



Unlocking new insights into the somatic marker hypothesis with multilevel logistic models

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Abstract

The Somatic Marker Hypothesis, an influential neurobiological account of decision-making, states that emotional somatic markers (e.g., skin conductance responses) influence decision-making processes. Despite its prominence, the hypothesis remains controversial partly because of inconsistent results stemming from inappropriate statistical methods. Tasks designed to assess decision-making often use repeated measures designs, such as the Iowa Gambling Task (IGT), which requires participants to maximize profits by selecting 100 cards among four decks offering varying win–loss contingencies. Researchers often aggregate repeated measures into a single averaged value to simplify analyses, potentially committing an ecological fallacy by erroneously generalizing results obtained from aggregated data (i.e., interindividual effects) to individual repeated measurements (i.e., intraindividual effects). This paper addresses this issue by demonstrating how to analyze concurrent repeated measures of both independent and dependent variables using multilevel logistic models. First, the principles of logistic multilevel models are explained. Then, simulated and empirical IGT data are analyzed to compare the performance of traditional statistical approaches (i.e., general linear models) with multilevel logistic models. Our proposed multilevel logistic analyses address critical methodological gaps in decision-making research, ensuring more accurate interpretations of repeated measures data. This approach not only advances the study of the Somatic Marker Hypothesis but also provides a robust framework for similar research protocols, ultimately enhancing the reliability and validity of findings.

Keywords Decision-making · Somatic marker hypothesis · Statistical modeling · Repeated measures design · Emotion

In his seminal work, *Descartes' Error*, Antonio Damasio (1994) proposed one of the most influential neurobiological accounts of decision-making. Bridging together the fields

of affective, cognitive, and behavioral neuroscience, the Somatic Marker Hypothesis (SMH) highlights the role of emotions in the decision-making process (Damasio, 1994). According to the SMH, certain choice options become associated with emotional responses through repeated experiences. Initially, emotional responses follow decisions, because they are a consequence of the decision. When similar situations arise in the future, these emotional responses are retrieved and reexperienced before the individual makes a decision. These anticipatory emotional responses are expressed by specific bodily sensations (somatic markers), such as increased electrodermal activity. The SMH posits that these somatic markers then bias decisions (whether consciously or not) towards options associated with positive somatic markers and away from those with negative ones.

To test the SMH, Bechara & Damasio (1994) developed the Iowa Gambling Task (IGT), which requires participants to select 100 cards from four decks of cards associated with different win–loss contingencies. Using the feedback provided at each trial (indicating the losses and

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gains), participants must learn which decks are advantageous or disadvantageous in the long-term to maximize profits. To measure the somatic markers, anticipatory skin conductance responses (SCRs) are recorded before participants make each decision. The IGT provides a means for researchers to test specific predictions of the SMH. In accordance with the SMH, a recent meta-analysis has demonstrated that anticipatory SCR exerts a small to moderate influence on decision-making as assessed by the IGT (Simonovic et al., 2019).

Although promising, the SMH has faced substantial criticism since its inception. A prominent critic centers on the relative roles of cognitive and emotional processes in guiding decision-making in the IGT, specifically questioning whether somatic states (i.e., bodily signals) directly influence decision-making (Chiu et al., 2022; Colombetti, 2008; Dunn et al., 2006; Maia & McClelland, 2004, 2005; Overskeid, 2021). Proponents of the SMH acknowledge that its most vulnerable aspect is the limited quantity and quality of evidence (i.e., lack of causality) supporting the effect of peripheral somatic states (e.g., SCR) on decision-making, what they refer to as the body-loop mechanism (Poppa & Bechara, 2018; Reimann & Bechara, 2010). Furthermore, some researchers argue that the IGT may not be optimal to test SMH predictions, leading to varied (mis)interpretations of the hypothesis and, consequently, inconsistent findings (Bartol & Linnquist, 2015; Colombetti, 2008; Linnquist & Bartol, 2013). We suggest that a key limitation in the empirical testing of the SMH could be underlying many of the above-mentioned critics; numerous studies have used statistical methods to analyze the IGT that fail to capture a comprehensive and fine-grained understanding of ways somatic markers might influence decision-making (Dunn et al., 2006). We further argue that traditional analytical strategies may have led to erroneous conclusions about the SMH and propose a novel analytical approach to resolve these issues.

Objective

Our objective is to demonstrate why common analysis methods (i.e., general linear models) are not suited to test the SMH. This paper presents a multilevel modeling approach and the disaggregation of the SCR variable as a means to obtain precise insights into the nature of the SMH, specifically in modelling the predictive value of somatic states on individual decisions. The proposed analysis methods are then used to analyze simulated as well as empirical IGT data (obtained from an open-access database). The R code is provided and explained to allow researchers to implement this methodology in future studies that address multilevel data structures, such as those pertaining to the IGT.

Traditional statistical analyses

The SMH was initially proposed to explain the significant deficits in decision-making observed in patients with lesions to the ventromedial prefrontal cortex who showed impaired decision-making in the IGT, despite normal cognitive functioning (Bechara et al., 1994). Bechara et al. (1996) later demonstrated that compared with control participants, these patients did not exhibit an increase in mean SCRs preceding decisions, suggesting that SCRs were necessary to guide advantageous decision-making during the IGT. However, these patients also exhibited less intraindividual variability in SCRs throughout the task compared with controls, indicating that their SCR levels did not vary significantly from one decision to another. This solicits two interpretations: 1) individuals with more frequent or greater SCRs perform better (i.e., interindividual variability predicts decision-making), or 2) those with greater variability in SCRs throughout the task perform better (i.e., intraindividual variability predicts decision-making). Subsequent research on the SMH has focused disproportionately on the relationship between interindividual differences in SCRs and decision-making (i.e., between-subjects designs).

