confounded by differences in procedures or stimuli. In contrast, we aligned procedures and stimuli across all three measures, allowing them to vary only in structure. With the measures aligned in this way, we found that participants' responses corresponded across measures both in terms of accuracy-oriented controlled responding – replicating previous research – and also in terms of the tendency to respond "gun" versus "tool". That said, racial bias operationalized in terms of differences between Black and White Automatic process parameters did not correspond as consistently across measures: whereas racial bias estimates correlated moderately between the WIT and FPST, racial bias estimates did not correlate between the IAT and the other measures.

Moreover, the present research extends our understanding of racial bias as an individual difference. Indirect measures such as the WIT, FPST, and IAT routinely reveal racial bias effects in the aggregate (Payne et al., 2017; Payne & Correll, 2020), but the extent to which racial bias is a property of individuals has been a matter of considerable debate (e.g., Granados Samayoa & Fazio, 2017; Kurdi & Banaji, 2017). Low correlations among individuals' summary statistics of racial bias across measures along with consistent evidence of group-level racial bias in the aggregate has been interpreted to indicate that the construct assessed by indirect measures is a property of contexts rather than individuals (Payne et al., 2017). However, the high correlations among parameters across measures that we observed in the present research suggests that individuals may be able to rely on the same abilities across tasks - which would indicate that these measures tap into a common underlying construct (e.g., Ito et al., 2015; Olson & Fazio, 2003; Payne et al., 2005). Below we discuss how the patterns of correspondence across indirect measures we identified here provide insight into properties of individuals versus reveal important differences among the tasks themselves.

Correspondence across indirect measures of racial bias

Replicating previous research, Controlled process estimates correlated strongly across all indirect measures. This pattern of results indicates that participants' cognitive control abilities generalize across measures. These findings dovetail with other work showing that the WIT and FPST are related to executive functions like inhibition (Ito et al., 2015; Payne, 2005), and the IAT is related to updating and task switching (Ito et al., 2015; Klauer et al., 2010). Hence, the present research joins a body of literature connecting indirect measures of racial bias with a broad constellation of executive functions and other higher cognitive abilities.

An important finding to emerge from the present research is that Automatic process estimates correlated moderately to strongly across all indirect measures. By aligning measures across procedural features and stimuli and using MPT modeling to disentangle the joint contributions of multiple processes, we showed that the constructs reflected in each of the Automatic process estimates – one for each target group – correspond well across measures. The most straightforward interpretation of the Automatic process parameter is that it reflects participants' preference to respond with gun in comparison to tool. This preference can reflect the threat stereotypes that indirect measures are configured to assess, but it can also reflect recoding (Meissner & Rothermund, 2013), a simple hand-side preference, other dispositional characteristics like a threat-related attention bias driven by anxiety (Bar-Haim et al., 2007), a general threat superiority effect for gun targets (Rivera-Rodriguez et al., 2021; Subra et al., 2018), or guessing. Importantly, our findings show that this response tendency generalizes across indirect measures, which suggests that the preference to respond with gun versus tool may be a property of participants.

Additionally, Automatic process parameters provide insight into racial biases when we compare parameters estimated from trials that include Black versus White faces. Across all measures, participants demonstrated higher Automatic process parameters for "Black" than "White" targets, corresponding with the cultural stereotype of Black men as dangerous – which, in turn, provides a degree of validity

evidence that these measures can assess their intended construct. Nevertheless, future research is

necessary to better understand factors that moderate correspondence among processes that contribute

to racially biased responses on these measures.

Differences between indirect measures of racial bias

Though Controlled and Automatic process parameters correlated moderately-to-strongly across

all indirect measures, correlations between parameter estimates in isolation provide little insight into

the extent to which Black versus White people are differentially stereotyped as threatening. When we

operationalized racial bias as the difference between Black and White Automatic process parameters, we

found a more nuanced pattern of results. Specifically, racial bias operationalized in terms of the

difference between Automatic process parameters correlated moderately between the WIT and FPST,

but not between the IAT and the other two measures.

