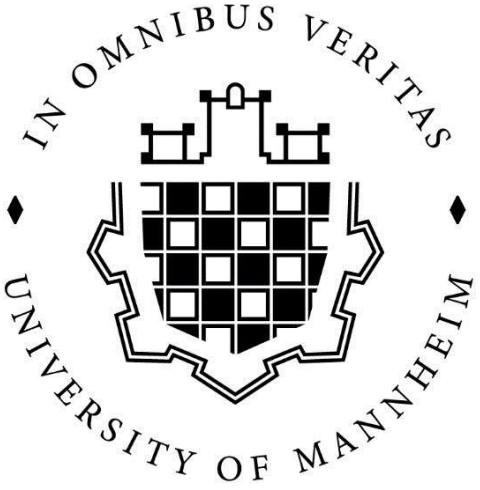
The neuropsychological basis of trust propensity and trust dynamics in older adults with mild cognitive impairment: A multi-modal neuroimaging approach



Inaugural dissertation

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1. Abstract

Mild cognitive impairment (MCI), an early stage of Alzheimer's disease, is associated not only with cognitive decline but also with social vulnerabilities, including heightened susceptibility to deception and withdrawal from relationships. Because trust is a cornerstone of social life, understanding how it changes in MCI is essential for both theory and practice.

This dissertation investigates the psychological and neural mechanisms of trust in older adults with MCI within the neuropsychoeconomic framework of trust, which integrates affect, motivation, social cognition, and executive cognition. It addresses three central questions: (1) Trust propensity (TP): Does MCI alter initial willingness to trust strangers, and which large-scale resting-state networks account for such differences?; (2) Structural underpinnings: Do gray matter reductions in MCI explain lower TP, and if so, through which psychological components do they exert their influence?; and (3) Trust dynamics: How does MCI affect the ability to build, maintain, and withdraw trust during repeated social interactions, and what neural and computational mechanisms underlie these alterations?

To answer these questions, three empirical studies were conducted. Experiment 1 combined a one-shot trust game with resting-state functional magnetic resonance imaging (fMRI) and connectome-based predictive modeling, showing that individuals with MCI exhibited reduced TP, explained by heightened betrayal sensitivity and increased reliance on the salience network. In contrast, healthy controls relied on social cognition and default-mode network connectivity. Experiment 2 used structural magnetic resonance imaging and voxel-based morphometry, revealing that atrophy in the anterior insula and thalamus mediated reduced trust in MCI through increased affective sensitivity to betrayal. Experiment 3 employed a multi-round trust game, computational reinforcement-learning modeling, and task-based fMRI. Results showed preserved trust-building with cooperative partners via compensatory activation in executive and social networks, but impaired trust reduction with non-cooperative partners, marked by slower updating, larger prediction errors, and disrupted executive–social connectivity.

Together, these studies demonstrate that MCI reduces initial trust through affective hyper-sensitivity and undermines adaptive trust updating through social and executive dysfunction, while compensatory mechanisms support trust in supportive contexts. These findings advance the neuroscience of trust by extending an integrative model to a clinical population, identify neural markers

of social vulnerability in MCI, and highlight trust as a potential target for early detection and intervention.

2. General Introduction

2.1 Trust as a Cornerstone of Social Life

Trust is a cornerstone of social life, enabling cooperation, reciprocity, and the functioning of complex societies despite uncertainty and risk (Coleman, 1990; Fukuyama, 1996; Hardin, 2002). At the interpersonal level, trust allows individuals to reduce social complexity (Luhmann, 1979), engage in mutually beneficial exchanges (Mayer et al., 1995), and sustain long-term relationships (Rousseau et al., 1998). Without trust, social interactions are limited to rigid rules or constant monitoring, which makes cooperative life inefficient and fragile (Gambetta, 1988; Putnam, 2000).

From a neuroscientific perspective, trust can be understood as a multi-component process that integrates affect, motivation, social cognition, and executive control (Krueger & Meyer-Lindenberg, 2019) (**Figure 1**). Each of these components has been linked to large-scale brain networks. The salience network (SAN), anchored in the anterior insula and dorsal anterior cingulate cortex, detects uncertainty and signals the relevance of emotionally salient information (Menon, 2015; Seeley et al., 2007). The reward network (RWN), including the ventral striatum and ventromedial prefrontal cortex (vmPFC), evaluates expected benefits and costs (Haber & Knutson, 2010). The default-mode network (DMN), involving medial prefrontal cortex (mPFC) and temporoparietal junction (TPJ), supports social cognition and mentalizing (Mars et al., 2012; Schilbach et al., 2008). Finally, the central-executive network (CEN), anchored in the dorsolateral prefrontal cortex (dlPFC) and posterior parietal cortex, regulates top-down control and integrates feedback for adaptive decision-making (Menon, 2011; Seeley et al., 2007). Together, these networks form the neurocognitive foundation of trust.

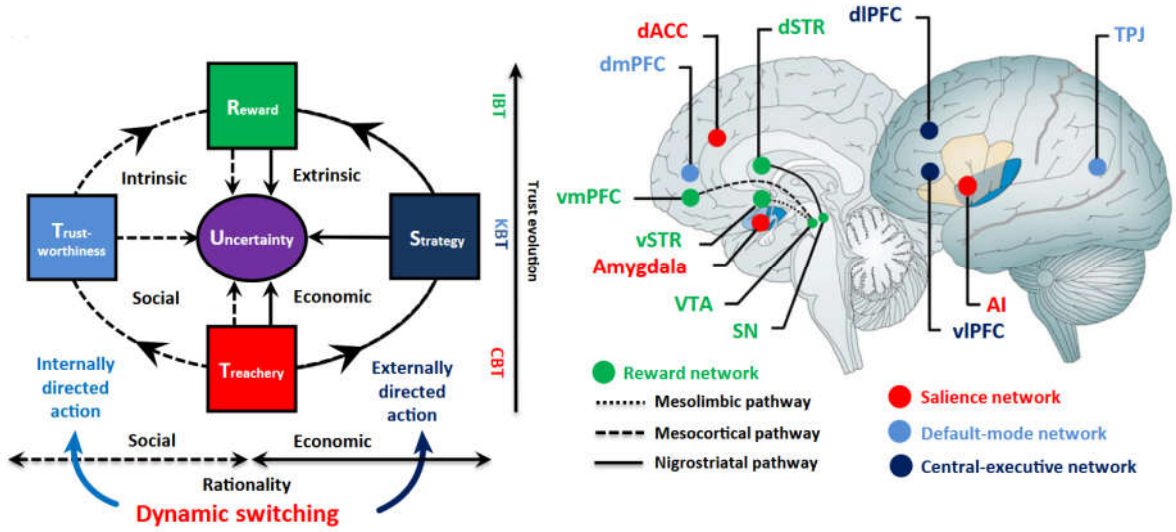

Figure 1. Neural model of trust formation and its core components. Trust formation relies on the dynamic integration of four core components: affect, motivation, social cognition, and executive cognition. Each component engages specific brain regions within large-scale domain-general networks. Trust emerges when the perceived probability of betrayal (affective system; salience network, SAN) conflicts with expectations of reciprocity (motivational system; reward, RWN), generating uncertainty that reflects the inherent vulnerability of trust. To resolve this uncertainty, the SAN acts as a neural switch, directing cognitive resources toward either the central executive network (CEN) for externally focused processing or the default mode network (DMN) for internally focused processing. When guided by extrinsic motivations, individuals rely on executive cognition (CEN) to pursue context-dependent strategies that maximize personal gains through economic rationality. When guided by intrinsic motivations, they draw on social cognition (DMN) to evaluate trustworthiness and promote relational success through social rationality. Adapted from Krueger & Meyer-Lindenberg (2019).

2.2 Dimensions of Trust: Propensity and Dynamics

Trust is not a unitary construct but can be distinguished into at least two dimensions that are central for both theoretical and empirical study. Trust propensity (TP) refers to a baseline tendency to trust strangers, independent of specific partners or contexts (Mayer et al., 1995; Rotter, 1967). TP reflects dispositional, trait-like aspects of trust that influence whether individuals are willing to initiate social exchanges. In contrast, trust dynamics describe how trust evolves over time, including the building, maintaining, or withdrawing of trust during repeated interactions. This dynamic dimension depends on feedback learning, adaptation to partner behavior, and flexible updating of expectations (Berg et al., 1995; Bohnet & Huck, 2004).

Both dimensions can be measured using the trust game, a widely employed economic paradigm introduced by Berg et al. (1995). In the one-shot version, an investor decides how much money to send to a trustee, which is then tripled, and the trustee decides how much to return. The amount invested

reflects TP, while the trustee's behavior reflects trustworthiness (**Figure 2A**). In multi-round versions of the trust game, trust dynamics can be observed as investors adjust their investments based on the trustee's prior returns (King-Casas et al., 2005) (**Figure 2B**). By combining behavioral measures with neuroimaging and computational modeling, the trust game provides a powerful tool to dissect the psychological and neural mechanisms underlying TP and trust dynamics (Delgado et al., 2005; Kosfeld et al., 2005; Krueger et al., 2007).

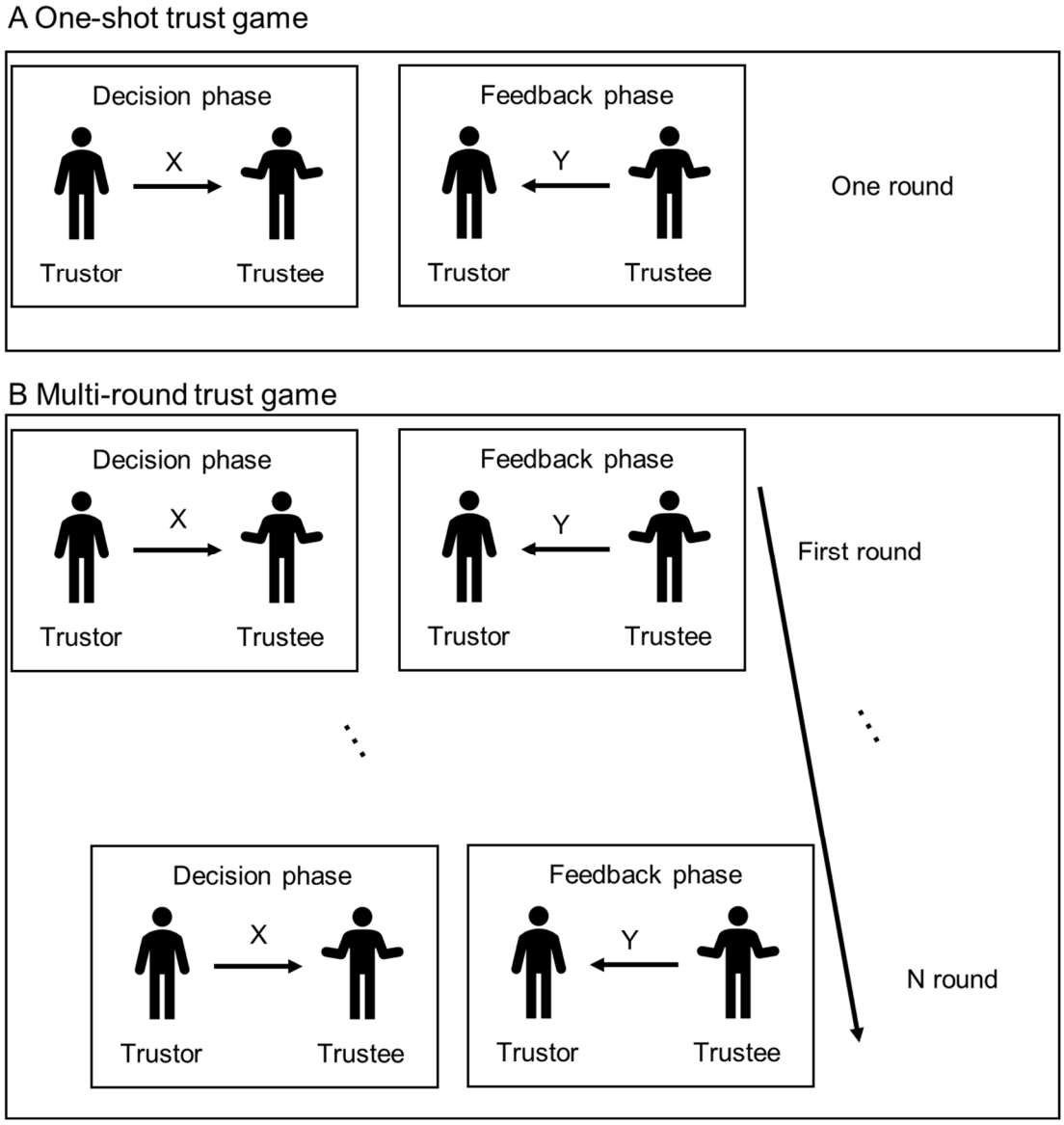

Figure 2. Conceptual model of the one-shot and multi-round trust games. (A) One-shot trust game. Two players (trustor and trustee) each make a single decision. In the decision stage, the trustor chooses an investment amount (X) from their endowment, which is then multiplied and transferred to the trustee. The trustee decides how much to return (Y) to the trustor. The amount invested reflects trust propensity (TP). **(B) Multi-round trust game.** Two players (trustor and trustee) interact repeatedly across multiple rounds. In each round, the trustor invests an amount (X), which is multiplied and transferred to the trustee, who then decides how much to return (Y). The trustor observes the trustee's decision in the feedback stage and adjusts subsequent investments accordingly. Changes in investments across rounds

reflect trust dynamics (trust building, maintenance, and withdrawal).

2.3 Trust in Aging and MCI

Aging is associated with both cognitive decline and changes in social functioning. Older adults often maintain or even increase TP, reflecting a "positivity bias" in social processing (Carstensen & Mikels, 2005; Castle et al., 2012). However, this can come at the cost of increased vulnerability to fraud and exploitation (Shao et al., 2019; Spreng et al., 2017). In the context of mild cognitive impairment (MCI), a prodromal stage of Alzheimer's disease, these vulnerabilities are magnified. Individuals with MCI show not only memory and executive dysfunction (Gauthier et al., 2006; Petersen, 2004) but also reduced social engagement (Li et al., 2019) and impaired decision-making (Zamarian et al., 2011). Studies have shown that older adults with MCI are more susceptible to deception and financial exploitation (Han et al., 2016; Martin et al., 2019).

Trust impairments may help explain this pattern. Lower TP could reduce willingness to form new relationships, contributing to social withdrawal, while impaired trust dynamics could prevent appropriate responses to betrayal, increasing susceptibility to fraud. Despite this importance, the mechanisms of trust dysfunction in MCI remain poorly understood. Addressing this gap requires an integrative approach that links behavior, neural function, and structural decline.

2.4 Neural Mechanisms of Trust in Healthy Adults

Neuroimaging studies in healthy adults have provided substantial insight into the neural substrates of trust decisions. Functional magnetic resonance imaging (fMRI) using the trust game has identified activation in multiple large-scale networks. The **SAN**, particularly the anterior insula and dorsal anterior cingulate cortex, is consistently engaged during the anticipation of betrayal and the evaluation of risk (Aimone et al., 2014; King-Casas et al., 2005; Krueger et al., 2007). The **RWN**, including the ventral striatum and vmPFC, responds to reciprocated trust, encoding the positive value of cooperation and reinforcing future trust decisions (Delgado et al., 2005; Fareri et al., 2012). The **DMN**, particularly the mPFC and TPJ, supports social cognition by enabling perspective-taking and the attribution of intentions to others (Rilling et al., 2004; Schilbach et al., 2008; Van Den Bos et al., 2009). Finally, the **CEN**, centered on the dlPFC and posterior parietal cortex, regulates top-down control and facilitates the

flexible adjustment of trust in response to partner behavior (Krueger & Meyer-Lindenberg, 2019).

In addition to functional activation, structural and connectivity studies in healthy individuals support the role of these networks. Gray matter volume (GMV) in vmPFC and striatal regions correlates with individual differences in TP (Haas et al., 2015a; Safari et al., 2024). Resting-state functional connectivity (RSFC) among the amygdala, striatum, TPJ, and dlPFC predicts the tendency to maintain cooperation in repeated exchanges (Bellucci et al., 2019; Lu et al., 2019). These findings converge on the idea that trust decisions in healthy adults are shaped by an interplay between affective vigilance (SAN), motivational valuation (RWN), social inference (DMN), and executive regulation (CEN).

2.5 Neural Mechanisms of Trust in MCI

In MCI, neurocognitive changes in these same networks are likely to disrupt TP. Neuroimaging studies of MCI and early Alzheimer's disease have revealed structural and functional alterations across SAN, DMN, and CEN regions. Atrophy in the anterior insula and thalamus, key nodes of the SAN, has been associated with impaired emotional regulation and heightened sensitivity to negative stimuli (Yang et al., 2012; J. Zhang et al., 2021). Functional hyperactivation of SAN regions has also been observed in MCI, suggesting compensatory or maladaptive responses to uncertainty (Song et al., 2021). In contrast, the DMN shows reduced connectivity and activity, impairing social cognition and theory of mind (Bora & Yener, 2017; Li et al., 2015). Similarly, CEN dysfunction in MCI undermines executive control and flexible adaptation to changing circumstances (Li et al., 2015; Traykov et al., 2007).

These network-level changes are consistent with behavioral findings that individuals with MCI exhibit emotional hyper-sensitivity and deficits in social and executive cognition. For example, studies have reported increased attention to negative information (Berger et al., 2015; Döhnel et al., 2008), reduced ability to infer others' intentions (Morellini et al., 2022), and impaired regulation of responses (Zamarian et al., 2011). Compensation may occur under low-demand conditions: MCI individuals can sometimes recruit additional prefrontal or parietal resources to support task performance (Li et al., 2015). However, these mechanisms often collapse under high cognitive or emotional load (de Rover et al., 2011).

Taken together, these findings suggest that MCI disrupts the balance among affective, social, and

executive components of trust. Increased reliance on the SAN and reduced engagement of the DMN and CEN may explain both reduced baseline TP and impaired adjustment to betrayal. At the same time, compensatory activation can provide support under low-demand conditions (e.g., cooperative contexts) but typically breaks down under higher cognitive or emotional load (e.g., non-cooperative contexts). This pattern underscores the complexity of trust processes in clinical populations.

2.6 Structural Underpinnings of Trust

Beyond functional activation, structural brain integrity plays an important role in trust decisions. GMV in regions such as the vmPFC, striatum, TPJ, and anterior insula has been associated with individual differences in TP (Haas et al., 2015a; Safari et al., 2024). For example, Haas et al. (2015) found that greater GMV in vmPFC predicted higher TP, while structural variability in striatal regions has been linked to differences in reward-based trust behavior. The TPJ, central to mentalizing and perspective-taking, has also been implicated in structural studies of trust (Morishima et al., 2012).

In clinical populations, structural decline in these areas is linked to altered trust behavior. In Alzheimer's disease and MCI, atrophy in the anterior insula and thalamus has been reported (Yang et al., 2012; Zhang et al., 2021). The insula, a hub of the SAN, integrates interoceptive and affective information, while the thalamus coordinates sensory and emotional processing (Menon, 2015). In major depressive disorder, gray matter reductions in the insula have been linked to heightened sensitivity to negative information (Schnellbächer et al., 2022). Structural degeneration in these regions may therefore amplify betrayal sensitivity and diminish baseline TP. At the same time, atrophy in prefrontal and parietal cortices reduces executive and social cognitive resources needed for adaptive trust regulation (Castle et al., 2012; Spreng & Turner, 2019).

These findings suggest that GMV alterations provide a potential neuroanatomical basis for impaired trust in MCI. Importantly, structural deficits may exert their effects indirectly, by heightening affective sensitivity or weakening social inference capacities. Understanding these pathways requires integrative approaches that link brain structure to specific psychological components of trust.

2.7 Trust Dynamics, Learning, and Prediction Error

While TP captures baseline willingness to engage in social exchange, trust dynamics reflect the ability to adjust behavior in response to partner feedback. Computational approaches, particularly reinforcement learning models, provide tools to quantify these processes (Zhang et al., 2020). Two parameters are especially important: **learning rate**, which determines how quickly individuals update their expectations, and **prediction error**, which signals the difference between expected and actual outcomes. In healthy adults, higher learning rates and accurate prediction error signaling enable flexible adjustment of trust to cooperative or non-cooperative partners (Haiyan, 2019; Nihonsugi et al., 2015).

Neuroimaging studies show that prediction errors during trust interactions are encoded in the striatum and vmPFC, regions within the RWN (Delgado et al., 2005; Fareri et al., 2012). The dmPFC and TPJ contribute to integrating these signals into social inferences about partner intentions (Rilling et al., 2004; Van Den Bos et al., 2009). The dlPFC supports executive regulation of behavior in light of feedback, consistent with the role of the CEN in adaptive decision-making (Krueger & Meyer-Lindenberg, 2019).

In MCI, evidence suggests that reinforcement learning mechanisms are disrupted. Studies have reported slower learning rates and exaggerated prediction errors in reinforcement tasks (Wang et al., 2013; Zhang et al., 2025). These impairments may reflect weakened integration of the CEN and DMN, which undermines flexible updating (Eyler et al., 2019; Yang et al., 2023). As a result, individuals with MCI may fail to reduce trust even in the face of repeated non-cooperation, leaving them vulnerable to exploitation.

Together, reinforcement learning models and neuroimaging findings provide a mechanistic framework for studying trust dynamics. By quantifying learning and prediction error processes, researchers can identify specific deficits in MCI and link them to underlying neural dysfunction. This approach allows for a fine-grained analysis of how trust evolves over time and how neurodegenerative changes distort adaptive social behavior.

2.8 Theoretical Framework

To integrate the diverse findings on trust, this dissertation adopts the **neuropsychoeconomic model of**

trust (Krueger & Meyer-Lindenberg, 2019). This framework conceptualizes trust as the outcome of interactions among four psychological components, each supported by a distinct large-scale brain network. **Affective processing**, linked to the SAN, evaluates potential risk and betrayal (Menon, 2015; Seeley et al., 2007). **Motivational processes**, associated with the RWN, compute expected benefits and reinforcement of reciprocity (Haber & Knutson, 2010). **Social cognition**, supported by the DMN, enables perspective-taking and inference of intentions (Mars et al., 2012; Schilbach et al., 2008). Finally, **executive control**, subserved by the CEN, regulates top-down control and adapts behavior to changing contexts (Menon, 2011; Seeley et al., 2007).

The model provides a systematic lens for understanding how TP and trust dynamics emerge from the coordinated operation of these components. For instance, SAN hyperactivation may bias decisions toward betrayal sensitivity, whereas disruption of the DMN and CEN compromises social inference and information integration. At the same time, Compensatory recruitment within DMN and CEN regions may temporarily support adaptive trust in cooperative contexts, but collapse under non-cooperative conditions. The RWN integrates reward prediction errors with motivational drives, further shaping trust learning and updating.

By framing trust within this four-component system, the model highlights both vulnerabilities and compensatory mechanisms. It also allows the translation of psychological constructs into testable neural hypotheses. Applied to MCI, the framework predicts that structural decline and functional imbalance across these networks will alter TP and trust dynamics. In this way, the neuropsychoeconomic model provides the theoretical backbone for the present dissertation and guides the formulation of specific research questions and hypotheses.

2.9 Overview and Research Questions

Building on the neuropsychoeconomic framework of trust (Krueger & Meyer-Lindenberg, 2019), this dissertation investigates how MCI alters TP and trust dynamics across behavioral, structural, functional, and computational levels. To achieve this, three complementary experiments were conducted (**Figure 3**).

- **Experiment 1** combined a one-shot trust game with resting-state fMRI and connectome-based predictive modeling to test whether TP is reduced in MCI and which large-scale networks predict this change.

- **Experiment 2** employed structural magnetic resonance imaging (MRI) and voxel-based morphometry to examine whether gray matter atrophy in SAN and related regions explains reduced TP, and whether trust-related psychological components mediate these effects.

- **Experiment 3** used a multi-round trust game, reinforcement-learning modeling, and task-based fMRI to assess how trust dynamics are disrupted in MCI, particularly the ability to build, maintain, and withdraw trust under cooperative and non-cooperative conditions.

Together, these studies were designed to address three overarching research questions:

1. **Trust propensity:** Does MCI alter initial willingness to trust strangers, and which resting-state networks explain this change?

2. **Structural underpinnings:** Do gray matter alterations in MCI underlie reduced TP, and through which psychological components do they exert their influence?

3. **Trust dynamics:** How does MCI affect the ability to build, maintain, and withdraw trust during repeated social interactions, and what psychological and neural mechanisms explain failures to update trust?

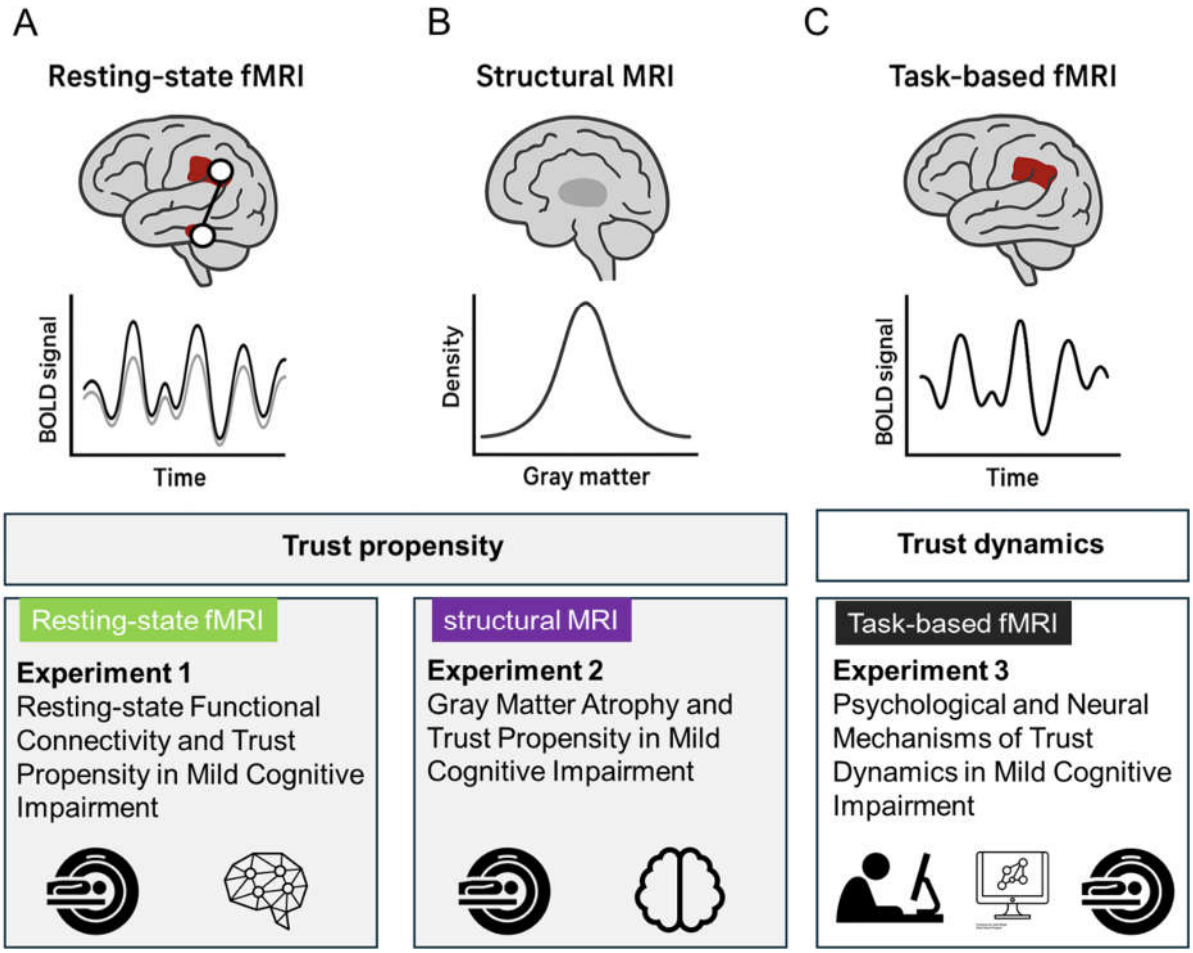

Figure 3. Conceptual overview of resting-state functional magnetic resonance imaging (fMRI), structural magnetic resonance imaging (MRI), and task-based fMRI, and their application in this dissertation. (A) Resting-state fMRI: Participants rest without an explicit task (eyes closed). Spontaneous blood oxygenation level dependent (BOLD) fluctuations are analyzed for interregional correlations, quantifying large-scale networks. In this dissertation, resting-state functional connectivity was used to predict trust propensity (TP). **(B) Structural MRI.** High-resolution anatomical images assess gray and white matter. Measures such as gray matter volume identify the structural underpinnings of TP in MCI. **(C) Task-based fMRI.** Participants perform repeated trust game decisions during scanning. Task-evoked BOLD responses and connectivity changes are analyzed, in combination with computational models, to assess trust dynamics, including trust building, maintenance, and withdrawal.

Overall Hypothesis

Compared with healthy controls, older adults with MCI would show impairments in both TP and trust dynamics, reflecting a shift from social-cognitive and executive mechanisms toward affective hyper-sensitivity and SAN over-reliance. Specifically, structural decline in the anterior insula and thalamus would amplify betrayal sensitivity, while disrupted integration of executive and social networks would impair adaptive trust updating. Compensation by executive and social systems would allow partial preservation of trust in cooperative contexts but would fail under conditions of betrayal or non-

cooperation.

Working Hypotheses

Based on prior behavioral, neuroimaging, and computational studies, the following hypotheses were formulated for each experiment:

- **WH1 (Experiment 1):** Individuals with MCI will show reduced TP compared to healthy controls, driven by heightened betrayal sensitivity and greater reliance on the SAN. In contrast, controls will rely more on social cognition supported by the DMN (Chen et al., 2024).

- **WH2 (Experiment 2):** GMV reductions in the anterior insula and thalamus will predict reduced TP in MCI. This effect will be mediated by betrayal sensitivity, consistent with evidence that structural decline in SAN regions amplifies affective hyper-sensitivity (Schnellbächer et al., 2022; Zackova et al., 2021).

- **WH3 (Experiment 3):** In cooperative contexts, older adults with MCI will show near-normal trust behavior supported by compensatory recruitment of CEN and DMN regions (Li et al., 2015). In non-cooperative contexts, however, they will fail to reduce trust appropriately, showing slower learning rates, exaggerated prediction errors, and disrupted connectivity between executive and social networks (Wang et al., 2013; Zhang et al., 2025).

By testing these hypotheses, the dissertation seeks to clarify how MCI alters trust at multiple levels of analysis, extend the neuropsychoeconomic model of trust to a clinical population, and identify potential behavioral and neural markers of social vulnerability in aging.

3. Experiment 1. Resting-state Functional Connectivity and Trust Propensity in Mild Cognitive Impairment

"Connectome-based prediction of decreased trust propensity in older adults with mild cognitive impairment: A resting-state functional magnetic resonance imaging study"

Chen, Y., He, H., Ding, Y., Tao, W., Guan, Q., & Krueger, F. (2024). Connectome-based prediction of decreased trust propensity in older adults with mild cognitive impairment: a resting-state functional magnetic resonance imaging study. NeuroImage, 292, 120605. https://doi.org/10.1016/j.neuroimage.2024.120605

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Connectome-based prediction of decreased trust propensity in older adults with mild cognitive impairment: A resting-state functional magnetic resonance imaging study

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ABSTRACT

Trust propensity (TP) relies more on social than economic rationality to transform the perceived probability of betrayal into positive reciprocity expectations in older adults with normal cognition. While deficits in social rationality have been observed in older adults with mild cognitive impairment (MCI), there is limited research on TP and its associated resting-state functional connectivity (RSFC) mechanisms in this population. To measure TP and related psychological functions (affect, motivation, executive cognition, and social cognition), MCI ($n = 42$) and normal healthy control (NHC, $n = 115$) groups completed a one-shot trust game and additional assessments of related psychological functions. RSFC associated with TP was analyzed using connectome-based predictive modeling (CPM) and lesion simulations. Our behavioral results showed that the MCI group trusted less (i.e., had lower TP) than the NHC group, with lower TP associated with higher sensitivity to the probability of betrayal in the MCI group. In the MCI group, only negative CPM models (RSFC negatively correlated with TP) significantly predicted TP, with a high salience network (SN) contribution. In contrast, in the NHC group, positive CPM models (RSFC positively correlated with TP) significantly predicted TP, with a high contribution from the default mode network (DMN). In addition, the total network strength of the NHC-specific positive network was lower in the MCI group than in the NHC group. Our findings demonstrated a decrease in TP in the MCI group compared to the NHC group, which is associated with deficits in social rationality (social cognition, associated with DMN) and increased sensitivity to betrayal (affect, associated with SN) in a trust dilemma. In conclusion, our study contributes to understanding MCI-related alterations in trust and their underlying neural mechanisms.

1. Introduction

Mild cognitive impairment (MCI) is a prodromal state of Alzheimer s disease, which is characterized by a decline in general cognitive function that exceeds age and educational norms but does not significantly impair daily functioning (Albert et al., 2011). MCI is also associated with deficits in social cognition (Bora and Yener, 2017) and social interaction (Wilson et al., 2015). Recent studies have shown that older adults with MCI experience difficulties in interpersonal interactions, including increased vulnerability to deception (Han et al., 2016), reduced social engagement (Li et al., 2019a, b), and smaller social networks (Fan et al., 2021). Trust, a vital component of interpersonal relationships, plays a crucial role in various functions, including vulnerability to deception (Shao et al., 2019), social network size (Awaworyi Churchill and Mishra, 2017), and subjective well-being (Poulin and Haase, 2015). Trust propensity (TP), as an essential aspect of trust, represents the initial trust in strangers (Mayer et al., 1995), and its deficit is associated with interpersonal difficulties, such as social exclusion (Derfler-Rozin et al., 2010). Our previous studies have shown that TP in older adults can be predicted by resting-state functional connectivity (RSFC, Chen et al., 2023), a method that provides insight into the neural mechanisms underlying cognition (Mennes et al., 2010). The default mode network (DMN), associated with social cognition, significantly contributes to the prediction of TP in older adults with normal cognition, which suggests that

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older adults are likely to rely on social cognition in trust decisions (Chen et al., 2023). Notably, deficits in social cognition (Bora and Yener, 2017) and in the DMN (Eyler et al., 2019) have been observed in older adults with MCI, indicating a potential change in TP. However, little research has focused on TP in older adults with MCI and its underlying RSFC correlates. Studying TP and its mechanism of RSFC in older adults with MCI can advance our understanding of their interpersonal challenges and help caregivers and medical professionals build trusting relationships with these groups to increase their acceptance and cooperation with treatment.