For simplicity, a common approach in IGT studies has been to aggregate the 100 decisions and anticipatory SCR observations by summing the total number of draws in the advantageous decks and averaging SCRs per individual. This procedure allows the use of general linear models, such as multiple regressions, which can be expressed as

$$y_i = b_0 + b_1 SCR_i + \epsilon_i$$

The left side of the equation represents the average number of draws in the advantageous decks (i.e., the dependent variable), b_0 is the intercept, b_1 is the regression coefficient of the averaged SCR for individual i , and ϵ_i is the residual error. General linear models only integrate the individual (i) level of variance and ignore intraindividual variability in SCR and decision-making. With the emphasis on the effect of aggregated SCR (interindividual variability), this may have led to inaccurate conclusions about the SMH. Statistically, this removes rich information about within-individual variability (i.e., the analyses focus only on between-individual differences) and limits the sample size (i.e., it does not consider the 100 repeated measures within individuals), which lowers the statistical power to detect any effect. Conceptually, this approach may lead researchers to draw inaccurate conclusions about intraindividual effects by inferring from interindividual differences, a logical flaw in the interpretation of statistical results known as the ecological fallacy (Robinson, 1950). Simpson's paradox represents a specific example of an ecological fallacy where a trend in a variable within individuals reverses or disappears when these

data are aggregated to conduct analyses between individuals (Leppink, 2019). For example, aggregating the 100 decisions in the IGT into a single value could give the impression that two individuals performed similarly, despite their actual decision-making patterns being reversed over time. For instance, one individual may begin by drawing cards from the risky decks and gradually pick from the safe decks, while the other might do the opposite. We believe that many researchers investigating the SMH using general linear models have fallen prey to the ecological fallacy, assuming that individuals are the sum of their decisions. Investigating the SMH not only involves being careful about the treatment of the repeated dependent variable (i.e., the decisions) but also the repeated independent variable (i.e., SCRs).

Electrodermal activity as an index of somatic markers

Electrodermal activity (EDA) is a physiological phenomenon that manifests as changes in the electrical properties of the skin in response to the activity of the sympathetic nervous system. Electrodermal activity has been utilized as a physiological marker of emotional and cognitive processing since the 1800s (Boucsein, 2012). Electrodermal activity is composed of tonic and phasic components, which characterize slow and rapid changes in skin conductivity, respectively (Boucsein, 2012). Skin conductance responses are phasic changes defined as discrete increases in EDA activity crossing a predetermined threshold. When these SCRs occur in response to a stimulus, they can be used as a proxy for physiological emotional responses. The tonic component of EDA is composed of the baseline skin conductance level and the nonspecific SCRs (i.e., SCRs appearing without any eliciting stimulus). The tonic component of EDA is primarily evaluated by aggregating non-specific SCRs that occur within a specified timeframe. Compared with baseline, the number of nonspecific SCRs increases during the completion of various cognitive tasks, which has been linked to higher arousal, increased selective attention, and task engagement (Boucsein, 2012; Dawson et al., 2017). For example, individuals who disengage from tasks that are too difficult exhibit a reduction in nonspecific SCRs relative to those who successfully complete the same task (Pecchinenda, 1996).

Studies investigating the SMH have generally operationalized anticipatory SCRs as the area under the curve of the five seconds preceding the decision (Figner & Murphy, 2011; Naqvi & Bechara, 2006). Consequently, this method quantifies the somatic state before the decision by assuming that this captures the somatic state of the participant while they reflect on which deck to choose. Although we believe this method to be adequate, it must be interpreted with caution. This 5-s time window is presumably a mixture of both

phasic and tonic EDA components, as nonspecific SCRs may be incorporated in the anticipatory SCR calculation.

Traditionally, the 100 anticipatory SCRs have been aggregated into a single value to use general linear models. However, the aggregation of SCRs spanning the completion of a task is predominantly used as a proxy for tonic EDA (Tronstad et al., 2022). Aggregating SCRs eliminates any intraindividual effect, which is problematic given that the latter is the primary focus of the SMH (i.e., somatic markers before a given decision will influence the decision at that specific moment for a given individual). Therefore, this method addresses substantially different questions, such as whether arousal, concentration, or involvement levels (i.e., the tendency to generate SCRs) correlate with the tendency to take risks. Given that individual differences in tonic EDA are related to performance in tasks demanding sustained attention (e.g., IGT; Dawson et al., 2017), individuals displaying greater aggregated SCR should perform better on the IGT. These issues cast doubt on the interpretation of the SMH literature. In fact, the inverse correlation between interindividual (and potentially tonic) SCR and risk-taking in the IGT could simply indicate that individuals who succeed are those who are engaged in the task.

To overcome this issue, one could reasonably approximate the intraindividual variability in SCR by including a term for the variance in SCR for each participant in a general linear model. However, this method would also be unsuitable as the independence assumption of general linear models remains violated. Moreover, summarizing intraindividual variability with a single variance measure would mask trial-by-trial SCR fluctuations over time, which are critical for testing the SMH. Finally, interpreting this variance as an individual-level variable could still lead researchers to commit an ecological fallacy, because it reduces SCR trial-level dynamics to a static person-level summary. Recently, more sophisticated statistical models have been increasing in popularity and can be used to circumvent ecological fallacies.

