Thinking, Fast and Slow: How Response Times Can Predict Cognitive Decline and (Bad) Financial Decision-Making at Older Ages

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Abstract

This study investigates the potential of response times (RT) as a predictor of cognitive decline, leveraging previously untapped data from the Survey of Health, Ageing, and Retirement in Europe (SHARE). Recorded automatically during Computer-Assisted Personal Interviews (CAPI), RTs offer a unique opportunity to study cognitive and decision-making processes without added respondent burden. We first validate RTs as meaningful predictors of cognitive decline, building on Sanders et al. (2025). Slower RTs – recorded automatically during standard cognitive modules – are strongly associated with lower baseline cognitive scores and greater subsequent decline, even after controlling for age, gender, and baseline cognition. RTs also predict deterioration across a range of health outcomes, including frailty, mental health, and mortality, underscoring their potential as early indicators of physiological aging.

We then examine the predictive content of RTs for financial outcomes. Slower RTs are associated with subsequent wealth losses, above and beyond what is captured by standard cognitive measures and interviewer fixed effects. Replicating the findings of Mazzonna and Peracchi (2024) in a European context, we show that individuals who experience cognitive decline without being aware of it are particularly vulnerable to wealth decumulation. Importantly, RTs remain predictive of wealth losses even when cognitive decline and (un)awareness are accounted for, and they are strongly associated with being unaware of one's own cognitive deterioration. This suggests that RTs can help identify individuals at risk of poor financial decision-making due to undiagnosed cognitive impairment. Finally, we document heterogeneity by gender, with stronger associations observed among male financial respondents.

Taken together, our findings demonstrate that response times – routinely collected but often ignored – contain rich information about both cognitive and financial vulnerability at older ages.

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1 Introduction

Maintaining cognitive health and financial well-being in older age is a growing concern in aging societies. As cognitive capacity declines, individuals may face increasing difficulties managing their health, preserving autonomy, and making sound economic decisions. Detecting early signs of cognitive decline is therefore of paramount importance—not only for individual well-being but also for designing preventive public policy interventions. Traditional survey-based cognitive assessments, however, tend to rely exclusively on test accuracy (e.g., word recall, numeracy), potentially overlooking subtle impairments that precede observable deficits. In particular, declines in processing speed—a core dimension of fluid intelligence—often manifest earlier than memory loss but remain understudied in large population surveys.

In this paper, we examine the potential of survey response times (RTs) as a complementary, low-cost, and scalable proxy for cognitive processing speed. Automatically recorded during Computer-Assisted Personal Interviews (CAPI), RTs provide a rare opportunity to measure aspects of cognition that go beyond standard accuracy-based indicators, without adding burden to respondents or interviewers. Drawing inspiration from the literature in psychology and neuroscience—most notably the Drift Diffusion Model (Ratcliff, 1978; Smith, 2000) —as well as from recent economic applications (e.g., (Sanders et al., 2025; Clithero, 2018; Liu and Netzer, 2023), we investigate whether longer response times in cognitive test items are predictive of health deterioration, cognitive decline, and economic vulnerability at older ages.

Neuroscientific studies have thus paved the way for applying RT analysis in population surveys, offering a bridge between lab-based cognitive neuroscience and real-world applications. Unlike many prior studies limited by small sample sizes or controlled laboratory environments, we utilize response time data from the eighth and ninth waves of the Survey of Health, Ageing, and Retirement in Europe (SHARE). These waves are unique in that they are the first to make detailed, automatically-recorded time stamps from Computer-Assisted Personal Interviews (CAPI) available to researchers via authorized access. This approach—pioneered by Sanders et al. (2025) using the National Social, Health, and Aging Project (NSHAP)—represents a significant methodological advance by leveraging large-scale, population-representative data. These recent SHARE waves also feature an expanded cognitive module, allowing for the construction of comprehensive indices like the Langa-Weir index.

Our empirical analysis proceeds in two parts.