Because trusting others can lead to either positive (reciprocity) or negative (betrayal) outcomes, trust relationships present a social dilemma that encourages individuals to carefully weigh costs and benefits (Evans and Krueger, 2011). Consequently, trust can be defined as a trustor s willingness to accept vulnerability in social dilemmas based on his or her expectations of anticipated rewards from the trustee s actions (Mayer et al., 1995). Trust can be understood in terms of TP and trust dynamics. Behavioral meta-analyses, including one-shot and multi-shot trust games (TG), suggest that trust is influenced by multiple game design factors, including trustee anonymity and trustee knowledge (Johnson and Mislin, 2011). Because of its advantage in minimizing the effects of past interactions and knowledge of the trustee, the one-shot TG is typically used to reflect an individual s general preference to trust strangers, measuring a stable trait known as TP (Berg et al., 1995; Camerer, 2003).

A recent neuropsychoeconomic model of trust proposes that trust behavior is shaped by affective, motivational, and cognitive (social and executive) components, which involve the formation and resolution of uncertainty (Krueger and Meyer-Lindenberg, 2019). In trust dilemmas, the betrayal aversion (affect) contrasted with the expectation of reciprocity (motivation) creates uncertainty. To resolve this uncertainty, trustors use either economic (executive cognition in the form of executive functions such as inhibition, working memory, and flexibility) or social (social cognition in the form of theory of mind, empathy, and social inference) bounded rationality to transform the possibility of betrayal into an expectation of positive reciprocity, thereby facilitating trust behavior. With economic rationality, individuals adopt a context-based strategy using extrinsic incentives based on executive cognition. With social rationality, individuals evaluate relationship-based trustworthiness using intrinsic incentives based on social cognition.

Each psychological component of trust is associated with different large-scale domain-general brain networks (Krueger and Meyer-Lindenberg, 2019). The affective component is anchored in the salience network (SN, Bellucci et al., 2017), which largely overlaps with the cingulo-opercular network (CON, Dragomir and Omurtag, 2021; Uddin, 2016). Increased activity and stronger connectivity within the SN regions at rest are associated with increased risk aversion (Han et al., 2012), emotional arousal (Touroutoglou et al., 2014), and worry (Saviola et al., 2020), suggesting an inhibitory effect on TP. Motivation is associated with the reward network, which generates reward anticipation and relies on the dopaminergic pathways (Ikemoto, 2010; Knutson et al., 2005). The RSFC of regions of the reward network is positively correlated with individuals sensitivity to reward (Adrián-Ventura et al., 2019) as a facilitating factor in TP. The executive cognitive component is associated with the central executive network (CEN), also known as the frontoparietal network (FPN, Witt et al., 2021), which is critical for facilitating goal-directed behavior (Miller and Cohen, 2001). The social cognitive component is connected to the DMN, which is essential for mentalizing and cooperative behavior (Amodio and Frith, 2006). Resting-state studies have shown that increased network strength within the CEN and DMN is separately associated with higher levels of executive (Raichlen et al., 2016) and social (Bisecco et al., 2020) cognition. Thus, the increased connectivity within the CEN and DMN can contribute to higher TP.

The trust model suggests that trust is driven by various psychological processes (affect, motivation, executive cognition, and social cognition) and is associated with large-scale networks that support the trust relationships employed in trust dilemmas (Krueger and Meyer-Lindenberg, 2019). Trust relationships can be categorized into three types of interpersonal trust: calculus-, knowledge-, and identification (with acquaintances)-based trust (Lewicki and Bunker, 1995). In one-shot TGs, trustors often adopt calculus-based trust. While cooperation has potential benefits, the unpredictability of unfamiliar trustees judgments leads trustors to increase their consideration of the possibility of betrayal (associated with SN) and engage in rational calculations (associated with economic rationality) to weigh the costs and benefits of establishing a relationship (Bellucci et al., 2017; Krueger and Meyer-Lindenberg, 2019).

Compared to younger adults, older adults tend to use knowledge-based trust rather than calculus-based trust. Knowledge-based trust relies less emphasis on cost-benefit calculations (economic rationality associated with the CEN) and instead relies more on acquiring knowledge about partners (social rationality associated with the DMN), which allows for predicting the trustee s behavior in uncertain situations (Lewicki and Bunker, 1995; Krueger and Meyer-Lindenberg, 2019). This is consistent with previous studies showing that older adults rely more on social cognition than executive cognition in decision-making (Bolenz et al., 2019; Zakirov and Krasilnikov, 2020; Zaval et al., 2015). A task-based fMRI study showed that older adults, compared to younger adults, exhibited stronger connectivity within the DMN during a TG (Fareri et al., 2022). In addition, our previous RSFC study showed that the DMN rather than the CEN significantly contributed to the positive prediction of TP in older adults (Chen et al., 2023).

Previous studies have shown that older adults with MCI have difficulties in interpersonal interactions (Li et al., 2019a, b) and show abnormal changes in emotion (Yates et al., 2013) compared to normal healthy controls (NHC), suggesting an MCI-related change in TP. Previous studies have demonstrated that older adults with MCI show an increase in worry (i.e., excessive fear of negative outcomes, Apostolova and Cummings, 2008) and are susceptible to emotional stimuli (Berger et al., 2015; Döhnel et al., 2008), making them vulnerable to interference from negative information. In addition, older adults with MCI experience a decline in motivation and an increase in apathy (Perry and Kramer, 2015), accompanied by structural atrophy in the dopaminergic mesocorticolimbic pathway (i.e., the reward network, Madsen et al., 2010). These findings suggest that in the uncertainty formation in trust dilemmas, older adults with MCI may be less affected by motivation (i.e., expectation of reward) but more affected by affect (i.e., betrayal aversion).

For uncertainty resolution, older adults with MCI have impairments in both economic (executive cognition, Traykov et al., 2007) and social (social cognition, Bora and Yener, 2017) rationality. In addition, the connectivity strength of key regions of the CEN and DMN is reduced in older adults with MCI (Eyler et al., 2019; Yang et al., 2023). They may find it difficult to translate betrayal aversion (affect) into expectations of reciprocity (motivation) when using a calculus-based or knowledge-based trust, which involves economic rationality (executive cognition) and social rationality (social cognition), respectively. Therefore, in a one-shot trust dilemma, older adults with MCI may have difficulty regulating the impact of the probability of betrayal (driven by the SN), leading to a decrease in TP.

In recent years, RSFC-based predictions have been widely used to explore the underlying neural activities of psychological processes (Castellanos et al., 2013; Smith et al., 2013). Previous studies have demonstrated that RSFC patterns are unique to each individual and contain physical and psychological information (Finn et al., 2015; Sheline and Raichle, 2013), providing valuable insights into the neural underpinnings of specific psychological functions (Finn et al., 2015). Connectome-based predictive modeling (CPM) is a popular RSFC prediction approach with advantages in interpretation, computation, and generalization (Shen et al., 2017; Sui et al., 2020). CPM has proven

successful in predicting individual differences in general cognitive functions (e.g., attention, Rosenberg et al., 2016; processing speed, Gao et al., 2020), social functions (e.g., empathy, Yao et al., 2022; TP, Chen et al., 2023), and personality (e.g., loneliness, Feng et al., 2019). It manifests in positive (RSFC positively associated with behavior) and negative (RSFC negatively associated with behavior) predictive CPM models, representing facilitators and inhibitors of predicted functions, respectively (Frith et al., 2021; Rosenberg et al., 2016). In addition, the combination of computational lesion analysis and CPM provides a safe and convenient method to investigate the contribution of a specific large-scale brain network to the prediction of behavior (Feng et al., 2018; Wang et al., 2021).

Our study aimed to examine the decline in TP (measured by one-shot TG) and its underlying RSFC (measured by resting state-fMRI, RS-fMRI) in older adults with MCI compared to an NHC group. We compared psychological measures assessing motivation (via the withdrawal-apathy [WAV] subdimension of the Geriatric Depression Scale [GDS]), affect (via the worry subdimension of the GDS), executive cognition (executive battery), and social cognition (one-shot dictator game, DG) between the two groups (MCI, NHC) and examined the correlations of these measures with TP in each group. In addition, we used CPM combined with lesion simulations to decode the underlying RSFC patterns associated with TP in both groups. The NHC group sample for this study included healthy participants who had participated in the previous study as well as newly recruited healthy participants (Chen et al., 2023).

At the behavioral level, because older adults with MCI show increased sensitivity to affective information and decreased motivation to deal with emotional issues, they are more influenced by affect than by motivation in uncertainty formation. In addition, executive and social cognition declines make it more difficult for older adults to resolve uncertainty, resulting in difficulty transforming betrayal aversion into reciprocal expectation in trust dilemmas. Therefore, we predicted that the MCI group, compared to the NHC group, would show a decrease in TP and a stronger relationship between TP and affect (i.e., lower TP scores would be associated with higher scores of the affect measure).

At the brain level, previous studies indicate that the TP of NHCs is predicted only by the positive CPM models, which emphasizes the contribution of the DMN, suggesting that older adults resolve uncertainty in trust dilemmas mainly by using social rationality. In comparison, older adults with MCI do not use economic or social rationality due to deficits in executive and social cognition, and there are likely to be changes in TP-related RSFC in terms of connectivity pattern and strength. As discussed above, because older adults with MCI are susceptible to the inhibition of affect rather than the positive influences of other components that increase TP (motivation, executive cognition, and social cognition), we predicted that the TP of the MCI group would be predicted only by the negative CPM models related to inhibitory factors rather than the positive CPM models related to facilitating factors and that the SN underlying the affect component would be a major contributor to the negative CPM models of TP.

2. Methods

2.1. Participants

A cohort of older adults was recruited from communities in Shenzhen, China, consisting of an MCI group ($n = 51$) and an NHC group ($n = 138$, note that the NHC group included 120 individuals from our previous study, and additional participants were included in the current study due to continued data collection efforts; Chen et al., 2023). All participants had normal or corrected-to-normal visual acuity, were right-handed, and had no history of head injury or neurological or psychiatric disorders. Written informed consent was obtained from all participants for this study, which the Institutional Review Board of Shenzhen University, China, approved.

After neuropsychological testing and neuroimaging, nine subjects with MCI and 23 NHCs were excluded for the following reasons: (i) excessive head motion during imaging (MCI=6, NHC=17; see Image acquisition), (ii) falling asleep during MRI scanning (MCI=3, NHC=4), and (iii) disbelief in the authenticity of a real partner during the one-shot TG (NHC=2, see Procedure). A total of 42 individuals with MCI (30 females; age [mean ± SD] = 65.98 ± 7.87 years; education = 9.79 ± 3.72 years) and 115 NHCs (80 females; age = 65.05 ± 6.46 years; education = 11.10 ± 3.12 years) were included in the behavioral and neuroimaging analyses. Participants received compensation in the form of a variable monetary reward that was randomly determined for each participant based on the outcome of one of the two games (i.e., TG and DG; see the One-shot trust game and Assessment of TP-related psychological components sections for details) for each participant and ranged from 20 to 45 Chinese Yuan (CNY, approximately $2.82 to $6.34). The final payments were delivered over three or four days after the experiment.

2.2. Diagnosis of mild cognitive impairment

To exclude potential dementia patients, the Chinese version of the Mini-Mental State Examination (MMSE, Folstein et al., 1975) was used to assess general cognitive function, and a combined version of the Physical Self-Maintenance Scale and the Instrumental Activities of Daily Living Scale was administered to assess activities of daily living (ADLs, Lawton and Brody, 1969). Participants were included in this study if they had an MMSE score higher than 24 and a score of zero on the ADLs. These measures were used to reduce potential confounding effects due to dementia or impaired ADL functioning.

Eleven neuropsychological tests were conducted to identify participants with MCI and evaluate five cognitive domains. These domains include: (1) memory assessed by the Auditory Verbal Learning Test (AVLT, Schmidt, 1996), Rey-Osterrieth Complex Figure Recall Test (Rey-Recall, Shin, et al., 2006), and Digital Span Test (DST, Blackburn and Benton, 1957); (2) executive cognition assessed by Trail Making Test Part B (TMT-B, Gordon, 1972) and Stroop test (Koss et al., 1984); (3) attention assessed by Trail Making Test Part A (TMT-A, Gordon, 1972) and Symbol Digit Modalities Test (SDMT, Smith, 1973); (4) language assessed by Category Verbal Fluency Test (CVFT, Mok et al., 2004) and Boston Naming Test (BNT, Knesevich et al., 1986); and (5) visuospatial ability assessed by Rey-Osterrieth Complex Figure Copy Test (Rey-Copy, Shin et al., 2006) and Clock Drawing Test (CDT, Shulman, 2000).

Cognitive dysfunction within a specific domain was identified as present if scores on the two tests in that domain fell below the 1.5 standard deviation (SD) cutoff (i.e., 1.5 SD below the overall mean derived from the Chinese norms (Li et al., 2013). Following Petersen s criteria for MCI (Petersen, 2004), participants were identified as having MCI if they showed cognitive dysfunction in any of the five domains assessed.

2.3. One-shot trust game

TP assessed by TGs is insensitive to social desirability biases and provides a more accurate indicator of individuals behavior in trust dilemmas (Lanz et al., 2022). In addition, one-shot TGs effectively capture TP without the confounding influence of reputation formation, reciprocity expectations, or learning effects, compared to multi-round TGs (Tzieropoulos, 2013). To access TP, a one-shot TG was administered with two players - a trustor and a trustee (Berg et al., 1995) (Fig. 1**A**). Participants were instructed on the game s rules. Both players were initially given 10 points equal to 30 CNY (with each point equal to 3 CNY). Within a range of 0 to 10 points, in increments of one, the trustor determined the amount of money to send to the trustee (labeled X). The money sent by the trustor (X) was tripled (3•X) by the experimenter before being transferred to the trustee. The trustee then decided the amount of money (denoted Y) to return to the trustor within a range of

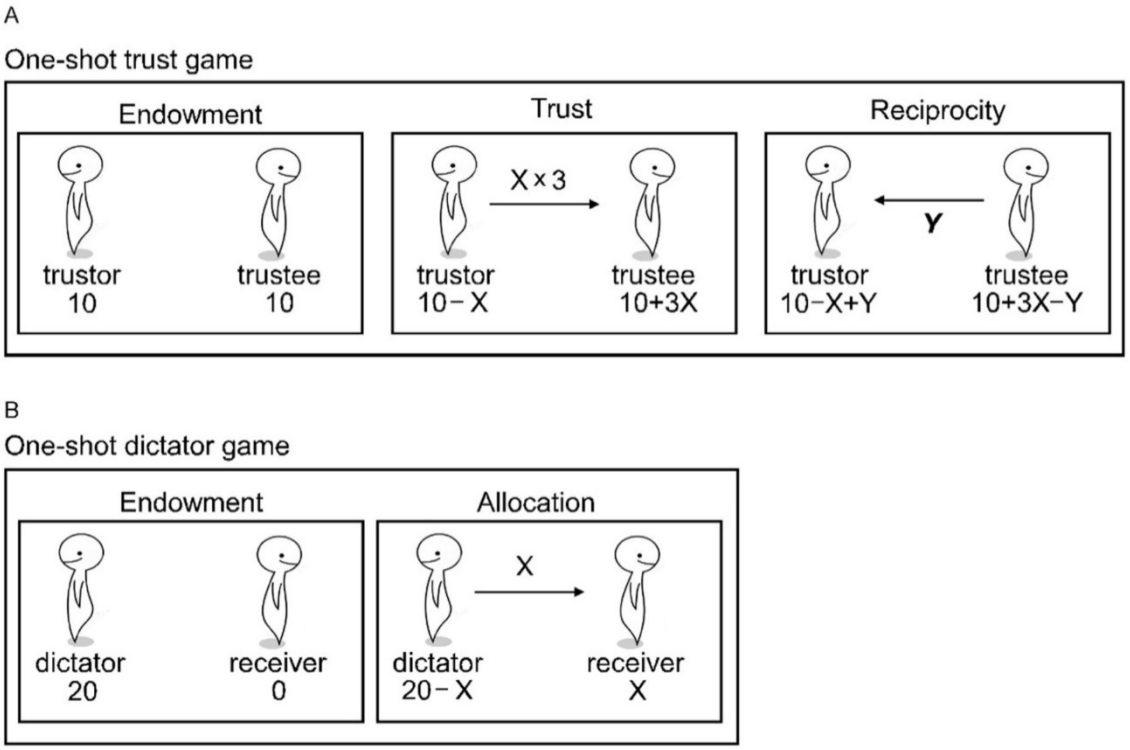

Fig. 1. Experimental game paradigms. A. The one-shot trust game (TG). Both players referred to as the trustor and the trustee, begin with an initial endowment of 10 points each. The trustor can invest any portion of their endowment (X, ranging from 0 to 10 points) with the trustee. The invested amount is then tripled by the experimenter and transferred to the trustee. Subsequently, the trustee decides how much of the tripled investment to return to the trustor (reciprocity; Y, ranging from 0 to 3X). All participants are informed that they are randomly assigned to play the role of the trustor and must make an investment decision (trust propensity, TP). A computer program determines the returns, ranging from 40 % to 60 % of the trustee s tripled investment. B. The one-shot dictator game (DG). One player, referred to as the dictator, is initially endowed with 20 points, while the other player, known as the receiver, starts with 0 points. The dictator can allocate any portion of his endowment (X, ranging from 0 to 20 points) to the receiver. The receiver must accept the allocated amount without any choice. All participants are informed that they are randomly assigned to play the role of the dictator and must decide how many points to share with the receiver (altruistic preference).

0 to 3•X points, in increments of one. At the end of the exchange, the trustor and trustee received 10-X + Y points and 10 + 3 - X - Y points, respectively. The points (X) that each participant chose to send as a trustor in the one-shot TG was their TP.

To ensure that participants understood the task, they were given an exercise in which they had to calculate the total payoffs for both the trustor and the trustee based on the assigned values of X and Y. An example question might be: "If the trustor transfers 2 points (X) to the trustee and the trustee returns 4 points (Y), what would be the final payoff outcome for each party?" The correct answer was that the trustor would receive 12 points (10 - 2 + 4 points, equal to 36 CNY), while the trustee would receive 12 points (10 + 6 - 4 points, equal to 36 CNY). If a participant answered incorrectly, he or she was given another practice attempt until he or she got it right.

After the exercise, participants were informed that they had been randomly assigned as a trustor. They were told that an unidentified older adult in the next fMRI scan would act as the trustee in the game and decide the amount of money to be returned. It was clear that they would not be playing the trust game simultaneously with the trustee. In fact, the trustee s return was determined by a randomized algorithm and ranged from 40 % to 60 % of the trustor s initial investment. As a result, participants final scores ranged from 10 to 18 points, or 30 to 54 CNY.

2.4. Assessment of TP-related psychological components

In this study, the TP-related psychological components (affect, motivation, executive cognition, and social cognition) were assessed for each participant.

Affect and motivation. TP s affect and motivation components were assessed using the subdimensions of the GDS. The GDS is a 30-item standardized self-report questionnaire designed to assess depressive symptoms in older adults (Yesavage, 1988). Respondents rate statements according to their current situation using a 2-point scale (forward scoring: 1 = disagree; 0 = agree; reverse scoring: 1 = agree; 0 = disagree), with higher scores indicating more severe depression. GDS items can be divided into five subdimensions representing key factors underlying depressive symptoms in older adults, including dysphoric mood, WAV, hopelessness, cognitive difficulties, and worry (Adams et al., 2004). The worry subdimension consists of 4 items related to anxious thoughts and rumination (Afraid something bad will happen, Worry about the future, Bothered by thoughts, and Worry a lot about the past). Higher worry scores, associated with a greater focus on negative affective information, reflect increased inhibition of social interaction. The WAV dimension includes apathy and withdrawal behaviors that are commonly associated with reduced motivation in older adults with dementia (Tagariello et al., 2009). The WAV subdimension includes six items related to social withdrawal and loss of interest (Prefer to stay home, Avoid social gatherings, Dropped activities and interests, Find life very exciting, Hard to start new projects, and Full of energy). Higher WAV scores, indicating lower vigor and social engagement, reflect decreased motivation.

Executive cognition. The neuropsychological measure of executive

cognition was used to represent the executive cognition component in TP. A composite score of executive cognition was calculated based on the performance of each participant on the TMT-B and Stroop tests. Given the results indicating non-normality for both executive cognition tests (TMT-B: D [116] = 0.99, $p < 0.001$; Stroop Test: D [116] = 1.00, $p < 0.001$) from the Kolmogorov-Smirnov test, rank-transformation rather than z-transformation was used for each participant s TMT-B and Stroop scores separately. Specifically, the TMT-B and Stroop tests were ranked separately for 157 (42 MCI + 115 NHC) participants, obtaining the rank corresponding to each subject s performance. The ranks on both tests were then summed to obtain a composite executive cognition score for each subject.

Social cognition. In this study, a one-shot DG was used to evaluate participants altruistic preference to represent the social cognition component of TP (Forsythe et al., 1994) (Fig. 1**B**). Participants were given instructions on the rules of the game. Initially, the dictator received 20 points (with 1 point equal to 3 CNY), and the receiver received 0 points. The dictator determined the allocation of points to the receiver (labeled X) within a range of 0 to 20 points in increments of one. The receiver had no option but to accept the assigned allocation. Ultimately, the dictator kept 20 - X points, leaving the receiver with X points. The number of points (X) they shared as a dictator in the one-shot DG quantified each participant s altruistic preference. Participants completed a practice session to confirm their understanding of the game rule, in which they calculated final points for both the dictator and the receiver. Afterward, participants were informed of their assignment to the dictator role and that an anonymous older adult would join the game as the receiver in the near future. As a result, the final points of the participants ranged from 0 to 20 points (equivalent to 0 to 60 CNY).

2.5. Experimental procedure

Neuropsychological tests and the GDS were administered to participants in the community of Shenzhen City, China, within a three-month period prior to their fMRI scan session. In the neuroimaging session, participants first underwent an approximately 8-minute RS-fMRI scan, during which they were instructed to keep their eyes closed, remain awake, and avoid systematic thinking. Following the RS-fMRI scan, participants completed a 25-minute working memory fMRI task (the results of which will be published in a separate study). A 7-minute high-resolution structural scan (T1-weighted images) and a 5-minute routine clinical scan (T2-weighted images) were then acquired for medical reporting purposes. After scanning, participants first played the one-shot DG and then the one-shot TG outside the scanning room. Finally, participants completed a debriefing questionnaire to provide feedback on their mental states and activities during the experiment. This included whether they believed their partner in the TG was virtual and whether they had fallen asleep during the RS-fMRI scan. Those who answered yes to either question ($n = 6$) were excluded from further analysis.

2.6. Image acquisition

Neuroimaging data were collected using a 3T SIEMENS MAGNETOM Prisma scanner equipped with a 64-channel head coil at Shenzhen University. High-resolution structural brain images were acquired via a T1-weighted 3D magnetization-prepared rapid gradient-echo (MPRAGE) sequence with the following parameters: repetition time (TR) = 1.9 s, echo time (TE)= 2.23 ms, flip angle (FA) = 8°, field of view (FoV) = 220 × 220 mm^2, voxel size = 1.1 × 1.1 × 1.1 mm^3, number of slices = 224. Resting-state and task-based fMRI brain images were also acquired using a multi-band echo-planar imaging (EPI) sequence with total volumes = 315 (resting-state) and 1013 (task-based), TR = 1.5 s, TE = 30 ms, FA = 75°, FOV = 192 × 192 mm^2, voxel size = 2 × 2 × 2 mm^3, number of slices = 72, slice thickness = 2 mm, multi-band = 4, acceleration factor = 2. For this study, only the T1-weighted structural and RS-fMRI images were used.

2.7. Behavioral analysis

Statistical analyses were performed using MATLAB 2018b (The MathWorks, Natick, MA). A significance level of 0.05 (two-tailed) was used as the alpha error threshold. The Kolmogorov-Smirnov test and the Levene s test were performed to assess the normality and homogeneity of the measures of TP and TP-related components (affect, motivation, executive cognition, and social cognition). Given the non-normality of the measured TP (see Behavioral results), non-parametric statistical methods were used for all TP-related analyses in this study. Between-group differences in TP and TP-related components were examined using Wilcoxon signed rank tests. In addition, partial Spearman correlations were calculated between group and TP scores, controlling for the potential influences of age, gender, and education, to validate whether the TP was lower in the MCI group than in the NHC group using a one-tailed *t*-test. To examine the group differences in the relationships between TP and TP-related components (affect, motivation, executive cognition, and social cognition), partial Spearman correlations were calculated for both groups, controlling for age, gender, and education as covariates, and then Fisher s z-tests were used to compare correlation coefficients between groups (Fisher, 1992). To address the issue of multiple comparisons, the false discovery rate (FDR) correction was applied using the gretna_FDR function in Matlab.

2.8. Image preprocessing

Neuroimaging data were preprocessed using DPABI (Data Processing & Analysis for [Resting-State] Brain Imaging, Yan et al., 2016). The preprocessing pipeline included the following steps: (1) removal of the first ten volumes to allow signal stabilization; (2) slice timing correction; (3) spatial realignment; (4) evaluation of image quality, with manual reorientation conducted if abnormal origin or orientation was detected; (5) co-registration of T1-weighted images to the mean functional images; (6) image segmentation using the Diffeomorphic Anatomical Registration Through Exponentiated Lie algebra toolbox (DARTEL) (Ashburner and Friston, 2000); (7) nuisance regression with white matter signal, cerebrospinal fluid signal, global signal, 24 head motion parameters, and polynomial trend parameter set to 1 for linear detrending by the component-based noise correction method (CompCor) (Behzadi et al., 2007); (8) normalization of image data to MNI space and resampling voxel size to 3 × 3 × 3 mm^3; spatial smoothing using a 4 mm full-width-at-half-maximum Gaussian kernel; and (10) band-pass filtering (0.01–0.1 Hz). Participants exhibiting maximum translation greater than 3 mm, maximum rotation exceeding 3°, or mean framewise displacement (FD) above 0.25 were excluded from analyses (Yan et al., 2013).

2.9. Construction of the RSFC matrix

In this study, the RSFC matrix was constructed using Dosenbach s atlas, which contains six general large-scale networks consisting of 160 nodes (Dosenbach et al., 2010). Due to missing cerebellar images in some participants, the cerebellum (18 nodes) was excluded, resulting in 142 nodes grouped into five large-scale networks: DMN (34 nodes), FPN (21 nodes; we used CEN to denote it in this study), CON (32 nodes, we used SN to denote it in this study), sensorimotor network (SMN, 33 nodes), and occipital network (OccN, 22 nodes). The BOLD signal time course of each node was averaged from voxels within a 5-mm radius sphere centered on the node coordinates for each participant. RSFC was calculated by computing the Pearson correlation between the time courses of each pair of nodes. The correlation coefficients were then subjected to Fisher s z-transformation, resulting in a 142 × 142 symmetrical matrix representing the RSFC profile for each participant.

2.10. Connectome-based predictive modeling

The CPM method was employed separately based on the RSFC matrix for the MCI group and the NHC group to predict TP (Gao et al., 2020; Shen et al., 2017) (Fig. 2). Based on the guidelines for neuroimaging-based prediction (Poldrack et al., 2020; Scheinost et al., 2019), a leave-one-out cross-validation (LOOCV) approach was used due to the small sample size ($n < 200$). In each iteration of the LOOCV approach, n-1 participants ($n = 41$ for MCI or $n = 114$ for NHC) were used as the training dataset, with the remaining participants serving as the test data. The training data were processed: (1) normalizing the TP and the RSFC; (2) calculating partial Spearman correlations, controlling for age, gender, years of education, and head motion between TP and each edge in the RSFC matrix. Then, significant edges ($p < 0,01$) were selected and divided into positive (edges that have a positive correlation to TP) and negative (edges that have a negative correlation to TP) networks; (3) calculating network strengths by summing all selected edges in the positive or negative network; and (4) training linear regression

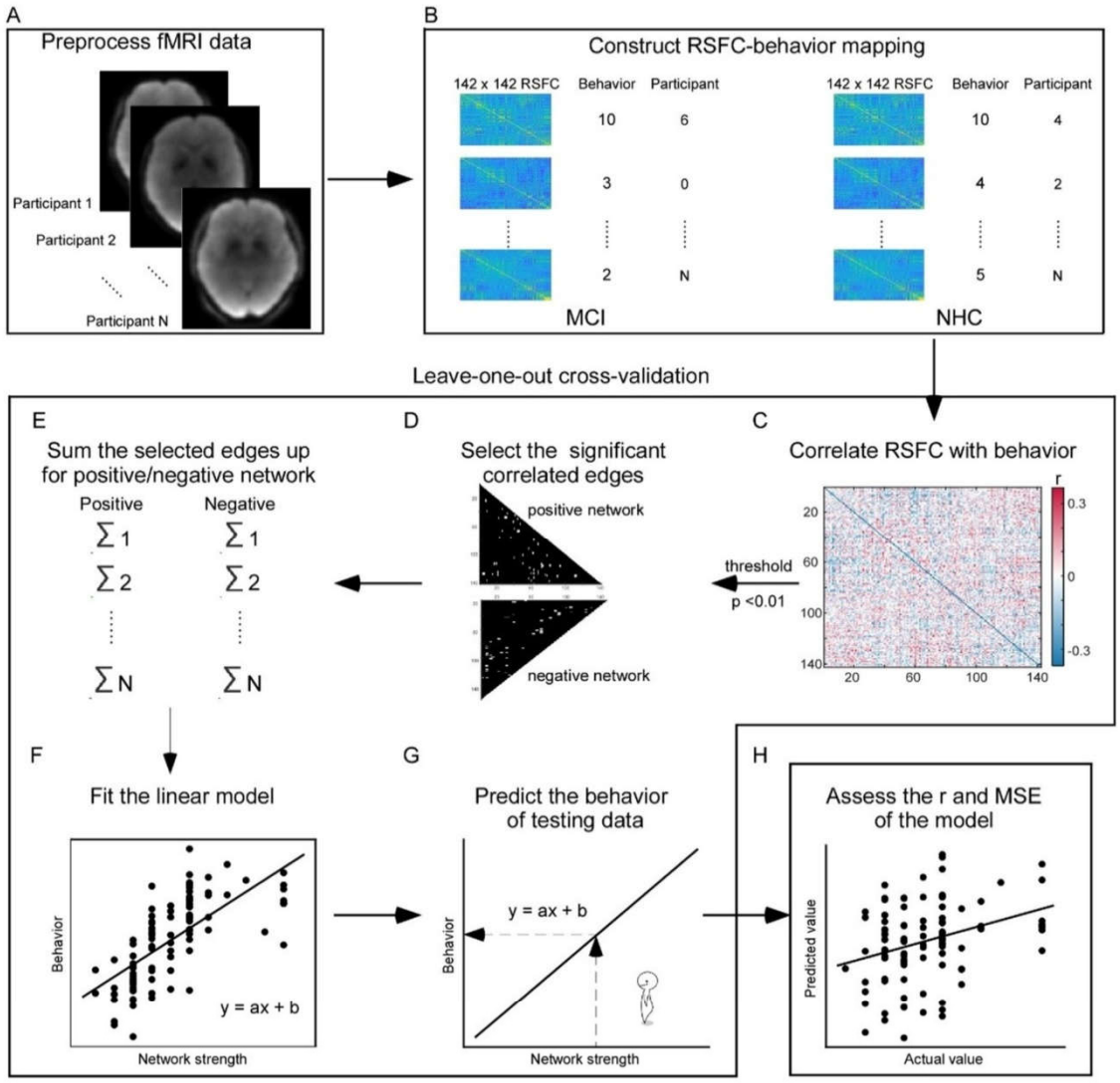

Fig. 2. A schematic diagram of connectome-based predictive modeling. A. Data preprocessing. Each participant s resting state magnetic resonance imaging (rs-fMRI) was preprocessed. B. RSFC-behavior mappings in the mild cognitive impairment (MCI) and normal healthy controls (NHC) groups. The behavioral measure (trust propensity, TP) and the RSFC matrix were calculated for each MCI and healthy control group participant. The area of solid lines represents the course of the Leave-one-out-cross-validate (LOOCV), where each participant was used once as test data, while the remaining participants served as training data. C. Correlation between RSFCs and behavior. During LOOCV, the Spearman correlation between RSFC and the behavioral measure was estimated using the training data. D. Feature selection. Significant edges ($p < 0.01$) were included in subsequent analyses and classified into positive or negative networks based on their positive or negative correlation with behavior. E. Summation of selected edges. The strengths of the positive and negative networks were estimated by summing the respective edges within each network. F. Model fitting. Linear models relating the behavioral measure to the network strengths of both positive and negative networks were constructed using the training data set. G. Behavioral prediction. The trained models were used to predict the behavioral measures for the testing data. H. Model assessments. After the LOOCV, the Spearman correlation (r) and mean square error (MSE) between the predicted and actual behavior are calculated to assess the predictive model s performance.

models, which fit the relationships between normalized TP scores and the strengths of the positive and negative networks.

For the test data (i.e., the remaining participant), normalization to the TP and the RSFC matrices was performed using the normalization parameters (i.e., mean and SD) derived from the training data. The positive and negative edge sets selected during the training phase were identified, and their respective sums were calculated to generate the positive and negative network strengths for the test data. These network strength values were then entered separately into the trained positive and negative TP prediction models.

To illustrate the positive and negative networks, common edges that were consistently selected across all LOOCV iterations were identified. These common edges were then categorized into five large-scale brain networks (DMN, SN, CEN, SMN, OccN). To account for the impact of network size on the number of common edges, the proportion of common edges within each network was used as a representation.

2.11. Model assessment

The predictive performance of the models was quantified using the Spearman correlation coefficient (r) between predicted and actual TP and the mean squared error (MSE), which measures the average squared deviation between predicted and actual TP values. Permutation testing was employed to determine the statistical significance of the positive and negative network models for each group. For each permutation, the brain-behavior mapping was shuffled by randomizing the participant labels, and the same procedure of estimating the predictive models was performed, yielding the r and MSE between actual and predicted TP values. After 5000 permutations, null hypothesis distributions of r and MSE were generated for both the positive and negative models. The *p*-value for Spearman r was calculated as the proportion of permutation-generated r values that exceeded the actual r obtained from the non-permuted data. Similarly, the *p*-value for MSE was calculated as the proportion of permutation MSE values that were lower than the actual MSE. Statistical significance was set at an alpha level of 0.05 for the permutation tests.

2.12. Comparison of network strength between groups

To explore possible changes in the RSFC of TP in the MCI group, the differences in the network strength of the RSFC between the MCI and NHC groups were examined. For each participant, the network strength of the NHC-specific (positive) and MCI-specific (negative) networks was calculated separately. These specific networks were defined as positive or negative based on statistical significance in the CPM assessment. Note that these networks consisted of common edges selected in each LOOCV iteration. Normality (Kolmogorov–Smirnov test) and homogeneity (Levene s test) of the network strength were analyzed. Given the heterogeneity of network strength between the MCI and NHC groups within both networks (see Differences in groups network strength), the Wilcoxon rank sum test was used to examine group differences in network strength.

