Psychological Discrepancy in Message-Induced Belief Change:

Empirical Evidence Regarding Four Competing Models

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Abstract

Message discrepancy is the difference between the position of an advocated belief in a message and the position of a message receiver's initial belief, and psychological discrepancy is how the message's discrepancy is perceived by the receiver. The present study tests Fink et al.'s (1983) psychological discrepancy model plus three other models to determine whether psychological discrepancy affects the weight of a message, the scale value of the message, neither, or both. These models were tested in an experiment that manipulated psychological discrepancy with a 3 (high vs. moderate vs. low message scale value) × 3 (wide vs. moderate vs. narrow perspective) between-subjects design (N = 448). The original Fink et al. model was the most supported. These results help explain how psychological processes bring about belief change.

Keywords: belief change, discrepancy, scale value, weight, information integration, mathematical modeling

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The study of persuasion has been concerned with how attitudes, beliefs, and behaviors are formed, changed, or reinforced through communication (Miller, 2012; O'Keefe, 1990). Many theories and models have been proposed and have tested persuasion processes (Dillard & Shen, 2012; Eagly & Chaiken, 1993). The discrepancy model of belief change (Fink & Cai, 2012; Kaplowitz & Fink, 1997) is a parsimonious mathematical model that explains and predicts how a message's discrepancy affects the amount of induced belief change. In 1983, *Communication Monographs* published an article by Fink et al. that examined the role that psychological discrepancy played in persuasion. As we approach the fortieth anniversary of that publication, we delved more deeply into that persuasion process.

Message discrepancy is the difference between the position of an advocated belief in a message and the position of a message receiver's initial belief. As message discrepancy increases, belief change may increase linearly (Anderson, 1981), increase with a decelerating rate (Chung et al., 2008; Laroche, 1977), or increase and then decrease, so that the relationship between message discrepancy and belief change is an inverted-U (Aronson et al., 1963; Bochner & Insko, 1966; Chung et al., 2008; Fink et al., 1983; Freedman, 1964).

The other two key constructs in the discrepancy model are the weight, w, and the scale value, s, of a message, as provided by information integration theory (IIT; Anderson, 1981). We introduce the connection between discrepancy models and IIT's weighted averaging model, as well as why the construct of weight is necessary, in Online Supplemental Material 1. Conceptually, in message-induced belief change, weight represents the importance of an incoming message or the importance of a person's prior beliefs (Himmelfarb, 1975).[1]

The distinction between the conceptual meanings of weight and scale value can be stated as follows. In the most general sense, the scale value and the weight of a message captures the aspect of *what is said* (s) and the aspect of *how it is said* (w), respectively; the scale value and the weight of a person's *initial* belief (assuming that there is an initial belief on some topic) refer to *what this person believes about a topic* (s_0) and *how strong this belief is* (w_0). The conceptual distinction between weight and scale value enables a communicator to target different components in belief change. For example, based on IIT's weighted averaging model (see Online Supplemental Material 1), with the same message scale value, a message that has high source credibility may induce more belief change than a message that has low source credibility. In other words, the high-credibility message is more effective, because its weight is more massive than the low-credibility message (Kaplowitz & Fink, 1997, p. 77).

To further examine the possible inverted-U-shaped relationship between message discrepancy and amount of belief change, Fink et al. (1983) proposed the psychological-discrepancy-discounting model (the PDD model), which introduced *psychological discrepancy* as a receiver's *perception* of the difference between the advocated belief in a message and the receiver's initial belief. Although the PDD model effectively predicted belief change, ambiguity remained about the psychological mechanism involving psychological discrepancy in belief

[1] Although we use importance to define weight here, the psychological meanings of weight have been related to various concepts in different studies. For an incoming message, those concepts include a message's salience, relevance (Anderson, 1981), "amount of information" (Anderson, 2008, p. 43; Saltiel & Woelfel, 1975), and informativeness (Fiske, 1980). The message weight can also be operationalized as message evaluation (Cacioppo et al., 1983; Eagly & Telaak, 1972), attention (Fiske, 1980; Meffert et al., 2006), and perceived importance (Anderson & Alexander, 1971; Zalinski & Anderson, 1989). Because these concepts are all expected to facilitate belief change, we use them to operationalize the weight construct in our experiment (see the Method section later in this manuscript for detail). For a person's prior beliefs before message receipt, weight represents the strength (Anderson, 2008; Chung et al., 2012) or the certainty (Petty et al., 2007) of a person's pre-existing beliefs.

change. It has been unclear whether psychological discrepancy affected only the weight of a message, only the scale value of the message, neither, or both. The present research addresses this question and provides empirical evidence regarding how psychological discrepancy affects belief change by experimentally testing four mathematical models.

We begin this article by explaining the PDD model (Fink et al., 1983). Next, we present the functional forms and the underlying psychological processes of our four models: Each model corresponds to one of four assumptions about the role of psychological discrepancy. From these models we derived competing hypotheses. The method and results present the detailed test of these four models. Finally, we conclude with a discussion of the theoretical, methodological, and practical implications of the findings from this study. A notation glossary is provided in Online Supplemental Table 1.

Model Assumptions, Functional Forms, and Hypotheses

The Original Model: Fink et al. (1983)

The predicted nonlinear relationship between message discrepancy and belief change may have different functional forms. The relationship may be increasing and decelerating, or it may have an inverted-U shape (Aronson et al., 1963; Bochner & Insko, 1966; Chung et al., 2008; Fink et al., 1983; Freedman, 1964; Laroche, 1977; see Fink & Cai, 2012, and Kaplowitz & Fink, 1997, for a thorough discussion). Several theoretical approaches accounted for this nonlinear relationship. The social judgment approach (Sherif & Hovland, 1961) stated that an extremely discrepant message would be perceived by a message receiver as more psychologically discrepant than it actually was (i.e., a contrast effect) and therefore it would be less persuasive. The cognitive dissonance approach (Aronson et al., 1963) stated that, in an ordinary lab setting, a subject should disparage the message (i.e., reduce the importance of the message) in order to reduce the dissonance generated by an extremely discrepant message (see also Bochner & Insko, 1966, p. 614). Information integration theory (IIT; Anderson, 1981) stated that a message receiver assigned less weight to a message due to less attention paid to it or due to its inconsistency with prior beliefs. Among the above theoretical accounts, only IIT provided a general approach that examined persuasion using mathematical models. Unlike some theories of persuasion in which propositions about the relationship between concepts were stated verbally, the significance of using a mathematical model was to state the model's assumptions explicitly, to derive hypotheses symbolically, and to make precise predictions (Kaplowitz et al., 1983; see also Hunter et al., 1984).[2]

Building on IIT's weighted averaging model, Fink et al.'s (1983) PDD model made a conceptual distinction between message discrepancy and psychological discrepancy (i.e., the level of discrepancy as *experienced* by a message receiver) by assuming that the same level of message discrepancy could be experienced differently. These researchers proposed that, even while keeping message discrepancy constant, as a message receiver's psychological discrepancy increases, the receiver would discount the message weight more, which lessened the effectiveness of the message. Fink et al.'s PDD model (Fink et al., 1983) stated that

$$\tilde{R} = \frac{w_0 s_0 + w\Delta(\psi)s}{w_0 + w\Delta(\psi)}, \text{ and} \tag{1}$$

[2] Earlier theoretical accounts also included the cognitive response approach (Brock, 1967), which posited that a message receiver should generate more counterarguments to a highly discrepant message than to a moderately discrepant one, which reduced the change induced by an extremely discrepant message. This theoretical proposition was inconsistent with later evidence showing that discrepancy did not correlate with the number of generated counterarguments (Kaplowitz & Fink, 1991). This evidence suggested that cognitive elaboration was not involved in the effect of discrepancy on final position. However, when participants were given a longer time to think about their final positions, a positive and significant correlation between discrepancy and number of counterarguments was found (Kaplowitz & Fink, 1997, p. 92). This finding suggested that the effect of discrepancy on final position could be switched from peripheral processing to central processing so that cognitive responses could be activated. For our purpose, because our study design aligned more with the design by Kaplowitz and Fink (1991), where participants were not given extra time to think about their final positions, we assumed that cognitive elaboration was not involved in the effect of discrepancy on final position in our study.

$$\Delta(\psi) = e^{-\gamma\psi} \text{ (Fink et al., 1983, p. 418),} \tag{2}$$

where $\hat{R}$ is the reported final position in equilibrium after message receipt, s_0 is the initial position, s is the advocated position ($\hat{R}$, s_0, and s assumed to be on the same unidimensional scale), w_0 is the weight of the initial position, and w is the weight of the advocated position, $\Delta(\psi)$ is a function of ψ, and ψ represents psychological discrepancy.[3, 4] In Equation 1, the relationship between s and $\hat{R}$ is an inverted-U shape (Fink et al., 1983). In Equation 2, γ is a parameter that affects the rate of change in $\Delta(\psi)$ with respect to ψ. Equation 2 shows an exponential decay function assuming $\gamma > 0$, which indicates that as ψ increases, $\Delta(\psi)$ decreases, with γ being a constant.[5] Given this exponential decay function and the term $w\Delta(\psi)$ in Equation 1, Fink et al. (1983) assumed that an increased level of ψ would discount the weight (importance) of a message, while the message scale value remained constant.