In the first part, we build on the methodology of Sanders et al. (2025) and validate the informational content of RTs using this newly available SHARE data. We document strong descriptive associations between slower response times and lower cognitive scores, both cross-sectionally and over time. These associations are robust to controls for age, gender, education, and baseline cognitive ability, and they follow a clear gradient across clinically validated cognitive categories. Importantly, we find that the relationship between RTs and performance is task-specific: for most cognitive tasks, longer response times are associated with higher error rates—suggesting processing difficulties—except in a few cases such as delayed recall, which may reflect more deliberative processes. We then extend this analysis by showing that RTs predict not only future cognitive scores but also other dimensions of health deterioration, such as functional limitations, mental health decline, frailty, and mortality. By demonstrating that RT is associated with multiple health domains, our findings highlight the versatility of RT as a predictive tool, with potential applications in identifying individuals at risk for a range of adverse health outcomes.

In the second part of the paper, we ask whether RTs also contain predictive power for financial outcomes. Building on the literature linking cognition to wealth accumulation (Banks et al., 2010; Smith et al., 2010), we find that individuals with slower response times in the cognitive module are more likely to experience a decline in wealth in subsequent survey waves. This result holds even after controlling for interviewer fixed effects, and baseline cognitive scores, and it suggests that RTs provide additional information beyond standard cognitive measures.

We then turn to the role of awareness in mediating the relationship between cognition and wealth trajectories. Following the approach of (Mazzonna and Peracchi, 2024), we identify individuals whose cognitive health deteriorates between waves but who do not report a perceived decline in memory. Consistent with their findings—originally established in a U.S. context—we show that these ”unaware” individuals are significantly more likely to experience financial losses. Importantly, we replicate this result in a European setting, where household wealth is less sensitive to individual-level financial decision-making, which suggests that (un)awareness of cognitive decline matters for financial security, even in more protective institutional environments.

Adding to this evidence, we show that RTs continue to predict wealth losses even in models that already include cognitive decline and (un)awareness. This implies that time stamps contain information not captured by standard cognitive measures or by awareness alone. Most notably, we find that slower response times are predictive of being unaware of one’s own cognitive deterioration. This is a critical result, as unawareness has been shown to be a key channel through which cognitive decline translates into financial vulnerability. By helping to identify this high-risk group, RTs offer a valuable and policy-relevant signal—available at no additional cost—of potential mismanagement of financial resources due to undiagnosed cognitive impairment.

Last but not least, we document meaningful heterogeneity by gender: the association between cognitive decline, unawareness, and wealth losses is more pronounced among male financial respondents, suggesting that gender roles in financial decision-making may shape vulnerability to cognitive decline (Smith et al. (2010)).

Taken together, our findings suggest that response times offer a valuable and underutilized signal of cognitive and financial vulnerability in older populations. While we remain cautious in interpreting these associations as strictly causal, the patterns we uncover are consistent, robust, and policy-relevant. Our contribution lies in demonstrating the feasibility and predictive value of using RTs in large-scale survey settings, thereby offering a novel, costless dimension for early detection of cognitive and financial risks amongst aging populations.

2 The Informational Content of Response Times

Seminal work in Psychology and Neuroscience has introduced the Drift Diffusion Model (DDM) as a framework for modeling how individuals accumulate information over time when making binary choices, such as yes/no decisions (Ratcliff, 1978). This model conceptualizes decision-making as a noisy process where evidence is accumulated sequentially until a pre-set threshold is reached, at which point a response is executed. The total time elapsed is therefore a composite of multiple cognitive stages, including evidence accumulation (the 'drift rate'), the amount of evidence required (the 'decision threshold'), and non-decisional processes like encoding and motor response. Subsequent work has extended and validated the DDM across a broad range of cognitive tasks. For example, Ratcliff and Rouder (1998) demonstrated its power in modeling item recognition memory, while Smith (2000) provided a foundational mathematical primer that solidified its use for interpreting both the speed and accuracy of choices. These papers highlight a critical point: focusing only on accuracy discards a wealth of information contained in how long it takes to arrive at a correct (or incorrect) answer. A crucial insight from this literature, particularly for the study of aging, comes from Ratcliff et al. (2010), who analyzed the effects of aging on decision-making. They found that the slower response times common in older adults are often explained by strategic adjustments—specifically, an increase in the decision threshold, reflecting a more cautious, accuracy-focused approach—rather than purely a decline in the rate of information processing. This distinction is vital for differentiating normal, strategic cognitive aging from the pathological decline that may affect the core processing speed itself.