2.13. Lesion simulation

A simulated lesion approach was implemented to investigate the contribution of different large-scale brain networks in predicting TP in the MCI and NHC groups. CPMs were constructed using connectivity matrices that systematically excluded each of the five major networks defined in the Dosenbach atlas (DMN, SN, CEN, SMN, OccN). Specifically, for each exclusion model, the nodes corresponding to one of the five networks were omitted from the full RSFC matrix, leaving a reduced connectivity matrix as input to the CPM. For example, when simulating a "lesion" to the SMN, the 33 SMN nodes were removed, resulting in a 109 $\times$ 109 RSFC matrix for model estimation. The predictive performance of each lesion model was quantified by the Spearman correlation coefficient (r) between predicted and actual TP scores. One-tailed Steiger s z-tests (Steiger, 1980) were then performed to determine whether the r value for a given lesion model was significantly lower than that of the whole-brain CPM model (i.e., without any network exclusions). A significant decrease in predictive performance for a lesion model relative to the whole-brain model would indicate that the excluded network plays a crucial role in predicting TP. This explanation assumes that simulating a "lesion" to a network that is highly relevant to the behavior of interest should substantially impair predictive accuracy. FDR correction was used to correct for multiple comparisons between the five lesion models.

3. Results

3.1. Behavioral results

Both groups demographic information and behavioral performance are shown in Table 1. Across all neuropsychological tests, the NHC group showed significantly higher cognitive function levels than the MCI group, including memory tests (*ps* < 0.001). TP scores were non-normally distributed in both the MCI group (D [41] $= 0.83$, $p < 0.001$) and the NHC group (D [114] $= 0.91$, $p < 0.001$) (Fig. 3**A**). The results of Levene s tests showed no significant difference in the variance of TP between the two groups (F [1, 155] $= 1.42$, $p = 0.28$). The Wilcoxon signed rank test revealed that the TP was significantly lower in the MCI group (3.40 $\pm$ 2.04 points, 34 % of the endowment) compared to the NHC group (4.31 $\pm$ 2.40 points, 43 % of the endowment, $Z = -1.97$, $p < 0.05$) (Fig. 3**B**). A follow-up partial Spearman correlation analysis showed a significant correlation between TP and the diagnostic group (MCI vs. NHC) even after controlling for age, education, and gender as covariates (r [156] $= -0.14$, $p < 0.05$). In addition, the composite scores of executive cognition were significantly lower in the MCI group compared to the NHC group ($Z = 5.67$, $p < 0.001$) (Table 1).

Furthermore, lower TP was significantly associated with higher scores on the affect measure in the MCI group (worry, r [41] $= -0.47$) but not in the NHC group (r [114] $= 0.11$), suggesting a stronger inverse relationship between TP and affect in older adults with MCI ($Z = -3.33$, $p < 0.001$) (Table 2). However, no significant group differences were found in the correlation between TP and other TP-related psychological components (motivation, executive cognition, and social cognition).

3.2. Connectome-based predictive models of trust propensity

The performance of positive and negative CPMs in predicting TP was evaluated within both the MCI and NHC groups. In the NHC group, TP was significantly predicted by the positive model ($r = 0.41$, $p < 0.01$, MSE $= 0.96$, $p < 0.05$) (Fig. 4**A~C**), indicating that higher positive CPM network strength was associated with higher TP, instead, it was not significantly predicted by the negative model ($r = 0.20$, $p = 0.38$, MSE $=$ 1.10, $p = 0.33$) (Fig. 4**D**). In the MCI group, TP was significantly predicted by the negative model ($r = 0.45$, $p < 0.05$, MSE $= 1.03$, $p < 0.05$) (Fig. 4**J~L**), indicating that higher negative CPM network strength was associated with lower TP, instead, TP was not significantly predicted by the positive model ($r = 0.40$, $p = 0.06$, MSE $= 1.06$, $p = 0.07$) (Fig. 4**G**).

To examine the network related to TP, the proportion of common edges in each significant network was calculated for each group (Fig. 4**E & H**). For the negative model in the MCI group, the SN had the highest proportion of common edges, followed by the CEN, DMN, SMN, and OccN. OccN had the highest proportion of common edges for the positive model in the NHC group, followed by SMN, CON, DMN, and CEN.

3.3. Differences in groups network strength

To investigate possible impairments in the RSFC pattern of TP in the MCI group, a comparison of network strength between the MCI and NHC groups was performed for the MCI-specific negative network (Fig. 4**I**)

Table 1
Group differences in demographic information, cognitive function, Geriatric Depression Scale, and TP-related components between the MCI and NHC groups.

Domain	Measure	MCI (Mean [SD])	NHC (Mean [SD])	t/Z	*p*
Demography					
	Age (year)	66.38 (7.85)	64.88 (6.50)	0.79	0.43
	Gender (Percentage of females)	0.71 (0.46)	0.70 (0.46)	0.22	0.823
	Education (year)	9.59 (3.72)	11.20 (3.12)	−2.70	0.008
Cognitive function					
	MMSE	25.50 (2.75)	28.11 (1.77)	−5.60*	<0.001
Memory	Rey-recall	6.98 (5.30)	14.99 (6.87)	−6.21*	<0.001
	AVLT	17.00 (7.05)	30.17 (8.26)	−7.34*	<0.001
	DST	9.21 (2.81)	11.32 (2.32)	−4.28*	<0.001
Executive cognition	TMT-B (ms)	243.74 (132.13)	143.88 (48.86)	5.71*	<0.001
	Stroop (ms)	104.57 (41.98)	75.16 (19.97)	4.20*	<0.001
Attention	TMT-A (ms)	79.59 (36.07)	54.23 (17.77)	4.59*	<0.001
	SDMT	23.84 (12.43)	38.06 (11.25)	−6.45*	<0.001
Language	CVFT	33.35 (8.42)	44.83 (8.35)	−6.51*	<0.001
	BNT	20.73 (8.63)	23.73 (3.03)	−4.79*	<0.001
visuospatial ability	Rey-copy	27.07 (6.68)	33.11 (3.53)	−6.00*	<0.001
	CDT	17.52 (8.80)	24.80 (4.83)	−5.06*	<0.001
GDS					
	Total scores	6.95 (3.66)	5.22 (4.62)	3.19*	0.001
TP-related psychological components					
Affect	Worry	1.07 (1.25)	0.74 (1.17)	1.88	0.059
Motivation	WAV	1.79 (1.28)	1.36 (1.37)	2.08	0.038
Executive cognition	Composite score	113.07 (42.94)	66.56 (39.77)	5.67*	<0.001
Social cognition	One-shot DG	8.07 (3.13)	8.96 (2.99)	−1.39	0.163

MCI, mild cognitive impairment; NHC, normal healthy control; TP, trust propensity; SD, standard deviation; MMSE, Mini-Mental State Examination; Rey-recall, Rey-Osterrieth Complex Figure Recall Test; AVLT, Auditory Verbal Learning Test; DST, Digital span Test; TMT-B, Trail Making Test Part B; TMT-A, Trail Making Test Part A; SDMT, Symbol Digit Modalities Test; CVFT, Category Verbal Fluency Test; BNT, Boston Naming Test; Rey-copy, Rey-Osterrieth Complex Figure Copy Test; CDT, Clock Drawing Test; GDS, Geriatric Depression Scale; WAV, Withdrawal–Apathy–Vigor; DG, dictator game. With the exception of the TMT -A and -B, the Stroop Test, and the executive cognition composite score, the higher the score on the other cognitive tests, the better the performance. Higher total, Worry, and WAV scores on the GDS indicate more severe depression. * indicates significant results after false discovery rate correction ($p_{FDR} < 0.05$).

and the NHC-specific positive network (Fig. 4**F**), respectively. The Levene s tests revealed a significant heterogeneity of network strength between the MCI and NHC groups within both networks (MCI-specific negative network: F [1, 156] = 28.84, $p < 0.001$, NHC-specific positive network: F [1, 156] = 16.10, $p < 0.001$). In the NHC-specific positive network, the total network strength was significantly lower in the MCI group compared to the NHC group ($Z = -1.98$, $p < 0.05$; MCI: mean = 0.95, standard error [SE] = 0.37; NHC: mean =2.23, SE = 0.42) (Fig. 3**C**). In contrast, no significant difference in the total network strength was found between the two groups within the MCI-specific negative network ($Z = -0.21$, $p = 0.78$; MCI: mean = 6.51, SE = 0.98; NHC: mean = 4.87, SE = 0.29).

3.4. Lesion simulation results

Lesion simulations were performed to examine the contribution of a single large-scale network to the prediction of TP. Only the exclusion of the DMN significantly decreased the performance of the positive CPM models in predicting TP in the NHC group, whereas only the exclusion of the SN significantly decreased the performance of the negative CPM models in predicting TP in the MCI group (Table 3).

4. Discussion

This study aimed to investigate whether TP was reduced in the MCI group compared to the NHC group using a one-shot TG and to identify the RSFC associated with TP in this population using CPM. Our behavioral results showed that the MCI group showed lower trust in strangers (i.e., TP) than the NHC group. The correlation between higher TP and lower scores of affect (as measured by the Worry subdimension of the GDS) was significantly stronger in the MCI group than in the NHC group. Additionally, we found that the negative CPM models significantly predicted TP in the MCI group (higher network strength associated with lower TP), in which the SN made a significant contribution, as revealed by lesion simulation. In contrast, the positive CPM models significantly predicted TP in the NHC group (higher network strength associated with higher TP), in which the DMN played a significant role, as revealed by lesion simulation. The total network strength of the NHC-specific positive network was lower in the MCI group than in the NHC group. These results suggest a decrease in TP associated with an increased influence of affect in the MCI group and an MCI-related alteration in the TP-related RSFC pattern.

4.1. MCI-related decrease in TP and its association with TP-related components

Consistent with our hypothesis, the MCI group showed lower TP than the NHC group, which was significantly associated with increased sensitivity to the probability of betrayal (affect). Previous studies have shown that older adults with MCI pay more attention to negative aspects of social interactions and have more intense emotional responses to social challenges (Lin et al., 2022). In addition, older adults with MCI have deficits in motivation (Perry and Kramer, 2015), executive cognition (Traykov et al., 2007), and social cognition (Bora and Yener, 2017), which likely further reduce their ability to regulate emotions (Li et al., 2019a, b; Perach et al., 2021), increasing the affective impact on decisions in trust dilemmas. Although motivation and social cognition showed a decreasing trend without reaching statistical significance in the MCI group, this may be due to the limited sample size and indirect measures in this study. The decrease in TP and its strong association with affect in older adults with MCI suggest that this population may need more time to establish relationships with strangers and that negative information in trust dilemmas may significantly impact the establishment of trust. In addition, longitudinal studies have highlighted trust as a significant predictor of future depression risk in older adults (Dong et al., 2017) and emphasized its importance for interpersonal relationships, cooperation, and overall well-being (Poulin and Haase, 2015). Therefore, elucidating the factors underlying trust problems in older adults with MCI is critical to help caregivers and medical professionals build trusting relationships with this population to improve their adherence to treatment and overall quality of life.

4.2. Large-scale networks underlying TP in older adults with MCI

Consistent with our hypothesis, the SN significantly contributed to

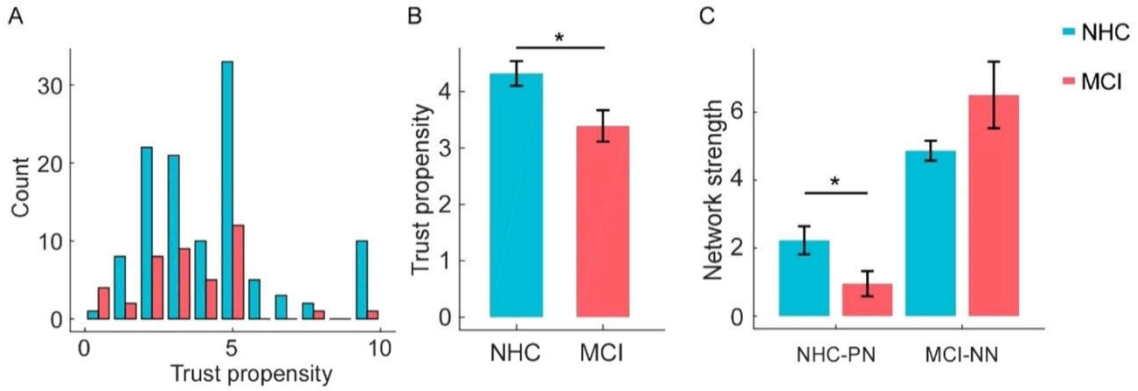

Fig. 3. Behavioral results of the one-shot trust game and the connectome-based predictive modeling results. A. The distributions of trust propensity (TP) in the mild cognitive impairment (MCI) group and the normal healthy controls (NHC) group. The distributions of TP in both MCI and NHC groups were non-normal, and there was no significant difference in the variance of TP between the two groups. B. TP in the MCI and NHC groups. TP was significantly lower in the MCI group than in the NHC group. C. Group network strength differences between the MCI and the NHC groups. Group effect on network strength was estimated using the Wilcoxon rank sum test. NHC-PN, the NHC-specific positive network in connectome-based predictive modeling (CPM); MCI-NN, the MCI-specific negative network in CPM. * indicates significant group differences between MCI and NHC ($p < 0.05$).

Table 2
Differences in correlations between trust propensity and its related components in the MCI and NHC groups.

	MCI (r)	NHC (r)	z	p
Affect				
Worry	−0.47	0.11	−3.33*	<0.001
Motivation				
WAV	−0.17	0.03	−1.10	0.273
Executive cognition				
Composite score	0.15	0.09	0.28	0.780
Social cognition				
One-shot DG	0.37	0.18	1.10	0.272

Abbreviations. TMT-B, Trail Making Test Part B; WAV, Withdrawal-Apathy-Vigor; DG, Dictator game. * indicates significant results after false discovery rate correction ($p_{FDR} < 0.05$).

the negative models of TP in the MCI group, and the DMN played a significant role in the positive models in predicting TP in the NHC group. The SN is crucial for emotional recognition and arousal in older adults (Dolcos et al., 2014; Touroutoglou et al., 2018). The hyperactivity and increased strength of the SN have been associated with excessive emotional responses to negative stimuli in patients with depression (Williams, 2016) and increased socioemotional sensitivity (Toller et al., 2018). Therefore, the high contribution of the SN in predicting TP in the MCI group is consistent with our behavioral results, suggesting that older adults with MCI may be more vulnerable to the probability of betrayal in trust dilemmas. These results suggest that older adults with MCI may rely more on affective processes when making trust decisions. When interacting with older adults with MCI, it is advisable to avoid displaying negative traits.

Compared to the significant contribution of the DMN in predicting TP in the NHC group, the nonsignificant contribution of DMN in predicting TP in the MCI group suggests that older adults with MCI may have less reliance on social rationality (social cognition) in trust dilemmas. The DMN is involved in social cognition and plays a key role in our ability to understand other people s thoughts, feelings, and intentions (Mars et al., 2012). Although, we did not find significantly decreased altruistic preference in MCI on the one-shot DG, meta-analyses of behavioral (Bora and Yener, 2017) and fMRI (Badhwar et al., 2017) findings suggest that both social cognition and the DMN are impaired in MCI. Thus, it is likely that reduced social rationality makes it more difficult for older adults with MCI to evaluate others trustworthiness, resulting in a reduced ability to translate the perceived probability of betrayal into expectations of reciprocity and a decrease in trust. These findings broaden our understanding of the interpersonal challenges of older adults with MCI and help caregivers develop trusting relationships with them.

Our behavioral results showed no significant relationships between TP and executive cognition in either group (MCI or NHC). In addition, CPM results indicated that the CEN did not significantly contribute to the prediction of TP. The results suggest that both groups have reduced reliance on economic rationality (executive cognition) in trust dilemmas. As individuals age, there is a decline in reliance on deliberative strategies (executive cognition) in decision-making (Bolenz et al., 2019; Zaval et al., 2015), including TP (Chen et al., 2023). When making decisions, older adults with MCI have difficulty integrating information from multiple sources due to impaired executive cognition and rely more on intuitive strategies (Delazer et al., 2007; Zamarian et al., 2011). This implies that, similar to NHCs, older adults with MCI may rely less on economic rationality (executive cognition) and have difficulty reducing the impact of the probability of cheating in TGs by weighing risks and benefits, leading to a decrease in TP. In addition, executive cognition impairments may expose older adults with MCI to greater uncertainty of being cheated (Benavides-Varela et al., 2020; Han et al., 2016). This suggests that the impact of executive dysfunction on older adults with MCI may be far-reaching (Corbo and Casagrande, 2022; Zhang et al., 2007), affecting not only their cognitive abilities but also potentially their social functioning.

4.3. The positive and negative relationships between TP and RSFC in the two groups

Our results showed that TP in the NHC group was predicted only by the positive CPM models, and TP in the MCI group was predicted only by the negative CPM models, which was consistent with our hypothesis. The implication of significant positive or negative CPM models has been debated. Some argue that positive and negative models implicate similar information, and combining them does not improve the predictive accuracy of models (Rosenberg et al., 2016). However, alternative perspectives suggest that the positive and negative models contain different connectivity patterns and represent different psychological functions (Frith et al., 2021; Wang et al., 2021). Previous studies argue that positive models reflect high-functioning patterns associated with

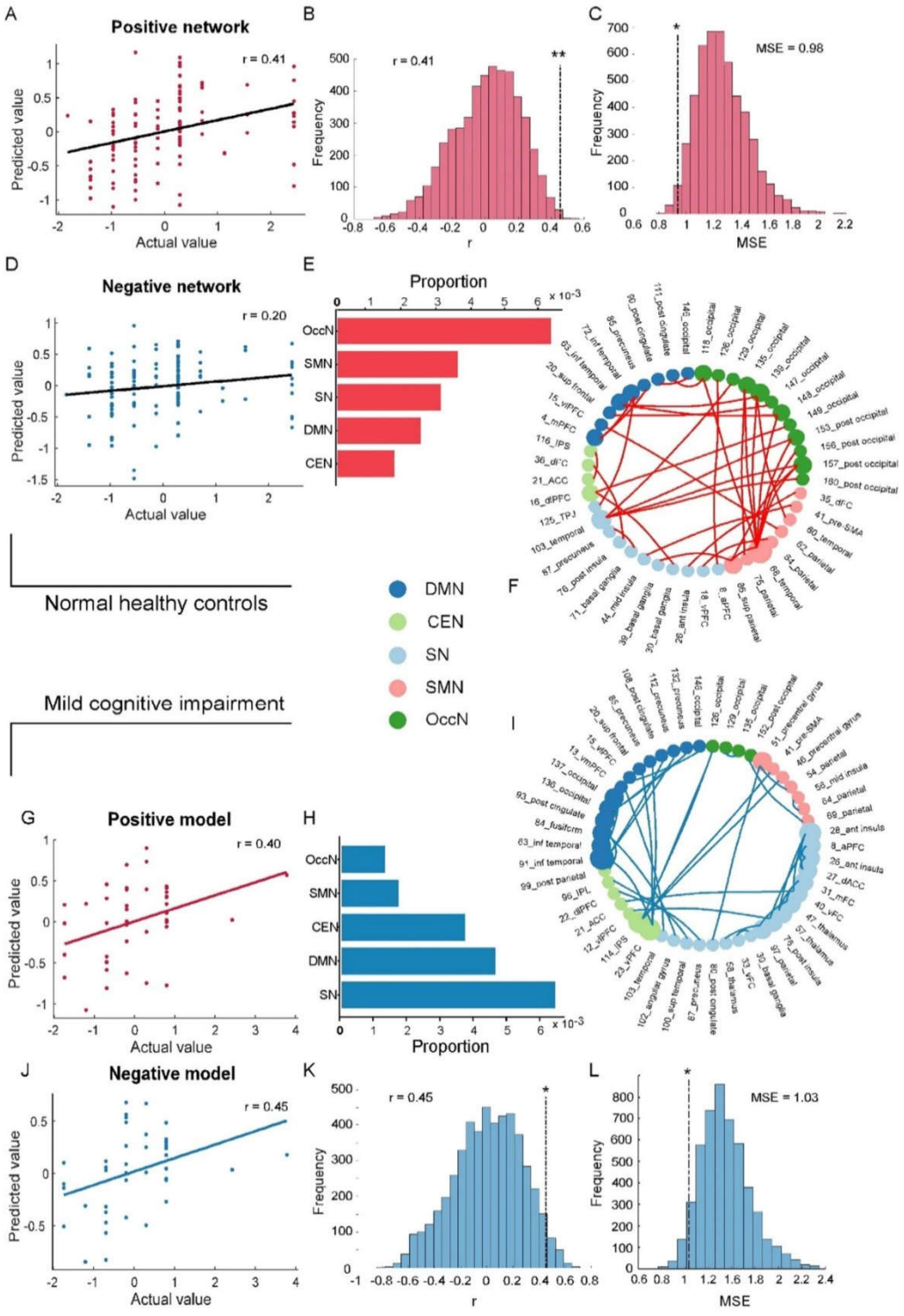

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Fig. 4. Predictive models associated with trust propensity (TP) in the mild cognitive impairment (MCI) group and the normal healthy controls (NHC) group. A. Predictive performance of the positive models in the NHC group. The scatterplot indicates a significant correlation, as assessed by the Spearman correlation, between actual TP and predicted TP in the positive models in connectome-based predictive modeling (CPM). B & C. Null hypothesis permutation tests of the positive models in the NHC group. Histograms show that both the Spearman correlation coefficient (r) and the mean squared error (MSE) of the positive models in CPM are significant. The p-value of r was defined as the ratio of permutation-generated r values higher than the actual r, and the p-value of MSE was defined as the ratio of permutation-generated MSE values lower than the actual MSE. D. The predictive performance of the negative models in the NHC group. The scatterplot indicates that the correlation between actual TP and predicted TP in the negative models in CPM, as assessed by the Spearman correlation, was insignificant. E. The contribution of each large-scale network to the positive models in the NHC group. The bar chart shows the proportion of common edges (selected in all iterations in leave-one-out cross-validation) of each large-scale network. F. Chord plot of the positive network in NHCs. The chord plot shows the common edges of the positive network in detail. G. Predictive performance of the positive models in the MCI group. The scatterplot shows that the correlation between actual TP and predicted TP, as assessed by the Spearman correlation, was not significant for the positive models in CPM. H. The contribution of each large-scale network to the negative models in the MCI group. The bar chart shows the proportion of common edges of each large-scale network. I. Chord plot of the negative network in older adults with MCI. The chord plot shows the common edges of the negative models in detail. J. The predictive performance of the negative models in the MCI group. The scatterplot shows that the correlation, as assessed by the Spearman correlation, between actual TP and predicted TP in the negative models in CPM was significant. K&L. The null hypothesis permutation tests of the negative model in the MCI group. Histograms show that both the r and the MSE of the negative models in CPM are significant. The size of a node in the chord plots (F) & (I) indicates the number of edges connected to that node.

Table 3
Results of Lesion simulation in the predictive model of trust propensity in both the MCI and NHC Groups.

lesion	Predict power	Different from the whole-brain model	
	r	Steiger s Z	*p*
Positive network of NHC group			
DMN	0.35	2.33*	0.010
CEN	0.38	1.52	0.064
SN	0.40	0.13	0.449
SMN	0.38	0.52	0.301
OccN	0.34	0.93	0.177
Negative network of MCI group			
DMN	0.38	1.40	0.081
CEN	0.41	0.58	0.279
SN	0.23	2.74*	0.003
SMN	0.58	−2.78	0.997
OccN	0.54	−2.41	0.992

Abbreviations. DMN, default mode network; CEN, central executive network; SN, salience network; SMN, sensorimotor network; OccN, Occipital network. * indicates significant results after false discovery rate correction ($p_{FDR} < 0.05$).

facilitators of predicted functions, and negative models represent low-functioning patterns associated with inhibitors of predicted functions (Frith et al., 2021; Rosenberg et al., 2016).

Our results support the argument that positive and negative models have different implications. The positive models significantly predicted TP in the NHC group, indicating that their TP is related to the facilitators (social cognition) of TP (Chen et al., 2023). In contrast, the network strength of the healthy RSFC pattern (the NHC-specific positive network) was significantly lower in the MCI group than in the NHC group, suggesting impaired high-functioning RSFC patterns in older adults with MCI. This is consistent with evidence that facilitators of TP, including motivation (Perry and Kramer, 2015), executive cognition (Traykov et al., 2007), and social cognition (Bora and Yener, 2017), are dysfunctional in the MCI group. The significant negative CPM models in the MCI group suggest a greater susceptibility to inhibitory factors, such as sensitivity to the probability of betrayal, potentially contributing to decreased TP.

4.4. Limitations

Our study focused on the TP in older adults with MCI and its underlying RSFC mechanisms compared to NHCs. However, several limitations should be acknowledged. First, this study lacks an objective and independent measurement of TP-related components in trust dilemmas. It will be valuable for future studies to include task-based measurements of affect (e.g., emotional arousal), motivation (e.g., reward sensitivity), and social cognition (e.g., theory of mind) in older adults with MCI to validate our findings. Second, our sample size, particularly for the MCI group, was not large enough, which may challenge the replicability of the RSFC prediction results (Marek et al., 2022). We will continue to collect data on TP and resting-state fMRI data from older adults with MCI and aim to replicate these findings with a larger sample size in the future. Third, besides trust-related factors in the trust model (Krueger and Meyer-Lindenberg, 2019), many other factors, such as personality traits (Freitag and Bauer, 2016) and social support (Baer et al., 2018), are associated with TP. However, it is unknown if these relationships change in older adults with MCI. Future research should investigate trust and its related factors in MCI to understand better the impact of trust on their social function and interpersonal interactions. Fourth, the RSFC results in our study were primarily based on the CPM method, which has limitations, including non-universally optimal parameter selection (Spisak et al., 2019), risk of overfitting (O Connor et al., 2021), and low interpretability (Clark et al., n.d.) of the model. Future studies should attempt to use other RSFC prediction methods, such as support vector regression and lasso regression, to validate the research findings and thereby enhance the reliability of the results. Despite these issues, our research contributes to the understanding that TP in older adults with MCI was less based on economic (executive cognition) and social (social cognition) rationality and more sensitive to the probability of betrayal (affect) than in older adults with normal cognition. More importantly, it helps people build trusting relationships with older adults with MCI and presents a potential biomarker for predicting their TP. This could be valuable in improving their social support networks and identifying those at risk of financial distress.

4.5. Summary and conclusion

Using a CPM approach, we examined the MCI-related changes in TP and the underlying RSFC mechanisms. Our findings showed that the MCI group had decreased TP and an increased correlation between TP and affect compared to the NHC group. The negative rather than positive CPM model significantly predicted TP in the MCI group, in which the SN played a significant role. In contrast, the positive rather than negative CPM model significantly predicted TP in the NHC group, in which the DMN played a significant role. The total network strength of the NHC-specific positive network was decreased in the MCI group compared to the NHC group. These findings show an MCI-related decrease in TP and alterations in its neural underpinnings, which are associated with the dysfunction of DMN, the increased reliance on the SN, and the enhanced sensitivity to the probability of betrayal in trust dilemmas. This study provides valuable insights into the interpersonal challenges faced by older adults with MCI and lays the groundwork for future research to identify and enhance TP in this population.

Data availability

The RSFC matrices, along with behavioral assessments, and all custom MATLAB analysis scripts used in this study have been made

publicly available on GitHub (https://github.com/yiqiqiyi/CPM-of-TP-in-MCI/tree/main).

CRediT authorship contribution statement

Yiqi Chen: Writing —review & editing, Writing —original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hao He:** Writing —review & editing, Validation, Funding acquisition. **Yiyang Ding:** Investigation. **Wuhai Tao:** Funding acquisition, Conceptualization, Methodology, Project administration, Supervision, Validation, Writing —review & editing. **Qing Guan:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation. **Frank Krueger:** Conceptualization, Methodology, Supervision, Validation, Writing —review & editing.

Declaration of competing interest

The authors are unaware of any conflicts of interest, financial or otherwise.

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4. Experiment 2. Gray Matter Atrophy and Trust Propensity in Mild Cognitive Impairment

"Linking gray matter structure to trust in mild cognitive impairment: a voxel-based morphometry study"

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Linking gray matter structure to trust in mild cognitive impairment: a voxel-based morphometry study

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Older adults with mild cognitive impairment (MCI) exhibit a reduction in trust propensity (TP), which is correlated with heightened affective sensitivity to betrayal. However, the mediating role of this affective component in declining TP in MCI and the influence of structural brain alterations on reduced TP via affect warrant further investigation. We conducted multiple mediation analyses to assess whether differences in TP between MCI and normal healthy controls (NHCs) were mediated by affect, motivation, executive function, and social cognition. Whole-brain mediation analyses identified neural substrates and moderated mediation analyses examined whether structural brain changes influenced TP via affect differently between the two groups. Our results revealed a significant mediating effect of affect on the group difference in TP. Atrophy within the thalamus and anterior insula (AI) in the MCI group was found to contribute to their diminished TP. Furthermore, moderated mediation analysis showed that the influence of the thalamus and AI on TP was mediated by affect within the MCI group but not NHCs. These findings suggest that reduced TP in MCI is primarily driven by the increased sensitivity to betrayal, which is underpinned by structural alterations within salience network regions rather than alterations in other trust-related cognitive domains.

Keywords: mild cognitive impairment; neuroeconomics; social dilemmas; trust; voxel-based morphometry.

Introduction

Mild cognitive impairment (MCI) is a prodromal state of Alzheimer's disease, characterized by cognitive decline that exceeds age and educational norms but does not significantly impair daily functioning (Albert et al. 2011). MCI presents challenges that extend beyond cognition, affecting social interaction and relationships. Older adults with MCI may experience increased susceptibility to deception (Han et al. 2016), withdrawal from social activities (Li et al. 2019), and a decline in the size of their social circles (Fan et al. 2021).

Trust in strangers, or trust propensity (TP), is essential for navigating social interactions (Mayer et al. 1995). Our previous work has shown that individuals with MCI exhibit reduced TP, accompanied by increased sensitivity to betrayal cues and functional changes in the brain's salience network (SAN) (Chen et al. 2024). These findings highlight the complex interplay among trust, brain function, and cognitive health. While reduced TP is evident in MCI, the complex interplay of affective processing and structural brain changes remains poorly understood. This study examines how these factors contribute to diminished trust in older adults with MCI. Specifically, we investigated whether affective processing mediates the link between brain structure and TP and how this interaction may impact social functioning. By elucidating these relationships, we aimed to provide valuable insights into the social difficulties experienced by individuals with MCI.

Trusting others inherently involves a social dilemma: It not only offers the potential for positive outcomes like reciprocity but also carries the risk of betrayal (Evans and Krueger 2011). Individuals must carefully weigh these potential costs and benefits when deciding to trust. Trust can be defined as the willingness to accept vulnerability in such social situations, based on expectations of the trustee's actions (Mayer et al. 1995). To measure an individual's baseline trust in strangers (i.e. TP), researchers often employ a one-shot trust game (TG) with an anonymous partner (Berg et al. 1995; Camerer 2003). This approach minimizes the influence of prior interactions and focuses on the individual's inherent tendency to trust.

A recent neuropsychoeconomic model of trust highlights the multifaceted nature of this social behavior, proposing that trust decisions are influenced by a complex interplay of psychological components (Krueger and Meyer-Lindenberg 2019). These affective, motivational, and cognitive (both social and executive) components are rooted in distinct, large-scale brain networks that play a crucial role in navigating uncertainty within social dilemmas. Specifically, the tension between affect (sensitivity to betrayal) and motivation (expectation of reciprocity) creates uncertainty in trust decisions. In one-shot TGs, the inherent partner uncertainty

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exposes individuals to considerable risk, triggering activation in salience network (SAN) regions associated with risk perception (Bressler and Menon 2010). Neuroimaging meta-analyses indicate that trust decisions during one-shot TGs primarily activate the anterior insula (AI) within the SAN (Bellucci et al. 2017).

In contrast, the motivation component involves the mesolimbic and mesocortical pathways, collectively referred to as the reward network (RWN). To resolve this uncertainty, individuals employ two distinct strategies: economic bounded rationality (relying on external cues and the central executive network, CEN) or social bounded rationality (relying on social cues and the default mode network, DMN) (Krueger and Meyer-Lindenberg 2019).

Emerging evidence suggests that altered affective processing may play a key role in the social difficulties experienced by individuals with MCI (Jin et al. 2023; Chen et al. 2024). For example, we have shown that older adults with MCI exhibit lower TP than their healthy counterparts, and this reduced trust is associated with an increased sensitivity to potential betrayal (Chen et al. 2024). This heightened sensitivity to negative social information is consistent with a broader pattern of negativity bias observed in MCI, including increased sensitivity to negative stimuli (Döhnel et al. 2008; Berger et al. 2015) and reduced reward motivation (Perry and Kramer 2015).

The social challenges faced by individuals with MCI are further compounded by difficulties in utilizing both economic and social reasoning. Impairments in executive function (Traykov et al. 2007) can disrupt the ability to weigh potential risks and rewards, while deficits in social cognition (Bora and Yener 2017) can hinder the accurate interpretation of social cues. This combination of cognitive challenges can amplify the impact of negative emotions on trust decisions, making individuals with MCI more susceptible to betrayal aversion and less likely to trust in uncertain situations.

Furthermore, impairments in executive function (Traykov et al. 2007) and social cognition (Bora and Yener 2017), which are frequently observed in MCI, can hinder the ability to effectively regulate emotions and make sound judgments in social situations. This may disrupt the delicate balance between the fear of betrayal and the expectation of reciprocity, further amplifying the impact of negative emotions on trust decisions. Consequently, in situations characterized by uncertainty and social risk, such as a one-shot TG, individuals with MCI may exhibit heightened sensitivity to the possibility of betrayal, leading to a decrease in TP.

The reduced TP observed in MCI appears to be rooted in structural alterations within key brain networks. The SAN, responsible for evaluating social and emotional salience, shows atrophy in regions associated with processing negative emotions and detecting potential threats (Zackova et al. 2021). This may explain the heightened sensitivity to betrayal and negative social cues often seen in MCI. Additionally, structural changes in the RWN, specifically the dopaminergic mesocorticolimbic pathway (Madsen et al. 2010), may contribute to reduced motivation and diminished expectations of reciprocity (Kazui et al. 2016). These combined neural alterations likely impair the ability to effectively navigate trust dilemmas.

Gray matter atrophy in specific brain regions may contribute to the diminished TP observed in MCI. Voxel-based morphometry (VBM) studies have revealed atrophy in the SAN, particularly the thalamus and AI, which may heighten sensitivity to potential betrayal (Chen et al. 2024). Furthermore, atrophy in the RWN, specifically the mesocorticolimbic pathway, may reduce motivation and expectations of reciprocity. Importantly, atrophy also affects regions associated with executive function (dorsolateral prefrontal cortex [dlPFC], within the CEN) and social cognition (dorsomedial prefrontal cortex [dmPFC], within the DMN) (Bressler and Menon 2010; Han et al. 2012). These combined structural changes likely impair the ability to effectively regulate emotions, interpret social cues, and make sound judgments in trust situations (Chen et al. 2024).