Multilevel logistic models

As with the repeated trials in the IGT, repeated measures designs confront researchers with a hierarchical 2-level data structure: level 1, representing the repeated measures within a participant (intraindividual component), and level 2, representing the interindividual differences. Owing to the 100 observations within the same individual in the IGT, the data violates the statistical assumption of independent observations of general linear models. Ignoring this assumption violation underestimates the standard errors and leads to a greater likelihood of Type I (false positive) errors (Musca et al., 2011). Given their ability to simultaneously model level 1 (within-individual) and 2 (between-individual)

variance components, multilevel models can account for these within-individual correlations. Many authors have discussed the mathematical principles of multilevel models in depth (Duplessis-Marcotte et al., 2022; Nezlek & Mroziński, 2020; Page-Gould, 2016; Sommet & Morselli, 2017). Briefly, the intercepts and slopes in general linear models are fixed. In other words, these models assume that the mean intercept and slope of the sample are representative of all individuals and that these parameters do not vary between individuals. Multilevel models are an extension of general linear models and address this issue by allowing these parameters to vary across individuals. As every decision in the IGT (rather than their sum) must be considered, the dependent variable is dichotomous (i.e., selection of a risky or safe deck). Consequently, multilevel logistic modeling is recommended (Sommet & Morselli, 2017). To test the SMH using the IGT, the following multilevel logistic model equation can be used:

$$\text{Logit}\left(\frac{P(y_{it}=1)}{1-P(y_{it}=1)}\right) = b_{0i} + b_{1i}\text{TIME}_{it} + b_{2i}\text{SCR}_{it},$$

$$b_{0i} = b_0 + \mu_{0i},$$

$$b_{1i} = b_1 + \mu_{1i},$$

$$b_{2i} = b_2 + \mu_{2i}.$$

The left side of the equation corresponds to the logit of the probability (i.e., the natural logarithm of the odds) that the participant picked from a risky deck. The t identifies level 1 variables (draws 0 to 99), whereas i identifies level 2 variables (i.e., individuals). On the right side, b_0 corresponds to the mean intercept, b_1 is the mean slope of learning, TIME is a specific draw from 0 to 99, b_2 is the mean slope of SCR, and SCR is the independent variable. The μ_{0i} , μ_{1i} , and μ_{2i} correspond to the variance in the intercept and slope of SCR according to an individual i .

Several authors have employed multilevel models in IGT studies in recent years (Priolo et al., 2021; Wright & Rakow, 2023; Yip et al., 2020). However, with one exception (Yip et al., 2020), most have not explicitly stated how they treated the SCR variable. Others treated SCR as a dependent variable and deck selections as an independent variable (Priolo et al., 2021; Wright & Rakow, 2023), which raises concerns for three reasons. First, this approach does not conceptually align with the SMH as it inverts the temporal sequence (i.e., anticipatory SCRs naturally precede decisions and should hence be modeled as predictors and not outcomes in the model). Second, the model impedes the investigation of variables potentially moderating the association between SCR and decision-making (e.g., emotional intelligence; Yip et al., 2020) and thus, renders the model less flexible. Third, modeling SCR as a dependent variable cannot readily distinguish between the intra- and interindividual variance components of SCR. Given that SCR is collected multiple times within an individual, its raw value

represents an uninterpretable mixture of intra- and interindividual variance (Wang & Maxwell, 2015). Its variance components must be partitioned to understand the impact of the phasic time-dependent (intraindividual variance) and tonic time-invariant (interindividual variance) components on decision-making. To do so, the variable must be centered within individuals (Enders & Tofighi, 2007), meaning that the mean SCR of each individual is subtracted from their own raw SCR values. This creates a new level 1 variable, which depicts within-individual variations in SCR throughout the task, that is orthogonal (i.e., uncorrelated) to the level 2 component (the mean SCR). In other words, the intraindividual SCR variable has a mean of 0 for all participants (corresponding to their personal mean SCR), whereas the interindividual SCR has a mean of 0 (representing the mean SCR value for all participants). With this, the aforementioned equation now becomes:

$$\text{Logit}\left(\frac{P(y_{it}=1)}{1-P(y_{it}=1)}\right) = b_{0i} + b_{1i}\text{TIME}_{it} + b_2(\bar{x}_{\text{SCR}_i}) + b_{3i}(\text{SCR}_{it} - \bar{x}_{\text{SCR}_i}),$$

$$b_{0i} = b_0 + \mu_{0i},$$

$$b_{1i} = b_1 + \mu_{1i},$$

$$b_{3i} = b_3 + \mu_{3i}.$$

Here, $\bar{x}_{\text{SCR}_i}$ is the interindividual SCR (i.e., the mean SCR for each individual) and $\text{SCR}_{it} - \bar{x}_{\text{SCR}_i}$ is the intraindividual mean-centered variable representing the SCR of individual i at draw t . The parameter (b_2) of the interindividual effect of SCR, $\bar{x}_{\text{SCR}_i}$ is now fixed at level 2, as level 1 variance is represented by b_{3i} (the parameter of the intraindividual SCR). This model now allows us to test whether the intraindividual (b_{3i}) and/or the interindividual (b_2) effects of SCR predict decision-making.

Although Bechara and Damasio (2005) did not initially consider this multilevel structure, they also proposed hypotheses at level 2. For example, they propose that background somatic states may interfere with discrete somatic markers during decision-making. Empirically, participants exposed to a stressor have indeed exhibited lower between-individual SCRs, resulting in riskier performance in the IGT compared with a control group (Yilmaz & Kafadar, 2022). By aggregating all level 1 data to level 2, the conclusions emerging from the analyses may only concern background (level 2) somatic states. In fact, lower interindividual SCR in the stressed group may infer lower tonic EDA activity (Dawson et al., 2017). This suggests that the poorer performance of the stressed group was attributable to fewer attentional resources allocated to the IGT, rather than an alteration in somatic markers. The use of multilevel models allows for the direct testing of the hypothesis by modeling the interaction between the level 2 component of SCR (i.e., background somatic state) and level 1 component (i.e., decision-specific SCR) on decision-making. Therefore, multilevel modeling is a flexible analytical tool allowing us to

test more fine-grained research questions regarding level 1, level 2, or cross-level interactions.