More recently, economists have begun to explore the usefulness of response time data. As put forward by Clithero (2018), RTs can improve out-of-sample predictions, and recent studies show they can help address identification issues in survey-based models by providing information about the strength of underlying latent traits (Liu and Netzer, 2023). This move from laboratory to large-scale surveys is supported by extensive validation work showing that survey-based cognitive measures are strongly correlated with clinical assessments of cognitive impairment and dementia (Crimmins et al., 2011). This reinforces their utility in measuring cognitive processes more precisely in population-representative samples.

Closer to our study, Mazzonna and Peracchi (2012) were pioneers in this area, using keystroke files from the first two waves of SHARE to measure processing speed, which they argued is a key dimension of cognitive deterioration with age. Specifically, they incorporated the time taken to answer cognitive test questions, such as orientation in time and word recall, to construct adjusted cognitive scores that combine accuracy with response speed. Their subsequent work has continued to leverage detailed cognitive measures from SHARE to tackle fundamental economic questions, such as the link between cognitive decline, self-awareness, and financial decision-making (Mazzonna and Peracchi, 2024). This approach aligns well with our study, which further explores response times as an informative signal in cognitive assessments. By incorporating RTs into models predicting cognitive, health, and financial trajectories, we extend the existing framework to show their value in predicting broader age-related vulnerabilities.

3 The Predictive Power of Cognition

Most of the literature in Economics using measures of cognition, cognitive functioning, and cognitive decline has looked at cognition as an outcome variable, for instance when investigating the causal effect of retirement on cognitive functioning (Rohwedder and Willis, 2010; Bonsang et al., 2012; Mazzonna and Peracchi, 2017; Celidoni et al., 2017), or the impact of early life conditions on later-life cognition (Case and Paxson, 2009). Here we shift our focus to cognition as a predictor, exploring its role in anticipating significant life outcomes such as health decline, mortality, and financial decision-making.

Measures of recall memory, which capture the ability to learn and retrieve information, have been shown to be particularly powerful in this regard. Recall memory tests, such as the immediate and delayed recall tasks used in the SHARE survey, are strongly associated with the onset of dementia. For example, Celidoni et al. (2017) demonstrate that a decline of more than 20% in recall scores between survey waves is a robust indicator of pathological cognitive impairments, a finding supported by validation efforts using clinical assessments in the Health and Retirement Study (HRS). Beyond dementia, key domains of cognitive functioning have been shown to correlate strongly with broader health-related outcomes, including increased risks of mortality from cancer, cardiovascular, and respiratory diseases (Batty et al., 2016), suggesting that cognitive test scores can serve as simple indicators for a variety of health risks.

The predictive power of cognition extends beyond health to financial and economic outcomes. Smith et al. (2010) demonstrate the role of numeracy in predicting household wealth, showing that higher numeracy levels among financial decision-makers are strongly correlated with greater wealth holdings. Banks et al. (2010) build on this by showing that cognitive abilities impact not only current wealth levels but also wealth trajectories over time. Recently, research has begun to use large-scale administrative data to detect the financial antecedents of a formal dementia diagnosis. Nicholas et al. (2021) find an increased risk of missing bill payments in the years prior to an ADRD diagnosis for seniors living alone. In a similar vein, Gresenz et al. (2024) merge Medicare data with consumer credit panel data, finding that payment delinquencies and weakening credit scores begin to appear years before an eventual diagnosis of a memory disorder. These studies underscore the real-world financial consequences of undiagnosed cognitive decline.