While previous research on the neural correlates of trust has primarily utilized functional magnetic resonance imaging (fMRI) (King-Casas et al. 2005; Krueger et al. 2007; Baumgartner et al. 2008), the relationship between trust and gray matter volume (GMV) remains relatively underexplored, particularly in older adults with MCI. Structural magnetic resonance imaging (sMRI) offers unique advantages for investigating brain structure, including greater stability and enhanced interpretability (van Atteveldt et al. 2018). VBM, a powerful tool for quantifying GMV (Ashburner and Friston 2000), has successfully identified neural correlates of various age-related changes, including cognitive decline (Nickl-Jockschat et al. 2012), emotional difficulties (Sturm et al. 2013), and personality shifts (Rodriguez et al. 2019) in MCI. Emerging evidence suggests a link between GMV and trust. For example, Hass's study found that individuals with greater GMV in the bilateral ventromedial prefrontal cortex and AI, regions associated with empathy and social cognition, reported higher levels of trust on a questionnaire (Haas et al. 2015). Furthermore, a whole-brain VBM study using the TG found that higher TP in males was associated with greater GMV in the precuneus, a region involved in social perspective-taking (Safari et al. 2024). Combining VBM with whole-brain mediation analysis offers a promising approach for identifying the specific brain regions that mediate the relationship between affective processing, motivation, and TP in older adults with MCI (Wager et al. 2008).

Our study pursued to unravel the complex factors contributing to reduced trust in older adults with MCI. Specifically, we aimed to (i) determine the relative contribution of affect, assessing whether heightened sensitivity to betrayal (affect) plays a more prominent role than other factors in explaining the lower TP observed in MCI; (ii) identify brain regions associated with reduced trust, pinpointing the specific structural brain regions that underlie reduced TP in MCI; and (iii) understand the mechanism, investigating whether alterations in these brain regions influence TP by impacting affective processing in individuals with MCI.

To investigate the complex relationships among group membership (MCI vs. NHC), trust behavior (TP), and underlying brain structure, we applied several analyses. First, we performed a multiple mediation analysis to determine which psychological components (affect, motivation, cognition) mediated the relationship between group and TP. Second, we employed VBM to obtain GMV data for each participant. A whole-brain mediation analysis was then conducted to identify specific brain regions that mediated the relationship between group and TP. Finally, we applied a moderated mediation model to examine whether reduced GMV in these regions influenced TP by impacting the affective component in the MCI group compared to the NHC group.

Based on previous research indicating heightened sensitivity to betrayal and reduced ability to process affective information in MCI (Chen et al. 2024), we hypothesized that the affect component would be a significant mediator of the relationship between group (MCI vs. NHC) and TP. At the behavioral level, we hypothesized that The MCI group would exhibit lower TP compared to the NHC group, and this difference would be primarily driven by the affect component. At the neural level, we predicted that reduced GMV in the SAN, specifically the thalamus and AI, would mediate the relationship between group and TP. Furthermore, this mediation effect would be moderated by affect, such that reduced GMV in

these regions would amplify the impact of betrayal sensitivity on TP in the MCI group but not in the NHC group. This moderated mediation model posits that structural alterations in the SAN contribute to reduced TP in MCI by exacerbating the influence of negative affect.

Materials and methods

Participants

A total of 209 older adults participated in this study, recruited from communities in Shenzhen, China, between 2021 and 2024. The sample consisted of 138 healthy controls (NHC group) and 71 individuals with MCI (MCI group). This sample includes a subset of participants (115 NHC, 42 MCI) who were part of a previous fMRI study (Chen et al. 2024), but with an expanded sample size due to ongoing recruitment. All participants were right-handed, had normal or corrected-to-normal vision, and had no history of head injury, neurological conditions, or psychiatric disorders. Written informed consent was obtained from all participants, and the study was approved by the Institutional Review Board of Shenzhen University, China (Reference No.: PN-202200120). The experiment on human subjects in this study was conducted in accordance with the ethical standards of the committee on human experimentation of Shenzhen University and the Helsinki Declaration of 1975 as revised in 2008.

Following neuropsychological testing and neuroimaging, 10 participants from the NHC group were excluded from further analysis. Two of them expressed disbelief in the presence of a real partner during the one-shot TG, which could have compromised the validity of the trust paradigm. Additionally, eight participants were excluded due to poor structural image quality (see VBM Data Analysis). The final sample included 199 participants: 135 in the NHC group and 64 in the MCI group (Table 1).

Participants received monetary compensation based on their performance in either the TG or the dictator game (DG) (see Assessment of TP-related Psychological Components). To avoid potential bias, one game was randomly selected for each participant to determine their reward. The reward amount ranged from 20 to 45 Chinese Yuan (CNY), equivalent to approximately $2.82 to $6.34 USD. Payments were disbursed to participants within 3 to 4 days after completing the experiment. Additionally, all participants received a separate reward of 20 CNY (approximately $2.82 USD) upon completion of the neuroimaging scan.

Diagnosis of MCI

To ensure that our sample consisted solely of individuals with MCI and healthy older adults, we implemented strict exclusion criteria. All participants underwent cognitive and functional assessments. The Chinese version of the Mini-Mental State Examination (MMSE) (Folstein et al. 1975) was used to screen for global cognitive impairment, and a combined version of the Physical Self-Maintenance Scale and the Instrumental Activities of Daily Living Scale (ADLs) (Lawton and Brody 1969) was used to assess daily living skills. Participants were included in the study only if they met the following criteria: (i) MMSE score above 24, indicating no significant cognitive impairment, and (ii) score of zero on the ADLs, indicating independence in daily activities. These criteria were essential for minimizing the potential confounding effects of dementia or functional limitations on our findings.

To assess cognitive function across multiple domains, participants completed a comprehensive battery of 11 neuropsychological tests. These tests evaluated the following cognitive domains: "Memory," assessed using Auditory Verbal Learning Test (AVLT) (Schmidt 1996), Rey–Osterrieth Complex Figure Recall Test (Rey-Recall) (Shin et al. 2006), and Digital Span Test (DST) (Blackburn and Benton 1957); "Executive Function," assessed with Trail Making Test Part B (TMT-B) (Gordon 1972) and Stroop test (Koss et al. 1984); "Attention," measured using Trail Making Test Part A (TMT-A) (Gordon 1972) and Symbol Digit Modalities Test (SDMT) (Smith 1973: 1); "Language," evaluated with Category Verbal Fluency Test (CVFT) (Mok et al. 2004) and Boston Naming Test (BNT) (Knesevich et al. 1986); and "Visuospatial Ability," assessed using Rey–Osterrieth Complex Figure Copy Test (Rey-Copy) (Shin et al. 2006) and Clock Drawing Test (CDT) (Shulman 2000). The neuropsychological test battery was instrumental in identifying participants with MCI. Cognitive impairment in a specific domain was defined as performance 1.5 standard deviation (SD) or more below the mean on both tests for that domain, based on Chinese norms (Li et al. 2013). In line with Petersen's criteria (Petersen 2004), participants were classified as having MCI if they showed impairment in any of the five cognitive domains assessed. This method allowed for a reliable diagnosis of MCI based on objective cognitive performance.

One-shot TG

The one-shot TG is widely used in the literature to assess individual differences in trust behavior toward strangers (ie TP) (Berg et al. 1995; Camerer 2003). Compared to questionnaires, TGs reduce the impact of social desirability bias (Lanz et al. 2022). "Meta-analytic findings reveal substantial variation in individual allocations, with an average endowment transfer of 50.2% (SD = 12.4%)" (Johnson and Mislin 2011).

A one-shot TG with two players was administered to access TP: a trustor and a trustee (Berg et al. 1995) (Fig. 1A). Both players started with an endowment of 10 points (equivalent to 30 CNY). The trustor chose an amount (X) between 0 and 10 points to send to the trustee, which was tripled (3•X) by the experimenter before being transferred. The trustee then decided how many points (Y) to return, ranging from 0 to 3•X. After the exchange, the trustor received 10—X + Y points, while the trustee received 10 + 3•X—Y points. The amount (X) sent by the trustors was used to measure their TP.

To ensure that participants understood the task, they completed a practice to calculate the total payoffs for both roles. For example, if the trustor transferred two points and the trustee returned four points, the trustor and trustee would both receive 12 points. If participants answered incorrectly, they were given another trial until they did it right. After the exercise, participants were informed that they were playing in the role of the trustor, while another older adult undergoing the next fMRI scan would act as the trustee. In fact, the trustee's return was determined by a randomized algorithm that varied between 40% and 60%, resulting in final scores of 10 to 18 points (about 30 to 54 CNY).

Assessment of TP-related psychological components

To gain a comprehensive understanding of the factors influencing TP, we assessed four key psychological components in each participant:

To assess the "affect and motivation components" related to TP, we utilized specific subdimensions of the Geriatric Depression Scale (GDS) (Yesavage 1988). This 30-item self-report questionnaire measures depressive symptoms in older adults, with higher scores indicating greater severity. While designed to assess depression, the GDS can be broken down into subdimensions that capture distinct facets of emotional and motivational experience

Table 1. Group differences in demographic information, cognitive function, Geriatric Depression Scale, and TP-related components between the MCI and NHC groups.

Domain	Measure	MCI (mean [SD])	NHC (mean [SD])	t/Z	P
Demography					
	Age (year)	66.75 (6.98)	65.40 (6.45)	1.34	0.181
	Gender (percentage of females)	0.66 (0.48)	0.69 (0.46)	−0.46	0.647
	Education (year)	9.06 (3.67)	11.51 (3.13)	−4.86	<0.001
Cognitive function					
	MMSE	26.02 (2.45)	28.03 (1.74)	−5.85	<0.001
Memory	Rey-recall	8.28 (5.83)	14.94 (7.02)	−6.19	<0.001
	AVLT	18.64 (7.51)	29.27 (8.22)	−7.39	<0.001
	DST	9.47 (2.25)	11.72 (4.26)	−5.42	<0.001
Executive cognition	TMT-B (s)	248.08 (104.57)	140.64 (47.07)	7.74	<0.001
	Stroop (s)	110.30 (38.94)	75.59 (20.28)	6.73	<0.001
Attention	TMT-A (s)	85.19 (33.26)	53.97 (17.45)	6.94	<0.001
	SDMT	23.95 (10.94)	38.29 (11.68)	−7.79	<0.001
Language	CVFT	35.45 (7.49)	45.15 (8.95)	−6.81	<0.001
	BNT	20.14 (7.41)	23.65 (3.00)	−5.96	<0.001
Visuospatial ability	Rey-copy	28.17 (6.10)	33.31 (3.39)	−6.28	<0.001
	CDT	18.96 (8.59)	25.16 (4.59)	−5.26	<0.001
GDS					
	Total scores	7.36 (4.76)	5.07 (4.09)	3.69	<0.001
TP-related psychological components					
Affect	Worry	1.30 (1.18)	0.74 (1.06)	3.55	<0.001
Motivation	WAV	1.86 (1.26)	1.40 (1.38)	2.58	0.010
Executive cognition	Composite score (s)	147.09 (55.66)	85.60 (52.71)	6.68	<0.001
Social cognition	One-shot DG	8.20 (2.80)	9.17 (2.76)	−2.34	0.019

Note. MCI, mild cognitive impairment; NHC, normal healthy control; TP, trust propensity; SD, standard deviation; MMSE, Mini-Mental State Examination; Rey-recall, Rey–Osterrieth Complex Figure Recall Test; AVLT, Auditory Verbal Learning Test; DST, Digital span Test; TMT-B, Trail Making Test Part B; TMT-A, Trail Making Test Part A; SDMT, Symbol Digit Modalities Test; CVFT, Category Verbal Fluency Test; BNT, Boston Naming Test; Rey-copy, Rey–Osterrieth Complex Figure Copy Test; CDT, Clock Drawing Test; GDS, Geriatric Depression Scale; WAV, Withdrawal–Apathy–Vigor; DG, dictator game; s, second. With the exception of the TMT-A and -B, the Stroop Test, and the executive cognition composite score, the higher the score on the other cognitive tests, the better the performance. Higher total, Worry, and WAV scores on the GDS indicate more severe depression.

(Adams et al. 2004). For our study, we focused on two specific subdimensions: (i) Worry subdimension, reflecting a tendency toward anxious thoughts and (ii) rumination, which can be interpreted as heightened sensitivity to negative information and potential threats, aligning with the concept of affect in the context of trust. The Worry subdimension consists of four items: "Afraid something bad will happen," "Worry about the future," "Bothered by thoughts," and "Worry a lot about the past." Elevated worry scores, indicating a greater focus on negative affective information, are associated with increased inhibition of social interactions. Prior research suggests that worry is a key factor in distinguishing early-stage degenerative disease (Shdo et al. 2020) and correlates with performance in social cognition (De Vito et al. 2019).

The Withdrawal and Apathy (WAV) subdimension captures social disengagement and loss of interest, reflecting reduced motivation and aligning with the motivation component of trust. This subdimension encompasses apathy and withdrawal behaviors frequently observed in older adults with dementia and reduced motivation (Tagariello et al. 2009). It includes six items related to social withdrawal and loss of interest: "Prefer to stay home," "Avoid social gatherings," "Dropped activities and interests," "Find life very exciting" (reverse-scored), "Hard to start new projects," and "Full of energy" (reverse-scored). Elevated WAV scores, indicating diminished vigor and social engagement, reflect decreased motivation. By employing these specific GDS subdimensions, our aim was to capture nuanced aspects of affect (worry) and motivation (withdrawal and apathy) relevant to trust behavior in older adults.

To evaluate the "executive cognition component" of TP, we created a composite score based on participants' performance on two neuropsychological tests: TMT-B (Gordon 1972) and Stroop test (Koss et al. 1984). Because the raw scores on both tests exhibited non-normal distributions (TMT-B: $D[198] = 0.99$, $P < 0.001$; Stroop Test: $D[198] = 1.00$, $P < 0.001$), as confirmed by the Kolmogorov–Smirnov test, a rank-transformation rather than a z-transformation was applied to standardize the scores. Specifically, participants' performance was ranked on each test separately and then averaged the ranks to create a composite executive cognition score. Higher composite scores indicated poorer performance and thus reflected a decline in executive cognitive abilities.

The DG is widely recognized as a valid tool for assessing altruistic behavior (Bardsley 2008; Engel 2011). Altruistic preferences are indicative of an individual's reliance on social rationality (social cognition) in trust decisions, with prosocial individuals demonstrating a greater tendency to utilize this rationality in social dilemmas compared to selfish individuals (Declerck et al. 2013). Importantly, the altruistic preferences measured by the DG are also associated with key social cognitive functions, including empathy (Edele et al. 2013) and theory of mind (Yu et al. 2016).

In the one-shot DG (Fig. 1B), participants acting as "dictators" received an endowment of 20 points, each valued at 3 CNY. They had the freedom to allocate any portion of these points to an anonymous "receiver," who had no choice but to accept the offer. Consequently, the dictator retained 20 − X points, resulting in the receiver receiving X points. The amount shared by the dictator, represented by the value of X, quantified each participant's altruistic preference. The amount shared by the dictator served as an indicator of their altruistic preferences and, by extension, their social cognition. Higher allocations reflected greater altruism and a stronger understanding of social norms and expectations. To ensure comprehension, participants completed a practice round

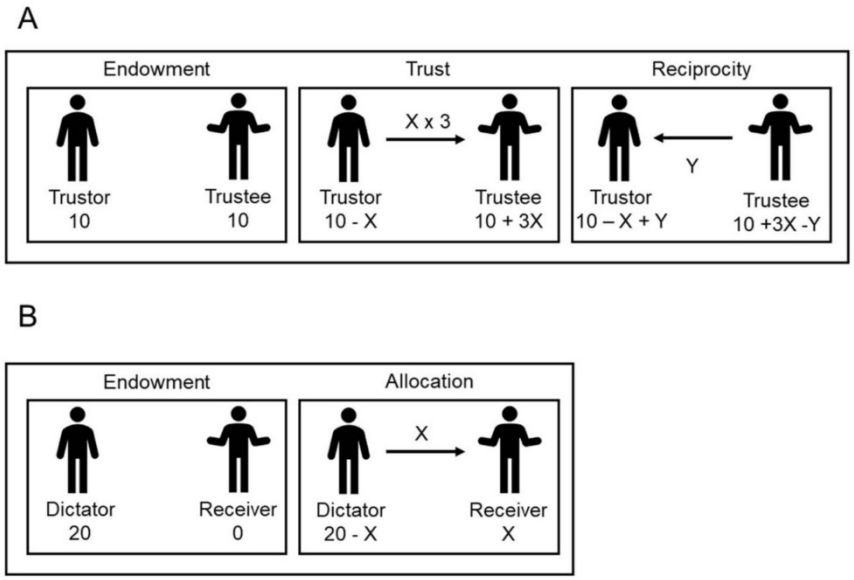

Fig. 1. Experimental game paradigms. A) The one-shot trust game (TG). This game involves two players: the trustor and the trustee, each starting with an endowment of 10 points. The trustor can choose to invest any portion of his or her endowment (denoted as X, where $0 \leq X \leq 10$) with the trustee. The invested amount is then tripled according to the game rules and transferred to the trustee. After receiving the tripled investment, the trustee decides how much of this amount to return to the trustor (denoted as Y, where $0 \leq Y \leq 3X$). All participants are informed that they are randomly assigned to play the role of the trustor and must make an investment decision (TP). The trustee's return to the trustor is determined by a computer program and ranges from 40% to 60% of the trustor's tripled investment. B) The one-shot dictator game (DG). This game involves two players: In this game, one player, known as the dictator, starts with an endowment of 20 points, while the other player, known as the receiver, begins with 0 points. The dictator has the authority to allocate any portion of his endowment (denoted as X, where $0 \leq X \leq 20$) to the receiver. Importantly, the receiver must accept the allocated amount without the option of refusing. All participants are informed that they are randomly assigned to play the role of the dictator and must decide how many points to share with the receiver (altruistic preference reflecting social cognition).

and were then informed of their role and the anonymous nature of the receiver. The final allocation made by each participant (ranging from 0 to 20 points, equivalent to 0 to 60 CNY) served as our measure of social cognition.

Experimental procedure

Participants underwent a multistage procedure. Initially, they completed a neuropsychological test battery and the GDS at a research facility within 3 months prior to their neuroimaging session. The neuroimaging session consisted of: (i) an 8-min resting-state fMRI scan; (ii) a 25-min working memory fMRI task (data to be reported elsewhere); (iii) a 7-min high-resolution sMRI scan (T1-weighted), and (iv) a 5-min routine clinical MRI scan (T2-weighted) for medical reporting. Following the scans, participants completed the one-shot DG and then the one-shot TG in a separate room. Finally, they answered a debriefing questionnaire to assess their understanding of the tasks and their mental state during the experiment. Crucially, the questionnaire included an item probing their belief in the authenticity of their partner in the TG. Two participants who indicated that they believed their partner was a virtual entity were excluded from further analysis to ensure the validity of the trust paradigm.

Image acquisition

Neuroimaging data were collected using a 3T SIEMENS MAGNETOM Prisma scanner equipped with a 64-channel head coil at the Magnetic Resonance Imaging Center, Shenzhen University. High-resolution sMRI images were acquired via a T1-weighted 3D magnetization–prepared rapid gradient-echo (MPRAGE) sequence with the following parameters: repetition time (TR) = 1.9 s, echo time (TE) = 2.23 ms, flip angle (FA) = 8°, field of view (FoV) = 220 × 220 mm^2, voxel size = 1.1 × 1.1 × 1.1 mm^3, and number of slices = 224.

Behavioral data analysis

Statistical analyses were performed using MATLAB 2018b (The MathWorks, Natick, MA) and IBM SPSS Statistics (IBM Corp., Armonk, NY). A significance threshold of $P < 0.05$ (two-tailed) was adopted for all analyses. First, the normality and homogeneity of variance for TP and the psychological components (affect, motivation, executive cognition, and social cognition) were assessed using the Kolmogorov–Smirnov test and Levene's test, respectively. Due to the non-normal distribution of TP (see Behavioral Results), nonparametric statistical methods for TP-related analyses were employed. Group differences (MCI vs. NHC) in TP were examined using the Wilcoxon signed-rank test. To assess the relationship between group membership and TP while controlling for potential confounding variables, partial Spearman correlations were computed, adjusting for age, gender, and education. A one-tailed t-test was then used to determine whether TP was significantly lower in the MCI group compared to the NHC group.

To assess and address potential common method bias among our variables (group, TP, age, education, gender, and psychological components), Harman's single-factor test was employed. Next, to examine the mediating role of different TP-related components in the relationship between MCI and TP, a multiple mediation analysis was conducted using PROCESS Model 4 in IBM SPSS Statistics (Preacher and Hayes 2004). This model investigated the relationship between group (MCI vs. NHC) as the independent

variable and TP as the dependent variable, with the psychological components of affect, motivation, executive cognition, and social cognition mediating this relationship and with age, gender, and education as covariates in the analysis. To estimate the effect size and construct confidence intervals (CIs), we used a bootstrapping method with 5,000 resamples. A CI that includes zero indicates that the null hypothesis cannot be rejected at the chosen significance level.

VBM data analysis

T1-weighted sMRI images were preprocessed using the default cross-sectional stream in the Computational Anatomy Toolbox (CAT12; http://www.neuro.uni-jena.de/cat/), implemented in SPM12 (http://www.fil.ion.ucl.ac.uk/spm/software/spm12) within MATLAB. This involved manually identifying image artifacts and setting the origin of each image to the anterior commissure. Participant images were then spatially normalized to the MNI template using DARTEL (Ashburner and Friston 2000) and resampled to 1.5 × 1.5 × 1.5 mm^3 voxels. Each image was segmented into gray matter, white matter, and cerebrospinal fluid, and finally, gray matter images were smoothed with an 8 mm Full Width at Half Maximum (FWHM) Gaussian kernel.

Following preprocessing, the total intracranial volume (TIV) for each participant was determined. Then, a quality control step was performed using the CAT12 "verify data quality" function to assess the homogeneity of the sample and the sMRI data. This analysis identified eight outliers who were excluded, resulting in a final sample of 199 participants (64 with MCI and 135 NHCs) for the whole-brain mediation analyses.

Whole-brain mediation analysis

Following VBM analysis of the T1-weighted structural images, a whole-brain mediation analysis was conducted to identify specific brain regions mediating the relationship between group (MCI vs. NHC) and TP. This analysis was performed using the Mediation Toolbox in MATLAB (Wager et al. 2008), which employs a bootstrapping approach to provide robust estimates of indirect effects and their CIs (Shrout and Bolger 2002). This analysis explored the mediation of GMV at the voxel level (M) in the relationship between group membership (MCI vs. NHC) as the independent variable (X) and TP as the dependent variable (Y), while accounting for the potential confounding effects of gender, age, education, and TIV. Using 10,000 bootstrapped resamples, we estimated the total effect (c), direct effect (c′), X-to-M effect (a), M-to-Y effect (b), and indirect effect (ab) for each voxel (Fig. 2A). To control for multiple comparisons and ensure robust findings, a cluster-level correction was applied with a significance threshold of $P < 0.005$ and a minimum cluster size of 5 voxels (Lieberman and Cunningham 2009), followed by cluster-based permutation tests.

Cluster-based permutation tests

To assess the statistical significance of the identified clusters and control for multiple comparisons, cluster-based permutation tests were performed (Dickie et al. 2015). For each cluster, the sum of the indirect mediation effects across all voxels as the cluster's total effect size (ab_n, where n is the number of clusters) was calculated. Then, the participant labels were randomly shuffled and the whole-brain mediation analysis was rerun 10,000 times, each time recording the maximum cluster-level indirect effect (ab_p, where p is the number of permutations). This generated a null distribution of ab_p, which was used to determine the statistical significance of the observed clusters. Due to the computational demands of performing bootstrapping within each permutation, the voxel-wise indirect effect was used with a significance threshold of $P = 0.005$ to threshold the permutation tests (Lieberman and Cunningham 2009). To address potential concerns about the representativeness of small clusters, regions of interest (ROIs) were created with a 5 mm radius around the peak MNI coordinates of each significant cluster and the average GMV was extracted within each ROI for further analysis.

Moderated mediation analysis for ROIs

To further investigate the interplay between brain structure, affect, and TP, and to understand how MCI influences these relationships, a moderated mediation analysis was conducted using PROCESS Model 59 in IBM SPSS Statistics (Preacher and Hayes 2004). This model allows for the assessment of a moderator's influence on each path of the mediation model. This analysis examined the moderated mediation of affect (M) on the relationship between average GMV within each ROI as the independent variable (X) and TP as the dependent variable (Y), with group status (MCI vs. NHC) serving as the moderator (W) to assess its influence, while controlling for age, gender, education level, and TIV. Bootstrapping with 5,000 resamples was employed to obtain robust estimates of the effects and their CIs. A CI containing zero indicates that the effect is not statistically significant at the chosen alpha level.

Sensitivity analysis

To investigate statistical discrepancies potentially arising from sample imbalance between the two groups, a balanced-sample bootstrapping analysis approach was conducted. In each iteration of the bootstrap procedure, all 64 MCI participants were included, while 64 NHC participants were randomly selected from the total pool of 135 NHC participants. Subsequently, Wilcoxon signed-rank tests, partial Spearman correlations, and multiple mediation analysis were performed (see Behavioral Data Analysis). If the bootstrapped statistical results from the balanced samples were significantly different from the original statistical results, this suggested that the unbalanced sample size had a significant impact on the overall statistical findings; otherwise, it was not.

The bootstrapping process was repeated 10,000 times, resulting in a distribution of 5,000 statistical values for each test. Subsequently, a 95% CI was calculated based on the mean-centered distribution. For the Wilcoxon signed-rank tests and partial Spearman correlations, significance was indicated if the CI did not encompass the original test statistic derived from the unbalanced samples. Otherwise, no significant difference was concluded. For multiple mediation analyses, an independent-samples t-test was employed to compare the distributions of balanced and unbalanced statistics, utilizing the mean and standard error (SE).

Machine learning analysis

To investigate the potential of TP (trust-related component: affect, motivation, social cognition, and executive cognition) and the GMV of its associated regions (thalamus and AI) as early markers of neurodegenerative diseases, a support vector machine (SVM) classification with leave-one-out cross-validation was conducted. Prior to training, all features were normalized. To effectively address the imbalance in sample sizes between the MCI ($n = 64$) and NHC ($n = 135$) groups, class weighting was implemented during training.

Additionally, a 5,000-iteration permutation test was conducted to evaluate the statistical significance of the classification results

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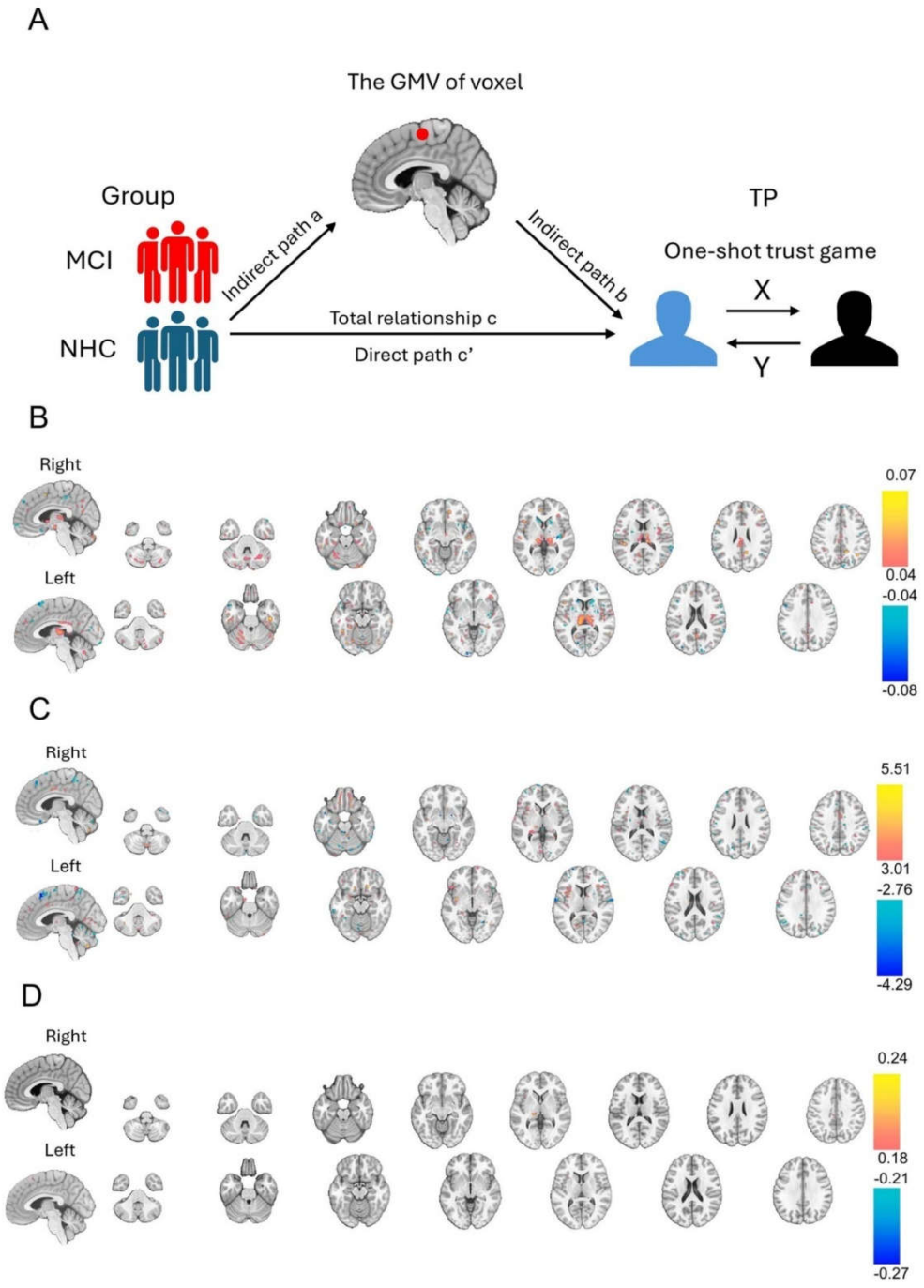

Fig. 2. Methods and results of whole-brain mediation analysis. A) The whole-brain mediation analysis. Group status (MCI vs. NHC) is used as the independent variable, TP as the dependent variable, and gray matter volume (GMV) of each voxel as the mediator. The analysis controls for gender, age, education level, and total intracranial volume. A bootstrapping approach with 10,000 resamples is used to estimate the total model effect (c), the direct effect (c'), the effect of the independent variable on the mediator (a), the effect of the mediator on the dependent variable (b), and the indirect effect (ab) of the mediation models with each voxel. B) The slice views of the statistics results for path a. The highlighted areas show the significant differences in GMV of voxels between the two groups (mild cognitive impairment [MCI] vs. normal healthy controls [NHC]). Regions showing a positive effect have a greater GMV in the NHC group, whereas those with a negative effect have a higher GMV in the MCI group. C) The slice views of the statistics results for path b. The patches indicate significant associations between GMV and TP within the voxels. Areas with a positive effect indicate regions where higher GMV corresponds to increased TP, while areas with a negative effect signify regions where greater GMV is linked to reduced TP. D) Slice views of the statistical results for the indirect effect. The patches indicate that the GMV of these voxels plays a significant role in mediating the relationship between group status and TP. Positive effects suggest that the GMV in these areas amplifies the impact of group on TP in the same direction, while negative effects signify that the GMV of these voxels alters the effect of group on TP in the opposite direction.

(accuracy, sensitivity, and specificity). This involved repeatedly shuffling the group labels (MCI vs. NHC) to generate a null distribution of classification accuracy. The P-value was then determined as the proportion of permuted accuracy values that were equal to or more extreme than the observed accuracy.

Results

Behavioral results

Demographic information and behavioral performance for both groups are presented in Table 1. As expected, the NHC group demonstrated significantly higher cognitive function across all neuropsychological tests compared to the MCI group (*Ps* < 0.001). The Kolmogorov–Smirnov test revealed non-normal distributions for TP and the psychological component scores in both the MCI group (TP: D [63] = 0.81, $P < 0.001$; Affect: D [63] = 0.52, $P < 0.001$; Motivation: D [63] = 0.70, $P < 0.001$; Social Cognition: D [63] = 0.95, $P < 0.001$; Executive Cognition: D [63] = 0.97, $P < 0.001$) and the NHC group (TP: D [134] = 0.92, $P < 0.001$; Affect: D [134] = 0.50, $P < 0.001$; Motivation: D [134] = 0.50, $P < 0.001$; Social Cognition: D [134] = 0.97, $P < 0.001$; Executive Cognition: D [63] = 1.00, $P < 0.001$). However, Levene's test indicated no significant differences in the variances of these variables between the two groups (all *Ps* > 0.05). These results confirm the expected cognitive differences between the groups and justify the use of nonparametric statistics for subsequent analyses involving TP.

The MCI group exhibited a significantly lower TP compared to the NHC group, as revealed by the Wilcoxon signed-rank test (MCI: $M = 3.66$, $SD = 2.32$, 36% of endowment; NHC: $M = 4.50$, $SD = 2.43$, 45% of endowment; $Z = -2.00$, $P < 0.05$). This group difference remained significant even after controlling age, gender, and education using partial Spearman correlations (r [198] = 0.12, $P < 0.05$). Furthermore, the MCI group showed significantly higher levels of affect ($Z = 3.55$, $P < 0.001$), motivation ($Z = 2.58$, $P < 0.05$), and executive cognition ($Z = 6.68$, $P < 0.001$) but lower social cognition ($Z = -2.34$, $P < 0.05$), compared to the NHC group.

Harman's single-factor test revealed no significant common method bias in our data. The first factor accounted for only 21% of the variance, falling below the 50% threshold (Podsakoff and Organ 1986).

Our mediation analysis indicated that the influence of group status (MCI vs. NHC) on TP was mediated by affect. Specifically, while the direct effect of group on TP was not significant, the indirect effect through affect was significant ($\beta = 0.23$, SE = 0.12, 95% bootstrapped CI = [0.04, 0.51], $P < 0.05$). This suggests that the lower TP observed in the MCI group was driven by their heightened sensitivity to betrayal. The indirect effects of group status on TP through motivation ($\beta = -0.09$, SE = 0.09, 95% bootstrapped CI = [−0.32, 0.05]), social cognation ($\beta = 0.10$, SE = 0.10, 95% bootstrapped CI = [−0.04, 0.34]), and executive cognition ($\beta = -0.17$, SE = 0.19, 95% bootstrapped CI = [−0.56, 0.21]) were not significant. As anticipated, group status significantly predicted all four psychological components, and affect, motivation, and social cognition were all significant predictors of TP (Fig. 3A).

Whole-brain mediation results

The whole-brain mediation analysis revealed two significant clusters ($P < 0.005$, >5 voxels) that mediated the relationship between group (MCI vs. NHC) and TP (Table 2). These clusters, identified through cluster-based permutation tests, were located in the left AI, specifically the dorsal AI (Kurth et al. 2010), and the left thalamus (Fig. 2D).