These findings dovetail with previous work demonstrating correspondence between the WIT and

FPST (Payne & Correll, 2020; Ito et al., 2015). The WIT and FPST are both configured to assess the

influence of race on fast behavioral responses to guns and non-threatening target objects. Furthermore,

both seminal articles introducing these paradigms explicitly refer to the behavior of police officers in

shooting unarmed Black men (Correll et al., 2002; Payne, 2001; Payne & Correll, 2020). Although the

traditional configurations of the WIT and FPST differ in stimulus presentation order (sequential versus

concurrent) and style (e.g., isolated stimulus in the center of the screen versus full-body images with

different backgrounds and different screen positions), they appear to assess similar constructs. In both

measures, participants view pictures of Black and White male faces, but do not need to attend to race –

or to the faces at all – to make a correct response on the WIT (i.e., categorizing "gun", "tool") or the FPST

(i.e., decide to "shoot", "don't shoot"). Interestingly, in the present research, response tendencies

towards the response "gun" were the same between White faces and the neutral face outline but

enhanced for Black faces for both the WIT and FPST. This finding may indicate that only Black faces elicit

an additional response tendency towards "gun", which aligns with claims that the WIT and FPST assess

threat stereotypes based on racial exemplars (Olson & Fazio, 2003; Livingston & Brewer, 2002).

In contrast, lack of correspondence between the IAT and the other two indirect measures may

reflect heightened category salience and direct contrasting of race categories as a function of the

structure of the IAT. Because of its dual-categorization structure, only the IAT requires participants to

attend to race to make a correct response to half of trials (i.e., to face stimuli). Because IAT task

instructions differ from the other two measures in this regard, they may lead participants to rely on

response strategies that are otherwise unnecessary or irrelevant on the other two measures. For

example, recoding is a task-simplification strategy by which participants can conceptually reduce the IAT

from four categories to two. Recoding guns and Black male faces into a single "threatening" category,

and recoding tools and White male faces into a single "non-threatening" category, simplifies the IAT to a

binary decision: threatening or not? Such simplification might be easier for one IAT block type (e.g.,

Black-guns) compared to the other block type (e.g., Black-tools), resulting in less errors in one than the

other, which itself represents a racial bias effect (Meissner & Rothermund, 2013). In the PDP, these

recoding effects would map on the Automatic process parameter together with other stereotype

influences.[11] Response strategies based on race categories may explain the observed Automatic process

parameter pattern for the three different IAT block pairings (i.e., Black versus White male faces; Black

versus neutral outline; White male faces versus neutral outline). Whereas the IAT block directly

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[11] Meissner and Rothermund (2013) implemented the ReAL model as MPT model which estimates the

contribution of recoding along with controlled and automatic processes to IAT responses. However, the

ReAL model is tailored to the IAT and requires specific procedures to produce valid parameter estimates

(Calanchini et al., 2021).

contrasting Black and White faces produced the expected racial bias effect (i.e., stronger threat

stereotypes for Black than White male faces), Black and White faces both elicited a threat response

tendency in blocks contrasted with the neutral face outline. This pattern of results suggests that male

faces in general (i.e., the superordinate category shared by both Black and White face stimuli) are

perceived as more threatening than the neutral face outline. Thus, our findings would seem to align with

other researchers who conclude that the IAT assesses threat stereotypes based on racial categories (De

Houwer, 2001; Olson & Fazio, 2003).

Overall, all three of the indirect measures we investigated in the present research appear to

assess racial stereotypes linking Black versus White male faces with threat. However, task specific

procedural differences may play a large role in racial bias expression even when measures are aligned on

several procedural dimensions (i.e., stimuli material, trial number, response time). Consequently, each

indirect measure may reflect a specific facet of racial bias. As a sequential-priming task, the WIT taps into

the early interference of threat-stereotypes in object identification (Klauer & Voss, 2008; Laukenmann et

al., 2023; Payne et al., 2005). In contrast, the FPST assesses the behavioral decision to "shoot" or "don't

shoot" at an armed or unarmed person, which ties the behavioral decision of target object identification

to the person holding it (Correll et al., 2015). The IAT, in its dual-categorization structure, explicitly

contrasts the two reference group categories, which may highlight racial categories in participants'

responding (De Houwer, 2001; Meissner & Rothermund, 2013). Hence, these measures would seem to

tap into different aspects of racial bias.

