Behavior Research Methods (2025) 57:78
https://doi.org/10.3758/s13428-024-02594-y

ORIGINAL MANUSCRIPT

The trajectory of crime: Integrating mouse-tracking into concealed memory detection

Xinyi Julia Xu[1] · Xianqing Liu[1] · Xiaoqing Hu[2] · Haiyan Wu[1]

Accepted: 18 December 2024

Abstract

The autobiographical implicit association test (aIAT) is an approach of memory detection that can be used to identify true autobiographical memories. This study incorporates mouse-tracking (MT) into aIAT, which offers a more robust technique of memory detection. Participants were assigned to mock crime and then performed the aIAT with MT. Results showed that mouse metrics exhibited IAT effects that correlated with the IAT effect of RT and showed differences in autobiographical and irrelevant events while RT did not. Our findings suggest the validity of MT in offering measurement of the IAT effect. We also observed different patterns in mouse trajectories and velocity for autobiographical and irrelevant events. Lastly, utilizing MT metric, we identified that the Past Negative Score was positively correlated with IAT effect. Integrating the Past Negative Score and AUC into computational models improved the simulation results. Our model captured the ubiquitous implicit association between autobiographical events and the attribute *True*, and offered a mechanistic account for implicit bias. Across the traditional IAT and the MT results, we provide evidence that MT-aIAT can better capture the memory identification and with implications in crime detection.

Keywords Mouse-tracking (MT) · Autobiographical implicit association test (aIAT) · Memory detection · Mock crime · Neural network model

Introduction

The attempts to detect deception and concealed memories have evolved for hundreds of years, and captured a broad interest from fields including psychology, forensics, neuroscience, and even ethics (Agosta & Sartori, 2013; Chassot, Klöckner, & Wüstenhagen, 2015; Verschuere, Ben-Shakhar, & Meijer, 2011; Vrij & Fisher, 2016; Wu, Fu, & Zang, 2010; Nahari, 2018). Classical behavioral lie detection methods mainly investigated the RT difference to different stimuli (of interest vs. irrelevant) as a behavioral index of deception, e.g., RT-based Concealed Information Test (RT-CIT; Lykken, 1959; Verschuere et al., 2011). Further, the autobiographical implicit test (aIAT) is an adaptation of the implicit association test (IAT) (Greenwald, McGhee, & Schwartz, 1998), which aims to identify the veracity of autobiographical memories by assessing the associative strength between subjects' autobiographical memories and objective events. It is usually quantified by D scores defined as the differences of the averaged RTs between incongruent and congruent conditions, which has been validated in memory detection.

RT-based aIAT does not reveal the real-time categorization processes, given that only the final behavioral output (RT and accuracy) is recorded (Yu, Wang, Wang, & Bastin, 2012; Smeding, Quinton, Lauer, Barca, & Pezzulo, 2016). Although RTs can be modeled (e.g., via drift-diffusion modeling Krajbich & Rangel, 2011), to more precisely isolate the different components that contribute to RT, the complexity of these approaches makes interpretation less straightforward. A promising approach to complete the aIAT is to provide a real-time measurement of categorization by adding mouse-tracking (MT) (Duran, Dale, & McNamara, 2010; Stillman, Shen, & Ferguson, 2018), which offers more precise millisecond-by-millisecond information on how cognitive processing underlying memory detection unfolds without the need for complex experimental setups (Stillman et al., 2018;

✉ Haiyan Wu
haiyanwu@um.edu.mo

[1] Centre for Cognitive and Brain Sciences and Department of Psychology, University of Macau, Taipa 999078, Macau, China

[2] Department of Psychology, The University of Hong Kong, Hong Kong 999077, Hong Kong, China

Published online: 27 January 2025

Freeman, Ambady, Rule, & Johnson, 2008; Freeman, Dale, & Farmer, 2011). Empirical analysis of MT data can capture the temporal dynamics of memory categorization in terms of spatiotemporal patterns (Sartori, Zangrossi, & Monaro, 2018; Freeman, 2018).

In the last decade, mouse-tracking has gained significant and increasing traction in various fields of cognitive science, primarily due to its methodological and theoretical benefits (Stillman et al., 2018; Melnikoff, Mann, Stillman, Shen, & Ferguson, 2021). Compared to traditional reaction times (RTs), MT has proven to be especially effective in isolating the dynamics of response conflict by measuring how directly participants approach their decisions (Freeman et al., 2008). This technique allows researchers to map out the stages involved in the decision-making process (Kieslich & Henninger, 2017), with the assumption that mouse movements (i.e., hand movements) are executed in parallel with the decision that participants are required to make (Freeman, Pauker, Apfelbaum, & Ambady, 2010). For instance, a quick and direct trajectory may indicate reliance on intuitive processing, while more convoluted paths could suggest a deliberative approach where options are pondered before settling on a choice. Consequently, mouse-tracking has been effectively applied across numerous areas, including language (Potamianou & Bryce, 2024; Spivey, Grosjean, & Knoblich, 2005; Richter, Lins, & Schöner, 2021), social cognition (Schoemann, O'Hora, Dale, & Scherbaum, 2021), and memory (Gatti, Rinaldi, Marelli, Mazzoni, & Vecchi, 2022). These studies converge in finding that measures derived from the manual dynamics of response, e.g., the mouse trajectories, are sensitive enough to capture small effects that often escape simple reaction time measures.

Recent work has successfully incorporated MT in deception tasks (Pang et al., 2022; Wu, Cao, Bai, & Chen, 2021) or with IAT (Yu et al., 2012; Monaro, Gamberini, & Sartori, 2017a). For example, Yu et al. (2012) integrated the mouse-tracking to a flower-insect IAT and two implicit self-esteem IATs, which showed both classical RT-based IAT effects and the potential of mouse trajectories in revealing the underlying process of IAT. Monaro, Negri, Zecchinato, Gamberini, and Sartori (2021b) also demonstrated the effectiveness of MT-IAT to assess implicit preferences towards social networks such as Facebook and Twitter, extending the MT-IAT to a novel field such as consumer research. The covert nature of MT and the real-time nature, continuous motor trajectories are also instrumental in memory detection tasks (Sartori et al., 2018; Papesh & Goldinger, 2012). For instance, in a word recognition task, participants made new/old decisions while being tracked to their mouse coordinates and then underwent a confidence assessment. By examining response trajectories and subsequent confidence, the researchers found that stronger memories corresponded to fast linear movements (Papesh & Goldinger, 2012). Taken together, MT could provide continuous spatiotemporal information in assessing attitudes and memory strength. Therefore, we combined MT with aIAT to test its effectiveness in detecting autobiographical memories.

RT and MT data of aIAT can also be incorporated with computational modeling (Wu et al., 2021; Xu, Yang, Huang, Wang, & Wu, 2023). A commonly used model in RT-based choices is the drift-diffusion model (DDM), which has been proven to be a powerful method for revealing internal properties of decision-making processes of both humans and rodents (Brunton, Botvinick, & Brody, 2013; Chen & Krajbich, 2018). In traditional DDM, the information begins at the postulated position z and accumulates with time at a speed v. The accumulation of information includes systematic and random influences. A decision is made when the accumulated evidence reaches the threshold (Klauer, Voss, Schmitz, & Teige-Mocigemba, 2007). If ambivalence in decision-making arises from the amount of information necessary to make a decision or the speed of information accumulation, individual variability in AUC (Bodily et al., 2015; Lopez, Stillman, Heatherton, & Freeman, 2018; Leontyev & Yamauchi, 2021) should be mirrored in the variability of the drift rate. One problem exhibited when incorporating DDM with IAT is that in standard binary decision-making tasks, such as the moving dot paradigm (Huk & Shadlen, 2005), sensory evidence in favor of each motor output is experimentally defined (i.e., as the relative proportion of dots moving in each direction). In the case of the IAT, however, it is less clear how sensory evidence should be established for each visual stimulus. To bridge the gap between the non-value-based experiment (aIAT) and this precisely described model, here we used the connectionist model (Bedder et al., 2019) to quantify the strength of sensory information, which was modulated by individual traits.