Based on Ostrom and Upshaw's (1968) perspective theory, to manipulate psychological discrepancy (ψ), Fink et al. (1983) manipulated the order of an extremely discrepant message and a moderately discrepant one. They hypothesized that by presenting an extremely discrepant message prior to a moderately discrepant message, the psychological discrepancy of the moderately discrepant message would be reduced. In other words, a moderately discrepant message would be perceived as less discrepant if presented *after* an extremely discrepant

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[3] This manuscript focuses on *static* belief change models rather than on a *dynamic* model (Chung et al., 2008). In a dynamic model, which examines belief change over time, after message receipt, a person's belief position can move toward an equilibrium position, with possible oscillation (i.e., oscillating with overdamped, critically damped, or underdamped motion; Kaplowitz et al., 1983). Here we assume that when a person's belief position after message receipt is measured, the person's belief position has reached a new equilibrium position. Time and oscillation are beyond the scope of this manuscript.

[4] The symbol e represents a transcendental number that may be defined as the limit of $(1 + 1/x)^x$ as x approaches infinity; $e = 2.71828\ldots$, and it is the base of natural logarithms.

[5] γ can be estimated in a nonlinear regression analysis based on data. In Fink et al. (1983, pp. 426-428), γ was estimated to be 0.004 (SE = 0.003) in their single-message condition, and 0.015 (SE = 0.004) in their double-message condition.

message than if it were presented alone. Further, the extreme-then-moderate order should generate more belief change than the moderate-then-extreme order. Fink et al.'s (1983) findings supported these hypotheses regarding psychological discrepancy. Their critical statistical test was a comparison of the linear discrepancy model (i.e., IIT's weighted averaging model) with the PDD model (Equation 1). The results from a nonlinear regression indicated that the PDD model significantly increased the amount of explained variance from the linear model. Therefore, Fink et al. concluded that the PDD model was supported by the data more than the linear discrepancy model was. However, the assumption that psychological discrepancy discounted message weight only and did not change message scale value was not tested.

Variations on a Theme: New Discrepancy Models

In subsequent research, to specify the exact functional form of psychological discrepancy based on perspective theory, Chung and Fink (2020) provided an updated functional form for the PDD model:

$$\tilde{R} = \frac{w_0 s_0 + w\Delta(\psi)s}{w_0 + w\Delta(\psi)}, \text{ where } \Delta(\psi) = e^{-\gamma\psi} \text{ and} \tag{3}$$

$$\psi = kD/P, \tag{4}$$

where k is a positive constant. Equation 3 is the same as Equations 1 and 2 above. As with Equation 1, the relationship between s and $\tilde{R}$ is an inverted-U shape (Huang, 2020, p. 227).

In Equation 4, psychological discrepancy (ψ) is an increasing function of positional discrepancy ($D = |s - s_0|$) and a decreasing function of perspective (P, where $P = U - L$). Perspective (P) is the difference between the upper bound (U) and the lower bound (L) of a range of a receiver's belief positions that this receiver takes into account (Ostrom & Upshaw, 1968). Equation 4 shows how the same level of D can be experienced differently due to individual and contextual differences. The individual factors include s_0, U, and L; the contextual factors are those that can be used to vary P, one of which is Fink et al.'s (1983) method of manipulating ψ that was explained in the section titled "The Original Model: Fink et al. (1983)" above.

Notice that in the numerator of Equation 3, the term $w\Delta(\psi)s$ appears. We can think of that term as $[w\Delta(\psi)] * s$ or as $w * [\Delta(\psi)s]$. The product itself does not differentiate these two possibilities, but we differentiate them in what follows. In the first case we can consider w as changing weight as a function of discrepancy and s as a constant (Assumption 1), and in the second case we can consider s as changing scale value as a function of discrepancy and w as a constant (Assumption 2). Fink et al. (1983) considered only Assumption 1 on the grounds that the importance of a message perceived as extremely discrepant was discounted according to cognitive dissonance theory (Aronson et al., 1963). Assumption 1 was also consistent with the scale value constancy assumption in IIT (Anderson, 1981; Himmelfarb, 1975; see also Tesser, 1968). However, Assumption 2 was consistent with the contrast effects or the assimilation effects (i.e., when a message is perceived as closer to one's initial position than it actually is) depending on the functional form of $\Delta(\psi)$ according to social judgment theory (Sherif & Hovland, 1961). The multiplicative term, $w\Delta(\psi)s$, also suggested a third possibility: Neither message scale value (s) nor message weight (w) was discounted as a function of ψ, thereby assuming that both w and s were constants independent of psychological discrepancy (Assumption 3). Finally, it was possible that w and s were both affected by ψ, so that $w_p = w\Delta(\psi)_w$ and $s_p = s\Delta(\psi)_s$ (Assumption 4), where $\Delta(\psi)_w$ and $\Delta(\psi)_s$ represent the effects of ψ on w and s, respectively, and the p subscript means "as perceived."

Our Four Discrepancy Models

We now present the functional forms of our four discrepancy models, each of which corresponds to one of the assumptions described above regarding the role of psychological discrepancy in the valuation process according to IIT.[6] For modeling simplicity, for all four models, we considered $s \geq s_0$. Our experimental stimuli were created based on $s \geq s_0$. Therefore, our results only represented models where $s \geq s_0$.

The conceptual meanings of the four models were displayed by the different roles of ψ (see Online Supplemental Table 2). The first model (Equation 3) was the original PDD model (Fink et al., 1983). This model assumed that w was discounted because of ψ, as could be seen in the product $w\Delta(\psi)$ in the denominator, whereas s was constant (i.e., $w_p = w\Delta(\psi)$ and $s_p = s$). In the current study, we refer to this model as *the psychological-discrepancy-weight-discounting model*, or weight discounting model for short. In favor of this model, information integration research has supported the assumption that message scale value (s) was not susceptible to change with different message combinations (Anderson, 1971, 1981, 2008; see also Fiske, 1980; Ostrom & Davis, 1979; Tesser, 1968; cf. Anderson & Jacobson, 1965; Himmelfarb & Anderson, 1975). However, very little research has examined the possibility that s could vary as a function of ψ in a single-message context. Based on social judgment theory (Sherif & Hovland, 1961), for a message receiver, the perceived s (s_p) could vary from s due to a contrast effect or an assimilation effect. Further, if a message's ψ is different from D (message discrepancy), this implies that s_p could differ from s. Whether this possibility could be supported empirically is tested in our study.

Whereas Equation 3 assumes that only message weight (w) was discounted, our second model, the psychological-discrepancy-scale-value-pullback model, or scale-value model,

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[6] The process of information integration has three components: valuation, integration, and response (Anderson, 1981). Valuation turns a stimulus's scale value into a subjective value. Integration is the process of combing different pieces of information via cognitive algebra (see Online Supplemental Material 1). Response turns the implicit result from integration into explicit ratings on some scale.

assumes that only the message scale value (s), and not weight (w), varies as a function of ψ:

$$\tilde{R} = \frac{w_0 s_0 + w\Delta(\psi)s}{w_0 + w}, \text{ where } \Delta(\psi) = e^{-\gamma\psi} \text{ and } \psi = kD/(U - L). \quad (5)$$

The key assumption of the scale-value model is that perceived message scale value (s_p) is not the same as s, but rather, as a message's psychological discrepancy increases, the resistance to change in the advocated direction increases, as if there were a force pulling $\tilde{R}$ back to s_0: $s_p = \Delta(\psi)s$, whereas $w_p = w$. This model is also consistent with a nonlinear relationship between D and the amount of belief change (Chung et al., 2008; Fink et al., 1983; Laroche, 1977).