Adding complexity to this narrative, Mazzonna and Peracchi (2024) explore the role of respondents' level of awareness regarding their cognitive decline. They find that individuals who are unaware of their cognitive deterioration are significantly more likely to experience wealth losses, primarily due to suboptimal financial decisions. Their findings suggest that cognitive decline—and the lack of awareness thereof—can undermine financial stability, even among those who were previously effective decision-makers.

An emerging frontier in this research is the use of response times (RTs) as a complementary measure of cognitive functioning. Using the NSHAP, Sanders et al. (2025) have shown that slower RTs are predictive of a higher rate of cognitive decline and mortality. Our study seeks to enrich this nascent literature by synthesizing these two streams of research. We investigate whether RTs, as a sensitive measure of processing speed collected within a survey, can not only predict health and cognitive trajectories but can also shed light on the financial vulnerabilities—potentially linked to unawareness—that have become a central focus in the economics of aging.

4 Data and Descriptive Analysis

4.1 SHARE

This study relies on data from the Survey of Health, Ageing and Retirement in Europe (SHARE), a large-scale, multi-country survey conducted across 28 European countries. SHARE collects detailed information on respondents' demographic characteristics, health, labor force status, household composition, and financial status. The survey targets individuals aged 50 and older who reside in participating countries and speak the respective country's language. Each wave includes both a longitudinal sample and new respondents, allowing for comprehensive tracking of aging populations. In cases where a respondent has passed away, SHARE also conducts end-of-life interviews with a close relative or partner.

For our analysis, we utilize data from SHARE's eighth and ninth waves, fielded between 2019 and 2022. These recent waves are pivotal for two reasons. First, they feature an expanded cognitive module that, for the first time, includes all components necessary to construct the comprehensive Langa-Weir cognitive function index, most notably the backwards counting task. This wave also newly incorporates a question on self-assessed memory change, which is essential for our analysis of awareness based on Mazzonna and Peracchi (2024).

Second, and central to our study, we were granted access to the time stamp data from these waves. This previously unavailable dataset, automatically generated during Computer-Assisted Personal Interviews (CAPI), records the precise time respondents take to answer each question. The availability of this response time data in SHARE, combined with the newly enriched cognitive and subjective measures, provides a rich source of information for studying cognitive and decision-making processes with a level of detail not previously possible in this survey.

4.2 Sample selection

Our sample is made of individuals aged 60 and over whose baseline interview occurred before Wave 8 since this is the subsample that was targeted by the extended cognition module. On top of that, we add the restriction that these individuals must be re-interviewed in Wave 9, since our models use information at Wave 8 to predict changes between Waves 8 and 9.

We exclude proxy interviews to ensure that our cognitive scores and, critically, our response time measures reflect the respondent's own cognitive processes, not the interpretation or pacing of a third party. The same goes for respondents with missing values in any of those tests scores and studied health outcomes at waves 8 and 9. The final sample is a balanced, two-period panel for 18,782 individuals. As shown in Table 2, individuals in our working sample are aged 72 on average at Wave 8, 56% are female, and 9% are migrants.

For the wealth analysis, following (Mazzonna and Peracchi, 2024), we focus on respondents below 80. This restriction helps us to address issues arising from mortality and institutionalization. Moreover, since wealth variables are asked to only one respondent of a household, we keep only one observation per household, the one corresponding to the individual chosen by the household as "the one most able to answer questions about [their] finances?', labeled as "financial respondent". This follows the precedent of Smith et al. (2010), who show that the cognitive skills of this specific individual are most salient for household financial outcomes.

4.3 Cognitive measures and their Time Stamps

The cognitive score Most of the literature on cognitive functioning using SHARE or its sister studies, such as HRS or ELSA, has focused on episodic memory measures (mainly recall tests) when examining cognitive aging (see Celidoni et al. (2017)), or on numeracy (e.g., percentage computation tasks, as in Banks et al. (2010); Smith et al. (2010)) when investigating cognitive skills in later life, without necessarily addressing cognitive decline.