In this study, we incorporated MT with aIAT in a mock crime scenario to demonstrate how the movements in hand can detect concealed autobiographical memories, and we employed model simulation to offer a more precise mechanistic account of aIAT. The specific objectives of the current study are to: 1) validate all the mouse tracking metrics (MAD, AD, AUC, and MD) and whether they possess IAT effects as RT does; 2) prove the MT offers complementary insights of RT IAT. Thus we hypothesized that: 1) MT metrics would be able to possess significant IAT effects to detect the concealed memory; 2) trajectories of crime-relevant and crime-irrelevant exhibit differences; 3) model simulations performs better when integrating the MT metric. Our work goes significantly beyond the current literature by providing memory detection that integrates mock crime, MT, and aIAT, with a more comprehensive analysis of the IAT effect and relevant MT dynamics.

Methods

Participants

Fifty-eight healthy undergraduate and graduate students (31 males, $M_{age} = 21.19$, $SD = 2.24$; 27 females, $M_{age} = 21.30$, $SD = 2.43$) participated in this experiment. They were randomly assigned to the congruent-block first group or the incongruent-block first group (see Section "Procedure"). Specifically, 33 participants (16 males, $M_{age} = 21.28$, $SD = 2.44$; 17 females, $M_{age} = 21.63$, $SD = 2.59$) signed up for congruent-block first task and 25 participants (14 males, $M_{age} = 21.09$, $SD = 2.07$; 11 males, $M_{age} = 21.04$, $SD = 2.08$) signed up for the other group. All participants were right-handed with normal or corrected-to-normal vision, and had not participated in any similar studies. Each participant signed informed consent prior to the formal experiment, and the local ethical review committee approved the experimental protocol. At the end of the study, the participants were paid 50–60 CNY.

Power calculation

To achieve greater than 80% power to detect a large effect of d = 0.80 at $\alpha = 0.05$ in our analyses of paired *t* tests, we calculated the minimal sample size, which was 14, using the package pwr in R (Champely et al., 2018). We oversampled and recruited 58 participants (33 participants for the congruent block first group and 25 participants for the incongruent block first group). We have also tested the power with other statistics. For the correlation between ZTPI score and IAT effect using MD (Fig. 5), the power was 0.54.

Procedure

Before starting the task, participants were asked to complete the interactive mentalizing questionnaire (IMQ) (Wu et al., 2022, 2020) and Zimbardo Time Perspective Inventory (ZTPI) (Zimbardo & Boyd, 2013).

Mock crime session

The mock crime setting has been used in existing aIAT studies (e.g., Sartori, Agosta, Zogmaister, Ferrara, & Castiello, 2008; Verschuere et al., 2009; Agosta et al., 2011; Hu et al., 2012). Participants were asked to select one out of two envelopes, deciding which task they were going to perform. The content in the two envelopes was actually the same – to steal the credit card (see Verschuere et al., 2009). However, they were informed that one of the tasks was to steal a credit card from a wallet, and the other was to copy a confidential file on a computer. This brought participants a sense of involvement to 'commit the crime' and drove them to perform the task with self-motivation. After revealing the task in the envelope, they were guided to a lab room (mock crime room) to find the wallet and steal the credit card. To increase the ecological validity, the experimenter informed participants before the session that they had to withdraw from the experiment if caught during the mock crime session.

The mock crime room was arranged before every participant came in. Stealing the credit card consisted of several steps that were the same for every participant (see Fig. 1A; for detailed steps for crime-relevant and crime-irrelevant events, see supplemental materials 1)

MT-aIAT task

After the mock crime session, participants were arranged to sit in front of a monitor in another lab room (testing room) to complete the aIAT session. The aIAT was performed using a procedure analogous similar to previous work (Sartori et al., 2008; Marini, Agosta, & Sartori, 2016), while implemented with a mouse tracker to record the mouse trajectories. The stimuli were presented through Mousetracker (http://www.mousetracker.org/), which recorded the mouse position (x and y coordinates) about 70 times per second (70 Hz). Participants were instructed to click START at the bottom center of the screen for each trial, then the event stimulus (see detailed stimuli in supplemental materials 1) showed up in the center. They were instructed to classify the stimulus by clicking the key at the left upper corner of the screen (R1) or the key at the right upper corner (R2) (see Fig. 1). Participants were required to move the mouse quickly and accurately in the task; otherwise, a reminder would appear to urge them to respond as quickly as possible.

The aIAT was structured in seven blocks, including three simple blocks (blocks 1, 2, and 5) and four combined blocks (blocks 3, 4, 6, and 7):

- Block 1 (20 trials) required all participants to make a binary classification based on the stimuli's logical attributes: they were asked to discriminate whether the sentence displayed was objectively true (e.g., "I am on the third floor") or false (e.g., "I am in a shop"), and click the corresponding key (R1 for true and R2 for false).
- In block 2 (20 trials) and block 5 (20 trials), participants classified the stimulus only depending on whether it was associated with the crime-relevant event (event 1: stealing the credit card from a wallet) they had committed (e.g., "I opened the wallet") or the crime-irrelevant event (event 2: copying a confidential file on a computer; e.g., "I inserted the USB"), and clicked the corresponding corner/area.
- Block 3 (60 trials), block 4 (200trials), block 6 (60 trials), and block 7 (200 trials) were the combined blocks, requiring participants to categorize both "objectively true or false" events and "crime -relevant or -irrelevant" events.

The four combined blocks were subdivided into congruent blocks and incongruent blocks. In the congruent blocks, event 1 and the objectively true sentences shared the same motor response R1 ('event1 + true'), while stimuli related to event 2 and objectively false sentences shared the same motor response R2 ('event2 + false'). In the incongruent blocks, the respondents learn a reversal of response assignment where the two combinations change to 'event1 + false' and event2 + true'.

To eliminate the order effect, block order was counterbalanced across participants. For the congruent-block first group, R1 corresponded to event 1 and R2 corresponded to event 2 in block 2 while the response pattern was reversed in block 5. Also, block 3 and block 4 were congruent blocks, while block 6 and block 7 were incongruent blocks. For the incongruent-block first group, R1 corresponded to event 2, and R2 corresponded to event 1 in block 2; while in block 5, the response pattern was reversed. Also, block 3 and block 4 were incongruent blocks, while block 6 and block 7 were congruent blocks.

Mouse-tracking data analysis

Mouse trajectory preprocessing

Standard mouse-tracking preprocessing was conducted temporally and spatially (Freeman & Ambady, 2010). In a typical binary choice design, trajectories end at either the left or the right response option. For those analyses where the overall spatial direction is irrelevant, all trajectories were remapped so that they would end on the same side. We used the R package 'mousetrap' (Kieslich & Henninger, 2017) to map the trajectories to the left by default, suggesting that trajectories that end on the right-hand side are flipped from right to left. We rescaled all mouse trajectories into a standard coordinate space (top left: [-1, 1]; top right: [1, 1]) so that the cursor always started at [0,0] (Sullivan, Hutcherson, Harris, & Rangel, 2015). Temporally, time normalization was applied to the trajectories such that the duration of each trial was divided into 101 identical time bins using linear interpolation to obtain the average of their length across multiple trials (Spivey et al., 2005; Dale, Kehoe, & Spivey, 2007; Freeman et al., 2008; Freeman et al., 2010; Duran et al., 2010; Sullivan et al., 2015).

Mouse trajectory measurements

To get the trial-by-trial category co-activation index, we calculated the signed maximum absolute deviation from the direct path (MAD), the average deviation from direct path (AD),the maximum deviation above the direct path (MD) and the area under the curve (AUC) of each mouse trajectory by R package Mousetrap (Kieslich & Henninger, 2017). Also, velocity as distance covered per normalized time interval was calculated.