The third model, the independent-psychological-discrepancy model, or independent model for short, has the same functional form as the scale-value model (i.e., Equation 5). That is, in the independent model, the net effect of belief change as a function of psychological discrepancy is the same as the scale-value model. However, the independent model differs from the scale-value model, because we made $\Delta(\psi)$ in Equation 5 to be independent of w and s. In other words, message weight and perceived message weight were equal ($w = w_p$), and scale value and perceived scale value were equal ($s = s_p$). The underlying psychological mechanism here is that the assimilation effects do not occur on s, but s_0 varies as a function of ψ. In other words, the scale-value model and the independent model are two sides of the same coin. To explain, subtract s_0 from $\tilde{R}$ in Equation 5. Then for the scale-value model, we have $\tilde{R} - s_0 = \frac{w[\Delta(\psi)s - s_0]}{w_0 + w}$; for the independent model, we can write $\tilde{R} - s_0 = \frac{w\Delta(\psi)[s - s_0/\Delta(\psi)]}{w_0 + w}$. In the former, as explained in the previous paragraph, $s_p = \Delta(\psi)s$; in the latter, $s_p = s$, but the perceived $s_0 = s_0/\Delta(\psi)$, which indicates a force pulling s_0 towards s, as ψ increases. Thus, one way to distinguish the two models is to measure s_p to see if ψ would have a significant effect on s_p. If so, then the scale-value model would be favored over the independent model.

The fourth model is the complex model, which assumes that ψ affected message weight (w) and message scale value (s) separately. The functional form is as follows:

$$\tilde{R} = \frac{w_0 s_0 + w\Delta(\psi)_w \cdot [s\Delta(\psi)_s + s_0]}{w_0 + w\Delta(\psi)_w},$$

$$\text{where } \psi = kD/(U - L),\ \Delta(\psi)_w = e^{-\gamma\psi},\text{ and } \Delta(\psi)_s = k'(1 - e^{-\gamma\psi}). \quad (6)$$

In Equation 6, $\Delta(\psi)_w$ and $\Delta(\psi)_s$ represent the effects of ψ on w and s, respectively, and k' is a positive scaling constant. $\Delta(\psi)_s$ suggests a positive relationship between s_p and ψ. This model assumes that the s_p of a high-ψ message is greater than that of a low-ψ message, and that $\psi = kD/(U - L)$, which is consistent with perspective theory (Judd & DePaulo, 1979; Ostrom & Upshaw, 1968). In addition, the weight of a high-ψ message is discounted more than that of a low-ψ message. This assumption is consistent with the PDD model (Fink et al., 1983). Moreover, s_p is assumed to be equal to or greater than the person's s_0, so $\tilde{R}$ is always greater than s_0 when $s > s_0$. In other words, a boomerang effect is not allowed in this model.[7]

Hypotheses

We have presented four models. To empirically examine which model had the best fit with data, our general approach was to identify where the difference in a model property existed across the four models. By model property, we mean any propositions regarding the relationships between the model parameters that could be derived either mathematically or based on model assumptions. We then used these contradictory model properties to construct competing hypotheses. Among many possible model properties to be compared, we selected those that

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[7] We summarize the theoretical basis of the four assumptions as follows: Information integration theory is the basis of all the models in our study. The cognitive dissonance approach explains the weight discounting model as well as the weight discounting component in the complex model. The social judgment approach explains the scale-value model, the independent model, as well as the scale value varying component in the complex model. Perspective theory is the framework that leads to Equation 4, which determines how we can manipulate psychological discrepancy empirically.

included key variables that could be readily manipulated and measured in an experiment, and those that could be used to differentiate the four models. Table 1 shows which model posits which hypotheses.

We used three approaches to derive competing hypotheses. The first two approaches were strictly based on mathematical derivation. For the first approach, the algebraic expressions of the first-order partial derivatives of $\vec{R}$ with respect to s ($\partial\vec{R}/\partial s$) and with respect to P ($\partial\vec{R}/\partial P$) were calculated using the *SymPy* package (Meurer et al., 2017) in Python 2.7.14 (Python Software Foundation, 2017). The goal of calculating the first-order partial derivatives of $\vec{R}$ with respect to both s and P was to examine whether $\vec{R}$ changed differently across the four models as a function of s and as a function of P.

The sign of a first-order partial derivative was determined using either an analytic proof alone or a combination of an analytic proof and a computational approximation (see Online Supplemental Table 2; for detailed derivation procedures, see Huang, 2020, pp. 227-241). In an analytic proof, the sign of a derivative could be determined directly. In a computational approximation, we calculated many values to examine the sign of a derivative.[8] The reason for selecting parameters s and P was that these were the two parameters affecting ψ (see Equation 4, above) that we planned to manipulate orthogonally in our experimental design (a between-subjects 3 [high vs. moderate vs. low s] × 3 [wide vs. moderate vs. narrow P] factorial design; see Method section). Based on our examination of the first-order partial derivatives, the

[8] In a computational approximation, we first specified a distribution for each parameter. Then we randomly drew a certain number of values given the specified distribution. The next step was to create a list of combinations of parameter values. For example, if there were three parameters and we drew five values from each parameter, there would be 15 combinations of parameter values. If the derivative was with regard to P, we specified a wide range of P values and let the computer calculate a series of derivatives for each of the 15 combinations. The sign of each calculated derivative was evaluated to discern a pattern.

following hypotheses were proposed:

H1a: As s increases, $\grave{R}$ increases then decreases (predicted by the weight discounting model and the complex model).

H1b: In the wide P condition, the relationship between s and $\grave{R}$ is an inverted-U shape; in the narrow P condition, as s increases, $\grave{R}$ decreases (the scale-value model and the independent model).

H2a: As P increases, $\grave{R}$ increases (the weight discounting model, the scale-value model, and the complex model).

H2b: As P increases, $\grave{R}$ increases then decreases (the complex model).

We also derived competing hypotheses regarding boomerang effects, because boomerang effects can be readily tested in an experiment and can differentiate the four models (Table 1). We compared the scale-value model and the independent model that *by construction* allowed for a boomerang effect with the weight discounting model and the complex model that *by construction* did not allow for a boomerang effect (see Laroche, 1977, p. 255). To do this, the sign of $\grave{R} - s_0$ was examined (Huang, 2020, p. 230). Based on the derivation's results, we proposed:

H3a: The mean of $\grave{R}$ is greater than the mean of s_0 (the weight discounting model and the complex model).

H3b: The proportion of cases with a boomerang effect in the largest scale value (s) condition is greater than the proportions in the smaller s conditions (the scale-value model and the independent model).

For the third approach to hypothesis derivation, assuming perceived message weight (w_p) and perceived message scale value (s_p) could be measured, we derived competing hypotheses based on the model assumptions regarding the effects of psychological discrepancy on w_p and s_p

as stated in the section titled “Our Four Discrepancy Models” above. H4 tested whether w_p is a function of ψ in the form of $w_p = w\Delta(\psi) = we^{-\gamma\psi}$, where $\psi = kD/P$. The weight discounting model and the complex model predicted $w_p = w\Delta(\psi)$, whereas the scale value model and the independent model predicted that ψ has no substantial effect on w_p. H5 tested whether s_p is a function of ψ: The weight discounting model and the independent model predicted that ψ has no substantial effect on s_p; the scale value model predicted $s_p = s\Delta(\psi) = se^{-\gamma\psi}$, where $\psi = kD/P$; the complex model predicted $s_p = s\Delta(\psi) + s_0 = sk'(1 - e^{-\gamma\psi}) + s_0$, where $\psi = kD/P$.

The wording of H4 and H5 is based on the analytical strategy used to test these hypotheses. The language “*D* is at its sample mean” reflects our mean-centering of *D* in the regression models to simplify any complexity due to multicollinearity (see the Results section). When we state that an independent variable predicts a dependent variable, we expect a linear relationship between the independent variable and the dependent variable.

H4a: $1/P$ negatively predicts $\ln(w_p)$ when *D* is at its sample mean (the weight discounting model and the complex model).

H4b: D/P negatively predicts $\ln(w_p)$ (the weight discounting model and the complex model).

H4c: $1/P$ does not predict $\ln(w_p)$ (the scale-value model and the independent model).

H4d: D/P does not predict $\ln(w_p)$ (the scale-value model and the independent model).

H5a: $1/P$ does not predict $\ln(s_p)$ (the weight discounting model and the independent model).

H5b: D/P does not predict $\ln(s_p)$ (the weight discounting model and the independent model).

H5c: $1/P$ negatively predicts $\ln(s_p)$ when D is at its sample mean (the scale-value model).

H5d: D/P negatively predicts $\ln(s_p)$ (the scale-value model).

H5e: $1/P$ positively predicts s_p when D is at its sample mean (the complex model).

H5f: D/P positively predicts s_p (the complex model).