In two significant clusters, we observed a positive relationship between GMV and TP. This was evidenced by positive effect sizes for both the path from group (X) to GMV (M) and the path from GMV (M) to TP (Y). The MCI group exhibited lower GMV in these clusters compared to the NHC group, and higher GMV was associated with higher TP. Figure 2B and C illustrates the significant effects for path a and path b, respectively.

Moderated mediation results for regions of interest

In the moderated mediation model involving thalamic GMV, we found that the indirect effect of GMV on TP via affect was significantly moderated by group status (MCI vs. NHC) ($\beta = -4.23$, SE = 2.06, 95% CI [−8.85, −0.77], $P < 0.05$). This indicates that the relationship between thalamic GMV, affect, and TP differed significantly between the MCI and NHC groups. Specifically, the indirect effect was significant in the MCI group ($\beta = 4.34$, SE = 2.04, 95% CI [0.85, 8.94], $P < 0.05$), suggesting that lower GMV in the thalamus increased affect, which, in turn, decreased TP. However, this indirect effect was not significant in the NHC group ($\beta = 0.11$, SE = 0.38, 95% CI [−0.77, 0.91]). Further analysis revealed that group status significantly moderated both the relationship between thalamic GMV and affect ($\beta = 4.63$, SE = 2.27, $P < 0.05$) and the relationship between affect and TP ($\beta = 0.67$, SE = 0.32, $P < 0.05$) (Fig. 3B).

Similarly, in the moderated mediation model involving the AI, we found that group status (MCI vs. NHC) significantly moderated the indirect effect of GMV on TP through affect ($\beta = -8.35$, SE = 2.97, 95% CI [−14.66, −2.99], $P < 0.05$). This indicates that the relationship between AI GMV, affect, and TP differed significantly between the two groups. In the MCI group, the indirect effect was significant ($\beta = 8.01$, SE = 2.95, 95% CI [2.77, 14.32], $P < 0.05$), suggesting that lower GMV in the AI heightened sensitivity to betrayal (affect), which, in turn, led to lower TP. However, this indirect effect was not significant in the NHC group ($\beta = -0.35$, SE = 0.46, 95% CI [−1.47, 0.39]). Furthermore, group status significantly moderated the relationship between AI GMV and affect ($\beta = 10.83$, SE = 2.77, $P < 0.001$) (Fig. 3B).

Sensitivity analysis results

The balanced bootstrapping analysis yielded results closely mirroring the original unbalanced analysis. Specifically, for TP (z = −2.00, 95% CI [−2.30, −0.28], $P = 0.17$), affect (z = 3.55, 95% CI [1.84, 3.90], $P = 0.18$), motivation (z = 2.58, 95% CI [1.05, 3.11], $P = 0.38$), social cognition (z = −2.34, 95% CI [−2.35, −0.17], $P = 0.05$), and executive cognition (z = 6.68, 95% CI [5.06, 6.36], $P < 0.01$), the bootstrapped distributions from the balanced samples did not significantly deviate from the original statistical findings.

Furthermore, the independent-samples t-test revealed no significant differences between the balanced and unbalanced mediation analyses for direct effects (original mean = 0.62, SE = 0.42; balanced mean = 0.72, SE = 0.51; $t = 0.14$, $P = 0.89$) or indirect effects of affect (original mean = 0.23, SE = 0.12; balanced mean = 0.45, SE = 0.20; $t = 0.92$, $P = 0.36$), motivation (original mean = −0.09, SE = 0.09; balanced mean = −0.13, SE = 0.12; $t = -0.20$, $P = 0.76$), social cognition (original mean = 0.10, SE = 0.10; balanced mean = 0.20, SE = 0.14; $t = 0.59$, $P = 0.55$), and executive cognition (original mean = −0.17, SE = 0.19; balanced mean = −0.24, SE = 0.22; $t = -0.24$, $P = 0.81$).

Machine learning results

The SVM model, trained with class weighting and evaluated via leave-one-out cross-validation, achieved a significant

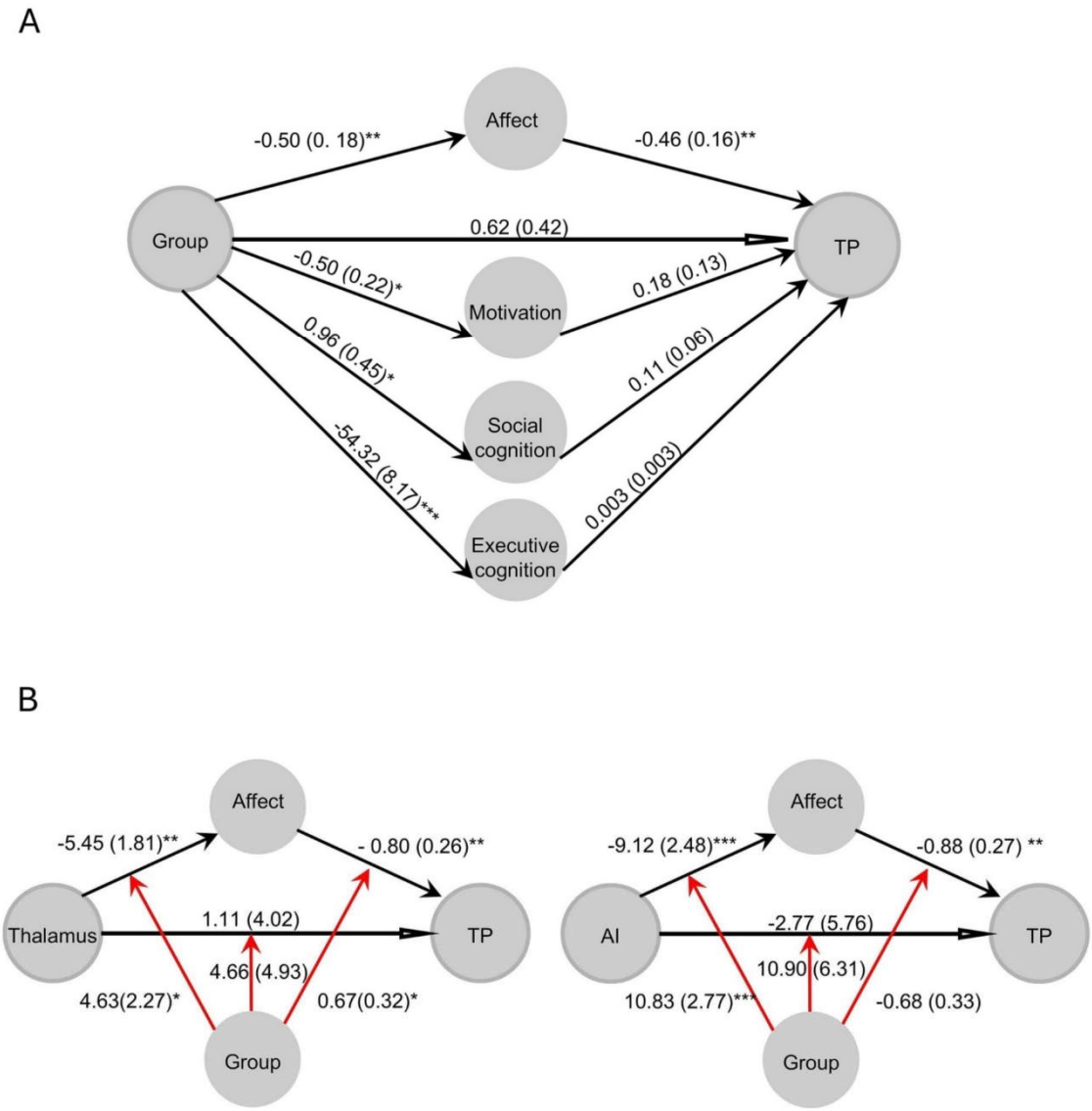

Fig. 3. The results of mediation model and moderated mediation models. A) Results of the mediation model. In this study, a multiple mediation analysis was conducted with group status (mild cognitive impairment [MCI] vs. normal healthy controls [NHC]) as the independent variable and TP as the dependent variable. The TP-related components (affect, motivation, executive cognition, and social cognition) served as mediators. The direct effect of group status on TP was not significant. Only the indirect effects via the affect component were significant. The indirect effect via motivation, social cognition, and executive cognition was not significant. B) Results of moderated mediation models. GMV of thalamus and anterior insula (AI) were treated as the independent variables, TP as the dependent variable, and affect as the mediator variable, with group status (MCI vs. NHC) as the moderating variable to assess its influence on the mediation pathways. The analysis was conducted with the covariates of age, gender, education level, and total intracranial volume. For the moderated mediation model involving GMV of the thalamus (left figure), the mediation effects on TP via the affect component were significantly moderated by group status. Specifically, the indirect effect of GMV of the thalamus on TP via the affect component was significant in the MCI group but not in the NHC group. Group status significantly moderated the relationship between GMV of the thalamus and the affect component. In the moderated mediation model with GMV of the AI (right figure), the mediation effects on TP via the affect component were significantly moderated by group status. The indirect effect of GMV of the AI on TP via the affect component was significant in the MCI group but not in the NHC group. Group status significantly moderated the relationship between GMV of the AI and the affect component. $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

classification accuracy of 76% ($P < 0.01$). The model demonstrated a sensitivity of 80% ($P < 0.01$) and a specificity of 68% ($P < 0.05$).

Discussion

Our study investigated the neural mechanisms underlying reduced TP in individuals with MCI. We examined whether GMV in specific brain regions mediated the relationship between group status (MCI vs. NHC) and TP and whether these regions influenced TP by modulating affect (sensitivity to betrayal). Using whole-brain mediation analysis with voxel-wise GMV from VBM, we found that reduced GMV in the left thalamus and AI mediated the relationship between group status and TP. Furthermore, moderated mediation analyses revealed that these brain regions

Table 2. The regions with a significant indirect effect in whole-brain mediation analysis.

Region	Hemisphere	Size	Peak	MNI coordination			P_{perm}
Positive effect							
Thalamus	Left	11	0.29	−17	−24	3	<0.001
Anterior insula	Left	5	0.21	−38	18	2	0.002
Hippocampus	Left	3	0.29	−24	−35	−2	0.004
Cingulate gyrus	Left	3	0.21	−6	−29	−41	0.008
Superior frontal gyrus	Left	2	0.20	−5	20	62	0.044
Insular	Left	2	0.25	−30	14	11	0.072

Note. MNI, Montreal Neurological Institute. Max Z, the largest indirect effect size in the region. P_{perm}, the *P*-value in the permutation tests.

influenced TP by increasing sensitivity to betrayal specifically in the MCI group but not in the NHC group. Our findings suggest that atrophy in the SAN, particularly the thalamus and AI, may contribute to heightened betrayal aversion and reduced trust in individuals with MCI.

Affect mediating the relationship between group and TP

Our findings confirm our behavioral hypothesis: the MCI group exhibited lower TP than the NHC group, and this difference was specifically mediated by heightened sensitivity to betrayal (affect). This aligns with previous research indicating that individuals with MCI tend to focus on negative social cues and experience more intense emotional responses in social situations (Lin et al. 2022). While they also exhibit deficits in motivation (Perry and Kramer 2015), executive function (Traykov et al. 2007), and social cognition (Bora and Yener 2017), these factors did not significantly mediate the relationship between group status and TP. Our results underscore the vulnerability of individuals with MCI to negative social experiences and their heightened sensitivity to betrayal. This knowledge has important implications for caregivers and healthcare professionals. Understanding the trust-related challenges faced by older adults with MCI can guide caregivers to adopt strategies that foster trust and positive engagement. These strategies include demonstrating patience, highlighting positive aspects of interactions, and ensuring clear and consistent communication (Zegwaard et al. 2017). Due to their heightened concerns, it is advisable to minimize or deliver negative feedback with greater tact, which may strengthen trust and improve adherence to interventions.

TP and its associated features show promise as potential markers of early neurodegenerative changes. Our findings demonstrated their effectiveness in discriminating between MCI and NHC. Consistent with previous research showing that integrating multi-domain MCI-related features enhances MCI identification (Vieira et al. 2022; Franciotti et al. 2023), our results suggest that incorporating trust-related factors may improve detection accuracy. Furthermore, large longitudinal studies have linked trust to dementia risk factors like well-being (Poulin and Haase 2015) and depressive symptoms (Wang et al. 2024). These converging lines of evidence suggest that trust and related traits could be valuable in predicting the progression to neurodegenerative disease in older adults.

The progression of MCI appears to eliminate the positivity bias typically observed in normal aging. Healthy older adults generally exhibit this bias, focusing more on positive aspects of situations (Reed et al. 2014). The meta-analysis also indicates that older adults maintain higher levels of trust compared to younger individuals (Bailey and Leon 2019). Socioemotional selectivity theory posits that this prioritization of emotionally meaningful goals and positive processing arises from an awareness of limited future time (Carstensen and Reynolds 2023). However, this positivity bias tends to disappear in individuals with cognitive impairments (Kalenzaga et al. 2016). Meta-analyses further show that older adults with MCI experience more severe depressive symptoms than healthy peers (Yates et al. 2013; Ismail et al. 2017). Consequently, older adults with MCI tend to view situations more pessimistically and exhibit increased worry about the future and uncertainty. These findings suggest that MCI is associated with abnormalities in affective processing, leading to a focus on negative aspects and a diminished positivity bias, which may subsequently reduce trust decisions and hinder social interactions.

The structural mechanism underlying the difference in TP between MCI and NHC

Our neural findings corroborated our hypothesis: The difference in TP between the MCI and NHC groups was moderated by GMV in the left thalamus and AI. Moderated mediation analyses revealed that both regions significantly influenced TP by modulating affect (sensitivity to betrayal) exclusively in the MCI group. Gray matter atrophy in SAN regions, such as the thalamus and AI, has been correlated with increased depressive symptoms in individuals with MCI, encompassing greater worry and an enhanced focus on negative stimuli (Zackova et al. 2021). Therefore, in older adults with MCI, SAN atrophy is associated with increased worry, indicating a heightened sensitivity to negative information during trust-related situations, which, in turn, contributes to reduced trust.

Our study highlights the crucial role of the thalamus, a central hub within the SAN (Seeley 2019; Zhou et al. 2021), in regulating trust behavior in MCI. Consistent with meta-analytic findings (Nickl-Jockschat et al. 2012; Yang et al. 2012), our study showed reduced thalamic GMV in older adults with MCI. The thalamus plays a critical role in integrating sensory, motor, emotional, and cognitive information (Jones 2012), and it is also involved in regulating arousal (Van der Werf et al. 2002). Previous research has linked thalamic atrophy to heightened arousal symptoms in posttraumatic stress disorder (Yang et al. 2023). Therefore, the reduced thalamic GMV observed in our MCI group may impair arousal regulation, leading to increased sensitivity to the risk of betrayal and, consequently, lower TP. Interventions targeting thalamic function and structure, such as transcranial magnetic stimulation (Barredo et al. 2019; Yang et al. 2021), may hold promise for improving social functioning in individuals with MCI.

Consistent with findings from VBM-based meta-analyses, GMV in the thalamus, a critical node in the SAN, is reduced in older adults with MCI (Nickl-Jockschat et al. 2012; Yang et al. 2012). The thalamus is a critical brain region that connects and integrates

sensory, motor, emotional, and cognitive information (Jones 2012) and also plays a key role in regulating arousal levels (Van der Werf et al. 2002). Previous studies have shown that thalamic atrophy is associated with higher arousal symptom scores in patients with posttraumatic stress disorder (Yang et al. 2023). Therefore, in our study, the reduced GMV in the thalamus of older adults with MCI may impair their ability to regulate arousal levels, leading to heightened affective responses to the risk of betrayal and, consequently, a decrease in TP. Interventions that improve thalamic function and structure, such as transcranial magnetic stimulation (Barredo et al. 2019; Yang et al. 2021), may help to improve social functioning in older adults with MCI.

Like the thalamus, the AI is a crucial node in the SAN, involved in multiple psychological processes, including emotional, sensory, and cognitive functions (Uddin et al. 2017). A recent fMRI-based meta-analysis identified the AI as a key brain region in the one-shot TG, encoding subjective feelings of aversion related to the probability of betrayal (Bellucci et al. 2017). Recent research has further divided the AI into dorsal and ventral parts, each with distinct functional connections and roles in psychological processes (Uddin et al. 2017). The dorsal AI is primarily involved in cognitive processes, such as attention and executive cognition, whereas the ventral AI is more involved in affective processing, including subjective feelings and reward processing (Kelly et al. 2012; Chang et al. 2013). As a central node for integrating information within the SAN, the dorsal AI acts as a switch, modulating the activity of the DMN (social cognition) and CEN (executive cognition) (Molnar-Szakacs and Uddin 2022). During trust dilemmas, the dorsal AI can engage either cognitive social processes or cognitive executive processes to translate the probability of betrayal into reciprocity expectations (Krueger et al. 2020). The MRI-based meta-analysis suggests that the dorsal AI, which mediates cognitive processes, is involved in predicting their partner behavior in the one-shot trust decision. In contrast, the ventral AI, which mediates aversive feelings that drive norm enforcement, is associated with reciprocal behavior (Bellucci et al. 2018). This evidence suggests that older adults with MCI experience gray matter atrophy in the dorsal AI, which impairs their ability to integrate risk information and translate the probability of betrayal into reciprocity expectations, which, in turn, increases betrayal aversion and leads to decreased TP. These findings highlight that AI abnormalities in older adults with MCI critically impact not only cognitive functioning (Xie et al. 2012) but also social functioning.

Finally, meta-analytic evidence reveals gray matter atrophy in the thalamus and AI in both MCI and major depressive disorder, implying that these brain regions are important for the manifestation of depressive symptoms in older adults with MCI (Zackova et al. 2021). Building on meta-analytic findings that deep transcranial magnetic stimulation can alleviate depression in major depressive disorder (Gellersen and Kedzior 2018), it is plausible that physical interventions targeting deep brain structures, such as the insula and thalamus, could ameliorate depressive symptoms in MCI. This, in turn, might enhance patients' confidence and social engagement.

Limitations

Our study revealed the structural mechanisms underlying reduced TP in older adults with MCI and investigated the brain regions that decreased TP via increased betrayal aversion in older adults with MCI. However, several limitations of our study should be acknowledged. Firstly, the sample size in this study, particularly the small number of older adults with MCI, is limited. Future larger-scale studies are necessary to validate these findings and enhance their reliability. Research indicates that in VBM analyses, both the stability and replicability of results improve with larger sample sizes, with greater reliability typically achieved when the sample size exceeds 180 participants. Therefore, future studies will aim to continue data collection, particularly from older adults with MCI, to validate the findings of this study with a larger sample. In addition, investigating common factors that influence both trust and MCI, such as gender, may provide important insights into the underlying mechanisms of trust among older adults with MCI.

Secondly, our study lacks an objective and independent measure of TP-related components in trust dilemmas. Although our study used the one-shot DG to assess social cognition, it should be noted that the DG primarily reflects altruistic preferences—which may indicate an individual's reliance on social cognition when making trust decisions—rather than serving as a direct measure of social cognition itself. In addition, while subscales of the GDS and cognitive tests have been used to assess trust-related components (e.g. affect, motivation, and executive cognition), these questionnaires do not directly measure of individual trust-related components in actual trust dilemmas. Future research should include task-based measures of affect (e.g. emotional arousal), motivation (e.g. reward sensitivity), executive cognition (e.g. strategy), and social cognition (e.g. theory of mind) to validate our findings.

Finally, our study utilized cluster-based permutation tests to address the issue of multiple comparisons in whole-brain mediation analysis. Although this method is more sensitive than traditional parametric corrections, such as family-wise error, permutation tests can be affected by factors such as initial *P*-value thresholds and spatial smoothing. Future research could consider employing whole-brain mediation analysis with threshold-free cluster enhancement to evaluate the study's hypotheses further.

Despite these issues, our research contributes to the understanding that the atrophy of the SN regions, such as the thalamus and AI, in MCI increased their sensitivity to the probability of betrayal in trust dilemmas, which contributed to lower trust in strangers. More importantly, it reveals the reasons for lower trust in older adults with MCI and helps people build trusting relationships with older adults with MCI. This could be valuable in improving their social support networks and social engagement.

Conclusion

Using whole-brain mediation analysis and a moderated mediation analysis, we investigated which specific brain regions influence TP through the affect component and how the progression of MCI moderates these relationships. Our results showed that TP was lower in the MCI group than in the NHC group, and the affect component mediated the difference in TP between the MCI and NHC groups. The reduced GMV in the thalamus and AI in the MCI group contributed to the decreased TP. Moderated mediation analysis further indicated that both thalamus and AI had a direct effect on TP and an indirect effect on TP via affect in the MCI group but not in the NHC group. This study provides important insights into the gray matter atrophy behind the social interaction challenges faced by older adults with MCI and establishes a foundation for future research focused on identifying and improving TP in this population. In addition, our research will have a positive impact by helping caregivers and family members to build more effective trust relationships with older adults with MCI thereby improving their daily lives.

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Author contributions

Yiqi Chen (Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing—original draft, Writing—review & editing), Hao He (Data curation, Funding acquisition, Writing—review & editing), Yiyang Ding (Investigation), Wuhai Tao (Conceptualization, Funding acquisition, Writing—review & editing), Qing Guan (Funding acquisition, Project administration, Resources, Writing—review & editing), Frank Krueger (Conceptualization, Project administration, Supervision, Validation, Writing—review & editing).

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Conflict of interest statement: None declared.

Data availability

The data and code used in this study are publicly available at: https://github.com/yiqiqiyi/VBM_mediation_trust.

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Original Article

5. Experiment 3. Psychological and Neural Mechanisms of Trust Dynamics in Mild Cognitive Impairment

"Compensatory and impaired trust updating in mild cognitive impairment: Evidence from computational modeling and fMRI"

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Compensatory and impaired trust updating in mild cognitive impairment: Evidence from computational modeling and fMRI

Abbreviated title

Trust Dynamics in MCI

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Abstract

Trust dynamics—how trust is formed, maintained, and adjusted—are essential to interpersonal functioning. Older adults with mild cognitive impairment (MCI) are known to exhibit social vulnerabilities, but the evolution of trust over time and its neural basis in this population remain unclear. Here, we combined computational modeling with task-based functional magnetic resonance imaging (fMRI) to investigate trust updating during a multi-round trust game (MTG). Behaviorally, MCI participants showed slower trust reduction, larger prediction errors (PE), lower learning rates, and greater interference when interacting with non-cooperative partners, while responding similarly to cooperative ones compared to healthy controls. Neurally, fMRI analyses revealed increased activation in executive and social cognition networks—including the right middle frontal gyri, precuneus, and temporoparietal junction (TPJ)—during cooperative interactions, suggesting compensatory recruitment. In contrast, MCI participants showed reduced activation in the superior frontal gyri (SFG) and middle temporal gyrus during non-cooperative interactions. Critically, PE-modulated psychophysiological interaction (PPI) analyses revealed diminished functional connectivity between the SFG and TPJ under non-cooperative conditions. These findings suggest that while older adults with MCI can compensate during supportive interactions, they struggle to adapt trust in adverse contexts. This impaired updating may underlie heightened susceptibility to social exploitation and declining interpersonal functioning.

Keywords: mild cognitive impairment, trust dynamics, trust game, reinforcement learning, social cognition, functional magnetic resonance imaging, prediction error, computational modeling

1. Introduction

Mild cognitive impairment (MCI) is a transitional stage between normal aging and dementia, marked by cognitive decline that exceeds age-related expectations but does not yet interfere with daily independence [1]. While much research has focused on cognitive deficits in MCI, emerging evidence highlights broader social impairments in this population. Older adults with MCI are more susceptible to deception [2], engage less in social activities [3], and tend to experience shrinking social networks [4], underscoring potential deficits in interpersonal functioning.

Trust dynamics—the process of building, maintaining, and adjusting trust across repeated interactions—are fundamental to healthy interpersonal relationships and are shaped by past experience [5]. Although older adults with MCI exhibit clear social vulnerabilities, few studies have investigated whether their ability to regulate trust over time is disrupted. Even fewer have explored the psychological and neural mechanisms that may underlie such impairments.

Trust involves a social dilemma: while it enables reciprocity and cooperation, it also entails the risk of betrayal [6]. It is commonly defined as a willingness to accept vulnerability based on expectations about another person's intentions and behavior [7]. Scholars distinguish between trust propensity—a stable tendency to trust unfamiliar others—and trust dynamics, which refer to how trust evolves across repeated interactions [5]. The latter can be studied using multi-round trust games (MTGs), which simulate real-world social exchanges and capture how individuals form, maintain, or withdraw trust in response to cooperative or exploitative behavior [8].

According to a neuropsychoeconomic framework, trust behavior arises from the interaction of affective, motivational, executive, and social cognitive processes, supported by distinct large-scale brain networks [9]. Specifically, the salience network (SAN), including the anterior insula and dorsal anterior cingulate cortex, mediates betrayal aversion and threat sensitivity [10], while the reward network (RWN), including the ventral striatum and ventromedial prefrontal cortex, supports anticipation of reciprocity and reward learning [11]. Trust updating under uncertainty also engages executive functions via the central executive network (CEN)—including the dorsolateral prefrontal cortex (dlPFC) and posterior parietal cortex—and social cognition via the default mode network (DMN), encompassing the medial prefrontal cortex, posterior cingulate cortex, and temporoparietal junction (TPJ) [12,13].

In MTGs, individuals initially rely on calculus-based trust, a cautious strategy shaped by betrayal risk and cost-benefit reasoning. With repeated interactions, they shift toward knowledge-based trust, drawing on CEN and DMN resources to integrate contextual and partner-specific information. Eventually, trust may evolve into identification-based trust, motivated more by social bonding and anticipated reward than by risk aversion [9].

Older adults with MCI show disruptions across all key components of trust behavior. Prior studies have linked MCI to reduced trust propensity, heightened betrayal sensitivity, increased SAN activity [12], and functional impairments in reward-related brain regions [13]. These biases may lead older adults with MCI to enter social interactions with increased distrust and affective reactivity.

Despite impairments in executive [14] and social cognition [15], older adults with MCI may partially compensate by recruiting additional brain resources within the CEN and DMN [16]. This compensatory activation may allow them to maintain trust during relatively low-stress, cooperative interactions. However, compensatory mechanisms often fail under greater cognitive load—such as in interactions with non-cooperative partners—leading to reduced neural activation and impaired behavioral adjustment [17]. Such interactions pose greater betrayal risk [18], elicit stronger negative affect [19], and demand more cognitive resources, which may challenge the bounded rationality required for adaptive trust updating.

Computational modeling offers a powerful approach to uncover latent mechanisms of trust behavior, especially those not directly observable from behavior alone [20]. In trust games, reinforcement learning simulate how individuals update expectations based on feedback and generate trial-by-trial estimates of learning rate, prediction error (PE), risk sensitivity, and interference [21,22,23,24]. These parameters can be integrated with neuroimaging data to explore how behavioral adaptation is supported by underlying neural processes through model-based fMRI and psychophysiological interaction (PPI) analyses [25,26] .

To investigate the psychological and neural mechanisms underlying trust dynamics in older adults with MCI, we combined computational modeling with task-based fMRI during an MTG. A belief-based reinforcement learning model was used to simulate participants' trust behavior, with parameters that reflect core trust components—affect, motivation, executive cognition, and social cognition. We then

examined brain activation patterns and PE-modulated connectivity during cooperative and non-cooperative interactions.

Based on prior findings, we hypothesized that older adults with MCI would exhibit: (1) lower initial trust, higher PEs, slower trust reduction, and reduced learning rates during non-cooperative interactions; (2) compensatory activation in CEN and DMN regions during cooperative interactions; and (3) diminished PE-modulated activation and connectivity under non-cooperative conditions. These findings may provide critical insight into social vulnerability in MCI and inform interventions aimed at improving interpersonal functioning in aging populations.

2. Results

2.1 Behavioral results

Demographic and Neuropsychological Comparisons

Group comparisons revealed no significant differences between the MCI and normal healthy control (NHC) groups in age, gender distribution, or education. Specifically, the mean age did not differ significantly between the MCI group ($M = 67.79$, $SD = 6.51$) and the NHC group ($M = 67.22$, $SD = 5.44$), $t = 0.22$, $p = 0.829$. Gender distribution was nearly identical across groups (MCI: 69% female; NHC: 69% female), $z = 0.28$, $p = 0.978$. The groups also did not differ substantially in years of education (MCI: $M = 10.54$, $SD = 3.32$; NHC: $M = 11.87$, $SD = 3.45$), $z = -1.78$, $p = 0.075$. In contrast, significant group differences emerged on all neuropsychological measures. The MCI group scored lower across domains of memory, executive function, attention, language, and visuospatial ability (**Tab. 1**), confirming expected cognitive impairment.\

Table 1. Group differences in demographics, cognitive function, Geriatric Depression Scale scores, and trust paradigm–related components between the mild cognitive impairment (MCI) and normal healthy control (NHC) groups.

Domain	Measure	MCI (n=41) (Mean [SD])	NHC (n=45) (Mean [SD])	t/Z	p
Demographics					
	Age (year)	67.79 (6.51)	67.22 (5.44)	0.21	0.829
	Gender (Percentage of females)	0.69 (0.47)	0.69 (0.47)	0.28	0.978
	Education (year)	10.53 (3.32)	11.87 (3.45)	-1.78	0.075
Cognitive functions					
	MMSE	25.95 (2.38)	28.09 (1.40)	-4.37	<0.001
Memory	Rey-recall	8.51 (6.12)	16.93 (8.00)	-4.68	<0.001
	AVLT	20.31 (7.43)	28.38 (8.05)	-4.15	<0.001
	DST	9.51 (1.76)	12.60 (6.57)	-4.19	<0.001
Executive cognition	TMT-B (ms)	261.67 (99.78)	144.09 (53.20)	5.98	<0.001
	Stroop (ms)	108.33 (33.86)	74.09 (19.69)	4.98	<0.001
Attention	TMT-A (ms)	90.33 (41.35)	53.80 (13.47)	5.56	<0.001
	SDMT	23.97 (10.74)	38.71 (11.99)	-5.19	<0.001
Language	CVFT	37.02 (8.91)	46.80 (9.28)	-4.36	<0.001
	BNT	19.72 (4.47)	23.53 (2.88)	-4.79	<0.001
visuospatial ability	Rey-copy	29.79 (5.92)	35.09 (1.55)	-5.02	<0.001
	CDT	21.98 (6.44)	26.06 (4.48)	-3.47	<0.001
Risk propensity	Lottery game	4.92 (2.62)	5.11 (2.44)	-0.48	0.634

Note: Values are presented as mean (standard deviation). *t* or *Z* values indicate the test statistic from independent-samples *t*-tests or Mann–Whitney U tests (as appropriate). MMSE = Mini-Mental State Examination; Rey-recall = Rey–Osterrieth Complex Figure Recall Test; AVLT = Auditory Verbal Learning Test; DST = Digit Span Test; TMT–A/B = Trail Making Test–Part A/B; SDMT = Symbol Digit

Modalities Test; CVFT = Category Verbal Fluency Test; BNT = Boston Naming Test; Rey-copy = Rey–Osterrieth Complex Figure Copy Test; CDT = Clock Drawing Test. Higher scores indicate better performance on all cognitive tests, except for TMT–A/B, Stroop, and the executive function composite, where lower scores indicate better performance.

Investment Behavior in the Trust Game

Mean investment levels across the MTG were analyzed using an Aligned Rank Transform ANOVA with group (MCI vs. NHC) and partner condition (cooperative vs. non-cooperative) as factors. There was no significant main effect of group on investment, with MCI participants (M = 6.25, SD = 1.16) and NHC participants (M = 5.82, SD = 1.60) showing similar overall investment levels, $F(1, 84) = 0.03$, $p = 0.86$, $\eta^2_p < 0.001$. A significant main effect of partner condition was observed, with higher investments made toward cooperative partners (M = 6.99, SD = 1.54) than non-cooperative partners (M = 5.05, SD = 2.02), $F(1, 84) = 17.23$, $p < 0.001$, $\eta^2_p = 0.17$. Importantly, a significant group-by-condition interaction emerged, $F(1, 84) = 4.97$, $p < 0.05$, $\eta^2_p = 0.06$. Post hoc rank-sum comparisons showed that in the cooperative condition, there was no significant difference between MCI (M = 6.85, SD = 1.33) and NHC (M = 7.11, SD = 1.71) participants, $z = 0.99$, $p = 0.32$, $r = 0.11$. However, under the non-cooperative condition, MCI participants made significantly higher investments (M = 5.67, SD = 1.66) than the NHC group (M = 4.52, SD = 2.17), $z = -2.69$, $p < 0.01$, $r = 0.29$. These results indicate that while cooperative behavior was interpreted similarly across groups, the MCI group exhibited reduced trust retraction in the face of exploitation.

Reaction Times

Reaction times (RTs) during the MTG were examined using a repeated-measures ANOVA. The main effect of group was not statistically significant, with MCI participants showing numerically longer RTs (M = 3.50, SD = 0.74) compared to NHC participants (M = 3.23, SD = 0.65), $F(1, 84) = 2.74$, $p = 0.10$, $\eta^2_p = 0.03$. However, a significant main effect of partner condition emerged, with longer RTs during non-cooperative interactions (M = 3.62, SD = 0.74) than cooperative ones (M = 3.13, SD = 0.63), $F(1, 84) = 39.88$, $p < 0.001$, $\eta^2_p = 0.33$. Furthermore, a significant group-by-condition interaction was observed, $F(1, 84) = 5.60$, $p < 0.05$, $\eta^2_p = 0.07$. Follow-up independent-samples t-tests revealed no significant group difference in the cooperative condition (MCI: M = 3.15, SD = 0.63; NHC: M = 3.10, SD = 0.62), $t(84) = 0.33$, $p = 0.74$, Cohen's $d = 0.08$. In contrast, the MCI group showed significantly longer RTs under the non-cooperative condition (MCI: M = 3.85, SD = 0.77; NHC: M = 3.40, SD = 0.68), $t(84) =$

3.38, $p < 0.01$, Cohen's $d = 0.62$, indicating increased decision conflict or cognitive load.

Trial-by-Trial Investment Patterns

Group differences in initial trust were assessed using investment on the first trial of the MTG. No significant group difference was found between MCI ($M = 6.77$, $SD = 2.55$) and NHC ($M = 5.69$, $SD = 2.88$) participants, $z = 1.70$, $p = 0.09$, $r = 0.18$. Trial-by-trial investment behavior was further analyzed using Wilcoxon rank-sum tests with cluster-based permutation correction. Under the non-cooperative condition, MCI participants invested significantly more than NHC participants during trials 20–25 and 27–30 (corrected cluster-level $p < 0.05$; **Fig. 1A**). No significant group differences were observed in the cooperative condition after correction. Group comparisons on post-experiment questionnaire items also revealed no significant differences ($ps > 0.05$).