Discussions by Rohwedder and Willis (2010), Mazzonna and Peracchi (2012) and Mazzonna and Peracchi (2018) emphasize the dual role of episodic memory and numeracy in capturing fluid and crystallized intelligence. Fluid intelligence, representing basic information-processing mechanisms, begins to decline early in life and is closely tied to biological and physical factors, including processing speed (Horn and Cattell, 1967; Salthouse, 1985). Crystallized intelligence, on the other hand, reflects accumulated knowledge from education and life experiences. It continues to develop until midlife, typically around age 50, before stabilizing and gradually declining. According to Salthouse (1985), cognitive functions such as orientation, memory, fluency, and numeracy represent varying combinations of these two dimensions of intelligence, underscoring the importance of incorporating multiple cognitive domains in understanding cognitive aging.

Building on this framework, we adapt the Langa-Weir score, originally developed for the HRS, to the newly extended cognitive module introduced in SHARE Wave 8. Two versions of the Langa-Weir classification exist: the Langa-Weir 36, which includes a broader range of cognitive tests, and the Langa-Weir 27, which excludes orientation and object naming items to maintain comparability across different age groups. We adopt the Langa-Weir 27 approach, which relies on memory (word recall), working memory (serial 7s substraction), and attention-processing speed (backwards counting), as these core domains have been validated against clinical diagnoses from the Aging, Demographics, and Memory Study (ADAMS). ADAMS, a sub-study of the HRS, provides a ”gold standard” for assessing cognitive impairment and dementia through detailed neuropsychological evaluations. The Langa-Weir classification was developed to align with ADAMS using equipercentile equating methods, ensuring that cognitive classifications drawn from large-scale surveys reflect clinically meaningful classifications (see Crimmins et al. (2011) for more details).

Thus, following Langa et al. (2020), we construct a 26-point cognitive functioning scale based on three tests:

A ten-word-list recall test: The respondent is asked to learn a list of ten common words (e.g., hotel, river, tree) and recall them in any order, first immediately and then after an interference period (delayed recall), approximately five minutes later.[2] This component is computed as the sum of words remembered in both recalls (score range: 0 to 20), following prior studies (Rohwedder and Willis, 2010; Bonsang et al., 2012; Celidoni et al., 2017; Mazzonna and Peracchi, 2024). A serial subtraction test (”serial 7s”): The respondent subtracts 7 from 100 repeatedly for a total of five trials (score range: 0–5). A backwards counting test: The respondent is asked to count backwards from 20 to 10 as quickly as possible (1 point). This is where the 1-point different with the 27-point Langa-Weir comes from, as this task is only asked once in SHARE, starting from number 20 (it starts from numbers 20 and 86 in HRS).

Although the extended cognitive module in SHARE includes additional elements such as clock drawing, object naming, and orientation tasks, we exclude these measures in line with prior applications of the Langa-Weir 27 approach. As noted by Crimmins et al. (2011), these additional items were omitted in HRS for individuals under 65 years old to maintain consistency across age groups and to ensure that cognitive scores reflect core memory and processing abilities rather than broader knowledge-based assessments.

The Langa-Weir classification then maps onto the 26-point scale in the following way, as shown in Table 3: individuals are classified as “Normal” for scores between 12 and 26 (85% of our sample in Wave 8), “Cognitively Impaired but not Demented (CIND)” (13% in Wave 8) for scores between 7 and 11, and Demented (1.2% in Wave 8) for scores between 0 and 6.

The time stamp of the cognitive score Our analysis relies on three key constructs derived from the SHARE data: the Langa-Weir cognitive score, the response times (RTs) taken to complete the corresponding cognitive tests, and a classification of cognitive decline awareness.

We first construct the aforementioned 26-point cognitive functioning score based on Langa et al. (2020).

Second, our primary predictor of interest is the response time (RT) taken to complete these tasks, which we aggregate to create a measure of overall cognitive processing speed.[3] We are motivated by the work of Mazzonna and Peracchi (2012), who first used SHARE’s time-stamp data to capture processing speed, a core component of

[2]More specifically, each word in the list appeared on-screen for 1.5 seconds, separated by two-second intervals, after which the respondent had two minutes to recall as many words as possible.