Comparison of general linear and multilevel logistic analyses of simulated IGT data

Pseudorandom data were generated to test different modeling approaches to analyze IGT data. This allowed us to compare whether the specified parameters used to generate the data are retrievable using different analysis methods (e.g., general linear or multilevel logistic models). For details on data generation, the complete scripts and data sets used in this study are available at https://osf.io/e7ang/?view_only=2209d066bf7d43fea9cf2803ce44ba58. All procedures were conducted in R (R Core Team, 2024). Based on commonly used sample sizes in IGT studies, we generated data for a fictitious study comprising 80 individuals. A variance–covariance matrix was constructed to generate the level 1 parameters for all simulated individuals. Each individual has their own intercept (i.e., baseline tendency to take risks), slope of time (i.e., learning rate throughout the IGT), and slope of SCR (i.e., the intraindividual effect of SCR).

A total of six scenarios (i.e., data sets) were generated using different combinations of intraindividual and inter-individual SCR estimates, which are depicted in Table 1 as the specified parameters. The dependent variable had a dichotomous scale indicating whether the individual picked from the risky A or B decks (value of 1) or the safe C or D decks (value of 0) on a given draw. The meta-analysis by Simonovic et al. (2019) indicated that aggregated

between-individual SCR is negatively associated with risk-taking in the IGT. The first three scenarios included a negative level 2 SCR parameter ($b_2 = -0.5$) with either a positive ($b_{3i} = 0.3$), negative ($b_{3i} = -0.3$), or null effect ($b_{3i} = 0.0$) of level 1 SCR. This meta-analysis also revealed that some studies did not find any significant effect of SCR in the IGT. Therefore, the three remaining scenarios were generated using a null level 2 SCR effect ($b_2 = 0.0$), with the three variations in level 1 SCR estimates. The specified standard errors were 0.115 for the effect of intra-SCR (level 1) on risk-taking and 0.121 for the effect of inter-SCR (level 2).

All six scenarios were initially analyzed using general linear models with the native linear regression *lm* function in R. The percentage of risky deck selections was taken to obtain a single value indicating the number of times individuals selected decks A and B across the 100 deck choices. The SCR value utilized was the mean of the SCRs across the 100 draws, which corresponds to the interindividual SCR component. The following syntax was employed to compute the linear regression: `lm(total/100 ~ inter_SCR, data=wide_data)`, where *total* is a continuous variable representing the sum of the binary choices and *inter_SCR* is the mean SCR value across the 100 draws.

The six scenarios were then analyzed with the proposed multilevel logistic models, using the *glmer* function in the package *lme4* (Bates et al., 2015). The first analyses were run using the raw aggregated SCR variable, which represents a mixture of intra- and interindividual SCR effects. Therefore, the model included a fixed effect of time (i.e., the learning rate) and SCR, as well as their random effects. The syntax was as follows:

```
glmer(binary ~ time + SCR + (time + SCR|ID), data, family = binomial.
```

Table 1 Recovered estimates and standard errors of SCR for general linear models, multilevel logistic models with aggregated and disaggregated SCR

Specified parameters		Recovered SCR estimates			
Intra-SCR	Inter-SCR	General linear model	Aggregated multilevel	Disaggregated multilevel	
				Level 1	Level 2
−0.3 (.115)	−0.5 (.121)	−0.072 (.024)	−0.299 (.124)	−0.285 (.128)	−0.409 (.125)
−0.3 (.115)	0.0 (.121)	0.022 (.024)	−0.277 (.114)	−0.291 (.118)	0.103 (.131)
0.0 (.115)	−0.5 (.121)	−0.111 (.023)	−0.034 (.119)	−0.005 (.122)	−0.595 (.125)
0.0 (.115)	0.0 (.121)	−0.013 (.023)	0.008 (.103)	0.008 (.107)	0.031 (.108)
0.3 (.115)	−0.5 (.121)	−0.053 (.024)	0.289 (.107)	0.320 (.111)	−0.348 (.125)
0.3 (.115)	0.0 (.121)	0.021 (.024)	0.234 (.117)	0.241 (.122)	0.112 (.125)

Coefficients in logit scale (standard errors). Intra-SCR=intraindividual skin conductance response (SCR). Inter-SCR=interindividual SCR. Aggregated multilevel=multilevel logistic model with the raw aggregated SCR variable. Disaggregated multilevel=multilevel logistic model with the SCR variable disaggregated into its level 1 (intraindividual) and level 2 (interindividual) variance components. The specified parameters and standard errors of intra-SCR and inter-SCR were used to generate the six simulated data sets. For parsimony, we did not depict a positive association between inter-SCR and risk-taking considering that the scientific literature consistently reveals either a negative or a null association between inter-SCR and risk-taking (see the meta-analysis by Simonovic et al., 2019), but the conclusions remain the same for this scenario

Here, *binary* is the dichotomous dependent variable (1 = risky decks, 0 = safe decks) and “I” denotes the level of the random effects, which is the individual identifier “ID”. The second multilevel analysis required an additional step to separate the raw SCR variable into its inter- and intraindividual SCR components. Previous studies have addressed the issues regarding centering and disaggregating between- and within-variance components in multilevel models (Curran & Bauer, 2011; Wang & Maxwell, 2015). A person-mean-centering approach is

recommended to obtain two orthogonal variables representing the intra- and interindividual SCR components, which facilitates interpretation (Wang & Maxwell, 2015). The interindividual SCR is the mean of the person and the intraindividual SCR represents the deviation of a person’s given SCR value from that same person’s mean. This method necessitates the inclusion of two variables in the analyses instead of a single SCR value. The syntax now becomes:

```
glmer(binary ~ time + inter_SCR + intra_SCR + (time + intra_SCR|ID), data, family = binomial).
```

Here, *intra_SCR* represents the person-mean-centered SCR variable.