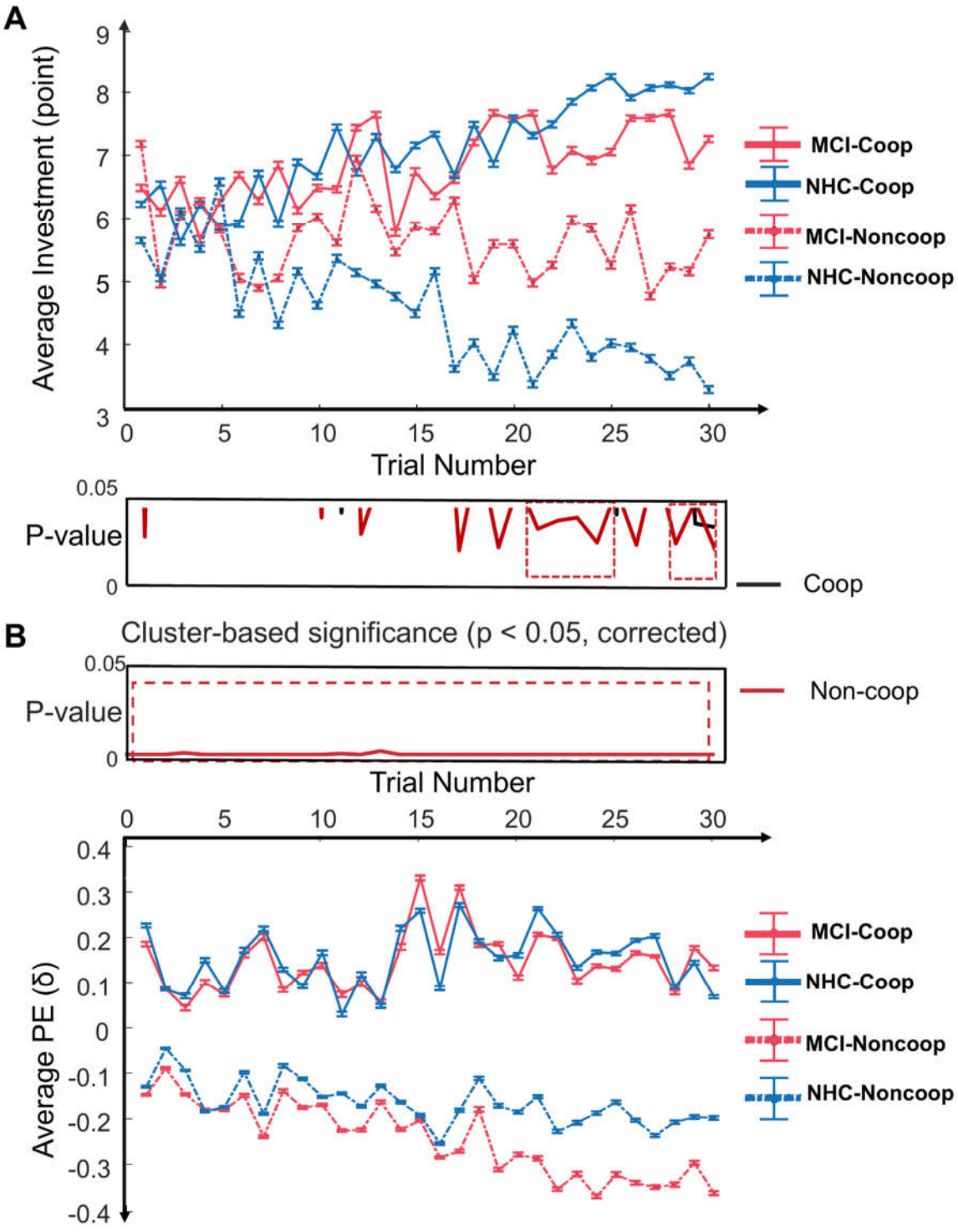

Figure 1. Behavioral performance and prediction error (PE) dynamics during the multi-round trust game (MTG). A. Investment behavior. *Upper panel:* Mean trial-by-trial investment amounts for participants with mild cognitive impairment (MCI) and normal healthy controls (NHC), shown separately for cooperative and non-cooperative partners. Error bars represent standard errors. *Lower panel:* Trial-wise group differences in investment were assessed using Wilcoxon rank-sum tests. Clusters of consecutive trials with significant differences ($p < 0.05$, cluster-based permutation corrected) are highlighted with dashed red rectangles. MCI participants invested significantly more than controls when interacting with the non-cooperative partner during trials 20–25 and 27–30. **B. Prediction error (PE) estimates.** *Upper panel:* Trial-by-trial average PE values, derived from computational modeling, are shown for MCI and NHC groups across partner conditions. *Lower panel:* Trial-wise group

differences in PE values were analyzed via Wilcoxon rank-sum tests. Significant clusters ($p < 0.05$, cluster-corrected) are highlighted in dashed rectangles. MCI participants showed significantly larger absolute PE values for the non-cooperative partner across all trials, indicating less accurate outcome predictions.

2.2 Computational model results

Prediction Error Dynamics

Trial-by-trial PE values derived from the computational model were compared between groups. Under the non-cooperative condition, MCI participants exhibited significantly larger absolute PE values than NHCs across trials 1–30 (corrected cluster-level $p < 0.05$; **Fig. 1B**), indicating less accurate expectation updating. No group differences in PE were observed in the cooperative condition.

Model Parameters

Parameter estimates from the belief-based reinforcement learning model revealed selective group differences. The learning rate for non-cooperative partners (α_bad) was significantly lower in the MCI group ($M = 0.43$, $SD = 0.30$) compared to the NHC group ($M = 0.60$, $SD = 0.37$), $Z = 3.09$, $p = 0.001$. Additionally, the MCI group exhibited a significantly higher interference factor (η), indicating greater cognitive spillover between partner evaluations (MCI: $M = 0.63$, $SD = 0.61$; NHC: $M = 0.33$, $SD = 0.48$), $Z = -2.17$, $p = 0.03$. No significant group differences were found for the learning rate for cooperative partners (α_good: MCI: $M = 0.45$, $SD = 0.26$; NHC: $M = 0.47$, $SD = 0.28$; $Z = 1.13$, $p = 0.87$), inverse temperature (β: MCI: $M = 6.69$, $SD = 3.97$; NHC: $M = 7.13$, $SD = 3.94$; $Z = 0.71$, $p = 0.24$), reward sensitivity (γ: MCI: $M = 0.63$, $SD = 0.98$; NHC: $M = 0.65$, $SD = 0.70$; $Z = 0.99$, $p = 0.84$), or risk sensitivity (λ: MCI: $M = 1.35$, $SD = 1.08$; NHC: $M = 1.70$, $SD = 1.06$; $Z = 1.04$, $p = 0.15$; **Tab. 2**).

Table 2. Group differences in belief-based reinforcement learning parameters between mild cognitive impairment (MCI) and normal healthy control (NHC) participant

Parameter	MCI (Mean [SD])	NHC (Mean [SD])	Z	P
Learning rate (good)	0.34 (0.34)	0.41 (0.31)	-1.09	0.274
Learning rate (bad)	0.20 (0.23)	0.34 (0.32)	-2.41	0.016
Inverse temperature	7.68 (3.79)	8.87 (2.73)	-1.72	0.084
Reward sensitivity	0.41 (0.29)	0.35 (0.23)	0.64	0.524
Risk sensitivity	1.85 (1.19)	2.22 (1.08)	-1.12	0.264
Interference factor	0.22 (0.35)	0.08 (0.23)	2.81	0.005

Note: Values are presented as mean (standard deviation). Group comparisons were performed using Mann–Whitney U tests; Z and p-values are reported. SD = standard deviation. Parameters include: Learning rates for cooperative ("good") and non-cooperative ("bad") partners; Inverse temperature (β): decision consistency; Reward sensitivity (γ): non-linear transformation of expected utility; Risk sensitivity (λ): aversion to outcome variance; Interference factor (η): cross-partner learning interference.

Parameter-Cognition Correlations

Correlation analyses between model parameters and relevant behavioral or neuropsychological measures showed a significant positive relationship between the interference factor and executive cognition as measured by TMT-B ($r = 0.33$, $p = 0.002$). Risk sensitivity (λ) was significantly and negatively correlated with risk aversion as measured by the one-shot lottery game ($r = -0.21$, $p = 0.047$), providing convergent support for the model's construct validity.

2.3 Control analysis results for computational modeling

Control analyses confirmed the reliability and explanatory value of the computational model. Restricted model comparisons showed that each individual parameter—learning rates (α_good, α_bad), inverse temperature (β), reward sensitivity (γ), risk sensitivity (λ), and interference factor (η)—significantly contributed to model fit. Furthermore, a parameter recovery analysis demonstrated that key parameters, specifically the learning rates for cooperative and non-cooperative partners (α_good and α_bad) and the

inverse temperature (β), were robustly recovered, supporting the identifiability and reliability of the model estimates (see Supplementary Materials S4).

2.4 Model-based fMRI activation results

Feedback Phase: Cooperative Partner Condition

Model-based activation analyses were conducted to compare brain activations between older adults with MCI and NHCs under cooperative and non-cooperative partner conditions of the MTG. During the feedback phase, in the cooperative partner condition, the MCI group showed significantly greater activations in the right middle frontal gyrus (MFG; MNI: 34, 62, 4; k = 98; T = 4.41; p = 0.01), precuneus (MNI: 2, -44, 42; k = 99; T = 4.45; p = 0.01), and angular gyrus (MNI: 60, -52, 30; k = 91; T = 4.38; p = 0.01), which also belong to the TPJ [27] (Fig. 2A, Table 3). Increased activation was also observed in the left cerebellum (CRB; MNI: -6, -84, -40; k = 68; T = 4.41; p = 0.05). The MFG, specifically within the dlPFC, is a key component of the CEN and is involved in behavioral regulation and strategy updating [28]. The precuneus and angular gyrus are key components of the DMN, associated with social cognition and self-referential processing [30,31]. These results suggest compensatory recruitment of CEN and DMN regions in older adults with MCI to support adaptive trust behavior during cooperative social interactions.

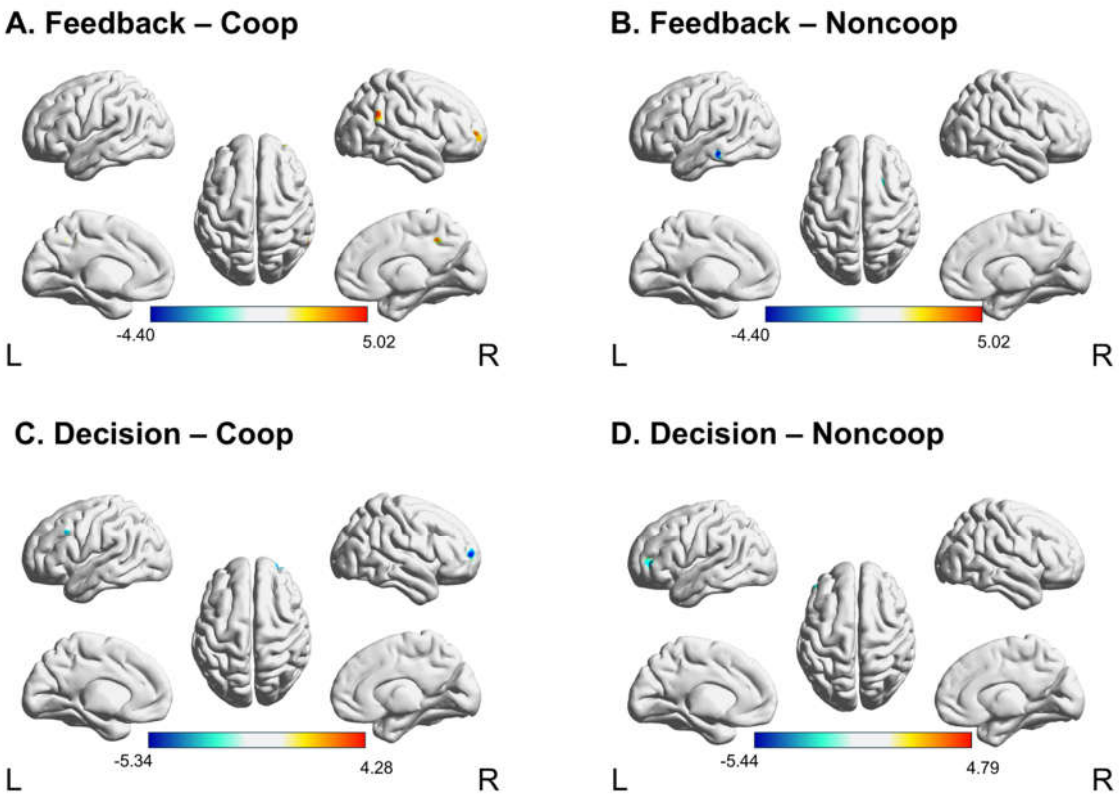

Figure 2. Group differences in brain activation during feedback and decision phases of the multi-round trust game. A. Feedback phase – cooperative partner. Compared to the NHC group, the MCI group showed significantly greater activation in the right middle frontal gyrus, precuneus, and angular gyrus—overlapping with the temporoparietal junction (TPJ). **B. Feedback phase – non-cooperative partner.** MCI participants exhibited significantly reduced activation in the right superior frontal gyrus (SFG) and left middle temporal gyrus relative to the NHC group. **C. Decision phase – cooperative partner.** The MCI group demonstrated significantly lower activation than the NHC group in the right SFG and left inferior frontal gyrus (opercular part). **D. Decision phase – non-cooperative partner.** MCI participants showed significantly reduced activation in the right inferior frontal gyrus and right MFG compared to controls. Statistical maps are displayed on a standard MNI template (surface rendering), thresholded at $p < 0.001$ (voxel-level, uncorrected) and $p < 0.05$ (cluster-level, FWE corrected). Color bars represent t-values; L = left, R = right.

Table 3. Significant clusters from group-level activation analyses during the feedback and decision phases of the multi-round trust game.

	MNI (x,y,z)	k	T	p	Hemisphere	region
Feedback phase						
Cooperative (positive)	-6 -84 -40	68	4.41	0.05	L	CRB
	2 -44 42	99	4.45	0.01	R	Precuneus
	34 62 4	98	4.41	0.01	R	MFG
	60 -52 30	91	4.38	0.01	R	Angular Gyrus
Non-cooperative (negative)	-66 -32 -15	77	4.82	0.05	L	MidTG
	24 20 51	149	4.11	0.001	R	SFG
Decision phase						
Cooperative (negative)	32 60 9	141	4.75	<0.001	R	SFG
	-56 20 38	89	4.56	0.02	L	IFGoper
Non-cooperative (negative)	-40 42 4	181	4.54	<0.001	L	IFGtri
	22 50 4	101	4.46	0.01	R	MFG

Note: Coordinates are reported in Montreal Neurological Institute (MNI) space. *k* = cluster size in voxels; *T* = peak *t*-value; *p* = cluster-level family-wise error (FWE) corrected *p*-value. L = left hemisphere; R = right hemisphere.
Abbreviations: CRB = cerebellum; MFG = middle frontal gyrus; MidTG = middle temporal gyrus; SFG = superior frontal gyrus; IFGoper = inferior frontal gyrus, opercular part; IFGtri = inferior frontal gyrus, triangular part.

Feedback Phase: Non-Cooperative Partner Condition

In the non-cooperative partner condition, participants in the MCI group showed significantly less

activation in the left middle temporal gyrus (MNI: -66, -32, -15; k = 77; T = 4.82; p = 0.05) and right SFG (MNI: 24, 20, 51; k = 149; T = 4.11; p = 0.001) compared to the NHC group (**Fig. 2B, Tab. 3**). The middle temporal gyrus, as part of the DMN, is involved in semantic processing and conceptual integration [31], and has been shown in quantitative reviews to exhibit strong connectivity with the TPJ, contributing to theory of mind processes [27]. In contrast, the SFG are components of the CEN, contributing to working memory and conflict control [32]. These findings suggest that although MCI participants may fail to engage brain regions necessary for social-contextual inference and executive monitoring under negative feedback conditions.

Decision Phase: Cooperative Partner Condition

During the decision phase under the cooperative partner condition, the MCI group showed significantly reduced activation in the right SFG (MNI: 32, 60, 9; k = 141; T = 4.75; p < 0.001) and the left inferior frontal gyrus, opercular part (IFGoper; MNI: -56, 20, 38; k = 89; T = 4.56; p = 0.02), compared to the NHC group (**Fig. 2C, Tab. 3**). Both regions are part of the CEN [33], with the SFG involved in working memory and top-down control [32], and the IFGoper playing a role in language-related executive functions and inhibition. The reduction in activation during the decision phase—despite increased activation during feedback—suggests that MCI participants may struggle to maintain stable recruitment of cognitive control resources when making trust-related choices, even in cooperative contexts.

Decision Phase: Non-Cooperative Partner Condition

In the non-cooperative partner condition during the decision phase, MCI participants showed significantly reduced activation in both the left inferior frontal gyrus, pars triangularis (IFGtri; MNI: -40, 42, 4; k = 181; T = 4.54; p < 0.001) and the right SFG (MNI: 22, 50, 4; k = 101; T = 4.46; p = 0.01) compared to the NHC group (**Fig. 2D, Tab. 3**). The IFGtri is part of the broader inferior frontal cortex and has been associated with strategic planning and higher-level cognitive control during socially complex decisions [34]. Taken together, these decision-phase results support the interpretation that under increased cognitive load and uncertainty—especially when facing a potentially untrustworthy partner—older adults with MCI have difficulty engaging frontal networks involved in trust regulation and social judgment.

2.5 PE-Modulated Activation and Functional Connectivity

PE-Modulated Activation

During the feedback phase, model-based fMRI analyses were conducted to identify brain regions whose activity was modulated by trial-by-trial PE values. In the cooperative partner condition, the MCI group showed significantly greater PE-modulated activation in the right fusiform (MNI: 18, -62, -3; k = 67; T = 4.97; p = 0.05) than the NHC group (**Fig. 3A, Tab. 4**). The fusiform gyrus, which is part of the ventral visual pathway, plays a crucial role in high-level visual processing [35]. According to meta-analytic evidence, it also contributes to PE tracking in socially relevant contexts, which guides adaptive behavior [36]. This result suggests that MCI participants may recruit this region more strongly to compensate for cognitive demands when updating trust under cooperative conditions.

In contrast, in the non-cooperative partner condition, MCI participants exhibited significantly reduced PE-modulated activation in the right SFG (MNI: 10, 8, 69; k = 66; T = 4.63; p = 0.05) relative to the NHC group (**Fig. 3B, Tab. 4**). The SFG is implicated in top-down control processes and PE-based belief updating within the CEN [32]. Reduced activation in this area reflects diminished responsiveness to negative social feedback, which likely contributes to impaired trust recalibration.

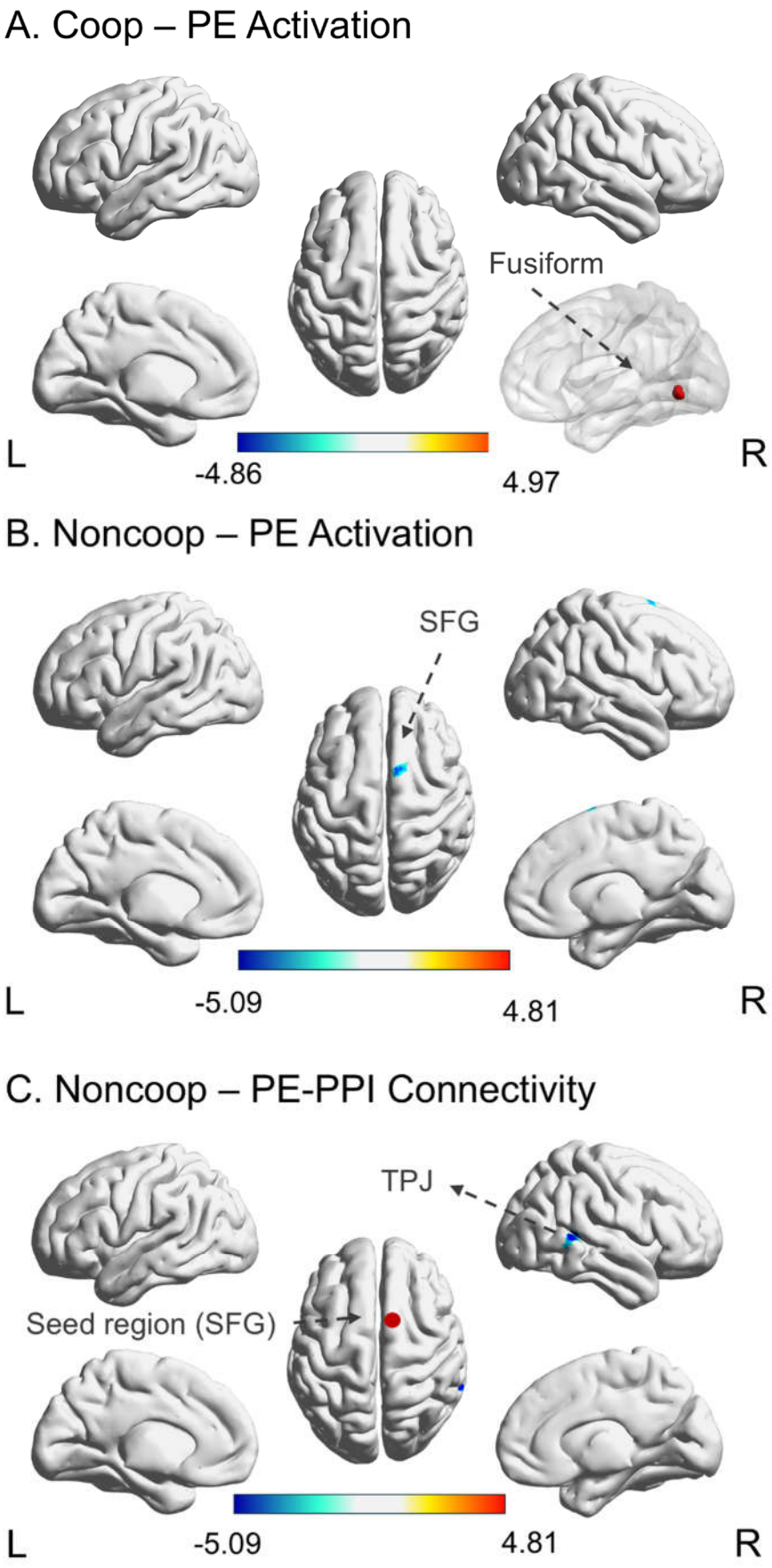

Figure 3. Prediction error (PE)-modulated activation and functional connectivity results. A. PE-

modulated activation – cooperative partner. Compared to the NHC group, the MCI group showed significantly greater PE-modulated activation in the right Fusiform during interactions with the cooperative partner. **B. PE-modulated activation – non-cooperative partner.** Under the non-cooperative partner condition, the MCI group exhibited significantly greater PE-modulated activation in the right superior frontal gyrus (SFG) relative to the NHC group. **C. PE-modulated psychophysiological interaction (PPI) – non-cooperative partner.** The MCI group displayed significantly reduced PE-modulated functional connectivity between the right SFG (seed region) and the right temporoparietal junction (TPJ) compared to the NHC group during non-cooperative interactions. All statistical maps are projected on a standard MNI surface brain template. Thresholding was applied at $p < 0.001$ (voxel-level, uncorrected) and $p < 0.05$ (cluster-level, FWE corrected). Color bars represent t-values; L = left hemisphere, R = right hemisphere.

Table 4 Significant clusters from group-level prediction error (PE)–modulated activation and psychophysiological interaction (PPI) analyses during the feedback phase.

	MNI	K	T	p	Hemisphere	region
Activation						
Cooperative (positive)	18 -62 -3	67	4.97	0.05	R	Fusiform
Non-cooperative (negative)	10 8 69	66	4.63	0.05	R	SFG
PPI						
Non-cooperative (negative)	60 -42 8	300	5.01	<0.001	R	STG
	14 -75 -28	90	4.69	0.02	R	CRB

Note: Coordinates are reported in Montreal Neurological Institute (MNI) space. *k* = cluster size in voxels; *T* = peak *t*-value; *p* = cluster-level family-wise error (FWE) corrected *p*-value. L = left hemisphere; R = right hemisphere.
Abbreviations: SFG = superior frontal gyrus; STG = superior middle temporal gyrus; CRB = cerebellum.

Psychophysiological Interaction Results

PPI analyses were conducted to examine functional connectivity patterns modulated by PE during the feedback phase. The right SFG, identified from PE-modulated activation under the non-cooperative condition, was selected as the seed region. Results revealed that, compared to NHC participants, the MCI group showed significantly reduced PE-modulated functional connectivity between the right SFG and the right superior temporal gyrus (MNI: 60, -42, 8; k = 300; T = 5.01; p < 0.001), a region also

belonging to the TPJ [27] (**Fig. 3C, Tab. 4**). Additional reductions in connectivity were observed in the right cerebellum (MNI: 14, -75, -28; k = 90; T = 4.69; p = 0.02). The SFG and TPJ are core nodes of the CEN and DMN, respectively [28,30], and their interaction is essential for integrating executive control and social cognitive processes such as mentalizing and perspective-taking [37].

Impairments in this connectivity suggest that MCI participants may have difficulty coordinating executive and social systems when processing PE signals in adverse social contexts. As a result, they may fail to update beliefs about untrustworthy partners, leading to persistent overtrust behavior and reduced behavioral flexibility.

3. Discussion

3.1 Overview of Findings

Our study combined computational modeling and task-based fMRI to investigate the psychological and neural alterations underlying trust dynamics in older adults with MCI. At the behavioral level, older adults with MCI exhibited a similar pattern of trust behavior to healthy controls when interacting with cooperative partners. In contrast, they demonstrated slower trust reduction, more negative PE, lower learning rates, and greater interference during interactions with non-cooperative partners. These behavioral findings were accompanied by dissociable neural responses. During cooperative interactions, MCI participants exhibited increased activation in the CEN regions such as the right MFG, and in the DMN regions such as the right precuneus and TPJ. During non-cooperative interactions, however, they showed decreased activation in the SFG and left middle temporal gyrus. Consistently, model-based fMRI analyses revealed increased PE-modulated activation in the right fusiform in the MCI group during cooperative feedback, but decreased PE-modulated activation in the right SFG and reduced connectivity between the right SFG and the right TPJ during non-cooperative feedback. These results suggest that while older adults with MCI can compensate for cognitive deficits in supportive interactions, their impaired executive and social cognition limits the ability to transform the probability of betrayal (affect) into updated expectations (motivation), leading to sustained overtrust in risky social contexts.

3.2 Neural Compensation During Cooperative Interactions

As predicted, older adults with MCI performed similarly to healthy controls when interacting with cooperative partners. Computationally, learning rates and PE values were comparable across groups

under these conditions. Neurally, however, MCI participants exhibited greater activation than controls in key CEN and DMN regions—including the right MFG, precuneus, and TPJ—suggesting functional compensation. The MFG, located within the dlPFC, is essential for behavioral flexibility and updating decision strategies [28]. A recent meta-analysis also demonstrated the involvement of the dlPFC in PE processing during reward learning tasks [38], consistent with our finding of increased PE-modulated activation in the right MFG during cooperative feedback.

The precuneus and TPJ are central DMN nodes involved in social cognition and self-referential processing [30,31,38]. Their increased engagement in the MCI group may reflect enhanced reliance on mentalizing to maintain positive expectations about others. Together, these results suggest that older adults with MCI are capable of drawing on additional executive and social-cognitive resources to support trust formation in low-conflict situations.

This interpretation is in line with prior research showing compensatory brain activation in MCI populations across various domains, including memory [40], activities of daily living [41], and theory-of-mind tasks [42]. Such compensation reflects the brain's plasticity and capacity for functional adaptation despite underlying degeneration [43]. Our findings extend this literature by demonstrating that MCI-related compensation also supports adaptive social behavior. Importantly, these compensatory mechanisms may serve as targets for interventions to bolster social functioning in early-stage neurodegeneration.

3.3 Impairments in Trust Updating During Non-Cooperative Interactions

As hypothesized, MCI participants exhibited significantly impaired behavior when interacting with non-cooperative partners. They demonstrated a slower reduction in trust, elevated PE signals, and lower learning rates compared to controls. These behavioral deficits were accompanied by diminished neural responses. During the feedback phase, MCI participants showed reduced activation in the SFG and middle temporal gyrus—regions linked to conceptual integration [31] and theory of mind [27]. During decision-making, they also showed reduced activation in the right SFG and inferior frontal gyrus, consistent with impaired engagement of cognitive control systems under elevated uncertainty [44].

The computational model further revealed increased interference between partner representations in the MCI group, suggesting difficulty in maintaining distinct mental models across changing social

contexts. Correlations between this parameter and executive function scores support its interpretive validity. These deficits are consistent with prior studies showing that older adults with MCI are more vulnerable to scams and social manipulation [2,45]. By failing to reduce trust even in the face of repeated betrayal, MCI individuals may be especially prone to exploitation in real life. Our findings underscore the importance of recognizing trust behavior as a potential early marker of social dysfunction in this population.

3.4 Disrupted PE-Driven Network Interactions

In addition to altered activation, MCI participants also showed impaired PE–modulated functional connectivity during feedback. Specifically, PPI analyses revealed reduced connectivity between the right SFG and the right TPJ under non-cooperative partner conditions. The SFG and TPJ are core nodes of the CEN and DMN, respectively [29,32], and their interaction supports the integration of top-down control with social inference [37]. This SFG–TPJ connectivity is thought to be crucial for generating context-sensitive mental models of others during uncertain or ambiguous interactions.

Reduced PE-modulated connectivity in the MCI group suggests a breakdown in this executive–social interface, consistent with their observed failure to revise expectations under threat. Although MCI participants may compensate within isolated regions during cooperative interactions, their ability to flexibly coordinate across large-scale networks appears limited under negative social contingencies. These findings highlight PE-based connectivity as a mechanistic marker of vulnerability in social decision-making, particularly when trust must be dynamically recalibrated in response to betrayal.

3.5 Differences in Initial Trust between One-and Multi-round Trust Game

Interestingly, we did not find significant group differences in initial trust during the first round of the MTG. This contrasts with previous findings showing reduced trust propensity in MCI using one-round paradigms [12]. One likely explanation is that trust decisions in the MTG reflect a mix of trust propensity and instrumental trust—that is, expectations about long-term cooperation [69]. In repeated interactions, betrayal is not final, and participants may perceive greater control or reversibility, reducing reliance on affective cues in early trials.

Moreover, our computational model indicated no group differences in risk sensitivity, and parameter recovery confirmed model validity [50]. These findings suggest that the observed deficits in

MCI are less driven by baseline trust (trait) and more by impaired updating based on social feedback. This distinction between static and dynamic trust mechanisms may explain inconsistencies across paradigms and highlights the unique contribution of MTG-based approaches.

Limitations and Future Directions

Several limitations should be acknowledged. First, our computational model was validated indirectly via correlations with neuropsychological and behavioral measures. Future studies should include task-based assessments of affect (e.g., emotional arousal [46]), motivation (e.g., reward sensitivity [47]), and social cognition (e.g., theory of mind [42]) to directly map model parameters to psychological constructs. Second, although our partner manipulation was effective, real human partners may produce more nuanced responses. Future studies could simulate realistic trustee behavior using large-scale behavioral datasets [22]. Third, our design did not include real-life social functioning measures. Including instruments like the Social Participation Questionnaire [48], Social Engagement Scale [49], or Lubben Social Network Scale [50] could clarify how trust deficits in MCI relate to everyday social vulnerability. Despite these limitations, our study offers novel insights into the dynamic mechanisms of trust in cognitively vulnerable populations. It demonstrates how behavior, computation, and brain connectivity jointly contribute to adaptive social learning and where these processes may break down.

3.6 Conclusion and Practical Implications

In sum, this study combined a MTG, computational modeling, and fMRI to examine how trust dynamics are impacted by MCI. The results reveal a dissociation between preserved behavior and compensatory activation under cooperative conditions and impaired learning, reduced activation, and weakened connectivity under non-cooperative conditions. These impairments likely limit the ability of individuals with MCI to update expectations and reduce trust when facing betrayal.

Our findings have practical implications for caregivers, clinicians, and policymakers. Caregivers should monitor shifts in trust behavior as early warning signs of vulnerability. Clinicians could incorporate social decision-making tasks into assessments. Policymakers should consider structural safeguards to reduce the exploitation risk for older adults with cognitive impairment. By identifying the mechanisms underlying trust dysregulation, we take a step toward more targeted interventions that support autonomy and social safety in aging populations.

4. Methods

4.1 Participants

Eighty-nine older adults were recruited from community centers in Shenzhen, China. Following neuropsychological screening and fMRI quality control, three participants were excluded due to excessive head motion, resulting in a final sample of 86 participants: 45 in the NHC group and 41 in the MCI group.

All participants were right-handed, had normal or corrected-to-normal vision, and reported no history of neurological, psychiatric, or head trauma conditions. The two groups did not differ significantly in demographic characteristics. The MCI group had a mean age of 65.98 years (SD = 7.87) and a mean education level of 9.79 years (SD = 3.72), with 28 females. The NHC group had a mean age of 65.05 years (SD = 6.46) and a mean education level of 10.10 years (SD = 3.12), with 31 females.

Written informed consent was obtained from all participants. The study protocol was approved by the Institutional Review Board of Shenzhen University (PN-202200120) and conducted in accordance with the Declaration of Helsinki. Participants were financially compensated based on their performance in the MTG, receiving between 56 and 82 Chinese Yuan (approximately 7.89–11.55 USD).

To ensure task engagement and ecological validity, only participants who reported in the post-experiment questionnaire that they believed the MTG partners were real individuals were included in the final analyses.

4.2 Diagnosis of mild cognitive impairment

Participants were classified into the MCI or NHC group based on a structured, multi-step diagnostic protocol adapted from Petersen's criteria for MCI [51]. Individuals with dementia or significant functional impairment were excluded.

Cognitive status was initially screened using the Chinese version of the Mini-Mental State Examination (MMSE) [52]. A minimum score of 24 was required to rule out global cognitive impairment consistent with dementia. Functional independence was assessed using the combined Chinese versions of the Physical Self-Maintenance Scale and the Instrumental Activities of Daily Living (ADLs) scale [53]. Only participants who scored zero—indicating no impairment in daily functioning—were included.

Domain-specific cognitive performance was assessed using an extensive battery of standardized

neuropsychological tests covering five cognitive domains: memory, executive function, attention, language, and visuospatial ability. Memory was assessed using the Auditory Verbal Learning Test (AVLT) [54], Rey-Osterrieth Complex Figure Recall Test (Rey-Recall) [55], and the Digit Span Test (DST) [56]. Executive function was evaluated using the Trail Making Test Part B (TMT-B) [57] and the Stroop Test [58]. Attention was measured using the Trail Making Test Part A (TMT-A) [58] and the Symbol Digit Modalities Test (SDMT) [59]. Language abilities were assessed with the Category Verbal Fluency Test (CVFT) [60] and the Boston Naming Test (BNT) [61]. Visuospatial ability was evaluated using the Rey-Osterrieth Complex Figure Copy Test (Rey-Copy) [55] and the Clock Drawing Test (CDT) [62].