Method

Procedure

The following research procedure was approved by our university's Institutional Review Board. This study manipulated message scale value (s) and perspective (P) independently. Our experiment was a between-subjects 3 (high vs. moderate vs. low s) × 3 (wide vs. moderate vs. narrow P) factorial design. Participants were randomly assigned to one of the nine conditions. We used the criminal-sentencing topic for messages, which was successfully used in the past (Chung et al., 2008; Kaplowitz & Fink, 1991; Ostrom, 1970). We recruited participants from Amazon Mechanical Turk (MTurk) via TurkPrime (Litman et al., 2017).[9] Qualtrics (2018) was used to create and host online questionnaires (see the questions in Online Supplemental Material 2). After participants read the online consent form and agreed to take part in the study, they read a brief statement about public beliefs toward the criminal justice system in the U.S. and public opinion on a specific federal crime, armed bank robbery. The participants read a description of a (fictitious) armed robbery case. The perpetrator was labeled Convict X.

Participants first read a sentencing guideline that gave a recommended number of years

[9] To be eligible to participate in the study, an MTurk worker must have had 5,000 or more approved MTurk tasks and a 98% or above approval rating for completed tasks. These criteria were set to maintain a desirable level of data quality. Each participant was paid \$2.20. This payment was decided according to the U.S. federal minimum wage, \$7.25 an hour (effective in November 2019; U.S. Department of Labor, 2009). Given that the estimated time to complete the survey for the main study was 18 minutes (based on pilot studies), \$7.25 / 60 × 18 ≈ \$2.20. The actual completion time approximately met our expectation, M = 19.96 minutes, Mdn = 15.84 minutes, N = 448.

of imprisonment for Convict X. This sentencing guideline was an effort to establish participants' common message scale value (s_0) so that D was manipulated by varying s without varying s_0 (recall that D is message discrepancy, where $D = s - s_0$). Because perspective (P) is the difference between the upper bound (U) and the lower bound (L) of a message receiver's belief positions ($P = U - L$), we manipulated P by varying the upper bound (high vs. moderate vs. low U) while keeping the lower bound (L) constant. To manipulate U, participants were given a fictitious maximum sentence for armed bank robbery from the past. Participants then read a sentencing decision by Judge Walters (a fictitious judge) that specified one of three lengths of imprisonment for Convict X, which served as the manipulation of s. Finally, the participants were asked to report an appropriate length of imprisonment ($\grave{R}$ measured, where $\grave{R}$ is a participant's belief position after receiving a message) and their evaluation of the judge's decision (i.e., ψ, w_p, and s_p measured). At the end of the questionnaire, participants read the true purpose of this study.

Prior to the main study, we conducted six pilot studies to find out participants' s_0, U, and L about sentencing Convict X (Pilot Study 1), the appropriate values of U to be used for the upper-bound manipulation (Pilot Studies 2 to 4), and the appropriate values of s to be used for the message-scale-value manipulation (Pilot Studies 5 and 6). The main study used 15, 30, and 50 years for both s and U. An a priori power analysis was conducted to determine the sample size (450) for the main study using G*Power 3.1 (Faul et al., 2007).[10]

The data for the final study were winsorized and transformed to correct for outliers and nonnormal distributions (Fink, 2009). If the skewness (Sk) of a variable was significantly

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[10] With an alpha level of .05 and a 5% chance of falsely retaining a false H_0 (i.e., power = .95), a total sample size of 450 (i.e., 50 participants in each condition) would be needed to detect a significant interaction effect with a Cohen's (1988) f between 0.20 and 0.25.

different from zero and was positive, then values greater than the 95th percentile were recoded to the value at the 95th percentile. If skewness was still significantly different from zero, positively skewed variables were transformed (Fink, 2009; see Online Supplemental Tables 3 to 6 for the descriptive statistics and transformations used in this study). SPSS (2011) Version 20.0.0 was used for data analysis. The logarithm and the anti-logarithm in our data analysis were to the base *e*. The significance level (alpha) was .05 for hypothesis testing (two-tailed). All regression coefficients mentioned in the text were unstandardized.

Participants (N = 448)

After debriefing, two participants withdrew from the study. Participants comprised 240 males (54%), 204 females (46%), and four other (1%). The participants' average age was 37.60 years (*Mdn* = 35.00, *SD* = 11.00, *Min* = 19.00, *Max* = 72.00). There were 244 Democrats (55%), 137 Republicans (31%), 53 Independents (12%), and 14 Others (3%).

Measures

Initial Belief Position **(s_0)**

After reading the sentencing guideline (10 years), participants were asked, "What do you believe is the most appropriate sentence (in number of years) for Convict X?" Of the 448 participants, 388 (87%) reported an s_0 between 5 and 15 years (inclusive; M = 10.17, *Mdn* = 10.00, *SD* = 7.52), which was close to the 88% reported in Kaplowitz and Fink (1991).

Self-Report Measure of Psychological Discrepancy (ψ)

After reading the stimulus message, ψ was measured using magnitude scales (Fink et al., 1983; Lodge, 1981). Participants were asked, "How different is Judge Walters' decision about Convict X from your own view?" They were told that a moderate degree of difference corresponded to a rating of 100, a rating of zero indicated no difference, and there was no upper bound to the scores (after winsorization and transformation, *M* = 10.73, *Mdn* = 10.95, *SD* = 5.86, *N* = 448). To become more familiar with the magnitude scales, participants first completed two practice tasks irrelevant to the criminal sentencing case (see Online Supplemental Material 2).

Perceived Message Scale Value (s_p *)*

We used two items to measure s_{p}, using the magnitude scales as described above. The questions asked how harsh and how punitive Judge Walters' sentence was. We assumed that the greater the number of years that the judge sentenced Convict X to, the harsher and more punitive participants would view the judge's decision. The harshness item and the punitiveness item were winsorized at the 95$^{\text{th}}$ percentile and then transformed by taking their square root (after winsorization and transformation, harshness: *M* = 12.07, *SD* = 5.51; *Mdn* = 12.25; *Sk* = -0.08 [*SE* = 0.12], kurtosis (*Ku*) = -0.07 [*SE* = 0.23]; punitiveness: *M* = 12.36, *SD* = 4.98; *Mdn* = 12.25; *Sk* = 0.12 [SE = 0.12], *Ku* = 0.21 [*SE* = 0.23]). The two-item measure was reliable, with a Spearman-Brown statistic of .86 (see Eisinga et al., 2013).

Perceived Message Weight (w_p *)*

We used 11 items to measure w_{p} based on several concepts related to weight (see Footnote 1). Perceived message weight (w_{p}) was first measured with an *importance* rating (see Zalinski & Anderson, 1989). Participants were asked, "How important was Judge Walters' sentence when you decided what an appropriate sentence should be for Convict X?" We also used two other measures for w_{p}. First, *message evaluation* was a composition of measures on specific features of the *source* and the *content* of a message (Cacioppo et al., 1983; Eagly & Telaak, 1972). For *message content*, the features included effectiveness, argument quality, and fairness (Eagly & Telaak, 1972, p. 391) of the message, how compelling the message was, and how convincing the message was (Cacioppo et al., 1983, p. 808). For *message source*, the features included unbiasedness, credibility, trustworthiness, and expertness of the source (see Online Supplemental Materials 2). The measures of the above 10 items all used magnitude scales in which a moderate level is 100, with a lower bound of zero and no upper bound. Second, attention was defined as the allocation of cognitive effort (Kahneman, 1973). To operationalize attention to a message, we measured the amount of time a participant spent reading Judge Walters' sentence (see Fiske, 1980; Meffert et al., 2006). Because we assumed that the above operationalized variables all facilitated belief change (i.e., increasing the effectiveness of a message; see Online Supplemental Material 1), we assumed a congeneric relationship between items.[11] Based on exploratory factor analysis, the attention item was excluded; we used the 10-item average as a composite score for w_p (ω = .93, 95% CI [.91, .94]).[12]

Final Belief Position (R)

After reading the judge's sentence, participants were asked, "To how many years in prison do you think Convict X should have been sentenced?" (M = 14.30, Mdn = 10.00, SD = 10.97, N = 448).

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[11] A congeneric relationship means that the relationships between item true scores are linear. "The congeneric model assumes that each individual item measures the same latent variable, with possibly different scales, with possibly different degrees of precision, and with possibly different amounts of error" (Graham, 2006, p. 935).

[12] An exploratory factor analysis (EFA) using maximum likelihood extraction and the direct-oblimin rotation with four factors revealed that the attention item loaded extremely poorly on all factors. Therefore, the attention item was excluded from the subsequent analyses. An EFA based on the remaining 10 items using the same extraction and rotation method with four factors indicated a good fit, $\chi^2(11, 443) = 18.45$, $p = .07$. After reviewing the pattern of loadings and the intercorrelations between the factors (see Online Supplemental Tables 7 to 9), we averaged the 10 items to form a single w_p score based on the fact that (1) the subscales constructed based on the EFA results were all significantly and positively correlated with each other (see Online Supplemental Table 9); (2) the determinant of the correlation matrix of the 10 items was .00045, indicating strong linear dependence among these items; (3) there was only one factor that had an eigenvalue greater than one (see Online Supplemental Table 7), indicating strong evidence of unidimensionality; (4) the four items that loaded highly on the first factor had a sufficient level of reliability, ω = .91, 95% CI [.90, .93]; (5) the Pearson correlation coefficient between the first factor's factor score and the 10-item average was .90, $p < .01$, indicating that the first factor was well represented by the 10-item average. Although we believe that we have presented strong evidence showing that our measurement of perceived weight and use of the 10-item average was reasonable, there may be other variables that can be used to further improve the measurement of perceived weight.