Temporal analysis

After preprocessing the mouse trajectories, we split the trials into congruent and incongruent conditions. To test the significant temporal difference between trajectories statistically, we calculated the x positions and velocity along with time bins of every trial and compared them through paired *t* test (Chemin, Huang, Mulders, & Mouraux, 2018; Kieslich & Henninger, 2017). Besides, we split trials into crime-relevant and crime-irrelevant events, and further examined the discrepancy between the two conditions (congruent vs. incongruent).

IAT effect

Data from blocks 4 and 7 were extracted for analysis. Trials with RTs of > 10 s and participants who have $> 10\%$ of trials with RTs < 300 ms are excluded. In addition, RTs for error trials were removed. The IAT effect was calculated through all metrics (RT, MAD, AD, MD, AUC) by the mean metric across congruent trials subtracted from the mean metric across incongruent trials, normalized by the standard deviation of all trials (Eq. 1).

$$\text{IAT effect} = \frac{\bar{metric}_{incon} - \bar{metric}_{con}}{STD_{all}} \quad (1)$$

Simulations of the IAT effect

Connectionist model

The connectionist model is comprised of four neural sub-populations that respond to the perception of four features, including crime-relevant (CR), and crime-irrelevant (CI), True, False within the agent (see Fig. 4B) (Bedder et al., 2019). When the agent perceives stimuli related to themselves (CR or True), a neuro-modulatory signal allows synaptic connections between active sub-populations encoding CR and True to be strengthened by a Hebbian learning rule (Hebb, 2005). In this case, the simulated agent committed crime-relevant events as our participants did, such that the connectionist model comes to encode strong associations between neurons encoding crime-relevant (CR) and True features. During subsequent perception, sensory input to sub-populations encoding the features of that agent generates additional activity in the network via recurrent synaptic connections if those features overlap with the encoded features(see Fig. 4B).

To examine changes in the dynamics of the connectionist model when Past Negative Score (PN) of simulated agents is systematically varied (Fig. 4B, left panel) and affects IAT effect of crime-relevant events (Fig. 4A), we simply modulate the level of external stimulation to neurons in the connectionist model coding for CR and True during the initial 10-s and subsequent 2-s learning periods, such that those neurons fire at a lower rate while the agent encodes associations between its autobiographical features. Specifically, we vary the level of constant current to neurons encoding CR and True between I_ext=0.8 and I_ext=1.3, which is linearly dependent on the Past Negative (PN) Score. All other neurons encoding features of the simulated agent receive a constant current input of I_ext=1.3. For detailed algorithms, see Supplementary Materials 2.

Drift-diffusion models (DDM)

Behavioral performance on the aIAT can be modeled with DDM (Wong, Huk, Shadlen, & Wang, 2007; Klauer et al., 2007; Van Ravenzwaaij, van der Maas, & Wagenmakers, 2011) consisting of two self-excitatory but mutually inhibitory neural populations (Bedder et al., 2019). These two neural populations code for left and right motor outputs, respectively (see Fig. 4C, left panel). External sensory evidence integrated with noise accumulates until the firing rate of one population reaches a pre-defined decision threshold (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Koop & Johnson, 2013; Ratcliff & Rouder, 2000). The time taken to reach the decision threshold produces an RT, while the winning population corresponds to the decision made. In our simulations, the sensory evidence provided to each DDM motor population in each aIAT trial is determined by activity in the connectionist model (see Fig. 4C, left panel). Neurons coding for the aIAT stimulus receive a set level of external sensory input, while additional input to either motor response population arises from recurrent excitation within the connectionist model. As a result, the left neural population in the congruent condition is the earliest one to reach the threshold; thus, the participants were most likely to choose the left option, and the RTs of the congruent condition was significantly smaller than those of incongruent condition.

Specifically, the variation in the dynamics of evidence accumulation is systematically dependent on the time constant τ_s (see Supplementary Materials 2). We modulate the level of τ_s according to MT metric AUC (see Fig. 4C, right panel) ranging from 55 to 65. For detailed algorithms, see Supplementary Materials 2.

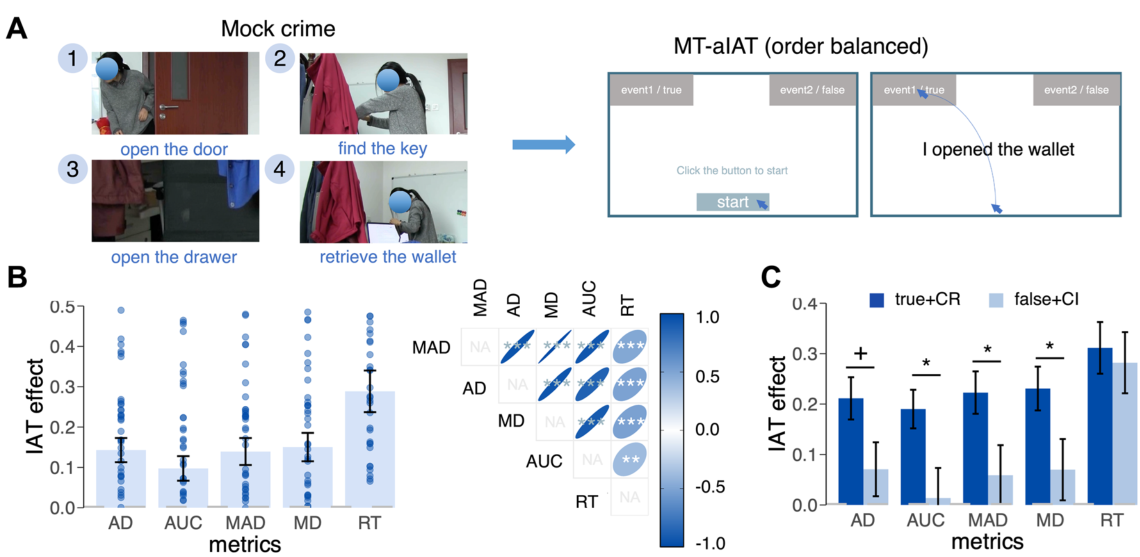

Fig. 1 **(A)** Task procedure. (*Left panel*) Participants were asked to steal the credit card in the mock crime room, which consisted of multiple steps e.g., opening the door, and finding the drawer key (for detailed steps for crime-relevant and crime-irrelevant events, see supplemental materials 1). (*Right panel*) Having stolen the credit card, they were arranged to perform the aIAT using a computer mouse. Every trial started with clicking of the START button at the bottom center of the screen. The stimuli then showed up in the center of the screen. Participants were instructed to classify the stimulus by clicking the key at the left upper corner of the screen or the key at the right upper corner. They were required to move the mouse quickly and accurately in the task; otherwise, a reminder would appear to urge them to respond as quickly as possible. **(B)** IAT effects calculated through RT and MT metrics (*left panel*) were highly correlated (*right panel*). **(C)** Separate IAT effects for true+CR stimuli and false+CI stimuli. IAT effect of RT was not significant between these two kinds of stimuli, while three of the MT metrics showed significant differences (for detailed statistical results, see Table S1 in supplemental materials 3)

Results

The data for the following results was based on block 4 and block 7.