A summary of the recovered estimates and standard errors for the linear regressions, multilevel logistic models with the raw aggregated SCR variable, and multilevel logistic models with the disaggregated SCR variables are presented in Table 1. Of note, only the disaggregation of SCR variance components in multilevel models enables the simultaneous estimation of intra- (level 1) and interindividual (level 2) effects of SCR. The recovered estimates of the linear regressions did not correspond to the specified intra- or interindividual SCR effects. The estimates were influenced by variation in the effect of interindividual SCR, but systematically underestimated the true interindividual SCR in the scenarios with a specified parameter of -0.5 . This is because of the lack of consideration of the intraindividual SCR effect and the learning rate throughout the IGT. Another issue of general linear models is the violation of the assumption of normality of the residuals. Considering that the dependent variable in the IGT is bounded between 0 and 1 (i.e., it has a lower limit of 0% and an upper limit of 100% total cards drawn from the risky decks), and that individuals learn during the task (i.e., they choose less frequently the risky decks), the residuals are unlikely to follow a normal distribution. This means that linear models are inadequate to address nonlinear distribution and heterogenous variance of the residuals. Accordingly, Table S1 (see Supplemental Materials) shows that beta regressions, which account for bounded dependent variables and heteroscedastic variance, recovered more precise estimates of interindividual SCR compared to general linear models. Note that they remain less appropriate than multilevel models, as the latter allow to also estimate the effect of intraindividual SCR.

The recovered estimates of the multilevel logistic models using the raw aggregated SCR variable corresponded to the specified intraindividual SCR value. Yet, because the aggregated SCR is a mixture of level 1 and level 2 variances, the disaggregation of the intraindividual SCR variance from the interindividual SCR variance resulted in more accurate

level 1 parameter estimates (i.e., not influenced by level 2 variance). The results show that modeling random effects using multilevel logistic models with aggregated level 1 and level 2 SCR components recovers parameters that are mostly representative of level 1. Consequently, interpreting results from aggregated multilevel models and general linear models may be erroneous, because these estimate to a greater extent level 1 and level 2 variances, respectively. Future meta-analyses should distinguish whether the estimated effects reflect level 1 or level 2 SCR components as these could have opposing effects.

Because general linear models assume the independence of observations and do not account for random effects, the standard errors specified to generate the data sets (0.115 for the effect of intra-SCR and 0.121 for inter-SCR) were underestimated by the linear regressions (range 0.023–0.024) compared with both multilevel logistic models (range 0.103–0.131). A similar conclusion applies for beta regressions (see Supplemental Materials). This yields an overestimation of the test statistic and may cause greater Type I error rates (i.e., false positives; Musca et al., 2011). These results demonstrate that multilevel logistic models are more effective in recovering parameters. Disaggregating the SCR variable into its intra- and interindividual components allows for the accurate estimation of level 1 and level 2 parameters, as well as their standard errors.

The analyses of the simulated data show that multilevel logistic models allow for a more comprehensive understanding of the impact of somatic markers on decision-making than traditional methods. Since its inception, the SMH has rarely been tested in accordance with its intended purpose, as studies mainly focused on between-individual differences. Yet, the intra- and interindividual variances in anticipatory SCRs may predict distinct patterns of decision-making. Assessing intraindividual SCR directly tests the proposition of the SMH that experiencing a somatic marker can bias the subsequent decision and thereby, strengthens causal inferences. Furthermore, modeling the learning rate makes multilevel models highly flexible to test more

fine-grained hypotheses. For instance, the impact of SCR on decision-making may vary as participants learn throughout the task (Bechara & Damasio, 2005; Bechara et al., 1997). Including an interaction between the learning rate and the intraindividual SCR component could reveal important time-dependent effects. Somatic markers are thought to be implicit warning signals about the riskiness of choice options. At the beginning of the task, a positive relationship may be found between intraindividual SCR and risk-taking, such that an increase in SCR before selecting a card (relative to the individual's mean anticipatory SCR) enhances the probability of choosing from the risky decks. Once participants form intuitions about the win-loss contingencies of the decks, somatic markers may become a more conscious risk signal biasing them towards safer decks. Multilevel logistic models allow us to test this possible reversal in the relationship between intraindividual SCR and risk-taking throughout the task.

Empirical data demonstration

To assist researchers in implementing the proposed method for testing the SMH, we used the open access database from Priolo et al. (2021) for illustrative purposes. In their study, the authors investigated whether the use of irrelevant affective cues impacted risk-taking in the IGT. They used two experimental conditions with modified IGT procedures, and a control group which underwent standard IGT procedures. They used multilevel linear models with SCR as the dependent variable and learning rate and deck choices (binary) as independent variables. Skin conductance response was not found to differentiate risky from safe decks in the control condition. Because they employed deck choices as an independent variable, they were compelled to model the learning rate as a discrete variable representing five blocks for the draws 1–10, 11–20, 21–60, and 61–100. This was done to ensure that each cell included variability in deck choices. However, this technique does not allow to easily separate

level 1 and level 2 variance components in SCR, as SCR is modeled as a level 1 dependent variable.

We aimed to demonstrate how to disaggregate SCR components, implement multilevel logistic models, and interpret the results. We only applied our analytical strategy to their control condition, because it employed the standard IGT procedures. We show that the proposed analyses unravel new results that are coherent with the SMH.