Post-Manipulation Measures of U *and* L

After reading the maximum sentence for armed robbery, participants were asked "What do you believe is a maximally harsh or lenient sentence (in number of years) for a convict of armed bank robbery?" Based on random assignment, about half of the participants were asked about the harsh sentence first and then about the lenient sentence; for the other half, the order was reversed ($N = 448$; post-manipulation U, $M = 23.83$, $Mdn = 20.00$, $SD = 12.68$; post-manipulation L, $M = 9.52$, $Mdn = 6.00$, $SD = 10.80$).

Results

Manipulation Checks

Manipulation Check on U *and* L

To check the manipulation of the upper bound (U), we conducted a two-way analysis of covariance (ANCOVA) with the manipulated level of U and the order of the questions asking participants' U and L (U-then-L vs. L-then-U) as independent variables, participants' s_0 as a covariate, and U as the dependent variable. The ANCOVA revealed a significant main effect of U, $F(2, 441) = 61.38$, $p < .001$, $\eta^2 = .22$, and a significant $U \times$ order interaction, $F(2, 441) = 3.73$, $p = .03$, $\eta^2 = .02$. As expected, the linear contrast, in which participant's U was an increasing function of the manipulated U, was significant, $F(1, 441) = 122.54$, $p < .001$, $\eta^2 = .22$, whereas the quadratic contrast was not significant, $F(1, 441) = 0.84$, $p = .36$. Examining participants' U only, the manipulation of U was successful.

To further examine whether participants' perspective ($P = U - L$) increased as a result of the manipulation of U, participants' L was subtracted from U to obtain P. There were 12 participants who had a negative P. Because a negative P indicated that a participant failed to understand the questions measuring U and L, the 12 participants with $P < 0$ were excluded in the following analysis. For the remaining 436 participants, data were winsorized at the 95th percentile and P was transformed to approximate a normal distribution. The square root of the winsorized variable was used (M = 3.48, SD = 1.57, Sk = 0.07 [SE = 0.12], Ku = 0.20 [SE = 0.23], N = 436). The same two-way ANCOVA as described above was performed but with P as the dependent variable, revealing a significant main effect of the manipulated U, $F(2, 429) = 33.14$, $p < .001$, $\eta^2 = .13$, and a significant main order effect, $F(2, 429) = 5.83$, $p = .02$, $\eta^2 = .01$. The linear contrast, where P was an increasing function of the manipulated U, was significant, $F(1, 429) = 66.27$, $p < .001$, $\eta^2 = .13$, whereas the quadratic contrast was not significant, $F(1, 429) = 0.003$, $p = .96$. Manipulating P via U, while holding L constant, was successful.

Manipulation Check on s

To check the manipulation of s, a two-way ANCOVA was conducted with U and s as independent variables, s_0 as a covariate, and ψ as the dependent variable. We note ψ is an increasing function of s. Results revealed a significant main effect of s, $F(2, 426) = 57.19$, $p < .001$, $\eta^2 = .21$, and a marginally significant $U \times s$ interaction, $F(4, 426) = 2.39$, $p = .05$, $\eta^2 = .02$ (see Panel a in Figure 1). The linear contrast, in which ψ was an increasing function of s, was significant, $F(1, 426) = 107.26$, $p < .001$, $\eta^2 = .20$, and the quadratic contrast of s was also significant, $F(1, 426) = 7.23$, $p = .01$, $\eta^2 = .02$. The significant quadratic effect of s was not due to a downturn in ψ (see Panel a in Figure 1). Therefore, the manipulation of s was successful.[13]

Hypothesis Testing

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[13] We also used the perceived message scale value as the dependent variable to corroborate the successful manipulation of s. A two-way ANCOVA was conducted with U and s as independent variables, and s_p as the dependent variable. Results revealed a significant main effect of s, $F(2, 427) = 44.00$, $p < .001$, $\eta^2 = .17$. Neither the main effect of U nor the interaction effect was significant. The linear contrast, in which s_p is an increasing function of s, was significant, $F(1, 427) = 79.24$, $p < .001$, $\eta^2 = .16$, and the quadratic contrast of s was also significant, $F(1, 427) = 8.84$, $p = .003$, $\eta^2 = .02$. The significant quadratic effect of s was not due to a downturn in s_p.

H1a posits that as s increases, $\grave{R}$ increases then decreases, and H1b posits that in the wide P condition, the relationship between s and $\grave{R}$ is in an inverted-U shape; in the narrow P condition, as s increases, $\grave{R}$ decreases. H2a posits that as P increases, $\grave{R}$ increases, and H2b posits that as P increases, $\grave{R}$ increases then decreases.

To test H1 and H2, we conducted a two-way ANCOVA with U and s as independent variables, participants' s_0 as a covariate, and $\grave{R}$ as the dependent variable. Results revealed a significant main effect of s, $F(2, 438) = 12.53$, $p < .001$, $\eta^2 = .05$, and a significant main effect of U, $F(2, 438) = 2.40$, $p = .004$, $\eta^2 = .03$. The $U \times s$ interaction effect was not significant, $F(4, 438) = 1.95$, $p = .10$, $\eta^2 = .02$, which did not support H1b. The linear contrast, where $\grave{R}$ was an increasing function of s, was significant, $F(1, 438) = 12.27$, $p < .001$, $\eta^2 = .03$, and the quadratic contrast of s was also significant, $F(1, 438) = 12.90$, $p < .001$, $\eta^2 = .03$ (see Panel a in Figure 2). H1a was supported. The linear contrast, in which $\grave{R}$ was increasing function of U, was significant, $F(1, 438) = 11.06$, $p = .001$, $\eta^2 = .03$, and the quadratic contrast of U was not significant, $F(1, 438) = 0.04$, $p = .84$ (see Panel b in Figure 2). Therefore, H2a was supported, but not H2b. Among the four models, only the weight discounting model posits both H1a and H2a (see Table 1). Based on just these two hypotheses, the weight discounting model was favored over the other models.

H3a posits that the mean of $\grave{R}$ is greater than the mean of s_0. Out of 448 participants, 15 (3.35%) reported an $\grave{R} < s_0$. On average, there was a significant increase in participants' position after reading the judge's decision ($M = 3.52$, $SD = 0.96$) than before reading the judge's decision ($M = 3.04$, $SD = 0.64$), $t(447) = 14.79$, $p < .001$, $d = 0.70$. Therefore, H3a was supported.

H3b posits that the proportion of cases having a boomerang effect in the highest s condition is higher than the proportions in the smaller s conditions. The number of participants who had a boomerang effect was 7 (4.73%) in the s = 15 years condition (n = 148), 3 (2.00%) in the s = 30 years condition (n = 150), and 5 (3.33%) in the s = 50 years condition (n = 150). The proportion of participants who reported an $\tilde{R} < s_0$ did not differ by s, $\chi^2(2, N = 448) = 1.72$, p = .42. Therefore, H3b was not supported. Because the weight discounting model and the complex model posit H3a, but not H3b, these two models are favored over the other two models.

H4a posits that $1/P$ negatively predicts $\ln(w_p)$ when D is at its sample mean. H4b posits that D/P negatively predicts $\ln(w_p)$. H4c posits that $1/P$ does not predict $\ln(w_p)$. And H4d posits that D/P does not predict $\ln(w_p)$. To test the equation $w_p = w\Delta(\psi) = we^{-\gamma\psi}$, where $\psi = kD/P$, we linearized the relationship by taking the natural logarithm of both sides of the equation: $\ln(w_p) = \ln(w) - \gamma\psi$. Because $\psi = kD/P$, we tested this linear regression: $\ln(w_p) = a + b_1D + b_2(1/P) + b_3(D/\text{P}) + \epsilon$, where ϵ is the error term (see Blanton & Jaccard, 2006, for a way to test a multiplicative model).

In all, 50 participants were removed from this analysis: A negative P indicated that a participant failed to understand the questions that measured the upper and lower bounds (U and L, respectively); a zero P was not consistent with a mathematical model in which P was in the denominator ($\psi = kD/P$); and the situation of $D < 0$ was beyond the scope of this study. The 50 participants were excluded on the following basis: 36 participants had a nonpositive P, 12 had a negative D, and 5 had a missing value in one of the w_p items. Thus, 398 participants were included in this analysis.[14]

P was transformed to its inverse (i.e., $1/P$) and mean centered. D was also mean centered.