[3]If a respondent paused and resumed the backward counting task, we combine both time segments to obtain a complete measure.

cognitive aging that is particularly sensitive to deterioration (Salthouse, 1985). In their work, they addressed the complex relationship between speed and accuracy by creating a single ”adjusted” score that combined both pieces of information. In this paper, we take a different but complementary approach. Instead of combining accuracy and speed into a single index, our central goal is to test whether these two dimensions contain independent information. We therefore keep them separate to explicitly test whether RT has predictive power for future health and financial outcomes beyond that contained in the standard cognitive score.

To do this effectively, we must first characterize the properties of the RT variable itself. The interpretation of RT is not always straightforward, as a very short RT can be ambiguous: it could reflect high proficiency or task abandonment. This non-monotonic relationship is evident in our data, as shown in Figure 1. While the pattern is clear for the numeracy (serial 7s) and backwards counting tasks, where shorter response times are strongly associated with higher scores, the relationship for recall scores displays an inverse U-shape. This non-monotonicity for more demanding tasks is consistent with findings from other surveys. For instance, Sanders et al. (2025), in their NSHAP analysis, found that while RTs declined monotonically for simple tasks, for complex tasks like serial 7s, this only held for high-performing individuals. Respondents with severe cognitive issues often abandoned the task quickly, leading to very short response times. In these cases, lower cognitive ability can be linked to faster response times, as individuals do not engage with the task at all. Following their guidance, we perform robustness checks (i) modeling RT non-linearly and (ii) verifying that our main results hold when excluding the fastest 5% of respondents.

Finally, moving from the sub-tasks to the aggregate measure, we examine how the total RT relates to the overall Langa-Weir cognitive classification (see Table 4). As cognition worsens, RT rises monotonically: individuals with normal cognition take, on average, 120 seconds to complete the three tasks, those classified as CIND require 130 seconds, and respondents in the dementia range need 144 seconds. Equally informative is the growing spread of response times: the standard deviation widens from 36 seconds (Normal) to 42 seconds (CIND) and 48 seconds (Demented). The joint pattern—longer average RTs and greater variability at lower cognitive levels—underscores that RT captures both slower processing speed and heterogeneous task engagement among cognitively impaired respondents.

The awareness classification Last, we follow Mazzonna and Peracchi (2024) in their definition of a cognitive decline awareness classification in the HRS. To do so, we first define whether an individual goes through a memory loss event between the two waves, i.e. if his/her recall measure (the total numbers of words recalled in both the immediate and delay recall) goes down by at least 20% from wave 8 to wave 9, a threshold that has been validated by important studies. Indeed, while there is no universally established threshold in the literature to define cognitive decline based on word recall, a 20% drop in recall performance has been shown to capture changes in cognition that fall within the bottom quarter of the distribution of memory score variations across survey waves (see Celidoni et al. (2017); Mazzonna and Peracchi (2024)). By discarding small changes, a 20% threshold helps mitigate measurement error, as small declines may not necessarily reflect true cognitive deterioration but rather random variation in test performance. Other studies in the neuropsychological literature have favored an alternative approach, e.g. defining severe memory loss as a decline exceeding one standard deviation (Nasreddine et al., 2005), which corresponds in our case to a drop of approximately three words. However, as noted in Mazzonna and Peracchi (2024), relying solely on an absolute threshold may understate cognitive decline for individuals who started with lower memory scores in the previous wave (floor effect). By using a relative definition—considering a 20% decline—we account for individual baseline differences, ensuring that cognitive deterioration is consistently captured across the distribution. Additionally, validation using data from the HRS-ADAMS sample, where clinical dementia assessments are available, indicates that a high decline in cognition aligns with a clinical dementia diagnosis in 70% of cases (see Celidoni et al. (2017) for the validation exercise). Figure 3 displays the estimated density of the word recall memory score in both levels and differences. Extremely similar to what Mazzonna and Peracchi (2024) shows with data from the HRS, the mean of the memory score is equal to 10, and the mean difference in the memory score between waves 8 and 9 is only slightly negative, suggesting many respondents actually improve their score from one wave to the next, which might happen in presence of "re-testing" effects, if respondents remember some words from one wave to the next, or simply get better at the test after learning how to take it.[4]