SCR disaggregation

The initial step is to disaggregate the raw SCR variable. We subtracted the mean of the sample from all individual SCR measures, resulting in a variable with a mean of 0. Then, using the *group_by()* function of the *dplyr* package, we grouped the data by participant to compute the personal mean SCR for each participant, corresponding to the level 2 component (interindividual SCR). To compute the level 1 component (intraindividual SCR), we retained the data grouped by participant and subtracted their personal mean (interindividual SCR) from their individual SCR measures. This new intraindividual SCR variable has a mean of 0 for all participants. Therefore, this variable represents the variance in SCR relative to a given person's mean. Critically, the intra- and interindividual SCR variables are orthogonal, meaning that one represents only level 2 variance (interindividual SCR) and the other represents only level 1 variance (intraindividual SCR). Finally, we z-scored both the intra- and interindividual SCR variables to facilitate interpretation.

Model building and analyses

We fitted two multilevel logistic models using the *glmer* function of the *lme4* package (Bates et al., 2015). The first model included the raw aggregated SCR variable, which was z-scored and centered around the grand mean of all individuals and was specified using this formula:

```
glmer(isBad ~ SCRz * Trial + (Trial|ID), data = df_priolo, family = binomial).
```

Here, *isBad* is a binary variable indicating the selection of a risky deck (1) or a safe deck (0), and *Trial* is the learning rate variable (from draw 0.00 to 0.99). In

the second model, we used the disaggregated inter- and intraindividual SCR variables. The model was specified as

```
glmer(isBad ~ inter_SCRz + intra_SCRz * Trial + (Trial|ID), data = df_priolo, family = binomial),
```

where *inter_SCRz* and *intra_SCRz* represent the inter- and intraindividual z-scored SCR variables and *intra_SCRz*Trial* is the interaction term between *intra_SCRz* and *Trial*. As Priolo et al. (2021) reported an interaction in their

congruent condition (where SCR predicted choosing from the bad decks only in the last 60 draws or so), we included an interaction term between the intraindividual SCR variable and learning rate. Having a random slope for *Trial* and

Table 2 Results of the Multilevel Logistic Regressions of the Data from Priolo et al. (2021)

Predictors	Aggregated SCR			Disaggregated SCR		
	OR	95% CI	<i>p</i>	OR	95% CI	<i>p</i>
(Intercept)	1.20	1.01–1.44	.042	1.23	1.02–1.47	.027
Inter_SCRz				0.94	0.83–1.06	.299
Intra_SCRz				1.14	1.01–1.28	.030
Trial	0.32	0.20–0.52	<.001	0.32	0.20–0.51	<.001
Intra_SCRz * trial				0.83	0.67–1.02	.070
SCRz	1.10	0.97–1.23	.130			
SCRz * trial	0.88	0.72–1.08	.209			
Random effects						
σ^2	3.29			3.29		
$\tau_{00 \text{ ID}}$	0.24			0.24		
$\tau_{11 \text{ ID:Trial}}$	2.24			2.24		
$\rho_{01 \text{ ID}}$	−0.70			−0.71		
ICC	0.13			0.12		
N_{ID}	49			49		
Observations	4900			4900		
Marginal R^2 / Conditional R^2	0.028 / 0.150			0.030 / 0.151		

SCR=skin conductance response. σ^2 =residual variance. $\tau_{00 \text{ ID}}$ =variance of the random intercepts across IDs. $\tau_{11 \text{ ID:Trial}}$ =Variance of the random slopes for Trial across IDs. $\rho_{01 \text{ ID}}$ =Correlation between random intercepts and random slopes for Trial. ICC=intraclass correlation coefficient. The negative correlation between the random intercepts and slopes suggests that individuals with higher baseline odds of selecting from risky decks tend to have a more negative slope of Trial, meaning their odds of selecting risky decks decreased over trials. The ICCs of 0.13 / 0.12 indicate that 13 / 12% of the variance in deck selections is attributable to differences between participants

intra_SCRz produced a singular fit. This is likely due to the random effect structure being too intricate. We ran two additional models, removing one random slope at a time. Only the model with a random slope of *Trial* converged. Upon examination of the variance of the random slope of *intra_SCRz*, the model estimated a small random effect variance of 0.0004 between participants and may have contributed to insufficient variance.

The results of the two models are presented in Table 2. The models' total explanatory power was moderate (conditional R^2 of 0.150 and 0.151 for the aggregated and disaggregated models, respectively) and the portion related to the fixed effects alone was small (marginal R^2 of 0.028 and 0.030 for the aggregated and disaggregated models, respectively). The exponent of the logit estimates was taken to obtain odds ratios (OR). The main effect of *SCRz* in the model with aggregated SCR (OR = 1.10) falls between the *inter_SCRz* (OR = 0.94) and *intra_SCRz* (OR = 1.14) values of the model with disaggregated SCR. As expected, the aggregated SCR variable represents a combination of intra- and interindividual effects. Indeed, the odds ratio of interindividual SCR is below 1, although statistically non-significant. This result would indicate that individuals experiencing greater SCRs throughout the task take fewer risks, as reported in the meta-analysis by Simonovic et al. (2019). In contrast, the effect of

intraindividual SCR is statistically significant and greater than 1, implying that a one standard deviation increase in SCR before a given draw increases the odds of selecting from a risky deck by 14%.