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[14] We included 45 cases who did not have a missing value in one of the w_p items to conduct the same linear regression analysis for testing $w_p = w\Delta(\psi) = we^{-\gamma\psi}$ in H4. All estimated coefficients had the same sign and the same significance level as those reported in Table 2 (Panel a), which did not change the interpretation of the results.

Then, the natural logarithm of the 10-item average of w_p was regressed on the centered $1/P$, the centered D, and the product of these two centered variables. Here, b_2 represented the simple effect of $1/P$ on $\ln(w_p)$ when the mean-centered D was zero. Although both estimates of b_1 and b_2 were negative and significant, the estimated coefficient for D/P was not significant (see Panel a in Table 2), which indicated that the functional form in $\psi = kD/P$ was implausible. The linear regression results supported H4a, because $\ln(w_p)$ was found to be a decreasing function of $1/P$. However, H4b was not supported. Therefore, support for the weight discounting model and complex model is inconclusive.

H4c predicts that $1/P$ has no substantial effect on w_p, and H4d predicts that D/P has no substantial effect on w_p. When testing H4a, the null hypothesis H_0: $b_2 = 0$ was rejected; therefore, H4c was rejected. However, when testing H4b, the failure to reject H_0: $b_3 = 0$ did not indicate the acceptance of H4d, so equivalence testing (Levine et al., 2008; Weber & Popova, 2012) was conducted to test H4d. In this equivalence test, the measure of the effect size of a predictor in multiple regression was chosen to be the semipartial correlation, r_{sp}, between the predictor and the dependent variable (Cohen et al., 2003; Levine et al., 2008). The estimated r_{sp} between D/P and $\ln(w_p)$ was -.01. The goal of this equivalence test was to test whether the estimated $|r_{sp}|$ was significantly less than a minimum substantial effect. A minimum substantial effect, $\boldsymbol{\Delta}$, was defined as $(r^2/2)^{1/2}$ (Weber & Popova, 2012), where r was the average effect size that could be determined based on meta-analysis (Weber & Popova, 2012). The less the value of $|r|$, the more conservative the equivalence test was. According to a summary of percentiles of communication meta-analyses by topic area (Weber & Popova, 2012), $|r| = .11$ was the 50th percentile among the studies on persuasion effects. Therefore, for the current equivalence test, $|r| = .11$ was chosen. Further, $\boldsymbol{\Delta} = (r^2/2)^{1/2} = .08$. If H_0: $|\rho_{sp}| \geq .08$, then H_a: $|\rho_{sp}| < .08$. The noncentrality parameter, λ, and the empirical t value were calculated based on the formulas provided in Weber and Popova (2012). Finally, in a noncentral t distribution with $df = N - 2 = 396$ and $\lambda = 1.61$, a p value of .08 was calculated with $|t| \leq .18$. As a result, this equivalence test failed to reject the null hypothesis that the population r_{sp} between D/P and $\ln(w_p)$ were equal to or greater than a $\boldsymbol{\Delta}$ of .08. H4d was not supported. For H4, only H4a was supported. Therefore, the weight discounting model and complex model are here favored over the other two models.

H5a posits that $1/P$ does not predict $\ln(s_p)$. H5b posits that D/P does not predict $\ln(s_p)$. H5c posits that $1/P$ negatively predicts $\ln(s_p)$ value when D is at its sample mean. H5d posits that D/P negatively predicts $\ln(s_p)$. H5e posits that $1/P$ positively predicts s_p when D is at its sample mean. And H5f posits that D/P positively predicts s_p.

To test H5, we first tested the equation $s_p = s\Delta(\psi) = se^{-\gamma\psi}$, where $\psi = kD/P$. The strategy and procedure were the same as the one reported above for w_p. By taking the natural logarithm of both sides of the equation to linearize the relationship, the equation became $\ln(s_p) = \ln(s) - \gamma\psi$. Because $\psi = kD/P$, a test of the linearized equation could be conducted by testing this linear regression model: $\ln(s_p) = a + b_1D + b_2(1/P) + b_3(D/\mathrm{P}) + \epsilon$. The two-item average of s_p was used. Thirty-six participants with a nonpositive P and the 12 participants with a negative D were excluded. So 403 participants were included in this analysis.[15]

Only b_1 was positive and significant, which indicated that $\psi = kD/P$ was implausible (see Panel b in Table 2). The estimated b_2 and b_3 were positive and not significant, which did not support H5c or H5d, as predicted by the scale-value model. Failing to reject the null hypotheses

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[15] We included all cases to conduct the same linear regression analysis for testing $s_p = s\Delta(\psi) = se^{-\gamma\psi}$ in H5. The estimated coefficients for the intercept and D had the same sign and the same significance level as those reported in Table 2 (Panel b). The estimated coefficients for $1/P$ and D/P were negative but not significant, which did not change the interpretation of the results.

when testing H5c and H5d did not indicate the acceptance of H5a or H5b; therefore, equivalence testing was conducted to evaluate H5a and H5b. The procedure of equivalence testing was the same as the one reported above for the equivalence testing of H4d. For H5a, $t(401) = 0.12$, the noncentrality parameter $\lambda = 1.62$, $p = .07$; for H5b, $t(401) = 0.28$, the noncentrality parameter $\lambda = 1.62$, $p = .09$. Both equivalence tests were nonsignificant. Therefore, H5a and H5b are not here supported.

The equation $s_p = s\Delta(\psi) + s_0 = sk'(1 - e^{-\gamma\psi}) + s_0$, where $\psi = kD/P$, was predicted by the complex model. A nonlinear regression was used to fit this equation directly with 403 participants.[16] The specified equation was $s_p = b_0 s\{1 - \exp[b_1 D/P + b_2 D + b_3(1/P)]\} + b_4 s_0 + b_5 + \epsilon$. If either D/P, D, or $1/P$ positively predicts s_p, the corresponding estimated coefficient should be negative. The coefficients b_1, b_2, and b_3 were negative, and all had a 95% CI excluding zero (see Panel c in Table 2), which supported both H5e and H5f. Thus, for H5, only H5e and H5f were supported. Therefore, the complex model is here favored over the other three models.

Direct Fitting of Model Equations

With the same 403 participants noted above, four nonlinear regression models were fit, with $\tilde{R}$ (participant's belief position in equilibrium after receiving a message) as the dependent variable (see Online Supplemental Table 10). The model fit statistics were reported in Table 3, and the estimated coefficients are reported in Online Supplemental Table 11.

For the complex model, there were two versions: the full complex model and a restricted complex model in which k' was fixed at 1 (see Online Supplemental Table 10). For the full

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[16] We included all cases to conduct the same nonlinear regression analysis for testing $s_p = s\Delta(\psi) + s_0 = sk'(1 - e^{-\gamma\psi}) + s_0$. The result showed that the estimated b_1, b_2, and b_3 were nonsignificant. Despite the discrepancy in the result, we believe that our decision of excluding some of the participants is justified because those participants were considered out of the scope of the four models in various ways as explained earlier in the "Hypothesis Testing" section.

complex model, none of the coefficients had a 95% CI that excluded zero, so the restricted complex model with $k' = 1$ was the more plausible of the two versions.

The more parsimonious weight discounting model and scale-value model explained the variance in $\grave{R}$ more than did the complex model. The estimated coefficient for D/P was negative and significant in all three models. The coefficients for D and $1/P$ were negative in all three models, except for the coefficient for $1/P$ in the restricted complex model (Online Supplemental Table 11). The results for the estimated coefficients indicated that the multiplicative model of psychological discrepancy (ψ, Equation 4) is plausible with $\grave{R}$ as the dependent variable.

Because our nonlinear regression models were not nested, we used the Akaike information criterion (AIC), the AIC corrected for small sample size (AIC_c), and the Bayesian information criterion (BIC) as criteria for model selection (Burnham & Anderson, 2004).[17] The weight discounting model had the lowest AIC, AIC_c, and BIC among the four nonlinear regression models (Table 3). Therefore, among the four models, the weight discounting model is the most supported based on nonlinear regression analysis with the scale-value model being a close second, although the two models differed only slightly.[18]

Discussion

Based on hypothesis testing, the weight discounting model and the complex model were the most supported models; most of the hypotheses predicted by the scale-value model and the independent model were not supported. Results of the nonlinear regression analyses that fit the

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[17] In regression analysis, two models are nested when one of the models contains all the terms in the other model and at least one additional term. The tested models here were not nested (see Online Supplemental Table 10).