Beyond a specific memory deficit, we are also interested in whether our findings extend to a more "global cognitive decline." To investigate this, we construct a parallel classification based on the total 26-point Langa-Weir score. While the 20% decline in recall scores is a well-established indicator of meaningful memory loss, the literature has not converged on an equivalent standard for composite scores. We therefore define global cognitive decline as a drop of at least 20% in an individual's total Langa-Weir score. This choice maintains symmetry with our validated memory-loss measure, allowing for direct comparison, and identifies a substantively large deterioration corresponding to the lower tail of the distribution of cognitive change in our sample.

A potential challenge in this approach is that the subjective question in SHARE asks specifically about "memory" change, not general cognitive ability. It is therefore possible that we are measuring awareness of a global decline using a memory-specific proxy. However, we argue this approach is both reasonable and informative. First, for many older adults, the subjective experience of "losing a step" mentally is often framed and understood through the lens of memory, making it the most salient and relatable domain for self-assessment. Second, as argued by Reid and MacLullich (2006), subjective memory complaints, even when not perfectly correlated with objective memory scores, often act as a broader indicator of underlying neurological distress or incipient cognitive impairment across multiple domains. Therefore, we interpret the self-assessment question as capturing an individual's overall perception of their cognitive trajectory, even if it is anchored to the language of memory.

[4] In Waves 1 and 2, all respondents received the same word list, whereas from Wave 4 onwards, they were randomly assigned to one of four versions of the "ten-word list learning" task, therefore limiting potential restesting effects.

The cognition loss event is then interacted with respondents' self-reported perceptions of memory decline, i.e. a binary variable equal to 1 if the respondent reports worsening memory and 0 otherwise. This has only become possible in SHARE in the newly extended cognitive module introduced in Wave 8. The goal of the self-assessed memory change item is to detect potential memory problems before clinical tests can detect them (see Bergmann and Börsch-Supan (2021) for more details about this new item in SHARE Wave 8). As put forward in Reid and MacLullich (2006), subjective memory complaints, if only inconsistently related to current cognition, seem to be more strongly related to future cognitive decline. This is especially true for people with high levels of cognitive abilities since these people would still score high on cognitive tests despite an onset of cognitive decline. They also correlate significantly with personality traits (neuroticism) and depression, which is why a special attention should be given to these two potential confounders, luckily also measured in SHARE.

Table 10 shows how respondents rate their memory change since last wave, and how this translated into actual memory loss as measured by our 20% drop in memory score versus as measured by a 1-standard deviation drop in memory score. Amongst those who went through a severe memory loss episode since last wave, i.e. 26% according to the 20% drop threshold, (Panel A), and 12.6% according to the 1-sd drop threshold (Panel B), less than a third (roughly 30%) self-rate their memory as worse. This is not so far from the share of those who self-report their memory as worse while experiencing no severe memory loss episode (25%). [5]

We finally combine these two variables to define the following four categories of people: "No loss" individuals are those who suffered no cognitive decline and correctly assess the absence of memory loss; the "Pessimistic" are those who suffered no cognitive loss event but still assess their memory has worsened since the last wave; the remaining two categories went through cognitive loss, but one group of people is aware of it (the "Aware"), the other mistakenly believes their memory has not worsened (the "Unaware").

Figure 5 presents the distribution of the age at which individuals experience a severe memory loss, distinguishing between those who are aware and those who are unaware of their decline.

While we could go back in time for panel respondents in order to identify the first occurrence of a severe memory loss episode, the awareness classification does not exist prior to Wave 8. We therefore show the distribution of age for those who experienced a severe loss between waves 8 and 9. The aware and unaware seem to differ in one aspect: the probability of going through a memory loss episode increases with age for the aware, but the same does not seem to apply to the unaware, amongst whom memory loss seems to strike at a younger age (between 60 and 70), and less so at older ages (past 75).