A cognitive domain was considered impaired if the participant's performance on both tests within that domain was at least 1.5 standard deviations below age- and education-adjusted normative means, based on Chinese population norms [63]. Participants who met this criterion in at least one domain, while maintaining an MMSE score ≥ 24 and intact ADLs, were classified as having MCI. Participants with normal cognitive performance across all domains were assigned to the NHC group. This classification procedure ensured objective and reliable group assignment based on established diagnostic benchmarks.

Experimental Paradigm

Participants completed a multi-stage experimental protocol involving both behavioral assessments and neuroimaging. Within three months prior to the fMRI session, all participants completed an extensive neuropsychological battery at the research facility to determine group classification (MCI vs. NHC).

On the day of the MRI session, participants performed three behavioral tasks in a fixed sequence before entering the scanner. The sequence included: (1) a one-shot dictator game (results reported in a separate study [12,64]); (2) either a one-shot lottery game (assessing risk propensity) or a one-shot trust game (see Supplementary Materials S1 and S2 for task details); and (3) whichever task was not administered in the second slot. The order of the lottery and trust games was counterbalanced across participants by gender and diagnostic group.

The neuroimaging session consisted of four sequential components: (i) an 8-minute resting-state functional MRI scan; (ii) an 18-minute MTG performed during task-based fMRI acquisition; (iii) a 7-minute high-resolution T1-weighted structural MRI scan; and (iv) a 5-minute T2-weighted MRI scan

for clinical assessment. Following the scan, participants completed a debriefing questionnaire to assess their comprehension of the task instructions and their subjective psychological state during the experiment. Critically, this questionnaire included items verifying whether participants believed the partners in the one-shot trust game and the MTG were real individuals. Only participants who indicated belief in the partner manipulation were included in the final sample for analysis.

4.3 Experimental paradigm

A modified MTG examined trust dynamics in older adults [8]. The task was programmed in MATLAB (2021b) using Psychtoolbox [65]. On each trial, participants' investment decisions and response times were recorded. In each round, participants interacted with one of two virtual partners, who were presented randomly and identified by the surnames "Wang" and "Li." Assignment of partner roles (i.e., which partner served as cooperative or non-cooperative), the order of task phases, and the hand used for responses (left vs. right) were counterbalanced across participants by diagnostic group (MCI vs. NHC) and gender to control for potential confounds.

Cooperative and non-cooperative partner behaviors were systematically manipulated [66]. Initially, both partners had equal return probabilities of 33% for each of three return levels. Cooperative partners could return 100%, 150%, or 200% of the participant's investment, while non-cooperative partners could return 100%, 75%, or 50%. For cooperative partners, increases in participant investment raised the probability of the 200% return by 10% and simultaneously reduced the 100% and 150% return probabilities by 5% each. This adjustment continued until the maximum probability for the highest return reached 93%. For non-cooperative partners, increasing investments similarly raised the probability of the 50% return by 10% while decreasing the other two probabilities by 5% each, also capped at 93%.

Each trial began with a 2-second fixation cross, followed by the partner's surname displayed for 1.5 seconds (Fig. 4). Participants then selected an investment amount from five randomly ordered options: no investment (0 points), low (1–3 points), medium (4–6 points), high (7–9 points), or full investment (10 points). Specific values within each range were randomly assigned per trial. Using one hand, participants moved the selection frame left or right with designated buttons and confirmed their

choice with the other hand. Once confirmed, the selection frame turned red and the choice was locked in.

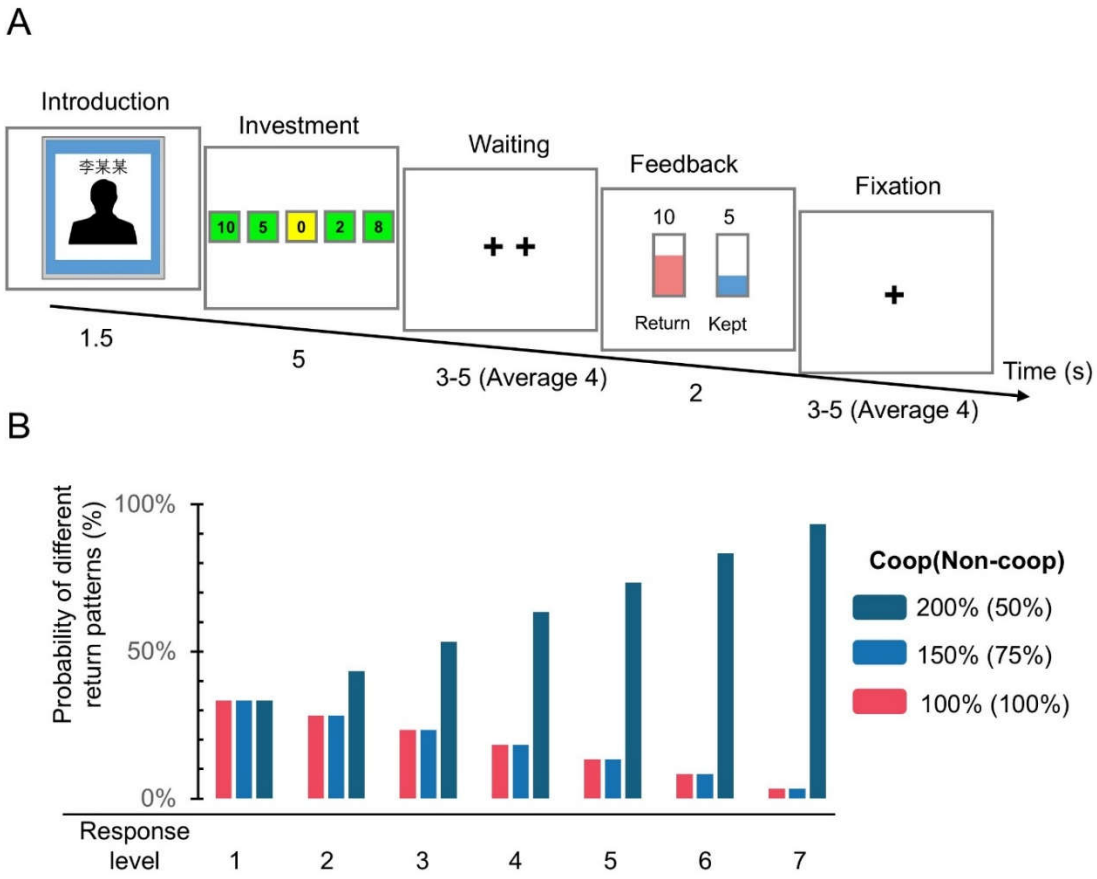

Figure 4. Task design of the multi-round trust game (MTG). A. Task schematic of the MTG. Each round begins with the display of a partner's surname. Participants (trustors) are told they are interacting with two distinct human trustees, though both are controlled by a computer algorithm. One trustee is programmed to behave cooperatively; the other non-cooperatively. Across 60 rounds (30 per partner), participants choose an investment amount from five options presented in random order: none (0 points), low (1–3), medium (4–6), high (7–9), or full (10). The investment is tripled and sent to the trustee, who returns a portion. Cooperative trustees return 100%, 150%, or 200% of the investment; non-cooperative trustees return 100%, 75%, or 50%. **B. Dynamic adjustment of return probabilities.**

The invested amount was then tripled and transferred to the partner, who determined how much to return. After a jittered delay of 3 to 5 seconds (mean = 4 s), the return amount was shown using two colored bars: red for the amount returned and blue for the amount retained by the partner. A second jittered fixation screen (3–5 seconds) followed each trial. All intervals were pseudo-randomly drawn from five durations (3, 3.5, 4, 4.5, 5 seconds) and optimized to reduce correlation across experimental conditions.

The full task consisted of 60 trials, each involving a randomized interaction with one of the two virtual partners. Partner presentation followed a pseudo-random sequence, with each partner appearing in 30 trials. The task was divided into two phases of 30 trials each. To control for confounding variables, partner assignment (cooperative vs. non-cooperative), task phase order, and response hand mapping were fully counterbalanced across gender and group. For example, one male MCI participant might complete Phase 1 followed by Phase 2 with "Li" as the cooperative partner using left-hand selection and right-hand confirmation, while another participant might complete the reverse order with the same partner mapping—ensuring full coverage of all eight possible counterbalancing permutations.

To ensure task comprehension, participants completed a structured practice session before entering the scanner. First, they solved hypothetical payoff calculations; participants who responded incorrectly repeated the task until they achieved full accuracy. Next, they completed 15 practice trials with randomized, computer-generated feedback from fictitious partners to familiarize themselves with the game mechanics. To enhance believability, participants were explicitly informed that their MTG partners were real older adults from the Shenzhen community. They were also told that their final payment would be based on performance in the formal task, using a fixed exchange rate (10 points = 1 CNY).

4.4 Experimental procedure

Participants followed a multi-stage experimental protocol. Within three months prior to scanning, they completed a comprehensive neuropsychological battery at the research facility.

On the day of the MRI session, and prior to scanning, participants completed three behavioral tasks in a fixed sequence: (1) a one-shot dictator game (data from this task are reported in a separate study [12,64]); (2) either a one-shot lottery game (measuring risk propensity) or a one-shot trust game (see Supplementary Materials S1 and S2 for task details); and (3) the remaining task. The order of the lottery game and trust game was counterbalanced across gender and diagnostic group.

The neuroimaging session included four sequential components: (i) an 8-minute resting-state fMRI scan, (ii) an 18-minute MTG performed during fMRI acquisition, (iii) a 7-minute high-resolution structural MRI (T1-weighted), and (iv) a 5-minute clinical T2-weighted MRI scan for routine medical assessment. Following the scan, participants completed a debriefing questionnaire that assessed their understanding of the task instructions and their psychological state during the experiment. Critically, the

questionnaire included items designed to verify whether participants believed that the partners in the one-shot trust game and the MTG were real individuals. Only those who affirmed belief in the partner manipulation were retained in the final sample. Participants then received monetary compensation based on their performance in the MTG.

4.5 Computational modeling

According to the neuropsychoeconomic model of trust [9], trust behavior is shaped by four key components: affect, motivation, executive cognition, and social cognition. To quantitatively characterize dynamic trust behavior and assess abnormalities in these components among older adults with MCI, we employed a belief-based reinforcement learning model [23] tailored to participants' choices in the MTG.

Previous studies have shown that individuals learn at different rates when they experience positive or negative outcomes [67]. Thus, two separate learning rates—α^{good} (range 0 to 1, initial value = 0.5) and α^{bad} (range 0 to 1, initial value = 0.5)—were included to represent the learning rates associated with cooperative (good) and non-cooperative (bad) partners, respectively. Initial expected value (EV) about cooperative partner returns (Q_1^{good}) and about non-cooperative partner returns (Q_1^{bod}) equal to 0.5, indicating no bias. Interference factor (η, range 0 to 1, initial value = 0.5) accounted for cognitive spillover effects due to the randomized presentation of partners (cooperative / non-cooperative) in the MTG. This parameter quantified how belief updates about one partner affected updates about the other, and served as an index of executive control in maintaining partner-specific evaluations. The corresponding value updating formula was

$$Q_{t+1}^{good} = Q_t^{good} + \alpha^{good} \times \delta_t^{good} + \eta \times (Q_{t+1}^{good} - Q_{t+1}^{good})$$

$$Q_{t+1}^{bad} = Q_t^{bad} + \alpha^{bad} \times \delta_t^{bad} + \eta \times (Q_{t+1}^{bad} - Q_{t+1}^{good})$$

Participants made investment decisions based on updated EV and individual biases in the decision phase. First, the expected returns EU(x) for each possible investment amount x were calculated as follows:

$$EU(x) = (10 - x) + 3x \cdot Q_t$$

Utility U(x), which incorporates motivational sensitivity, risk sensitivity, and subjective preference, was then calculated using the following transformation:

$$U(x) = EU(x)^{\gamma} - \lambda \cdot \sigma^2 \cdot (\mathrm{x}/10)^2$$

The function included two key parameters: Reward sensitivity exponent (γ, range 0 to 1, initial value = 0.5), representing motivational sensitivity through a non-linear transformation of expected utility. This captures diminishing marginal utility or increased sensitivity to larger rewards. The risk sensitivity parameter (λ, range 0 to 3, initial value = 1.5) adjusted expected utility by penalizing the variance of partner returns. Higher values of λ indicated greater risk aversion, reflecting higher expected costs of partner betrayal. σ^2 captures trial-wise uncertainty in partner returns within our experimental setting: it is the variance of the feedback (return-ratio) distribution determined by partner type (cooperative vs. non-cooperative) and response level, computed from discrete outcomes and their probabilities probs. Higher σ^2 indicates more volatile, less predictable returns on that trial and increases the influence of risk sensitivity (λ); lower σ^2 indicates concentrated probability on a specific return mode and reduce the influence of risk sensitivity.

A SoftMax decision function translated these value estimates into probabilistic investment decisions.

$$P(x) = exp(\boldsymbol{\beta} \cdot \boldsymbol{U}(\boldsymbol{x}))/\sum_{x\prime} exp(\boldsymbol{\beta} \cdot \boldsymbol{U}(\boldsymbol{x}'))$$

The inverse temperature parameter (β, range 0 to 10, initial value = 5), which controlled the balance between exploration and exploitation, with higher values reflecting more deterministic decisions and lower values indicating greater randomness, thus representing participants' social cognition, i.e., their ability to construct mental models of partners.

Individual model parameters—including learning rates (αgood, αbad), inverse temperature (β), reward sensitivity (γ), risk sensitivity (λ), and interference (η)—were estimated for each participant using maximum likelihood estimation (MLE). To evaluate the contribution of each parameter to model performance, restricted model comparisons were conducted. In each reduced model, one parameter from the full model was fixed at its initial value, while the remaining parameters were freely estimated. Each reduced model was then independently refitted to participants' behavioral data.

Model fit for each reduced version was compared to that of the full model using two standard information criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Paired-sample *t*-tests were conducted to statistically compare AIC and BIC values between each reduced model, the full model, and a null model that included no learning or social-cognitive structure.

These comparisons allowed us to assess whether fixing a given parameter significantly reduced model fit, and therefore whether that parameter meaningfully contributed to explaining observed behavior.

Importantly, in every reduced model, only one parameter was held constant at a time, allowing all other parameters to vary freely. This ensured that the impact of each parameter could be isolated while controlling for potential interactions among the remaining components. This parameter sensitivity analysis [68] provided a systematic method for quantifying the relative importance of each factor in capturing individual differences in trust learning and decision-making across cooperative and non-cooperative contexts.

4.6 Parameter recovery analysis

To assess the reliability and identifiability of the model parameters, we conducted a parameter recovery analysis (see Supplementary Materials S3). Synthetic behavioral datasets were generated using known parameter values, and the model was then re-fitted to these simulated datasets using the same estimation procedure applied to empirical data. Recovery accuracy was evaluated by computing correlations between the true and recovered parameter values. High correspondence confirmed that each parameter could be robustly estimated and reliably distinguished from the others [68].

4.7 Behavioral analysis

Independent-sample *t*-tests or Mann–Whitney rank-sum tests (when the Kolmogorov–Smirnov test revealed that assumptions of normality had been violated) were conducted using MATLAB 2021b (www.mathworks.com) to statistically evaluate group differences between older adults with MCI and NHCs in demographic characteristics and neuropsychological test scores. A two-tailed significance level ($p < 0.05$) was applied for all statistical analyses.

The Kolmogorov–Smirnov test indicated that mean investment values significantly deviated from normality, while the distribution of RTs did not. Accordingly, an Aligned Rank Transform ANOVA was used to analyze mean investment, and a standard repeated-measures ANOVA was used to analyze RTs, with both group (MCI vs. NHC) and partner condition (cooperative vs. non-cooperative) entered as factors. Partial eta squared (η^2_p) was reported as the effect size for all ANOVA results. When a significant interaction effect was observed, post hoc comparisons were conducted using Wilcoxon rank-sum tests for non-normally distributed variables (i.e., mean investment), and independent-samples *t*-tests for

normally distributed variables (i.e., RTs). Effect sizes were reported as *r* for rank-sum tests and Cohen's *d* for *t*-tests.

Because participants selected investment amounts from five predefined options, group differences (MCI vs. NHC) on each trial were assessed using Wilcoxon rank-sum tests. To capture group differences in initial trust, the first trial of the MTG was analyzed separately. In addition, trial-by-trial investment behavior was examined separately for cooperative and non-cooperative partner interactions.

To address multiple comparisons across consecutive trials, a cluster-based permutation correction procedure was applied. For each observed cluster of significant differences, its size (defined as the number of contiguous significant trials) was compared against a null distribution generated through 10,000 random permutations of group labels. This yielded corrected *p*-values at the cluster level. The same analytical approach was used to test for group differences in trial-by-trial PE values for cooperative and non-cooperative partner conditions. The resulting significant clusters identified specific segments of the MTG during which investment and PE values differed reliably between the MCI and NHC groups.

To clarify the cognitive and psychological significance of the computational model parameters, correlation analyses were conducted between each estimated parameter and its corresponding neuropsychological or behavioral measure. Specifically, learning rates between (α good, α bad), inverse temperature (β), reward sensitivity (γ), risk sensitivity (λ), and interference factor (η) were correlated with individual difference measures targeting affect (one-shot lottery game), motivation (a subscale of the Geriatric Depression Scale, GDS), social cognition (one-shot dictator game), and executive cognition (Trail Making Test Part B and the Stroop test).

As the Kolmogorov–Smirnov test revealed that all model parameters significantly violated assumptions of normality, Spearman's rank-order correlations were used for all analyses. Significant associations between parameters and corresponding psychological measures were interpreted as evidence for the cognitive validity and interpretability of the model.

Finally, group differences on two MTG-related debriefing questionnaire items—(1) whether participants believed their partners were real individuals, and (2) whether they could distinguish between the two partners in the task—were tested using chi-square analyses.

4.8 Image Acquisition.

Neuroimaging data were acquired using a 3T SIEMENS MAGNETOM Prisma scanner equipped with a 64-channel head coil at Shenzhen University. High-resolution structural brain images were collected using a T1-weighted 3D MPRAGE sequence (TR = 1.9 s, TE = 2.23 ms, flip angle = 8°, field of view [FOV] = 220 × 220 mm^2, voxel size = 1.1 × 1.1 × 1.1 mm^3, 224 slices). Task-based fMRI images were acquired using a multiband EPI sequence (TR = 1.5 s, TE = 30 ms, flip angle = 75°, FOV = 192 × 192 mm^2, voxel size = 2 × 2 × 2 mm^3, 72 slices, slice thickness = 2 mm, multiband factor = 4, acceleration factor = 2). The total number of volumes acquired was 660 for the task-based scan.

4.9 Image Preprocessing

Functional and structural neuroimaging data were preprocessed using Statistical Parametric Mapping software (SPM12) [69] implemented in MATLAB 2021b (www.mathworks.com). Preprocessing followed standard procedures and included the following steps: (1) Realignment: Functional images were realigned to correct for head motion across time. (2) Slice timing correction**:** Temporal alignment was applied to adjust for differences in acquisition time across slices due to interleaved scanning. (3) Co-registration: The high-resolution structural T1-weighted image was co-registered to the mean functional image from the realignment step to ensure anatomical alignment between structural and functional data. (4) Segmentation: Co-registered structural images were segmented into gray matter, white matter, and cerebrospinal fluid (CSF) using affine regularization based on the International Consortium for Brain Mapping (ICBM) template for European brains. (5) Normalization: Functional images were spatially normalized to Montreal Neurological Institute (MNI) space using deformation fields derived from the segmentation step. Functional volumes were resampled to an isotropic voxel size of 3 × 3 × 3 mm^3. (6) Smoothing: The normalized functional images were smoothed using an 8 mm full-width at half-maximum (FWHM) Gaussian kernel to increase signal-to-noise ratio and meet the assumptions of random field theory for subsequent statistical analyses.

4.10 Model-based functional magnetic resonance imaging analysis

First-level general linear models (GLMs) were constructed to characterize trial-by-trial neural responses associated with trust-related decision-making and belief updating processes during the MTG (Fig. 5A–F). Specifically, neural activation during the feedback phase was modeled for two experimental

conditions: interactions with cooperative versus non-cooperative partners. Trial-by-trial PEs (denoted as δ) derived from the computational model were entered as parametric modulators for each condition.

To account for potential motion-related confounds, six head motion parameters from the realignment preprocessing step were included in the GLMs as covariates of no interest. All task-related regressors (i.e., partner condition and corresponding PE modulators) were convolved with the canonical hemodynamic response function (HRF). A high-pass temporal filter with a cutoff of 1/128 Hz was applied to each voxel's time series to remove low-frequency drift and noise.

At the second level, random-effects analyses were used to examine between-group differences in brain activation during the feedback phase. Specifically, two-sample *t*-tests were conducted to compare MCI and NHC participants on brain activation associated with each partner condition, as well as on PE-modulated activation for both cooperative and non-cooperative partners.

Statistical maps were thresholded at a voxel-wise level of $p < 0.001$ (uncorrected), and a cluster-level family-wise error (FWE) correction at $p < 0.05$ was applied to control for multiple comparisons.

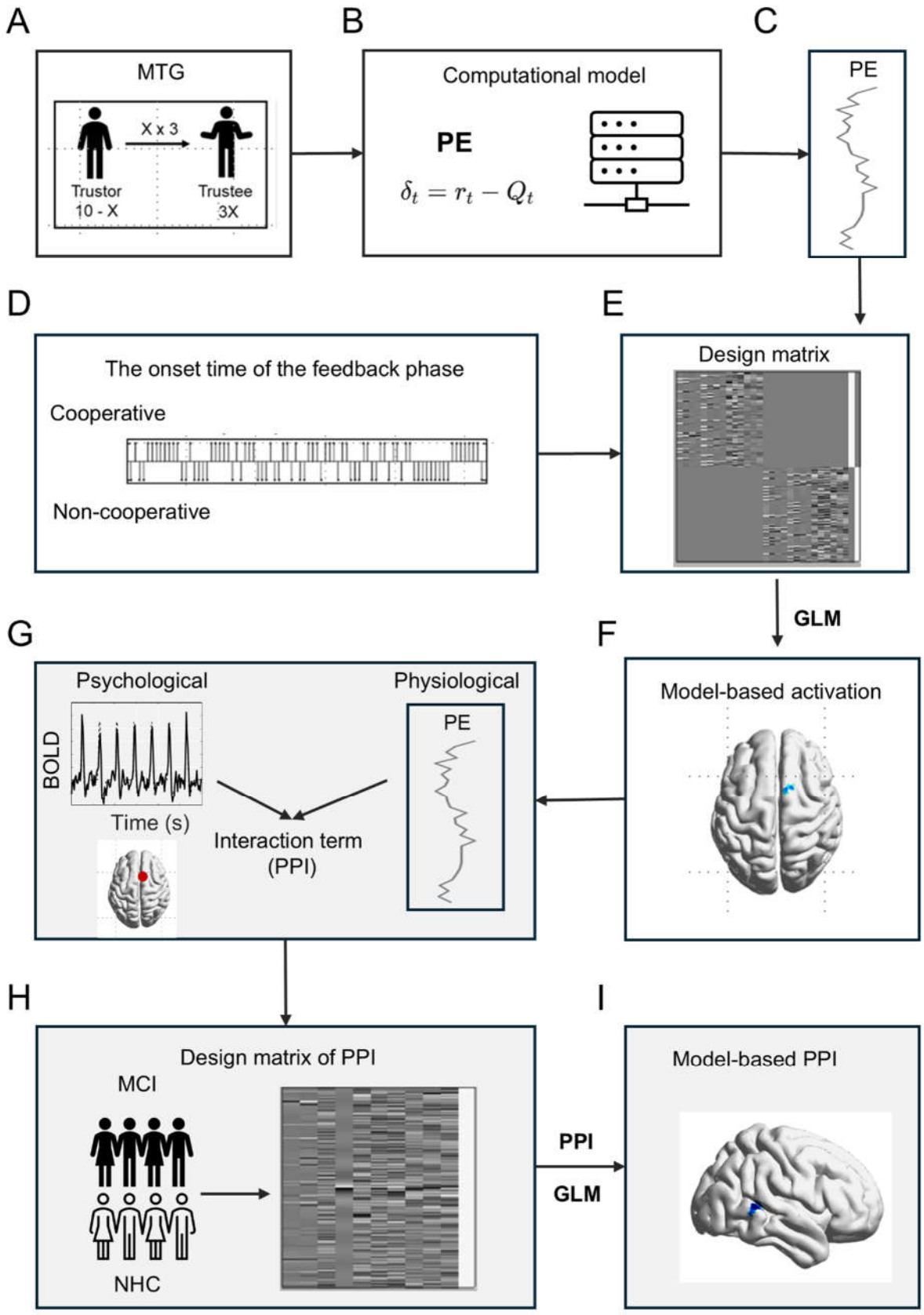

Figure 5. Procedures for model-based activation and psychophysiological interaction (PPI) analyses. A. Task design. Behavioral data were collected from each participant during the multi-round trust game (MTG), where the invested amount was tripled and returned in varying proportions by a cooperative or non-cooperative partner. **B. Computational modeling.** Participants' behavior was modeled individually using a belief-based reinforcement learning model. **C. Trial-by-trial prediction errors (T by T PE).** T by T PE were estimated for each trial. **D. Trial onset extraction.** Feedback onset

times and partner identities were extracted from experimental logs. **E. Model-based GLM construction.** General linear models (GLMs) were created using condition-specific onset times as regressors, trial-by-trial PEs as parametric modulators, and motion parameters as nuisance covariates. **F. Model-based activation analysis.** Individual-level GLMs were convolved with the canonical hemodynamic response function (HRF) to identify brain regions encoding PE signals. Group-level comparisons assessed differential PE-related activation between MCI and control participants. **G. PPI seed selection.** Regions showing significant group differences in PE-modulated activation were used as seed regions for PPI analysis. **H. PPI design matrix.** For each participant, the deconvolved BOLD signal (physiological variable), the convolved PE (psychological variable), and their interaction (PPI term) were entered into a GLM along with motion regressors. **I. PPI connectivity analysis.** At the individual level, model-based PPI analyses were performed to identify voxels whose connectivity with the seed region was modulated by PE. Group-level contrasts revealed regions with significant group differences in PE-dependent functional connectivity.

4.11 Psychophysiological interaction analysis

To examine group differences in the modulatory effects of trial-by-trial PEs on task-related functional connectivity, a generalized PPI analysis was conducted using SPM12 (**Fig. 5G–I**). Seed regions of interest (ROIs) were defined based on brain regions that showed significant between-group differences (MCI vs. NHC) in PE-modulated activation during the feedback phase. Each ROI was extracted as a sphere with a 6 mm radius centered on the peak voxel coordinates in MNI space, identified from the first-level parametric modulation analyses.

For each participant, the subject-level PPI model included three key regressors: (1) the deconvolved BOLD time series from the seed ROI (physiological regressor), (2) trial-by-trial PE values during the feedback phase (psychological regressor), and (3) the interaction term (PPI regressor), computed as the element-wise product of the physiological and psychological regressors.

Before multiplication, PE values were mean-centered and convolved with the canonical hemodynamic response function (HRF). Six motion parameters from preprocessing and task onset regressors were also included as nuisance covariates to control for motion-related and task-related confounds.

First-level GLMs were estimated for each participant to model PE-modulated changes in functional connectivity. The resulting contrast images for the PPI regressors were entered into second-level random-effects analyses. Two-sample *t*-tests were used to compare MCI and NHC groups. Statistical maps were thresholded at an uncorrected voxel-level threshold of $p < 0.001$, and a cluster-level family-wise error (FWE) correction at $p < 0.05$ was applied to control for multiple comparisons.

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Data and code availability statement

The code used in this study are publicly available at: https://github.com/yiqiqiyi/MTG_MCI, and the data can be accessed at https://pan.quark.cn/s/4cbc83ad98b1.

Declaration of Competing Interest

The authors are unaware of any conflicts of interest, financial or otherwise.

CRediT authorship contribution statement

Yiqi Chen: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Investigation, Conceptualization. Hao He: Writing – review & editing, Funding acquisition. Yiyang Ding: Investigation. Wuhai Tao: Funding acquisition, Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – review & editing. Qing Guan: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation. Frank Krueger: Conceptualization, Methodology, Supervision, Validation, Writing –review & editing.

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Supplementary Material

S1. One-shot Trust Game

A one-shot trust game (TG) was administered to assess trust propensity (TP), involving two players: a trustor and a trustee (Fig. 1A). Both players began with an initial endowment of 10 points (equivalent to 30 CNY). The trustor selected an amount (X) between 0 and 10 points to send to the trustee. The transferred amount was tripled ($3 \cdot X$) by the experimenter before being delivered to the trustee. The trustee then determined how much to return to the trustor (Y), with possible values ranging from 0 to $3 \cdot X$. Final payoffs were computed as follows: the trustor received $10 - X + Y$ points, and the trustee received $10 + 3 \cdot X - Y$ points. The amount invested by the trustor (X) served as the behavioral index of trust propensity.

To ensure task comprehension, participants completed a practice exercise in which they calculated payoffs for both roles. For example, if the trustor sent 2 points and the trustee returned 4, both would receive 12 points. If the response was incorrect, the practice was repeated until the participant responded correctly. After completing the exercise, participants were informed that they would play in the role of the trustor, while another older adult undergoing the next fMRI scan would serve as the trustee.

S2 One-shot lottery game

A one-shot lottery game was administered to assess risk propensity (Fig. 1B). Participants and a computerized system each began with an endowment of 10 points (equivalent to 30 CNY). Participants chose an amount (X) between 0 and 10 points to invest in the lottery. The invested amount was tripled ($3 \cdot X$) and passed to the computer, which randomly returned an amount ranging from 0 to $3 \cdot X$ points. The participant's final payoff was calculated as $10 - X +$ returned amount. The amount invested (X) served as the behavioral measure of risk-taking.

To ensure task comprehension, participants completed a practice trial in which they calculated hypothetical payoffs for different investment and return scenarios. For instance, if 2 points were invested and 4 were returned, the final payoff would be 12 points. Participants repeated the exercise until they responded correctly.

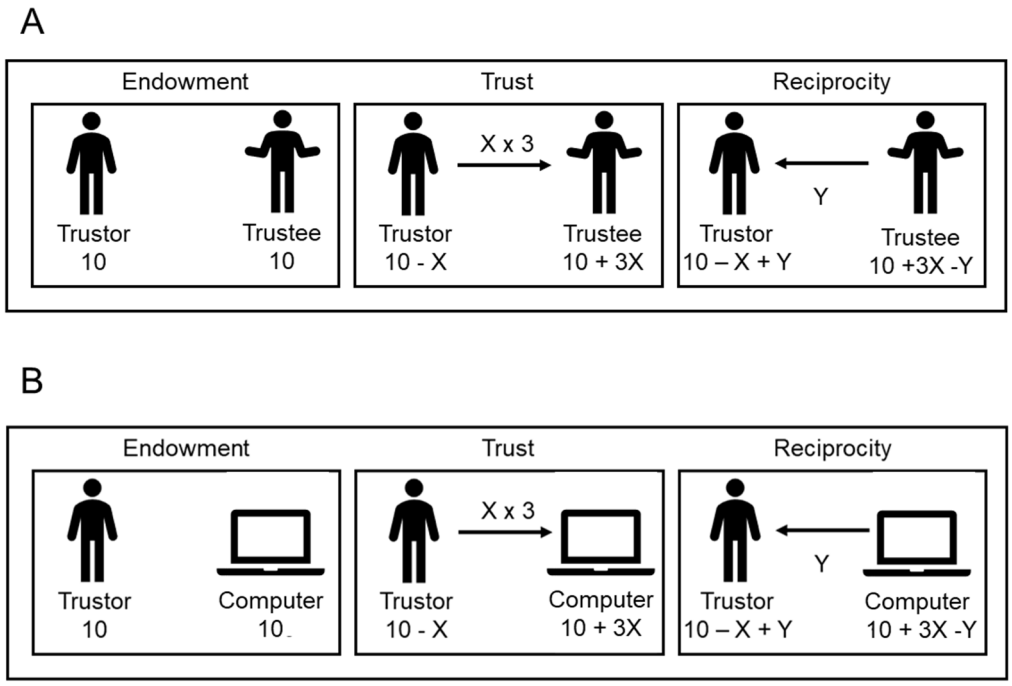

Figure 1. Task schematics for the one-shot trust and lottery games. A. One-shot trust game (TG): The participant (trustor) decides how much of their 10-point endowment (X) to send to a trustee. The transferred amount is tripled (3·X), and the trustee determines how much to return (Y). Final payoffs are calculated as: trustor = 10 − X + Y; trustee = 10 + 3·X − Y. **B. One-shot lottery game:** The participant chooses an investment amount (X) from their 10-point endowment. The invested amount is tripled and submitted to a lottery controlled by a computer, which returns a random amount from 0 to 3·X. The participant's final payoff is 10 − X + returned amount.

S3 Parameter recovery analysis

To evaluate the reliability and validity of the parameters estimated by the belief-based learning model, a parameter recovery analysis was conducted. This procedure assessed whether the model could accurately recover known parameter values from simulated behavioral data generated using predefined inputs (Wilson & Collins, 2019).

First, simulated datasets were generated based on the belief-based model described above. A total of 200 parameter sets were randomly sampled within predefined ranges to represent 200 virtual participants. These included learning rates for cooperative (αgood) and non-cooperative (αbad) partners, inverse temperature (β), reward sensitivity exponent (γ), risk sensitivity parameter (λ), and interference factor (η).

These parameters were used to simulate trial-by-trial investment behavior in the MTG. On each trial, expected utilities were computed based on the participant's current expected value (EV) (Q_t) for the partner (initially set [Q_0] to 0.5 for the first trial). A SoftMax function converted utilities into choice

probabilities, which determined investment decisions. Partner return probabilities dynamically changed based on consecutive investment behavior toward the same partner type (e.g., repeated investments toward a cooperative partner increased the likelihood of high returns). After each trial, prediction errors were computed, and Q-values were updated according to the belief-update formula described earlier.

Parameter recovery was evaluated by examining the correlation between the true parameter values used to generate synthetic data and the corresponding estimated values obtained from model fitting. Higher correlations indicate better parameter recovery and thus greater identifiability of the model parameters. This approach provides a standard and widely accepted assessment of the model's ability to recover underlying parameter values in computational modeling studies [1].

S4 Restricted model comparation and parameter recovery results

The restricted model comparisons revealed that fixing any single parameter resulted in increased Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, indicating a decline in model fit. Notably, the learning rates (αα_good, α_bad), inverse temperature (β), and reward sensitivity exponent (γ) exerted the strongest influence on model performance (see **Table 1**).