Although the interaction between *intra_SCRz* and *Trial* did not reach statistical significance, the *p*-value of 0.070 suggests a potential trend that warrants further investigation. The marginal moderation suggests that the effect of intraindividual SCR on the likelihood of choosing risky decks may vary as participants progress in the task. As illustrated in Fig. 1, one method for visualizing the data involves plotting the effect of intraindividual SCR at −1 and +1 standard deviation values to demonstrate how its effect varies over time. Importantly, for interpretation purposes, the two lines do not represent individuals exhibiting high or low intraindividual SCR, as would be the case with the interindividual SCR. Instead, the graph indicates that when a given person experiences an increase in SCR relative to their own mean SCR level, their likelihood of choosing a risky deck increases at the beginning of the task. Figure 2 represents the Johnson-Neyman plot of the marginal interaction, which identifies the specific values of the moderator variable (*Trial*) for which the effect of the predictor variable (intraindividual SCR) on the outcome (risk-taking) is statistically significant. It can be observed that the effect of intraindividual SCR is only marginal up to the 30th card draw.

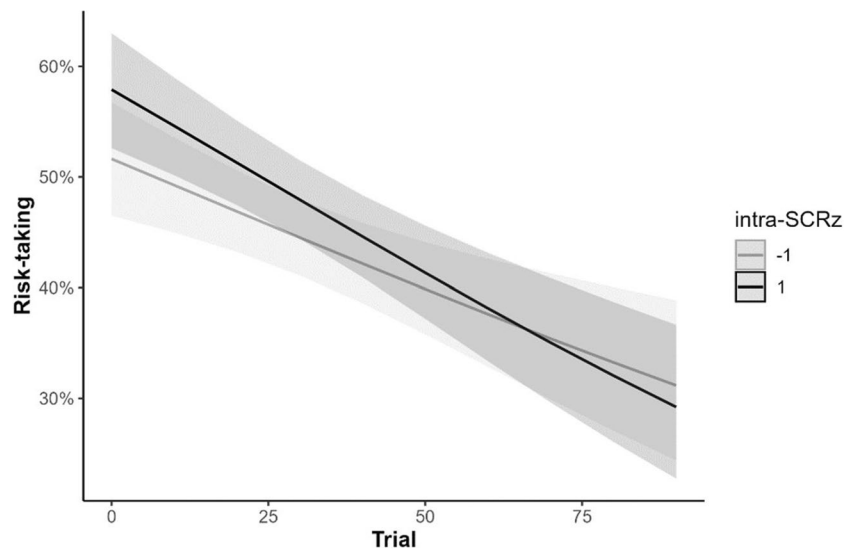


Fig. 1 Simple slope plot of the marginal interaction between intraindividual SCR and trial. Note. The y-axis represents the odds of selecting from the risky decks. The *intra-SCRz* represents the z-scored

intraindividual SCR variable at -1 and $+1$ standard deviations. The plot was created using *sjPlot* (Lüdtke et al., 2024)

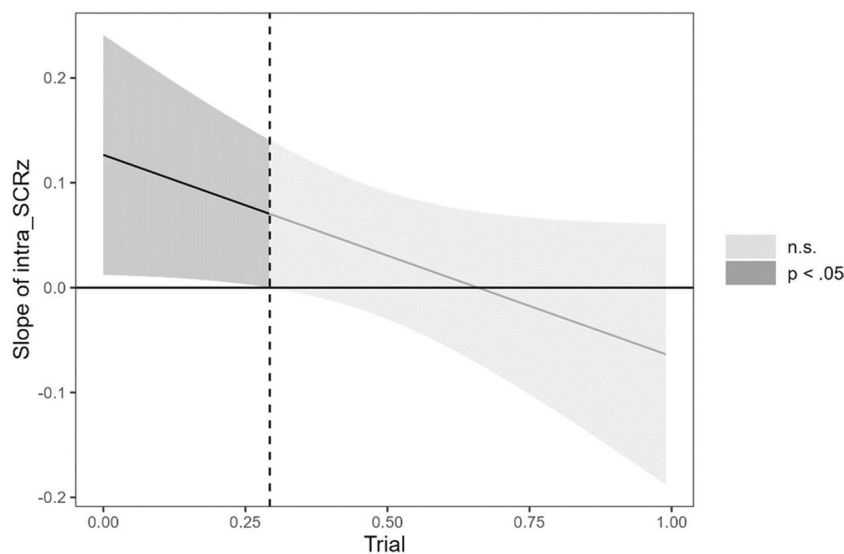


Fig. 2 Johnson-Neyman plot of the region of significance of the moderation. Note. Johnson-Neyman plot using the *interactions* package (Long, 2019). The y-axis represents the slope of the *intra-SCRz* at different values of *Trial* (card draws). It identifies the moments during

the IGT when the intraindividual SCR influences risk-taking and its corresponding slope. The region of significance is depicted in black ($p < .05$), whereas the grey portion indicates that the interaction is not significant ($p > .05$)

In their study, Priolo et al. (2021) used the raw aggregated SCR variable as a dependent variable and reported no significant association between SCR and decision-making in their control condition. Our analyses demonstrated that disaggregating the SCR variable into its intra- and interindividual components enabled us to capture a more comprehensive understanding of the modeled effects. The interaction between the intraindividual

SCR and the learning rate was marginal in our proposed analyses, with an effect of intraindividual SCR in the first 30 draws of the IGT. The marginal effect suggests that the sample size of 49 participants may be insufficient to detect the effect of intraindividual SCR on decision-making. Alternatively, other variables may need to be incorporated in the model to reveal a significant interaction between intraindividual SCR and learning rate in the

IGT. For instance, a recent meta-analysis demonstrated that men are quicker to learn which decks are risky in the IGT (Zanini et al., 2024). Therefore, including the sex of participants in the model may reveal sex-specific effects of somatic markers on decision-making. Unfortunately, individuals' sex was not available in Priolo et al.'s database. Although the interindividual SCR component was statistically non-significant, its effect was opposite to the intraindividual SCR component. As the aggregated SCR variable had a mixture of intra- and interindividual variances, its effect was far from being statistically significant (as found by Priolo et al., 2021). This underscores the necessity to employ SCR as an independent variable to disaggregate its variance components to prevent the masking of any opposing effects between the intra- and interindividual SCR components.