IAT effect of MT metrics

IAT effects were calculated using RT and all MT metrics respectively (see Methods "IAT effect"), which were significantly larger than 0 (see Fig. 1B, left panel; AD: $t_{57} = 4.76$, $p < 0.001$, 95% CI from 0.08 to 0.20; AUC: $t_{57} = 3.21$, $p = 0.002$, 95% CI from 0.04 to 0.16; MAD: $t_{57} = 4.17$, $p < 0.001$, 95% CI from 0.07 to 0.21; MD: $t_{57} = 4.27$, $p < 0.001$, 95% CI from 0.08 to 0.22; RT: $t_{57} = 5.59$, $p < 0.001$, 95% CI from 0.19 to 0.39). IAT effects calculated from MT metrics were significantly smaller than those calculated from RT (RT vs. AD: $t_{57} = 3.27$, $p = 0.002$, 95% CI from 0.06 to 0.23; RT vs. AUC: $t_{57} = 3.90$, $p < 0.001$, 95% CI from 0.09 to 0.29; RT vs. MAD: $t_{57} = 3.25$, $p = 0.002$, 95% CI from 0.06 to 0.24; RT vs. MD: $t_{57} = 3.07$, $p = 0.003$, 95% CI from 0.05 to 0.23). To validate the IAT effect of MT metrics, we performed pairwise correlation between all IAT effects, and found they were inter-correlated (see Fig. 1)B, right panel; for detailed statistical results, see Table S1 in supplemental materials 3). Our goal was to discriminate which 'crime' participants commit-

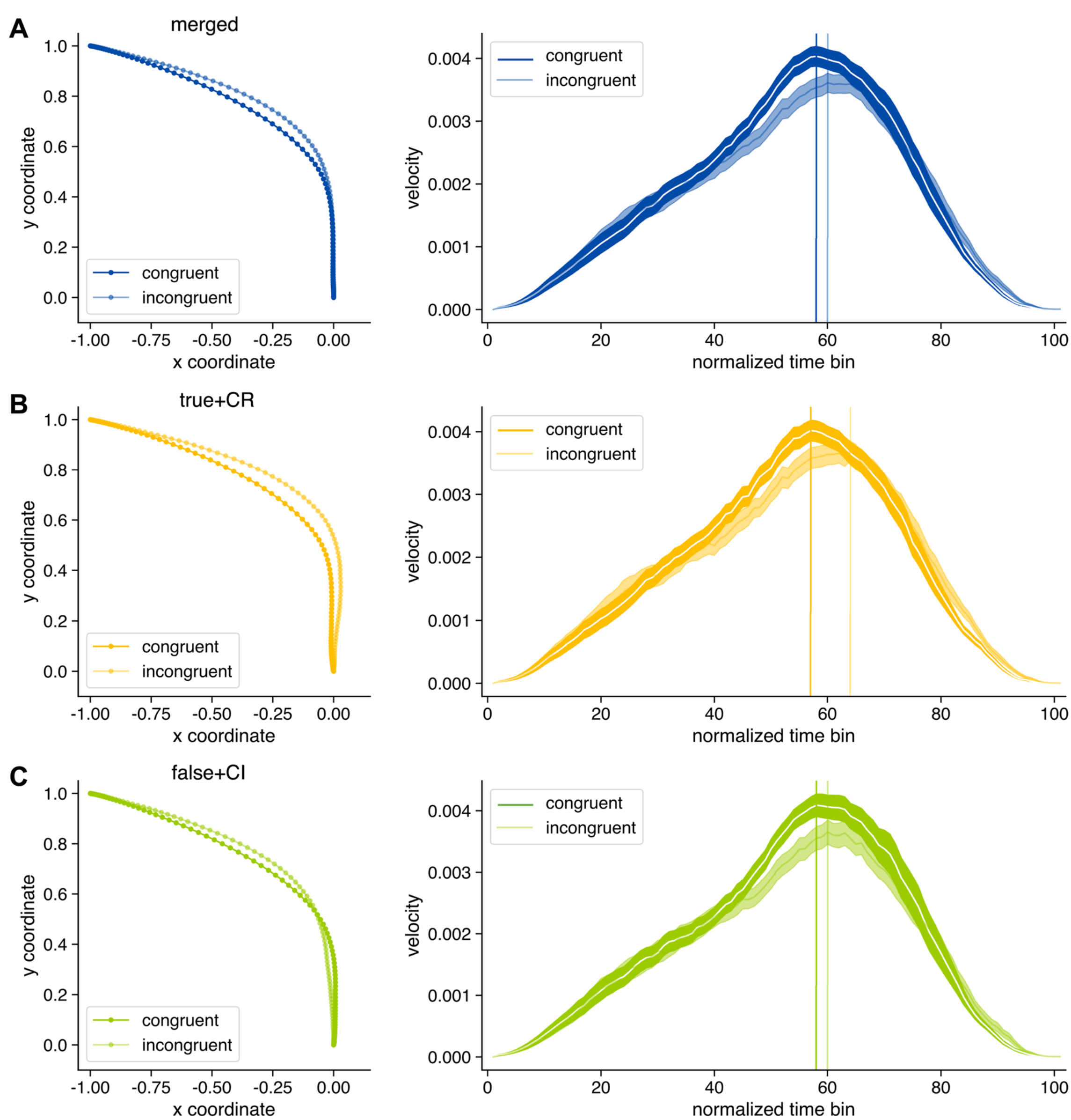

Fig. 2 Mean trajectories and velocity as a function of condition (congruent vs. incongruent) for **(A)** merged and respective events (**(B)** real vs. **(C)** unreal)

ted, so we compared IAT effects of real events (objectively true and crime-relevant events) and unreal events (objectively false and crime-irrelevant events). We found MT metrics presented larger IAT effect for real events than unreal events (AD: $t_{57} = 2.00$, $p = 0.05$, 95% CI from 0 to 0.28; AUC: $t_{57} = 2.35$, $p = 0.02$, 95% CI from 0.03 to 0.33; MAD: $t_{57} = 2.22$, $p = 0.03$, 95% CI from 0.02 to 0.31; MD: $t_{57} = 2.20$, $p = 0.03$, 95% CI from 0.01 to 0.31), while IAT effect of RT did not($t_{57} = 0.76$, $p = 0.45$, 95% CI from -0.05 to 0.11). Moreover, when we combined crime-irrelevant events with objectively true events and crime-relevant events with objectively false events to examine their IAT effect, there was no difference across all metrics (see Fig. S1 in supplementary material 3).

Mean mouse trajectories

Figure 2(left panel) visualizes the mean trajectories as a function of condition (congruent vs. incongruent) for respective events (real vs. unreal). Consistent with the IAT effect, mean trajectories of both events (merged) exhibited a significant difference between the two conditions was apparent (AUC: $t_{57} = 3.02$, $p = 0.004$, 95% CI from 0.01 to 0.05; see Fig. 2A upper, left panel). For only real events, mean trajectories exhibited a larger difference between the two conditions (AUC: $t_{57} = 4.86$, $p < 0.001$, 95% CI from 0.04 to 0.09; see Fig. 2A, middle left panel). In contrast, for the only unreal events, there was no difference between two conditions (AUC: $t_{57} = 0.26$, $p = 0.80$, 95% CI from -0.04 to 0.05; see Fig. 2A, lower left panel).

Velocity across normalized time bins was also calculated, since the changes in the velocity of trajectories were predicted by models assuming nonlinear competitive dynamics over time (Usher & McClelland, 2001). We found that for real events, velocity under two conditions reached the maximum in step 56 (congruent) and step 64 (incongruent), respectively, while for merged and unreal events, velocity under two conditions reached the maximum in step 57 (congruent) and step 59 (incongruent), which was less discriminable.

We also visualized the mouse trajectories and velocity for two subgroups (congruent-first group and incongruent-first group; Fig. 3). Though they exhibited different patterns as the data merging them together, there still were discrepancies between true+CI and false+CR stimuli either in trajectories or velocity for both subgroups.