Table 1. Results of restricted model comparisons.

parameter	AIC	P value	BIC	P value
Full model	175.85		171.18	
good Learning rate (αgood)	178.53	<0.05	186.17	<0.05
bad Learning rate (αbad)	184,70	<0.01	192.22	<0.001
inverse temperature parameter (β)	207.13	<0.001	209.51	<0.001
reward sensitivity exponent (γ)	205.46	<0.001	207.78	<0.001
risk sensitivity (λ)	181.50	0.06	183.34	0.08
interference factor (η)	174.75	0.35	176.56	0.38
Null model	209.62	<0.001	213.77	<0.001

Comparison of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for the full model, reduced models (with one parameter fixed), and the null model. Higher AIC and BIC values indicate worse model fit. Significant increases in AIC/BIC reflect the relative contribution of each parameter to the model's explanatory power.

The parameter recovery analysis indicated that moderate to strong correlations were observed between the true and recovered values for most parameters, such as learning rates (α_good, α_bad), risk sensitivity (λ), and interference factor (η), indicating reasonable parameter identifiability. However, greater variability and evidence of boundary estimates were observed for inverse temperature parameter (β) and risk sensitivity (λ), suggesting that recovery accuracy for these parameters was limited. Notably, the parameters with poor recovery rates are not involved in the main results of the present study and thus do not impact the key conclusions.

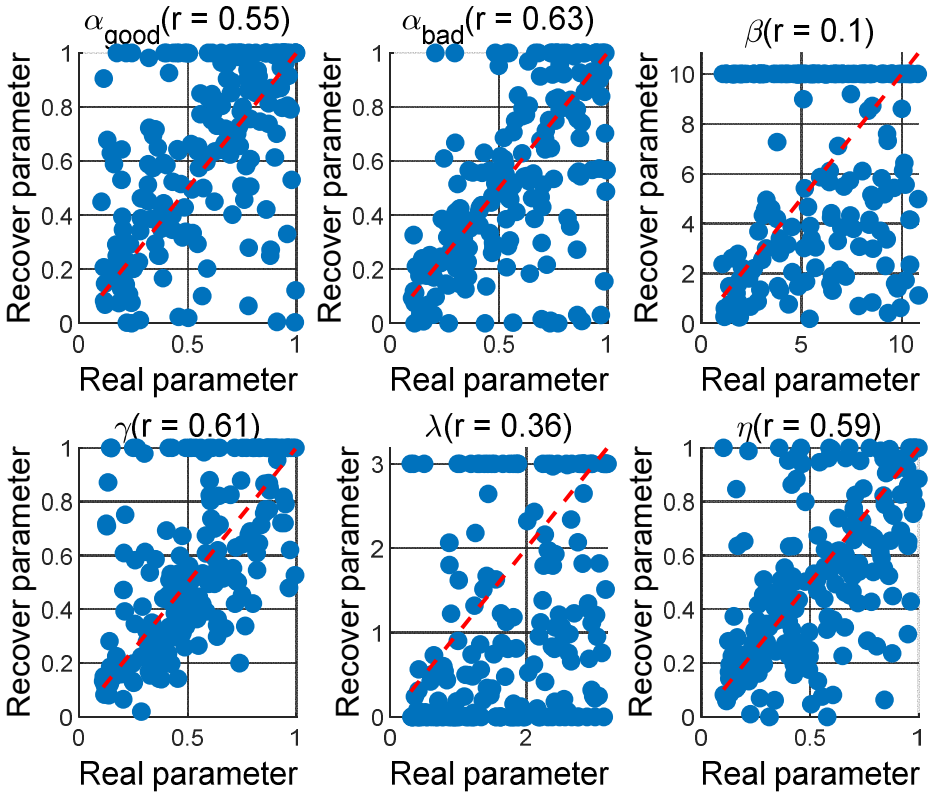

Figure 2. Parameter recovery results. Scatter plots show the relationship between the true (x-axis) and estimated (y-axis) parameter values for each model parameter. The red dashed line (y = x) indicate perfect recovery. Each point corresponds to a simulated subject. Overall, most parameters show moderate to strong correspondence between the true and estimated values, though some parameters exhibit more estimation noise and boundary effects.

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6. General Discussion

6.1 Summary of Studies and Research Questions

The primary aim of this dissertation was to clarify how MCI alters the psychological and neural mechanisms of trust. Guided by the neuropsychoeconomic framework of trust, which integrates affect, motivation, social cognition, and executive cognition, the work was structured around three central questions: (1) **Trust propensity:** Does MCI alter initial willingness to trust strangers, and which large-scale resting-state networks explain this change?; (2) **Structural underpinnings:** Do gray matter reductions in MCI underlie reduced TP, and through which psychological components do these effects operate?; and (3) **Trust dynamics:** How does MCI impact the ability to build, maintain, and withdraw trust during repeated social interactions, and what psychological and neural mechanisms explain failures to update trust?

To address these questions, three complementary experiments were conducted. Experiment 1 combined a one-shot trust game with resting-state fMRI and connectome-based predictive modeling, showing that individuals with MCI had lower TP than healthy controls, driven by heightened betrayal sensitivity and greater reliance on the SAN. In contrast, controls relied more on social cognition and DMN connectivity. Experiment 2 used structural MRI and voxel-based morphometry, revealing that atrophy in the anterior insula and thalamus predicted reduced TP in MCI, and this effect was mediated by affective sensitivity to betrayal. Experiment 3 employed a multi-round trust game with computational reinforcement-learning modeling and task-based fMRI, demonstrating that older adults with MCI behaved nearly normally in cooperative contexts through compensatory recruitment of executive and social networks, but failed to reduce trust in non-cooperative contexts, showing slower updating, larger prediction errors, reduced activation of the CEN and DMN, and disrupted executive–social connectivity.

Together, these findings provide convergent evidence that MCI reduces initial trust through affective hyper-sensitivity and impairs adaptive trust updating through social and executive dysfunction, while compensation helps preserve cooperation in supportive contexts.

6.2 Trust Propensity in MCI

The first research question asked whether MCI alters TP, and if so, which large-scale resting-state networks account for this change.

Experiment 1 addressed this question by combining a one-shot trust game with resting-state fMRI and connectome-based predictive modeling. The findings revealed that older adults with MCI exhibited reduced TP compared to healthy controls, and this difference was associated with heightened sensitivity to betrayal probability. At the neural level, the connectome-based model showed that TP in the MCI group was predicted primarily by negative networks, reflecting inhibitory influences. In particular, the SAN, associated with affective processing, was a key predictor of TP in MCI, whereas in the control group, positive network models predicted TP and implicated the DMN, linked to social cognition.

These results suggest that individuals with MCI rely more on SAN-driven affective processing when making trust decisions, while controls engage DMN-based social cognition to transform betrayal probability into reciprocity expectations. This interpretation is consistent with prior evidence that older adults with MCI show increased attention to negative social information (Berger et al., 2015; Döhnel et al., 2008) and impaired emotional regulation (Apostolova & Cummings, 2008; Mah et al., 2021). It also aligns with studies showing that the SAN reflects excessive emotional responses to negative stimuli (Baur et al., 2013; Edwards et al., 2024). By contrast, the DMN's role in social cognition may be diminished in MCI, preventing the use of social bounded rationality to support positive expectations of reciprocity.

Taken together, these findings highlight that reduced TP in MCI is not simply a general decline in social willingness but reflects a shift in the balance of neural mechanisms. Greater reliance on the SAN and reduced engagement of the DMN indicate that trust behavior in MCI is driven more by affective hyper-sensitivity than by social reasoning. This mechanism provides a plausible explanation for why older adults with MCI may hesitate to form new social relationships and may be more vulnerable to withdrawal from social interactions. Importantly, reduced TP may serve as both a behavioral marker of social vulnerability and a neurofunctional signature of altered decision-making in MCI.

6.3 Structural Underpinnings of Trust in MCI

The second research question asked whether GMV loss in MCI impacts TP, and through which trust-related components these effects are mediated.

Experiment 2 addressed this by combining structural MRI with assessments of trust-related components. Prior research has shown that GMV in regions such as the anterior insula, vmPFC, and TPJ correlates with individual differences in TP (Haas et al., 2015b; Safari et al., 2024). At the same time, meta-analyses indicate that MCI is associated with gray matter atrophy across multiple trust-related regions, including the anterior insula and thalamus within the SAN (Yang et al., 2012; Zhang et al., 2021). These findings raised the critical question of whether such structural decline affects TP in MCI and, if so, through which psychological components.

The results of Experiment 2 showed that reduced GMV in the anterior insula and thalamus predicted diminished TP in older adults with MCI. Mediation analysis revealed that this relationship was explained by affective sensitivity to betrayal: atrophy in SAN regions amplified emotional reactivity, which in turn led to lower TP. Notably, other trust-related components such as motivation, executive cognition, and social cognition did not mediate this relationship, underscoring the specificity of affective mechanisms in linking brain structure to trust behavior.

These findings provide strong evidence that structural alterations in SAN regions underlie reduced TP in MCI. The anterior insula is crucial for integrating interoceptive and affective signals (Uddin et al., 2017), while the thalamus serves as a relay hub for sensory and emotional information (Jones, 2012). Atrophy in these regions likely heightens betrayal sensitivity, biasing trust decisions toward caution and undermining baseline trust. This interpretation aligns with evidence that insular atrophy impairs emotion regulation and interoceptive awareness (Jones et al., 2010), while thalamic decline disrupts affective integration (Biesbroek et al., 2024).

From a theoretical perspective, these findings refine the neuropsychoeconomic model of trust by demonstrating that structural degeneration in SAN regions not only alters affective processing but also mediates its downstream effects on trust behavior. Clinically, they highlight the potential of SAN

atrophy as a biomarker for identifying older adults at heightened risk of social withdrawal and exploitation. Interventions aimed at modulating betrayal sensitivity—such as emotion regulation training or caregiver strategies that emphasize consistent positive reinforcement—may help buffer against these vulnerabilities.

In sum, Experiment 2 demonstrates that gray matter atrophy in the anterior insula and thalamus contributes to reduced TP in MCI, mediated specifically through affective sensitivity to betrayal. This provides convergent evidence that structural degeneration of the SAN translates into behavioral deficits in trust, establishing a key link between neurodegeneration and social vulnerability.

6.4 Trust Dynamics in MCI

The third research question asked how MCI affects the ability to build, maintain, and withdraw trust during repeated interactions, and which psychological and neural mechanisms underlie these changes.

Experiment 3 addressed this question with a multi-round trust game, reinforcement-learning modeling, and task-based fMRI. Behaviorally, individuals with MCI showed slower trust reduction, larger prediction errors, and lower learning rates than controls in non-cooperative contexts. By contrast, their behavior was relatively preserved in cooperative interactions. Neurally, cooperative contexts elicited compensatory hyperactivation in the CEN and DMN, consistent with evidence that older adults with MCI recruit additional cortical resources to sustain performance (Li et al., 2015). In contrast, during non-cooperative interactions, MCI participants exhibited reduced activation in the superior frontal gyri (SFG) and middle temporal gyrus, and diminished connectivity between executive and social regions, such as the SFG and TPJ. These patterns indicate that while cooperation can be maintained through compensation, withdrawal of trust under betrayal conditions is impaired.

This interpretation aligns with prior research. Computational and model-based fMRI studies have shown that reinforcement-learning mechanisms—particularly learning rate and prediction error—are central to trust updating (Haiyan, 2019; Nihonsugi et al., 2015). Evidence also indicates that MCI is marked by deficits in executive and social cognition (Bora & Yener, 2017; Corbo & Casagrande, 2022). Although compensatory activation can sustain cooperative behavior, these mechanisms often collapse under high

cognitive load (de Rover et al., 2011). Non-cooperative interactions amplify betrayal risk (Bohnet & Zeckhauser, 2003) and evoke strong negative affect (Delgado et al., 2005). Because individuals with MCI struggle to translate betrayal signals into negative reciprocity expectations, they persist in trusting uncooperative partners. This vulnerability aligns with findings that MCI increases susceptibility to deception in complex social settings (Han et al., 2016; Martin et al., 2019).

Taken together, Experiment 3 demonstrates that trust dynamics in MCI are context-dependent. Cooperation can be maintained via compensatory recruitment of social and executive networks, but adaptation under betrayal fails due to impaired integration of affective signals with social and executive cognition. This imbalance between emotional reactivity and cognitive updating explains why MCI patients remain overly trusting in risky contexts, leaving them vulnerable to fraud and exploitation.

6.5 Integration Across Studies

The three experiments in this dissertation provide convergent evidence that trust dysfunction in MCI arises from abnormalities in affective, social, and executive components. Together, they reveal a unified pattern: reduced TP due to affective hyper-sensitivity, and impaired trust dynamics due to failures in executive–social integration.

Experiment 1 showed that MCI individuals relied more heavily on the SAN to guide trust, with reduced engagement of the DMN. This reliance on affective rather than social cognition mechanisms aligns with findings that MCI individuals exhibit heightened emotional reactivity (Berger et al., 2015; Döhnel et al., 2008) and impaired emotion regulation (Apostolova & Cummings, 2008; Mah et al., 2021), as well as SAN hyperactivation (Song et al., 2021). In contrast, the DMN supports social cognition and perspective-taking (Amodio & Frith, 2006; Bressler & Menon, 2010), and its reduced influence in MCI is consistent with reports of social-cognitive impairments and DMN hypoconnectivity in this population (Bora & Yener, 2017; Eyler et al., 2019). Experiment 2 extended these results by demonstrating that gray matter atrophy in the anterior insula and thalamus predicted reduced TP, mediated specifically by betrayal sensitivity. This is consistent with evidence that MCI involves structural degeneration in SAN regions (Yang et al., 2012; Zhang et al., 2021), and that insular atrophy undermines interoceptive awareness and emotional regulation (Jones et al., 2010). Together, Experiments 1 and 2 establish both

functional and structural bases for affect-driven reductions in TP.

Experiment 3 then demonstrated that, in cooperative contexts, MCI participants could preserve trust through compensatory recruitment of CEN and DMN regions. This pattern reflects the broader literature on neural compensation in MCI, in which additional cortical resources are recruited to sustain performance across cognitive domains (Clément & Belleville, 2010; Li et al., 2015). However, under non-cooperative conditions, these compensatory mechanisms failed. Individuals with MCI showed reduced activation in executive and social regions and weakened connectivity between the CEN and DMN, leaving them unable to translate betrayal cues into adaptive reductions in trust. These findings align with prior evidence that executive and social cognition deficits are core features of MCI (Bora & Yener, 2017; Traykov et al., 2007), and that compensation is limited under high cognitive or emotional load (de Rover et al., 2011).

Taken together, the three studies converge on a model in which SAN-driven affective hyper-sensitivity lowers baseline TP, structural atrophy in the insula and thalamus exacerbates this vulnerability, and disrupted CEN–DMN integration undermines trust updating in adverse contexts. At the same time, partial compensation in supportive contexts shows that trust is not globally impaired, but rather context-dependent. This synthesis refines Krueger and Meyer-Lindenberg's (2019) neuropsychoeconomic framework by demonstrating how MCI shifts the balance between affective, executive, and social processes, providing a mechanistic account of selective vulnerability in trust.

These three experiments provide complementary perspectives on how MCI alters TP and trust dynamics across behavioral, structural, and functional levels. Figure 4 provides an integrated summary of the experimental design, changes in trust-related components, and the neural alterations that converge on trust dysfunction in MCI.

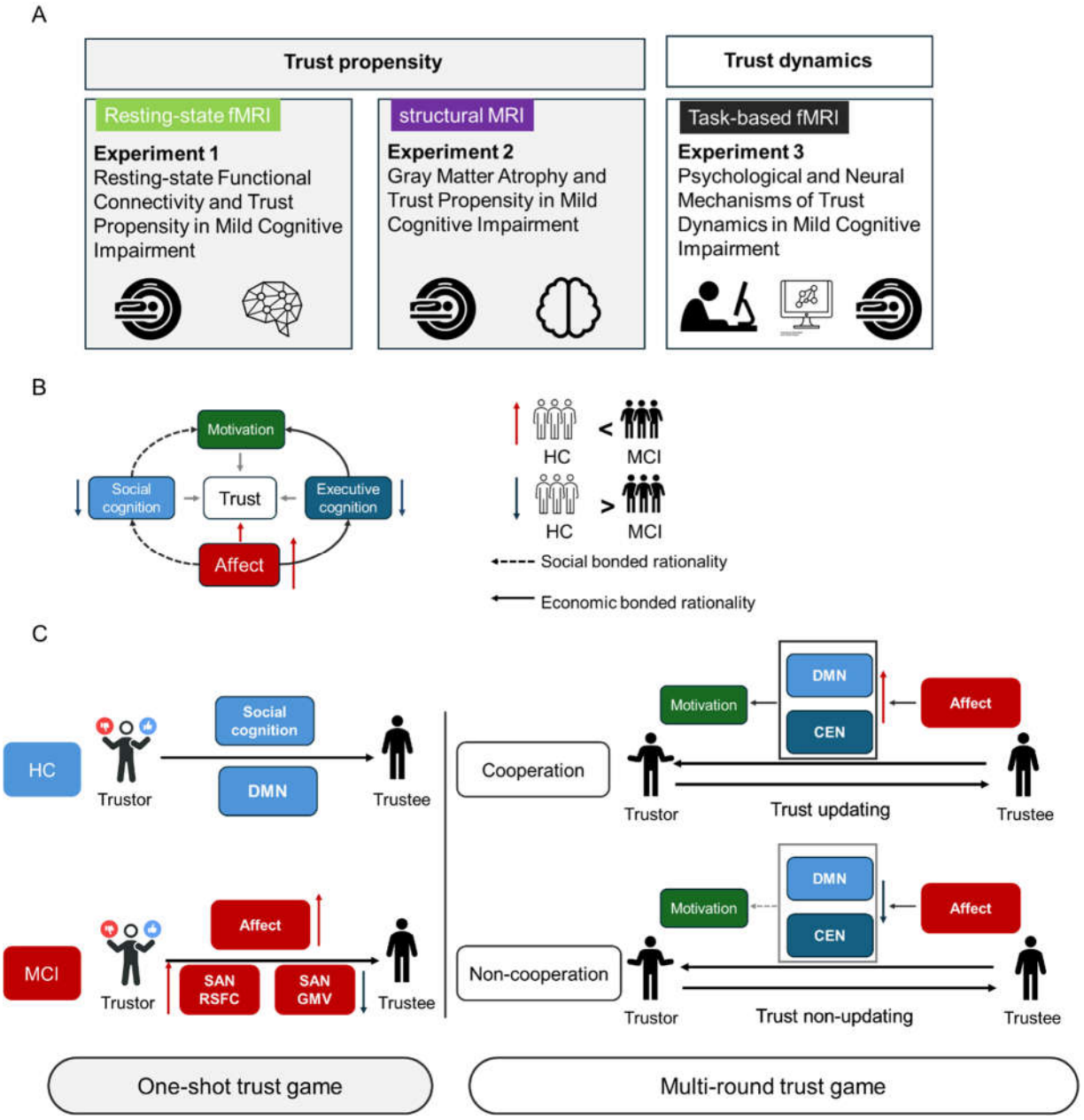

Figure 4. Summary of experiments and integrated model of trust dysfunction in MCI. (A) Overview of research studies. Experiment 1 tested trust propensity (TP) with a one-shot trust game and resting-state fMRI. Experiment 2 examined structural underpinnings of TP using voxel-based morphometry and mediation analyses. Experiment 3 investigated trust dynamics in multi-round trust games with reinforcement-learning modeling and task-based fMRI. **(B) Changes in trust-related components.** TP and trust dynamics are shaped by affect, motivation, social cognition, and executive cognition. In MCI, affective sensitivity is heightened (red upward arrows), while motivation, social cognition, and executive cognition are reduced (blue downward arrows). This imbalance impairs the transformation of betrayal probability into reciprocity expectations within bounded rationality (outer rings: dashed = social, dash–dot = economic). **(C) Neural alterations and impact on trust.** In one-shot games, healthy controls (HC) leverage social cognition and the default mode network (DMN) to enact socially bounded rationality, transforming affective signals into expectations of reciprocity and thereby fostering trust formation. By contrast, individuals with MCI show impairments in social and economic bounded rationality that constrain timely regulation of affect, leading them to rely more on affective component and salience network (SAN)–driven processes during trust decisions. Concomitantly, reduced SAN gray matter volume (GMV) heightens sensitivity to betrayal, further diminishing their TP. In multi-round games, cooperative contexts elicit compensatory activation in social and executive

systems, recoding affective signals into positive expectations of reciprocity, supporting trust updating and promoting the establishment of trust. Conversely, in non-cooperative contexts, task demands exceed compensatory capacity, hindering the translation of betrayal signals into negative expectations of reciprocity; consequently, individuals fail to down-regulate (update) trust, maintain prior trust levels, and overtrust defectors.

TP, trust propensity; GMV, gray matter volume; RSFC, resting-state functional connectivity; SAN, salience network; DMN, default mode network; CEN, central executive network; HC, healthy controls; MCI, mild cognitive impairment.

As shown in Figure 4, MCI is characterized by heightened affective sensitivity, structural decline in the SAN regions, and disrupted executive–social integration, which together reduce baseline trust and impair adaptive updating. This synthesis illustrates how the three studies jointly extend the neuropsychoeconomic model of trust to a clinical population.

From a broader perspective, this integrated model highlights trust as a multidimensional construct that is especially sensitive to neurodegenerative changes. Because trust supports both social engagement and protection against exploitation, the mechanisms identified here have important clinical implications. Reduced TP may serve as an early behavioral marker of social isolation (Chen et al., 2025), SAN atrophy could provide a structural biomarker for diagnosis, and impaired trust dynamics may help explain the heightened risk of fraud and manipulation in individuals with MCI (Han et al., 2016; Martin et al., 2019). These findings not only advance the theoretical neuroscience of trust but also lay the groundwork for translational applications in aging research, clinical assessment, and caregiver interventions.

6.6 Contributions of the Dissertation

This dissertation makes several contributions to the study of trust and MCI at theoretical, methodological, and clinical levels. By combining behavioral experiments with multimodal neuroimaging and computational modeling, it advances both basic science and translational perspectives on social dysfunction in MCI.

Theoretical contributions. The findings refine and extend the neuropsychoeconomic model of trust (Krueger & Meyer-Lindenberg, 2019) by showing how MCI alters the balance among affective, social, and executive components of trust. Experiment 1 demonstrated that reduced TP in MCI reflects a shift toward SAN–driven affective hyper-sensitivity rather than DMN–based social cognition, consistent with

prior evidence of altered emotional regulation in MCI (Apostolova & Cummings, 2008; Berger et al., 2015; Ismail et al., 2018). Experiment 2 further established that gray matter atrophy in the anterior insula and thalamus underlies this vulnerability, providing structural evidence for affective mechanisms of trust dysfunction (Yang et al., 2012; Zhang et al., 2021). Experiment 3 extended these insights into dynamic interactions, showing that while cooperative trust can be preserved through compensatory recruitment of the CEN and DMN (Clément & Belleville, 2012; Gigi et al., 2010; Li et al., 2015), adaptation fails under betrayal, reflecting impaired integration of executive–social pathways (Bora & Yener, 2017; Traykov et al., 2007). Together, these studies advance theoretical understanding by identifying trust as a selective and context-dependent domain of vulnerability in MCI.

Methodological contributions. This work demonstrates the value of integrating diverse approaches to study complex social behavior in clinical populations. Experiment 1 applied connectome-based predictive modeling of resting-state fMRI to predict individual differences in TP, extending prior research on baseline trust (Feng et al., 2021; Lu et al., 2019) and providing a tool for cross-population comparisons of trait-level neural mechanisms. Experiment 2 employed voxel-based morphometry with whole-brain mediation (Wager et al., 2008) and moderated-mediation analyses (Preacher & Hayes, 2004) to link gray matter atrophy to trust-related components, clarifying the structural basis of behavioral differences. Experiment 3 integrated reinforcement-learning models with task-based fMRI (Delgado et al., 2005; Fouragnan et al., 2013) to characterize prediction error–related dysregulation and its neural correlates in the trust dynamics of older adults with MCI. By combining these methods, the dissertation shows how multimodal evidence converges on a coherent account of trust dysfunction in MCI. This integrative methodological approach represents a contribution to both the neuroscience of trust and the study of clinical populations, illustrating how combining behavioral, neural, and computational levels yields richer insights than any single approach alone (Fareri, 2019).

Clinical contributions. Finally, this dissertation provides clinically relevant insights into social vulnerability in MCI. Reduced TP, linked to betrayal sensitivity, may serve as an early behavioral marker of risk for social withdrawal and exploitation (Bartley et al., 2024; Ishikawa et al., 2022). Structural atrophy in SAN regions such as the anterior insula and thalamus could serve as

neuroanatomical biomarkers for early detection of social dysfunction (Seeley et al., 2009). Impaired trust dynamics, especially the inability to reduce trust under betrayal, may explain why older adults with MCI are particularly susceptible to fraud and manipulation (Han et al., 2016; Spreng et al., 2016). These findings highlight potential targets for interventions: caregiver strategies that emphasize consistent positive interactions, emotion regulation training to reduce betrayal sensitivity, and policy measures to protect vulnerable individuals in financial and interpersonal contexts. By situating trust as a clinical marker, this work bridges basic neuroscience with applied concerns in aging and dementia research.

In sum, the dissertation contributes to theory by extending the neuropsychoeconomic model of trust to a clinical population, to methodology by demonstrating the power of multimodal integration, and to practice by identifying trust as a marker and intervention target for vulnerability in MCI.

6.7 Practical Implications

The findings of this dissertation carry several important practical implications for clinicians, caregivers, and policymakers who support older adults with MCI.

Health care professionals. For clinicians, the results underscore the importance of proactively cultivating trust with older adults with MCI. This population shows reduced TP, especially when confronted with potential betrayal, but the findings also reveal that compensatory mechanisms allow them to maintain trust in supportive contexts. This suggests that early establishment of a strong trust relationship between patients and providers can be a critical strategy for improving therapeutic engagement. Indeed, trust in medical professionals has been linked to adherence, satisfaction, and overall treatment outcomes (Grimes & Grimes, 2013; Polinski et al., 2014). Importantly, building this foundation of trust may also help clinicians detect subtle early-stage vulnerabilities that are not captured by standard cognitive assessments, making trust behavior a potential "soft marker" of social dysfunction. Clinicians should therefore be encouraged to integrate trust-building strategies into routine care, such as clear communication, consistent emphasis on the benefits and rationale of treatment, and validation of patients' concerns.

Caregivers. For caregivers, fostering and maintaining trust has direct benefits for daily interactions and

quality of life. Trust supports emotional well-being, social participation, and life satisfaction in later life (Awaworyi Churchill & Mishra, 2017; Poulin & Haase, 2015). By strengthening trustful bonds, caregivers can help older adults with MCI maintain social engagement, which is known to protect against loneliness and may slow cognitive decline (Zhou et al., 2025). The dissertation findings also show that individuals with MCI struggle to reduce trust in non-cooperative contexts, meaning they may persist in trusting unreliable or manipulative partners. This dual pattern — reduced baseline TP but excessive trust in risky contexts — calls for careful caregiver attention. Interventions could include emotion regulation training to reduce betrayal sensitivity, structured routines to provide consistent social reinforcement, and monitoring systems to detect potentially harmful social interactions. Caregivers play a dual role: encouraging healthy trust in supportive environments while actively safeguarding against misplaced trust that could lead to exploitation.

Policy. At the societal level, the findings highlight the urgency of structural safeguards to protect cognitively impaired older adults from exploitation and abuse. While individual- and caregiver-level strategies are essential, broader systems are equally important. For example, financial institutions could develop fraud detection systems tailored to patterns of vulnerability in older adults, and governments could implement legal protections that require stricter oversight of financial transactions involving individuals with MCI. Public awareness campaigns could educate families and communities about the risks of misplaced trust and the importance of early intervention. At the same time, policies that encourage positive social engagement — such as community-based programs that foster safe social interaction — may help strengthen the trust capacity that individuals with MCI can maintain under supportive conditions. By linking social-cognitive and neural mechanisms of trust dysfunction to real-world risks, this dissertation provides an evidence base for designing interventions that operate across multiple levels of society.

Cross-cutting implications. Taken together, these results emphasize that trust is not merely a theoretical construct but a practical determinant of health, well-being, and safety for individuals with MCI. Clinicians must build and sustain trustful therapeutic relationships, caregivers must balance trust promotion with protection, and policymakers must design safeguards that reduce systemic vulnerability.

Trust thus emerges as a cross-cutting theme that connects clinical care, everyday life, and public policy. By integrating trust considerations into these domains, it may be possible to reduce social vulnerability, strengthen resilience, and improve quality of life in this at-risk population.

6.8 Limitations and Future Directions

Despite providing novel insights into trust abnormalities in older adults with MCI, several limitations of this dissertation should be acknowledged.

Limitations. First, the measurement of trust-related components relied primarily on self-reports, which lack objective and independent validation in real trust dilemmas. Questionnaires may not fully capture affective, motivational, executive, and social processes as they occur during decision-making. This limitation constrains the ecological validity of the findings. Second, the neuroimaging approach was limited to resting-state connectivity, structural MRI, and task-based fMRI. While these methods yielded valuable insights, other modalities such as diffusion tensor imaging (DTI) could clarify white matter integrity underlying trust-related networks (Le Bihan et al., 2001), and electroencephalography (EEG) could provide fine-grained temporal resolution of neural activity during trust decisions (Fu et al., 2018). Third, although trust games simulate social interactions, they may not fully capture real-world interpersonal functioning. The findings were not directly linked to everyday social behaviors, such as social engagement or network size, reducing external validity. Finally, the studies were cross-sectional. This limits the ability to track how trust processes evolve across time and whether they predict conversion from MCI to dementia.

Future Directions. Future research should incorporate task-based paradigms to directly measure trust-related components, such as affective responses (e.g., emotional arousal; Sohn et al., 2015), motivation (e.g., reward sensitivity; Zebrowitz et al., 2018), and social cognition (e.g., theory of mind; Baglio et al., 2012). This would improve construct validity and help clarify the psychological meaning of computational modeling parameters. Expanding multimodal imaging to include DTI, EEG, and potentially other techniques would provide a more comprehensive account of the structural, functional, and temporal mechanisms underlying trust. Future work should also include validated measures of daily-life social functioning, such as the Social Engagement Scale (Qiang et al., 2022), the Lubben Social

Network Scale (Lubben, 1988), and everyday activity measures (Van Der Aalst et al., 2005), to better link laboratory findings to real-world outcomes. Longitudinal designs will be crucial for tracking trajectories of trust over time and testing whether abnormalities predict progression to dementia. Prior evidence suggests that reduced social participation and shrinking networks are risk factors for Alzheimer's disease (Fan et al., 2021; Zhou et al., 2025). It is therefore important to examine whether trust dysfunction accelerates decline via impaired social functioning. Additionally, future research should integrate trust measures into predictive modeling and machine learning approaches. Multimodal data combining cognitive, biological, and social-cognitive markers have been shown to improve prediction and classification of MCI (Rathore et al., 2017; Zheng et al., 2018). Finally, translational studies are needed to transform mechanistic insights into interventions. This could include caregiver training programs that promote effective trust relationships, as well as prevention strategies aimed at reducing susceptibility to financial exploitation. Neurobiological interventions such as neuromodulation could also be explored as potential ways to improve trust functioning and social engagement.

In summary, although the present dissertation provides strong initial evidence that MCI alters both TP and trust dynamics, future studies should address its methodological, ecological, and longitudinal limitations. Such efforts will deepen our understanding of how trust dysfunction contributes to social vulnerability in aging, and how it might serve as a marker and target for clinical intervention.

6.9 Conclusion

This dissertation set out to investigate how MCI alters TP and trust dynamics, and to identify the psychological and neural mechanisms underlying these changes. Guided by the neuropsychoeconomic framework of trust (Krueger & Meyer-Lindenberg, 2019), three complementary studies were conducted.

Experiment 1 showed that TP was significantly reduced in individuals with MCI, driven by heightened betrayal sensitivity and increased reliance on the SAN, whereas healthy controls engaged the DMN to support social cognition. Experiment 2 extended these findings by demonstrating that gray matter atrophy in the anterior insula and thalamus predicted reduced TP in MCI, with affective sensitivity mediating this relationship. Experiment 3 revealed that while trust building in cooperative contexts could be preserved through compensatory recruitment of executive and social networks, trust reduction under

betrayal failed due to impaired learning rates, exaggerated prediction errors, and disrupted connectivity between the CEN and DMN.

Together, these findings provide convergent evidence that MCI alters trust through both affective and cognitive (social and executive) pathways. Reduced baseline TP reflects an overreliance on affective hyper-sensitivity and structural decline in SAN regions, while impaired trust dynamics emerge from disrupted executive–social integration and weakened adaptive updating in non-cooperative contexts. At the same time, compensatory mechanisms demonstrate that trust is not globally lost, but selectively vulnerable depending on the social environment.

The results carry important theoretical, methodological, and clinical significance. Theoretically, they extend the neuropsychoeconomic model of trust to a clinical population, identifying selective vulnerabilities in affective and executive–social components. Methodologically, they demonstrate the value of integrating resting-state fMRI, structural imaging, computational modeling, and task-based fMRI to examine social cognition in MCI. Clinically, they highlight trust as both a behavioral marker and a potential intervention target for reducing social vulnerability in older adults at risk of dementia.

In conclusion, this dissertation provides novel evidence that MCI disrupts TP and dynamics through affective and executive–social mechanisms. These insights not only advance our understanding of social dysfunction in cognitive impairment but also suggest practical avenues for clinical screening, caregiver strategies, and policy interventions aimed at preserving autonomy and safety in aging populations. By framing trust as a cross-cutting theme that links neuroscience with clinical and societal concerns, this work establishes a foundation for future studies to develop targeted interventions and to explore trust as an early marker of disease progression.

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8. Further Publications During My Doctorate

Chen, Y., He, H., Lin, W., Yang, J., Tan, S., Tao, W., ... & Krueger, F. (2023). The connectome-based prediction of trust propensity in older adults: A resting-state functional magnetic resonance imaging study. Human Brain Mapping, 44(11), 4337-4351. https://doi.org/10.1002/hbm.26385

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9. Disclosure of Delegation to Generative AI

The authors declare the use of generative artificial intelligence (GAI) in the research and writing process. According to the GAIDeT taxonomy (2025), the following tasks were delegated to GAI tools under full human supervision:

- Code optimization

- Proofreading and editing

- Adapting and adjusting emotional tone

The GAI tool used was: ChatGPT-5.

Responsibility for the final manuscript lies entirely with the authors.

GAI tools are not listed as authors and do not bear responsibility for the final outcomes.

Declaration submitted by: Yiqi Chen

Additional note: Before and during use, I familiarized myself with the tool's capabilities and limitations and acknowledged risks such as factual errors, fabricated citations, semantic drift, and style homogenization. Accordingly, I manually reviewed and fact-checked all adopted language edits, accepting them only when they did not change the original meaning or scholarly intent. All AI-generated code was manually reviewed, verified, and corrected where necessary; parameter-recovery simulations were conducted to validate code correctness. No restricted or unpublished data were shared with AI systems.

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