Discussion

The objective of this paper was to demonstrate the benefits of using multilevel logistic models and disaggregating SCR into its intra- and interindividual components when investigating the SMH. Recent evidence suggests that somatic markers may have a small to medium effect on decision-making, such that greater mean SCR throughout the task predicts better performance (Simonovic et al., 2019). However, the heterogeneity in the results reported by the authors could be explained by statistical analyses that are unfit for data inherent to repeated measures research (such as with the IGT). Indeed, the assumption of independent observations of general linear models is violated, rendering their use inappropriate. Multilevel models circumvent this issue by explicitly modeling the variance in intercepts and slopes across individuals. As the repeated measures of SCRs are modeled, a person-mean centering approach can be used to generate two orthogonal values of SCR, representing purely level 1 (intraindividual) and level 2 (interindividual) variance components. These variables can then be utilized in multilevel logistic models to ascertain whether the effect of SCR on decision-making relies on its variation according to one's average level of SCR (intraindividual variance) or the mean level of SCR individuals exhibit throughout the task (interindividual variance). Our simulations demonstrated that common statistical methods (e.g., general linear models) result in confounded level 1 and level 2 variances of SCR. Moreover, general linear models underestimated the standard errors, increasing the odds of obtaining falsely positive results. We also demonstrated that disaggregating SCR into its intra- and interindividual variance components in a multilevel logistic model allowed us to explicitly estimate these two levels

of variance simultaneously and more precisely (compared with using the raw aggregated SCR variable).

Our reanalysis of the data from Priolo et al. (2021) provides a compelling demonstration of the pitfalls of using the raw aggregated SCR (i.e., overlooking significant intraindividual effects). Our results also shed light on new insights for an interesting finding in the study by Simonovic et al. (2019). Their two meta-analyses revealed that although greater SCR was associated with better performance on the IGT (i.e., less risk-taking), individuals experienced greater SCR before choosing from risky decks. These conflicting results can be reconciled by using a multilevel framework. Our results show that intraindividual SCR may indeed precede the decision to choose from risky decks but only at the beginning of the task. Other researchers have emphasized the importance of considering the learning rate during the IGT, because the SCR may serve different purposes throughout the task (Xu & Huang, 2020). In the beginning, as participants have little insight into the win-loss contingencies, somatic markers may develop as preconscious risky signals and precede the selection of risky decks. Once participants have gained a better understanding of the contingencies, intraindividual SCR may then become a signal with the potential to bias (consciously or not) towards the safer decks (Maia & McClelland, 2004). Testing these hypotheses is only possible if one explicitly models the intraindividual variance in SCR, given that its effect might reverse as individuals progress through the IGT.

The IGT has been critiqued for its intricacy, given the involvement of numerous cognitive functions and the associated challenges of decomposing task performance into distinct cognitive processes (Schonberg et al., 2011). Some recent analytical approaches address this issue by modeling intraindividual cognitive processes with computational methods that capture level 1 variance, as we proposed herein. These computational models aim to disentangle latent psychological processes, such as reward sensitivity and win frequency sensitivity, and have been shown to enhance the psychometric reliability of the IGT (Sullivan-Toole et al., 2022). However, no existing computational models developed for the IGT have incorporated physiological data to directly test the SMH. Our approach is not in opposition to these computational models; rather, it provides a detailed description and demonstration of how to incorporate physiological data to enhance their predictive power. By doing so, we could gain a more nuanced understanding of the interplay between cognitive and emotional processes in the IGT, which could ultimately help address long-standing debates about the SMH and the role of emotion in decision-making (Chiu et al., 2022; Maia & McClelland, 2004).

Because SCR is the most used somatic marker proxy to test the SMH, the current article emphasizes its effect on

decision-making. Of note, this methodology can be used with other proxies for somatic markers, such as heart rate or electroencephalogram recordings. The complete and annotated R syntax used for this manuscript is provided to guide researchers in using the proposed analyses. Moreover, the syntax can be adapted to include the four card decks if a research question is specific to each deck (rather than the dichotomous risky or safe decks). For example, this could be used to test the role of somatic markers in the prominent deck B phenomenon (Lin et al., 2007). Finally, the general concepts illustrated can be used in other paradigms using repeated measures, such as fear conditioning (Peyrot et al., 2024). Researchers interested in both intra- and interindividual variance components may benefit from employing the suggested approach, because it allows for a more comprehensive examination of the data and more precise hypothesis testing. By refining our analytical methods, we may finally be able to do justice to Damasio's groundbreaking hypothesis and uncover the true extent of the somatic marker's role in decision-making.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.3758/s13415-025-01271-7>.

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Availability of data and materials Data sets used in this study are available at: https://osf.io/e7ang/?view_only=2209d066bf7d43fea9cf2803ce44ba58.

Code availability The R scripts are available at: https://osf.io/e7ang/?view_only=2209d066bf7d43fea9cf2803ce44ba58.

Declarations

Conflicts of interest/Competing interests The authors have no relevant financial or non-financial interests to disclose.

Ethics approval This is a methodological study using simulated and open access data. No ethics approval was required.

Consent to participate Not applicable.

Consent for publication Not applicable.

Open practices statement None of the experiments were preregistered. The R scripts and data sets used in this study are available at: https://osf.io/e7ang/?view_only=2209d066bf7d43fea9cf2803ce44ba58.

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