Modulating implicit bias using Past Negative (PN) Score and AUC

Combining MT data and questionnaire data together, we found a correlation between Past Negative Score and the IAT effect of MD/MAD for real events (see Fig. 4A, upper panel; MD: $r = 0.27$, $p = 0.03$; MAD: $r = 0.27$, $p = 0.04$). In contrast, IAT effect calculated from RT for real events did not

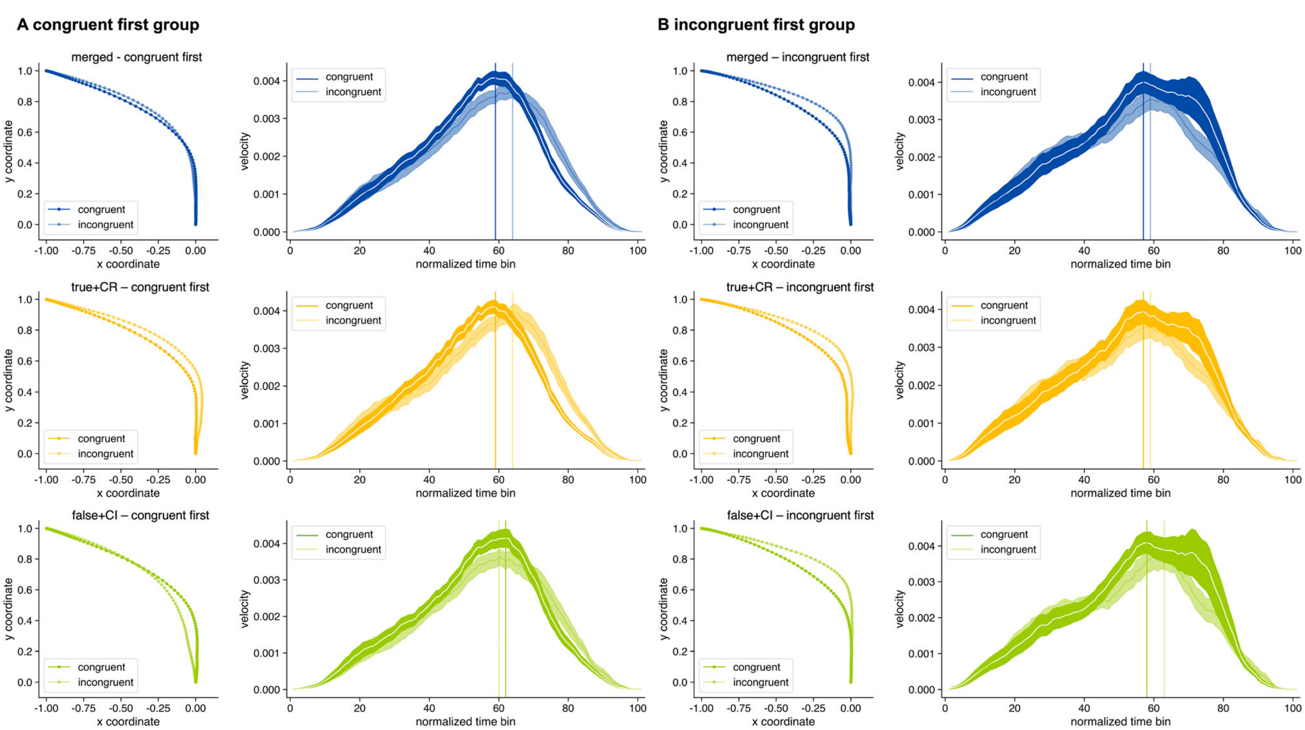

Fig. 3 Mean trajectories and velocity as a function of condition (congruent vs. incongruent) for **(A)** congruent first group and **(B)** congruent first group

show any correlation with Past Negative Score (see Fig. 4A, lower panel; $r = 0.04$, $p = 0.75$).

According to Bedder et al. (2019), the mechanistic explanation of implicit bias focuses on a 'self-image' network in the brain comprised of neurons that selectively respond to various features that might constitute elements of a person's self-image (i.e., events he/she has done, objectively true events in our case). These neurons are activated by external sensory input whenever those features are perceived. Importantly, perception of the agent's own features enables associations to develop between active neural populations in the self-image network through Hebbian learning (Hasselmo, 2006; Hebb, 1949); see Methods "Connectionist model"). Here, one important property of the self-image network is that feature encoding is not necessarily binary, which can be exploited to examine the effect of differences in Past Negative Score on the magnitude of IAT effects. When an agent is learning its own features, a lower PN score can be represented by reduced firing rates in the neural population encoding actual features, leading to lower synaptic weights between this population and those encoding other features in the self-image network (see Fig. 4B).

Having generated the firing rate in the self-image network, we required the model to generate behavioral output. Binary decision-making processes, such as the IAT, have been extensively modeled using drift-diffusion models. In these models, two self-excitatory but mutually inhibitory neural populations noisily integrate sensory evidence for opposing motor responses until a firing rate threshold is reached, resulting in a decision (Bogacz et al., 2006; Klauer et al., 2007). If ambivalence in decision-making arises from the amount of information necessary to make a decision or the speed of information accumulation, individual variability in AUC (Leontyev & Yamauchi, 2021; Lopez et al., 2018; Bodily et al., 2015) should be mirrored in the variability of the drift rate (Fig. 4C), that is, τ_s in Eq. 11 in supplemental materials 2.

The simulation results of IAT effect

To this end, we set up four models with a combination of PN and AUC as modulators (see Fig. S2 in supplemental materials 3). The simulated IAT effects were compared to empirical results in multiple indices, suggesting the model with both PN and AUC as modulators performed the best (see Fig. S3). First, we compared the simulated overall IAT effect with the empirical overall IAT effect, and found that overall IAT effect generated by model 1 not only correlates with the empirical data (Fig. 5A) but also showed no significant difference. After splitting the IAT effect into real events and unreal events, IAT effects generated by model 1 still correlated with the empirical IAT effects of RT and MT metrics. Finally, if we compared the simulated IAT effects between real and unreal events, the pattern of IAT effects was as same as empirical IAT effect calculated using MT metric rather RT ($t_{57} = 2.65$, $p = 0.01$, 95% CI from 0.09 to 0.64).

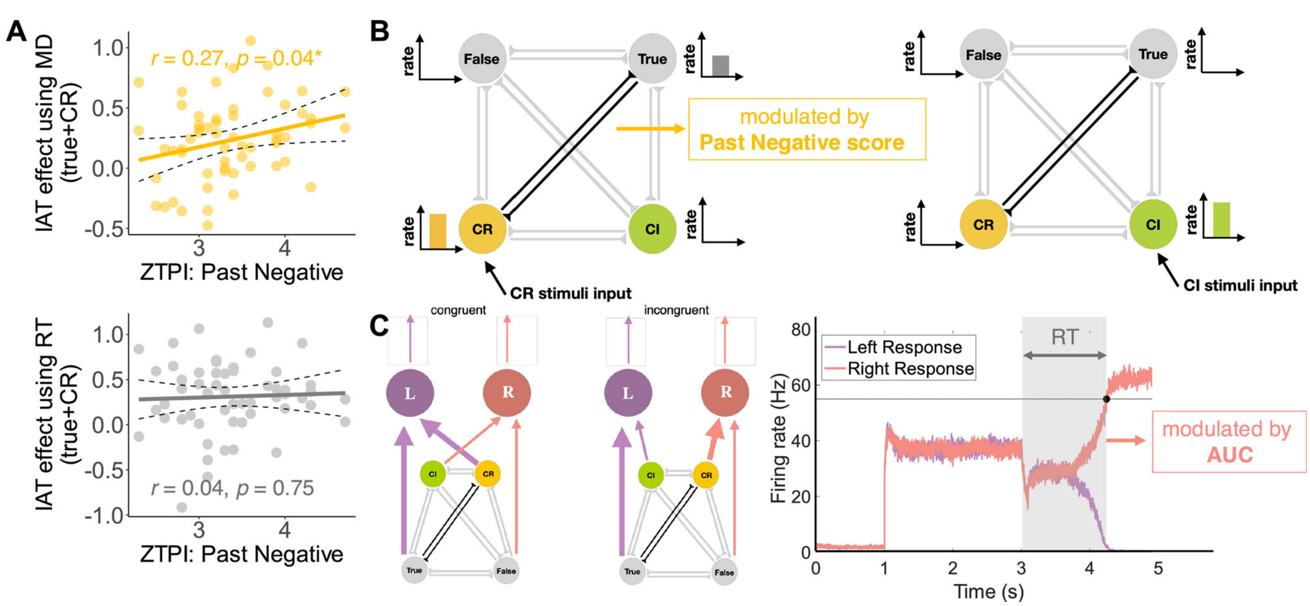

Fig. 4 **(A)** Correlation between Past Negative Score and the IAT effect of MD/MAD for real events (MD: $r = 0.27$, $p = 0.03$; MAD: $r = 0.27$, $p = 0.04$). In contrast, IAT effect calculated from RT for real events did not show any correlation with Past Negative Score ($r = 0.04$, $p = 0.75$). **(B)** Synaptic weights in the self-image network model are modulated by PN score. **(C)** The drift rate of DDM is modulated by AUC