Summary statistics of racial bias versus MPT model parameters

Racial bias effects emerged across all three indirect measures in terms of accuracy-based

summary statistics, such that all three indicate that guns are associated more strongly with Black than

White male faces in our sample of participants. However, these accuracy-based summary statistics only

corresponded weakly between the WIT and FPST, and not between the IAT and the other two measures.

Latency-based summary statistics revealed a racial bias effect only for the IAT, but the pattern of

correlations among measures was similar to what we observed with accuracy-based summary statistics, such that the WIT and FPST corresponded weakly with each other but not at all with the IAT.

In contrast, MPT modeling revealed correspondence among processes across measures, such that both Controlled and Automatic process parameters correspond well with conceptually analogous parameters across measures. In addition, racial bias estimates operationalized in terms of differences between model parameters correlated moderately between the WIT and FPST, demonstrating that MPT modeling can reveal a stronger correspondence between measures that summary statistics may otherwise obscure. Additionally, model-based analyses localized fatigue effects on Control process parameters, with Automatic parameters remaining consistent across measures. This finding aligns with previous research demonstrating that Control, but not Automatic process parameters and their derived racial bias estimates, may be tempered by prior mental exertion (Govorun & Payne, 2006). Taken together, the present research highlights one way in which summary statistics of racial bias can belie process-level relationships, and at the same time demonstrates the value of the theoretical precision provided by MPT models.

Limitations

Despite the strengths of the present research, it is also limited in some ways. For example, to test our primary research question about correspondence among indirect measures of racial bias, we aligned all three in terms of stimuli and procedural features. Such alignment positioned us to make apples-to-apples comparisons across measures. However, this comparability came at the cost of modifying these measures from their traditional form, which may affect the generalizability of our findings to how most researchers use these measures.

With that said, readers interested in the extent to which the traditional versions of the WIT, FPST, and IAT correspond with each other can consult Ito et al. (2015), who examined that very question. Moreover, though we did not rely on traditional versions of each of these measures in the present research, we varied them all on procedural dimensions that have varied in previous research. Indeed,

aligning measures on these dimensions allowed us to control for potential confounding stimuli effects

(Correll et al., 2002; 2011) and to obtain comparable levels of error rates (Ito et al., 2015).

Even what is arguably the biggest procedural change we implemented in the present research –

the inclusion of the neutral face outline along with Black and White faces – has precedent in this

literature (Rivers, 2017). The inclusion of a neutral face outline did not change the traditional structure of

the WIT or FPST, but it did change the structure of the IAT because it required additional sets of blocks

(i.e., Black/White, Black/neutral, White/neutral). However, this expanded IAT format closely aligns with

an existing version of the IAT: the multi-category IAT (Axt et al., 2014). Moreover, the expected bias

effects – indicating stronger threat stereotypes for Black versus White men – emerged across all three

measures, which suggest that these changes did not significantly alter the measures. Nevertheless,

previous research has demonstrated that task procedures (such as number of trials) affect the extent to

which different cognitive processes influence responses on indirect measures of racial bias (Calanchini et

al., 2021), so future research should continue to investigate the role of stimulus and structural effects in

indirect measures of racial bias.

Conclusion

The present research makes two key contributions to social cognition literature. The first

contribution is in demonstrating that three commonly used indirect measures of racial bias correspond

well on controlled responding and automatic response tendencies when procedurally aligned. The

second contribution is that racial bias may only correspond moderately across measures, suggesting that

each of these measures may assess specific aspects of racial threat stereotypes. Taken together, this

work offers a useful template for future researchers who seek to incorporate multiple

operationalizations of racial bias in their work and gain theoretically precise insight into the processes

that contribute to responses on indirect measures of racial bias.

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