[18] We conducted a sensitivity test due to the nonnormal distributions of regression residuals. This sensitivity test specified alternative models to the ones in Supplemental Table 10; these alternative models included religiosity (a measured variable) as a predictor (see Huang, 2020, pp. 212-213). The alternative weight discounting model and the alternative scale-value model had a milder violation of the normality assumption for the regression residuals than the models in Supplemental Table 10. Based on AIC, AIC_c, and BIC, the weight discounting model was still the most plausible model, with the scale-value model as a close second, although the two models differed only slightly.

model equations directly showed that the more parsimonious weight discounting model and scale-value model fit the data better than the complex model did. Overall, the weight discounting model (the PDD model) had the most support among the four models. Although convincing evidence from this study showed that message weight was discounted by psychological discrepancy in the form of $w_p = w\Delta(\psi)$, there was some evidence that supported a similar effect for scale value in the complex model: $s_p = \Delta(\psi)s$. H5e and H5f indicated that perceived message scale value (s_p) was an increasing function of psychological discrepancy.

Significance of the Study

This study has theoretical, methodological, and practical significance. The theoretical significance of this study is twofold. First, regarding discrepancy models in persuasion, there have been few attempts to examine the psychological process underlying the original psychological-discounting discrepancy (PDD) model. Fink et al. (1983) remarked on their study's limitation: "A mechanism explaining the discounting function needs to be explicated and tested" (p. 429). The original PDD model was based on the weight-discounting assumption, which was not directly compared against other alternative assumptions about the role of psychological discrepancy. Our study fills this gap by directly testing the weight-discounting assumption as well as three alternative assumptions with empirical evidence. We find that one of the alternative assumptions, in which ψ discounts message weight (w) and changes the message scale value (s), is supported by our research.

Second, because the PDD model (Fink et al., 1983) is based on Anderson's (1981) averaging model, this study has implications for information integration theory (ITT) by directly addressing one of the basic assumptions of the information integration approach: the scale value constancy assumption. This assumption had been validated through a series of experiments

(Anderson, 1971, 1973, 1981, 2008; Anderson & Hubert, 1963; Anderson & Jacobson, 1965; Tesser, 1968; see also Fiske, 1980, and Ostrom & Davis, 1979), but most of these experiments examined whether a message scale value changed depending on different message combinations. This line of research did not address how message scale value varies as a function of either message discrepancy or psychological discrepancy. Our study fills this gap by directly testing whether message discrepancy (D) and psychological discrepancy (ψ) have an effect on message scale value. More importantly, our study theorizes the valuation process in IIT (Anderson, 2008) and subjects some forms of this process to empirical tests. We find some evidence that perceived message scale value (s_p) is an increasing function of ψ, which is inconsistent with IIT's scale value constancy assumption. Our study presents the first evidence we know of that challenges the scale value constancy assumption using psychological-discrepancy models.

Note that we used numbers to represent a belief position (years of imprisonment). If a message with a vague advocated position (e.g., "a very long sentence" instead of "50 years") had been used, the evidence supporting the scale value flexibility assumption may have been stronger. Future studies should extend this study's findings to a multiple-message context, especially for the complex model, because it posits both a varying w and a varying s.

The methodological significance of this study is that it used a computational approach to derive hypotheses based on model equations. The general goal of mathematical modeling is to derive precise hypotheses (Kaplowitz et al., 1983). In certain situations, especially when working with complicated models, deducing a hypothesis analytically is difficult or possibly impossible. In this study, such a difficulty appeared when, in the complex model, we expressed a first-order partial derivative of $\hat{R}$ with respect to a parameter in purely symbolic terms and then tried to determine the sign of this first-order partial derivative. To determine the sign of this first-order partial derivative by using an analytic proof alone was, to say the least, difficult. A computational approach was a workaround for this difficulty, and it approximated some properties of a first-order partial derivative with a large number of hypothetical data points (see Footnote 8). This study shows that a hypothesis can be deduced using a computational approximation even for a model that involves many parameters.

As for the practical significance of this study, our results add one more piece of evidence that when a persuasive message is extremely discrepant from a message receiver's s_0, the weight of the message is discounted. Using strategies to widen the message receiver's perspective (P) about a topic issue by reducing L or by increasing U can make the message seem less discrepant. In this way, the message weight is discounted less. And not only can psychological discrepancy be manipulated, but the substantive meaning of the message can also change: If the message sender manipulates the context so that an extreme message is perceived as less extreme, the advocated position would seem closer to the receiver's initial position.

In our study, we assumed that cognitive elaboration was not involved in the effect of discrepancy on final position, because we did not give participants extra time to think about their final positions (see Footnote 2). If participants are given time to carefully think about their decisions, the results from studies on metacognition (Petty et al., 2002, 2007; Requero et al., 2020; Tormala & Petty, 2004a, 2004b) suggest another way to make an extremely discrepant message more effective. The self-validation hypothesis posits that high (vs. low) confidence in thoughts about a message leads to more attitude change when the thoughts about a message are positive; low (vs. high) confidence in thoughts about a message leads to more attitude change when the thoughts about a message are negative. This hypothesis had been supported (Petty et al., 2002; Requero et al., 2020). Given the weight discounting model, a great level of psychological discrepancy can reduce the message weight due to negative thoughts. Based on the self-validation hypothesis, given a setting that makes cognitive elaboration more likely, in order to induce more belief change for an extremely discrepant message, a communicator can reduce the level of a message receiver's thought confidence.

One limitation of our study is that the observed data was not completely consistent with the prediction made in Equation 4. We have provided a detailed discussion in Supplemental Material 3 and indicated that future research should further examine the functional form of Equation 4. Another issue is the measurement of perceived message weight. There may be other variables that can be used to further improve the measurement (see Footnote 12). Based on the results of our EFA, future research can use another sample to conduct a confirmatory factor analysis with other relevant items.

Conclusion

This study tested four models regarding psychological discrepancy. The empirical evidence favored the weight-discounting model and the complex model over the scale-value-pullback model and the independent-psychological-discrepancy model, with the weight-discounting model being the most supported. This study's theoretical, methodological, and practical significance indicates that further developing psychological-discrepancy models would be fruitful for future research on information integration theory and discrepancy models. This study shows that psychological discrepancy is an important concept, distinct from message discrepancy, for understanding the psychological processes underlying belief change. Although we did not conclusively validate the multiplicative model of psychological discrepancy, our conclusions in this regard point to a promising direction for future research to examine alternative models.

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Table 1

Hypotheses Predicted by the Four Models and Results

Competing hypotheses	Weight discounting model	Scale-Value model	Independent model	Complex model
H1a	×			×
H1b		×	×	
H2a	×	×	×	
H2b				×
H3a	×			×
H3b		×	×	
H4a	×			×
H4c		×	×	
H4b	×			×
H4d		×	×	
H5a	×		×	
H5c		×		
H5e				×
H5b	×		×	
H5d		×		
H5f				×

Note. A verbal statement of each hypothesis can be found in the main text. The symbol of × means that a specific hypothesis is predicted by a certain model. A shaded cell means that a hypothesis was supported in the main study. Each block separated by horizontal lines is composed of competing hypotheses (e.g., H4a vs. H4c, H4b vs. H4d). Labels for the four models: Weight discounting model: Psychological-discrepancy-weight-discounting model; scale-value model: Psychological-discrepancy-scale-value-pullback model; independent model: Independent-psychological discrepancy model; and complex model.

Table 2

Summary of Three Regression Analyses

(a)	Linear regression, DV = w_p, $N = 398$				**(b)** Linear regression, DV = s_p, $N = 403$			
	Unstandardized coefficient	*SE*	Standardized coefficient	Semipartial correlation	Unstandardized coefficient	*SE*	Standardized coefficient	Semipartial correlation
Intercept	4.61***	0.03			2.52***	0.02		
b_1 (D)	-0.01***	0.002	-0.25***	-.25	0.01***	0.001	0.44***	.44
b_2 ($1/P$)	-1.97***	0.34	-0.28***	-.28	0.04	0.28	0.01	.01
b_3 (D/P)	-.01	0.02	-0.01	-.01	0.01	0.02	0.01	.01
Model fit	R^2 =.14, adjusted R^2 = .13 $F(3, 394) = 21.09$, $p < .001$				R^2 =.20, adjusted R^2 = .19 $F(3, 399) = 32.23$, $p < .001$			

(c)	Nonlinear regression, DV = s_p, $N = 403$		
	Estimated coefficient	*SE*	95% Confidence Interval
b_0 (k')	0.03	0.01	[0.01, 0.05]
b_1 (D/P)	-0.69	0.23	[-1.14, -0.25]
b_2 (D)	-0.13	0.02	[-0.16, -0.10]
b_3 ($1/P$)	-10.58	3.91	[-18.27, -2.89]
b_4	-0.29	0.39	[-1.05, 0.48]
b_5	14.53	1.13	[12.32, 16.75]
Model fit	AIC, AIC_c, and BIC were 2,301.87; 2,302.16; and 2,329.87; respectively.		