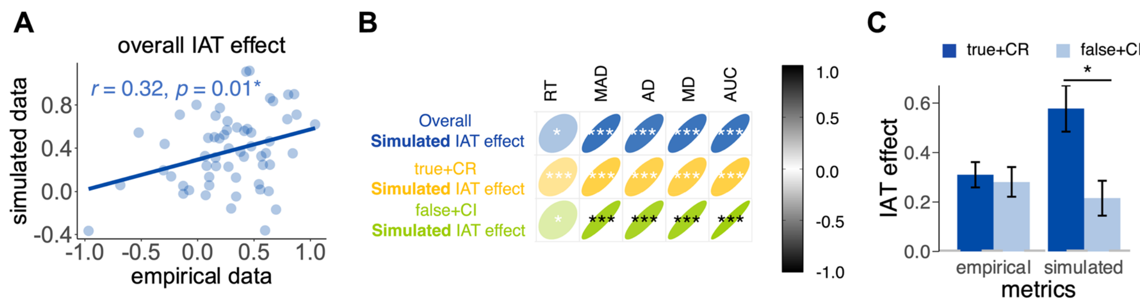

Fig. 5 **(A)** The simulated overall IAT effect correlated with empirical IAT effect. **(B)** The simulated IAT effects for overall events, real events and unreal events were all correlated with empirical effects using RT and MT metrics. **(C)** The simulated IAT effect for real events was larger than unreal events, which was different from the empirical IAT effect of RT, but was the same as the empirical IAT effect of MT metrics

Discussion

In general, the present results confirmed the validity of the MT metrics in memory detection. MT metrics replicated the classic RT-based IAT effects (see Fig. 1B). Moreover, MT metrics showed significant discrepancies between real and unreal events while RT did not(see Fig. 1C). MT metrics allowed us to quantify the extent and intensity of conflict during decision-making (Freeman et al., 2008). By calculating the IAT effect with MT metrics, we could identify the difference in hesitation between congruent and incongruent conditions was larger for true and crime-relevant events. MT metrics could also reveal the speed-accuracy trade-off in decision-making (Banholzer, Feuerriegel, Fleisch, Bauer, & Kowatsch, 2021). A quick, direct trajectory with a low AUC indicates a rapid decision-making process likely fueled by clear preferences or strong prior knowledge. The mouse trajectories and velocity also demonstrated different pattern under congruent and incongruent conditions for these two kinds of events (see Fig. 2). Our results demonstrated the feasibility of the MT method in aIAT for detecting memory or crime. Despite providing a static and dynamic view of the cognitive process, there are several other advantages to using mouse dynamics as an indicator of memory detection. First, MT can be implemented covertly, without participants' consciousness of the memory detection purpose (Sartori et al., 2018). Second, studies have shown high accuracy of the false identity detection task based on MT, indicating the reliability of MT-based memory detection in specific contexts (Monaro et al., 2017a; Monaro, Gamberini, & Sartori, 2017b). Third, the MT technique can be easily used among large samples (Sartori et al., 2018). Fourth, the validation of various mouse indices extended the form of congruency effect in traditional IAT that is only focused on RTs. It offered new indices on classifying the autobiographical event that could be used in machine learning methods, in some aspects improving the classification accuracy. Further, the practical implications of our mouse-tracking memory detection method for forensic applications are multifaceted and significant. By analyzing the subtle behavioral patterns captured through mouse tracking, investigators can identify inconsistencies or signs of fabrication that might not be apparent through traditional interrogation methods. Based on the above advantages, MT has some possible application prospects, such as false identity detection, concealed criminal memories detection, and malingering in the forensic and clinical field (Rosenfeld, 2018; Monaro et al., 2021a).

The basic idea of IAT is based on associations between the stimuli and the concept, which can be captured by both RT and MT. When participants perceived a stimulus, the stimulus automatically activates the concept itself as well as spreading activation to its linked associations. The strength of the associations varied between congruent and incongruent blocks. It is indicated that activation spreads faster if the association between concepts is strong, and spreads more slowly when the strength of association is weak (Verhulst & Lodge, 2013). Meanwhile, cues of prior experience could then trigger an essentially 'automatic' pattern of activation in memory that can be described in neural network or connectionist models (Hopfield & Tank, 1986; Queller & Smith, 2002). The strength of co-activation could be modulated by personal traits (Bedder et al., 2019). Following previous work using output from the self-image network to drive a DDM of binary decision (Bedder et al., 2019; Wong & Wang, 2006; Wong et al., 2007), we could also infer the magnitude and reactivation of the memory during the response. In our work, we postulate a simple connectionist model to quantify the strengths of sensory evidence as well as their associations and use the DDM to model behavioral performance after perceiving sensory information. Specifically, we varied the level of constant current to neurons encoding CR and True, which is linearly dependent on the Past Negative (PN) Score. Then we use the sensory evidence derived from the connectionist model to drive the DDM. We presented that the connectionist model could offer a mechanistic account of resonance with crime-related events, and explain mental associations and their influence on the aIAT performance.

DDM has a profound impact in providing a mechanistic account of binary decision-making (Wong et al., 2007; Wong & Wang, 2006), by which we were able to simulate the behavioral performance on the aIAT to measure the quantity of implicit association. The DDM assumes that a binary decision-making process equals the accumulation of two sides of competing evidence (Shen et al., 2023; Chen & Krajbich, 2018). Moreover, the decision is made once the one side of the evidence reaches the threshold (Ratcliff & Rouder, 2000). The accumulation speed of the autobiographical association will be faster due to the activation of memory, which can be reflected by AUC of MT (Bodily et al., 2015; Lopez et al., 2018). Therefore, we first show that IAT effect of MT metrics help us find the personal trait that affected the strength of the IAT effect. Then, we used the personal trait to modulate the level of constant current to neurons in the connectionist model. We also integrated AUC into the drift rate of DDM, so we could better capture the individual variability in IAT effect (see Fig. S3 in supplementary materials 3).

Taken together, the MT paradigm still has much room for further exploration and practice in the future, especially in combination with aIAT. It is essential to acknowledge the potential limitations of the mouse-tracking approach in real-world scenarios. Laboratory settings, where most mouse-tracking studies are conducted, differ markedly from real-life environments. Additionally, while mouse-tracking provides another layer of evidence, it should not be used in isolation. Forensic professionals must integrate these findings with other forms of evidence and expert analyses to form a comprehensive understanding of a case. Therefore, the applicability of lab-derived findings to real-world forensic contexts needs further validation through field studies and evidence combination in actual forensic conditions. To verify the accuracy advantage that MT brings to aIAT, additional experiments would be desirable, as this study is limited to only one mock crime condition in a laboratory context. Although we used a single experimental scenario setting to control experimental variables better so that factors affecting IAT effects, such as block order, could be effectively investigated, it would also make the generalizability of the findings limited. Though studies have shown high validity of MT-based memory detection in specific contexts (Monaro et al., 2017a, b), further efforts are needed to validate the predictive accuracy of aIAT with MT and refine the compatibility in various contexts. As MT is covert, the test can be administered to the participant without revealing its memory detection purpose (Sartori et al., 2018), researchers should be aware of the massive ethical implications of implementing an MT-based memory detection task and give informed consent to the subjects properly. Besides, a considerable controversy in IAT and aIAT is that discrimination of effect size on the individual level is not strong enough (Blanton et al., 2009; Vargo & Petróczi, 2013; Greenwald, Banaji, & Nosek, 2015), future efforts on improving the predictive validity can be one step further towards possible practical applications.

Conclusion

In sum, this study assesses and confirms the validity of MT in aIAT for detecting concealed memory in a mock crime scenario. The temporal MT data could investigate the discrepancy between different conditions for real and unreal events. Also, a connectionist model combined with DDM is used to offer a mechanistic account of how personal traits and MT metrics could help reveal the cognitive process of aIAT. The simulation results are not only consistent with the behavioral results but also can explain the individual variability.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.3758/s13428-024-02594-y.

Acknowledgements Besides, we would like to thank Tianyu Ma, Miao Chang, and Yutong Guo for their consistent help with the experiment. We would also like to thank Ziming Iris Li for developing the related website where people can upload their mouse tracking data and automatically obtain a similar analysis in our manuscript.

Author Contributions H. Wu conceived the research, H. Wu and X.J. Xu performed the research, X.J. Xu and H. Wu analyzed the data, X.J. Xu, X. Liu, X. Hu and H. Wu wrote the paper.

Funding This work was mainly supported by the Science and Technology Development Fund (FDCT) of Macau [0127/2020/A3, 0041/2022/A], the Natural Science Foundation of Guangdong Province (2021A1515012509), Shenzhen-Hong Kong-Macao Science and Technology Innovation Project (Category C) (SGDX2020110309280100), MYRG of University of Macau (MYRG2022-00188-ICI) and the SRG of University of Macau (SRG2020-00027-ICI).

Availability of data and materials The data supporting this study's findings are openly available in the lab GitHub at (https://github.com/andlab-um/aIAT-MT). The supplemental materials (supplemental materials 1–3) are available at https://github.com/andlab-um/aIAT-MT/tree/main/Supplementary_materials.

Code Availability The code supporting the findings of this study is openly available on GitHub (https://github.com/andlab-um/aIAT-MT). In addition, we developed a website (https://umandlab.shinyapps.io/IATwebsite) where people can upload their mouse-tracking data and automatically obtain a similar analysis in our manuscript.

Declarations

Conflicts of Interest The authors have no competing interests to declare that are relevant to the content of this article.

Ethics Approval The experimental protocol of this study was approved by the ethical review committee of the University of Macau (BSERE21-APP006-ICI).

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Consent for Publication The manuscript is approved by all authors for publication.

References

Agosta, S., Mega, A., & Sartori, G. (2011). Detrimental effects of using negative sentences in the autobiographical iat. *Acta Psychologica, 136*, 269–275.

Agosta, S., & Sartori, G. (2013). The autobiographical iat: A review. *Frontiers in Psychology, 4*, 519.

Banholzer, N., Feuerriegel, S., Fleisch, E., Bauer, G. F., & Kowatsch, T. (2021). Computer mouse movements as an indicator of work stress: Longitudinal observational field study. *Journal of Medical Internet Research, 23*, e27121.

Bedder, R. L., Bush, D., Banakou, D., Peck, T., Slater, M., & Burgess, N. (2019). A mechanistic account of bodily resonance and implicit bias. *Cognition, 184*, 1–10.

Blanton, H., Jaccard, J., Klick, J., Mellers, B., Mitchell, G., & Tetlock, P. E. (2009). Strong claims and weak evidence: Reassessing the predictive validity of the iat. *Journal of Applied Psychology, 94*, 567.

Bodily, R., Harris, S., Jenkins, J., Larsen, R., Sandberg, D., Stokes, S., ... Williams, P. (2015). A multi-experimental examination of analyzing mouse cursor trajectories to gauge subject uncertainty.

Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: A formal analysis of models of performance in two-alternative forced-choice tasks. *Psychological Review, 113*, 700.

Brunton, B. W., Botvinick, M. M., & Brody, C. D. (2013). Rats and humans can optimally accumulate evidence for decision-making. *Science, 340*, 95–98.

Champely, S., Ekstrom, C., Dalgaard, P., Gill, J., Weibelzahl, S., Anandkumar, A., ... De Rosario, M. H. (2018). Package 'pwr'. R package version 1.

Chassot, S., Klöckner, C. A., & Wüstenhagen, R. (2015). Can implicit cognition predict the behavior of professional energy investors? an explorative application of the implicit association test (iat). *Journal of Applied Research in Memory and Cognition, 4*, 285–293.

Chemin, B., Huang, G., Mulders, D., & Mouraux, A. (2018). Eeg time-warping to study non-strictly-periodic eeg signals related to the production of rhythmic movements. *Journal of Neuroscience Methods, 308*, 106–115.

Chen, F., & Krajbich, I. (2018). Biased sequential sampling underlies the effects of time pressure and delay in social decision making. *Nature Communications, 9*, 3557.

Dale, R., Kehoe, C., & Spivey, M. J. (2007). Graded motor responses in the time course of categorizing atypical exemplars. *Memory & Cognition, 35*, 15–28.

Duran, N. D., Dale, R., & McNamara, D. S. (2010). The action dynamics of overcoming the truth. *Psychonomic Bulletin & Review, 17*, 486–491.

Freeman, J. B. (2018). Doing psychological science by hand. *Current Directions in Psychological Science, 27*, 315–323.

Freeman, J. B., & Ambady, N. (2010). Mousetracker: Software for studying real-time mental processing using a computer mouse-tracking method. *Behavior Research Methods, 42*, 226–241.

Freeman, J. B., Ambady, N., Rule, N. O., & Johnson, K. L. (2008). Will a category cue attract you? motor output reveals dynamic competition across person construal. *Journal of Experimental Psychology: General, 137*, 673.

Freeman, J., Dale, R., & Farmer, T. (2011). Hand in motion reveals mind in motion. *Frontiers in Psychology, 2*, 59.

Freeman, J. B., Pauker, K., Apfelbaum, E. P., & Ambady, N. (2010). Continuous dynamics in the real-time perception of race. *Journal of Experimental Social Psychology, 46*, 179–185.

Gatti, D., Rinaldi, L., Marelli, M., Mazzoni, G., & Vecchi, T. (2022). Decomposing the semantic processes underpinning veridical and false memories. *Journal of Experimental Psychology: General, 151*, 363.

Greenwald, A. G., Banaji, M. R., & Nosek, B. A. (2015). Statistically small effects of the implicit association test can have societally large effects.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology, 74*, 1464.

Hasselmo, M. E. (2006). The role of acetylcholine in learning and memory. *Current Opinion in Neurobiology, 16*, 710–715.

Hebb, D. O. (2005). The organization of behavior: A neuropsychological theory. Psychology Press.

Hebb, D. O. (1949). The organization of behavior; a neuropsycholocigal theory. *A Wiley Book in Clinical Psychology, 62*, 78.

Hopfield, J. J., & Tank, D. W. (1986). Computing with neural circuits: A model. *Science, 233*, 625–633.

Huk, A. C., & Shadlen, M. N. (2005). Neural activity in macaque parietal cortex reflects temporal integration of visual motion signals during perceptual decision making. *Journal of Neuroscience, 25*, 10420–10436.

Hu, X., Rosenfeld, J. P., & Bodenhausen, G. V. (2012). Combating automatic autobiographical associations: The effect of instruction and training in strategically concealing information in the autobiographical implicit association test. *Psychological Science, 23*, 1079–1085.

Kieslich, P. J., & Henninger, F. (2017). Mousetrap: An integrated, open-source mouse-tracking package. *Behavior Research Methods, 49*, 1652–1667.

Klauer, K. C., Voss, A., Schmitz, F., & Teige-Mocigemba, S. (2007). Process components of the implicit association test: A diffusion-model analysis. *Journal of Personality and Social Psychology, 93*, 353.

Koop, G. J., & Johnson, J. G. (2013). The response dynamics of preferential choice. *Cognitive Psychology, 67*, 151–185.