Note. *$p < .05$. **$p < .01$. ***$p < .001$. AIC is the Akaike information criterion; AIC_c is the AIC corrected for small sample size; BIC is the Bayesian information criterion. In the nonlinear regression, the estimated coefficients are unstandardized coefficients.

Table 3

Direct Fitting of Model Equations: Model Fit Statistics

	Sum of squares	*df*	*F*	*p*	R^2_{adj}	SE_{est}[a]	*Sk*[b]	AIC	AICc	BIC
Total	343.28	402								
Explained by the weight discounting model	196.28	3	177.75	< .001	.57	0.61	0.91	747.25	747.40	767.24
Explained by the scale-value model	195.91	3	177.02	< .001	.57	0.61	0.92	748.25	748.40	768.25
Explained by the restricted complex model ($k' = 1$)	182.36	4	112.65	< .001	.53	0.64	1.06	785.70	785.91	809.69
Explained by the full complex model	188.38	5	96.65	< .001	.54	0.62	1.03	772.35	772.63	800.34

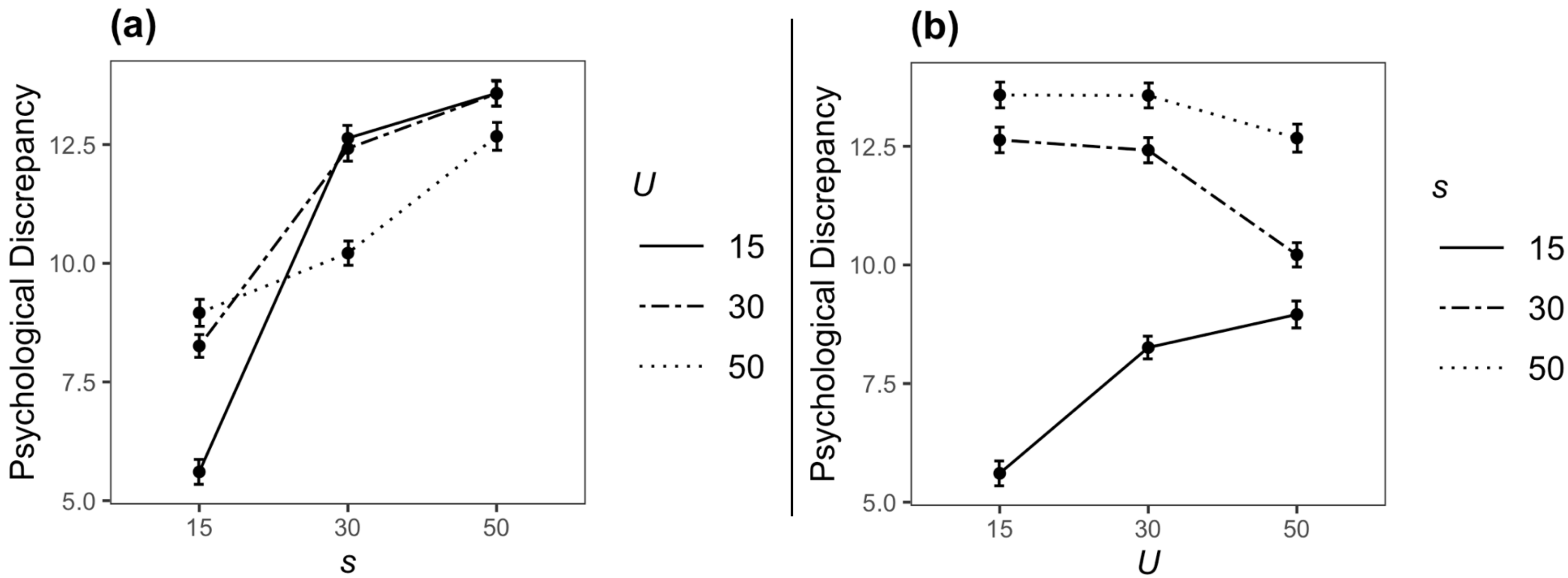
Note. $N = 403$. AIC is the Akaike information criterion; AIC_c is the AIC corrected for small sample size; BIC is the Bayesian information criterion. Labels for the four models: Weight discounting model: Psychological-discrepancy-weight-discounting model; scale-value model: Psychological-discrepancy-scale-value-pullback model; independent model: Independent-psychological discrepancy model; and complex model.

[a]SE_{est} is the standard error of the estimate, or the root mean squared error, which equals to $[\sum e^2/(N - v)]^{1/2}$, where e is the residual, and v is the number of estimated parameters.

[b]*Sk* is the skewness of residuals. The standard errors of *Sk* all equaled 0.12.

Figure 1

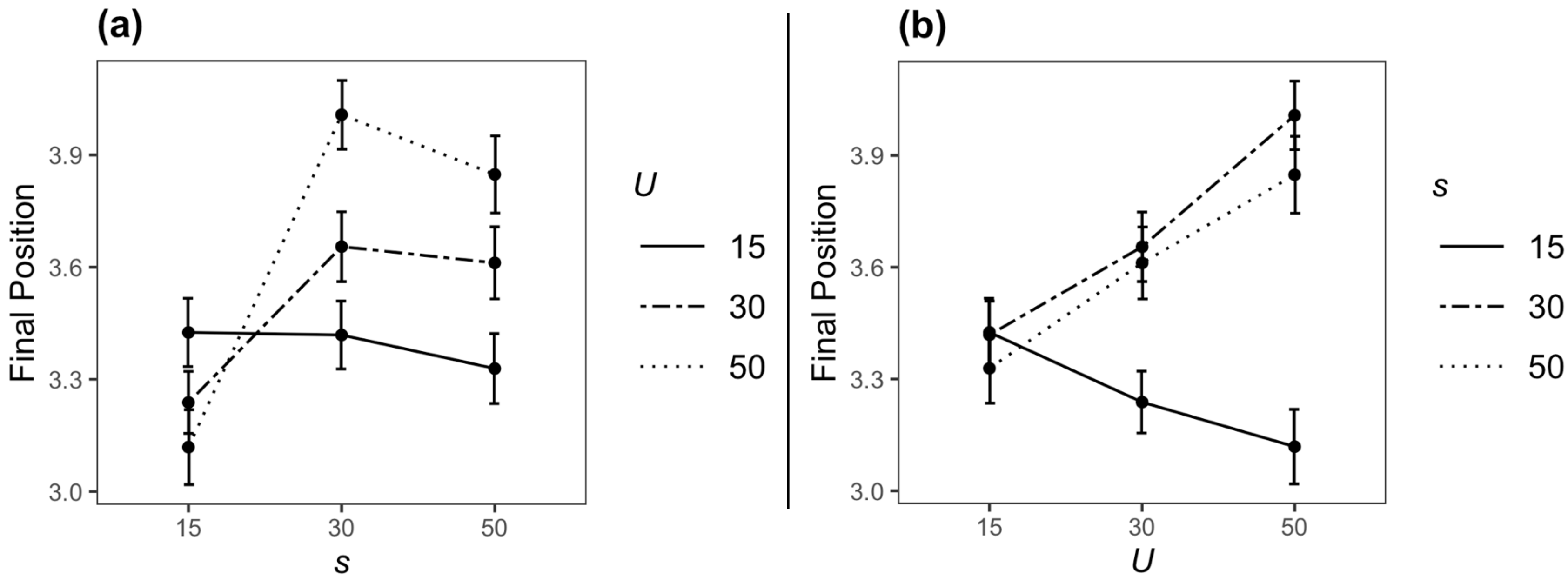
Two-Way ANCOVA: The Effect of the Manipulation of Message Scale Value on Psychological Discrepancy



Note. The y-axis represents the predicted value of the ANCOVA model based on the square root of the transformed psychological discrepancy (ψ). Covariate: participant's initial position. $N = 436$. In Panel a, the x-axis represents the message scale value (s), and each line represents one of the upper bound (U) conditions; in Panel b, the x-axis represents the upper bound (U), and each line represents one of the message scale value (s) conditions. Error bars show standard errors.

Figure 2

Two-Way ANCOVA on Final Position



Note. The y-axis represents the predicted value of the ANCOVA model based on the square root of the transformed final position ($\tilde{R}$). Covariate: participant's initial position. $N = 448$. In Panel a, the x-axis represents the message scale value (s), and each line represents one of the upper bound (U) conditions; in Panel b, the x-axis represents the upper bound (U), and each line represents one of the message scale value (s) conditions. Error bars show standard errors.