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences, 108*, 13852–13857.

Leontyev, A., & Yamauchi, T. (2021). Discerning mouse trajectory features with the drift diffusion model. *Cognitive Science, 45*, e13046.

Lopez, R. B., Stillman, P. E., Heatherton, T. F., & Freeman, J. B. (2018). Minding one's reach (to eat): The promise of computer mouse-tracking to study self-regulation of eating. *Frontiers in Nutrition, 5*, 43.

Lykken, D. T. (1959). The gsr in the detection of guilt. *Journal of Applied Psychology, 43*, 385.

Marini, M., Agosta, S., & Sartori, G. (2016). Electrophysiological correlates of the autobiographical implicit association test (aiat): Response conflict and conflict resolution. *Frontiers in Human Neuroscience, 10*, 391.

Melnikoff, D. E., Mann, T. C., Stillman, P. E., Shen, X., & Ferguson, M. J. (2021). Tracking prejudice: A mouse-tracking measure of evaluative conflict predicts discriminatory behavior. *Social Psychological and Personality Science, 12*, 266–272.

Monaro, M., Bertomeu, C. B., Zecchinato, F., Fietta, V., Sartori, G., & Martínez, H. D. R. (2021a). The detection of malingering in whiplash-related injuries: A targeted literature review of the available strategies. *International Journal of Legal Medicine*, 1–16.

Monaro, M., Gamberini, L., & Sartori, G. (2017b). Identity verification using a kinematic memory detection technique. In *Advances in neuroergonomics and cognitive engineering* (pp. 123–132). Springer.

Monaro, M., Negri, P., Zecchinato, F., Gamberini, L., & Sartori, G. (2021b). Mouse tracking iat in customer research: An investigation of users' implicit attitudes towards social networks. In *International Conference on Intelligent Human Systems Integration* (pp. 691–696). Springer.

Monaro, M., Gamberini, L., & Sartori, G. (2017). The detection of faked identity using unexpected questions and mouse dynamics. *PLoS ONE, 12*, e0177851.

Nahari, G. (2018). The applicability of the verifiability approach to the real world. In *Detecting concealed information and deception* (pp. 329–349). Elsevier.

Pang, L., Li, H., Liu, Q., Luo, Y. J., Mobbs, D., & Wu, H. (2022). Resting-state functional connectivity of social brain regions predicts motivated dishonesty. *NeuroImage, 256*, 119253.

Papesh, M. H., & Goldinger, S. D. (2012). Memory in motion: Movement dynamics reveal memory strength. *Psychonomic Bulletin & Review, 19*, 906–913.

Potamianou, H., & Bryce, D. (2024). How flexible is cognitive control?(mouse) tracking conflict adaptation across context similarities. *Psychological Research, 88*, 562–579.

Queller, S., & Smith, E. R. (2002). Subtyping versus bookkeeping in stereotype learning and change: Connectionist simulations and empirical findings. *Journal of Personality and Social Psychology, 82*, 300.

Ratcliff, R., & Rouder, J. N. (2000). A diffusion model account of masking in two-choice letter identification. *Journal of Experimental Psychology: Human Perception and Performance, 26*, 127.

Richter, M., Lins, J., & Schöner, G. (2021). A neural dynamic model of the perceptual grounding of spatial and movement relations. *Cognitive Science, 45*, e13045.

Rosenfeld, J. P. (2018). Detecting concealed information and deception: Recent developments.

Sartori, G., Zangrossi, A., & Monaro, M. (2018). Deception detection with behavioral methods: The autobiographical implicit association test, concealed information test–reaction time, mouse dynamics, and keystroke dynamics. In *Detecting Concealed Information and Deception* (pp. 215–241). Elsevier.

Sartori, G., Agosta, S., Zogmaister, C., Ferrara, S. D., & Castiello, U. (2008). How to accurately detect autobiographical events. *Psychological Science, 19*, 772–780.

Schoemann, M., O'Hora, D., Dale, R., & Scherbaum, S. (2021). Using mouse cursor tracking to investigate online cognition: Preserving methodological ingenuity while moving toward reproducible science. *Psychonomic Bulletin & Review, 28*, 766–787.

Shen, B., Chen, Y., He, Z., Li, W., Yu, H., & Zhou, X. (2023). The competition dynamics of approach and avoidance motivations following interpersonal transgression. *Proceedings of the National Academy of Sciences, 120*, e2302484120.

Smeding, A., Quinton, J. C., Lauer, K., Barca, L., & Pezzulo, G. (2016). Tracking and simulating dynamics of implicit stereotypes: A situated social cognition perspective. *Journal of Personality and Social Psychology, 111*, 817.

Spivey, M. J., Grosjean, M., & Knoblich, G. (2005). Continuous attraction toward phonological competitors. *Proceedings of the National Academy of Sciences, 102*, 10393–10398.

Stillman, P. E., Shen, X., & Ferguson, M. J. (2018). How mouse-tracking can advance social cognitive theory. *Trends in Cognitive Sciences, 22*, 531–543.

Sullivan, N., Hutcherson, C., Harris, A., & Rangel, A. (2015). Dietary self-control is related to the speed with which attributes of healthfulness and tastiness are processed. *Psychological Science, 26*, 122–134.

Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review, 108*, 550.

Van Ravenzwaaij, D., van der Maas, H. L., & Wagenmakers, E. J. (2011). Does the name-race implicit association test measure racial prejudice? *Experimental Psychology, 58*, 271.

Vargo, E. J., & Petróczi, A. (2013). Detecting cocaine use? the autobiographical implicit association test (aiat) produces false positives in a real-world setting. *Substance abuse treatment, prevention, and policy, 8*, 1–13.

Verhulst, B., & Lodge, M. (2013). Reaction time measures in implicit attitudes research. In *Political science research methods in action* (pp. 64–92). Springer.

Verschuere, B., Ben-Shakhar, G., & Meijer, E. (2011). Memory detection: Theory and application of the Concealed Information Test. Cambridge University Press.

Verschuere, B., Prati, V., & Houwer, J. D. (2009). Cheating the lie detector: Faking in the autobiographical implicit association test. *Psychological Science, 20*, 410–413.

Vrij, A., & Fisher, R. P. (2016). Which lie detection tools are ready for use in the criminal justice system? *Journal of Applied Research in Memory and Cognition, 5*, 302–307.

Wong, K. F., Huk, A. C., Shadlen, M. N., & Wang, X. J. (2007). Neural circuit dynamics underlying accumulation of time-varying evidence during perceptual decision making. *Frontiers in Computational Neuroscience, 1*, 6.

Wong, K. F., & Wang, X. J. (2006). A recurrent network mechanism of time integration in perceptual decisions. *Journal of Neuroscience, 26*, 1314–1328.

Wu, H., Cao, S., Bai, C., & Chen, K. (2021). Moral by default? the dynamic tradeoffs between honesty and self-interest.

Wu, H., Fu, G., & Zang, Y. (2010). The effect of motivation preparedness on deception-related p300. *Psychological Science, 4*.

Wu, H., Fung, B. J., & Mobbs, D. (2022). Mentalizing during social interaction: The development and validation of the interactive mentalizing questionnaire. *Frontiers in Psychology, 12*, 791835.

Wu, H., Liu, X., Hagan, C. C., & Mobbs, D. (2020). Mentalizing during social interaction: A four component model. *Cortex, 126*, 242–252.

Xu, X. J., Yang, G., Huang, J., Wang, R., & Wu, H. (2023). Unveiling consistency in flexibility: The role of reward and cognitive control in moral decisions. *bioRxiv*, 2023–06.

Yu, Z., Wang, F., Wang, D., & Bastin, M. (2012). Beyond reaction times: Incorporating mouse-tracking measures into the implicit association test to examine its underlying process. *Social Cognition, 30*, 289–306.

Zimbardo, P. G., & Boyd, J. N. (2013). Zimbardo time perspective inventory. *Journal of Personality and Social Psychology*.