This classification will be at the core of the second part of the analysis on financial outcomes, the first part being centered on Cognitive and other Health outcomes.

[5] Same as in Mazzonna and Peracchi (2024), very little information is lost when collapsing the 3-item scale of this variable into a binary one, as only 1.17% declare their memory has become better since last wave.

4.4 Health and Wealth Outcomes

To examine how response times relate to later–life health trajectories, we focus on five outcomes that capture complementary clinical dimensions: physical mobility, chronic disease burden, mental health, frailty, and mortality. Physical mobility is measured with two indicators, namely an indicator for reporting at least one limitation in activities of daily living (ADLs) and a continuous mobility score that ranges from 0 (no limitations) to 10. In addition, we include an indicator for limitations in instrumental activities of daily living (IADLs), such as managing finances, taking medication, or using transportation —tasks that require greater cognitive and executive functioning than basic ADLs and are conceptually distinct from mobility constraints.

Chronic disease burden is proxied by an indicator that equals one when respondents report two or more physician-diagnosed conditions. Mental health is assessed with the *EURO-D* depression scale (0–12, where 0 denotes an absence of depressive symptoms), which sums symptoms such as suicidal thoughts, sadness, no hopes for the future, excessive guilt, sleep issues, fatigue, irritability, loss of appetite, tearfulness, concentration issues, lack of enjoyment, and difficulties keeping up interest in things.

A key addition is a frailty index constructed on the 0–5 phenotype proposed by Fried et al. (2001), which aggregates unintended weight loss, self-reported exhaustion, weak grip strength, slow gait, and low physical activity; scores of three or more are widely interpreted as clinical frailty, a condition that sharply elevates the risk of disability, hospitalisation, and death. Recent evidence underscores both the prevalence of frailty in European cohorts and its strong prognostic power for adverse outcomes (Kim and Rockwood, 2024), reinforcing the importance of including this marker in our analysis.

Finally, we consider all-cause mortality from Wave 8 to Wave 9. A detailed mapping of survey items to each composite indicator is provided in Table 1.

We will explore health outcomes in their original continuous form, which retains the full variation in the data and allows for more precise estimation under standard linear assumptions. In parallel, we construct binary indicators based on clinically validated thresholds commonly used in the geriatric and epidemiological literature—for example, at least one ADL or IADL limitation, two or more chronic conditions, a EURO-D score of 4 or higher, and three or more frailty components. Results using these binary definitions are presented in Appendix Figure A.2.

Our wealth variable, "net worth" is defined as the sum of net financial assets and real assets, i.e. $Net\ Worth = (hgfass–liab) + (home * perho/100 + vbus * sbus/100 + car + ores–mort)$, i.e. household gross financial assets $hgfass$ (sum of bank accounts, bond, stock and mutual funds, and savings for long-term investments), minus financial liabilities ($liab$), plus the value of residence (depending on the percentage of the house owned), the value of businesses (depending on the share of business owned), value of cars, and of other residences minus mortgages. To account for non-negligible rates of item non-response (higher for monetary variables than for the others), we use the imputations module for the wealth variable, which we then adjust for purchasing power parity (Germany 2015=1) to account for cross-country differences.[6]

5 Empirical strategy

5.1 Response Times, Cognitive Decline, and Health Decline

To estimate the relationship between cognitive score and response times, measured at the same wave, we follow Sanders et al. (2025) and start with the following equation:

$$CogScore_{i,t} = \beta_0 + \beta_1 Time_{i,t} + \beta_2 X_{i,t} + \delta_{k,t} + \epsilon_{i,t} \tag{1}$$

where $CogScore_{i,t}$ denotes the 26-point cognitive score of respondent i at Wave t (Wave 8 here), $Time_{i,t}$ is the respondent's standardized response time in the three tasks used to build the cognitive score at Wave t, and $X_{i,t}$ is a vector of individual-level covariates at Wave t. Following Sanders et al. (2025), we control for age (centered at the sample mean) and include a quadratic in age to capture nonlinear patterns in cognitive performance. We further adjust for gender and a binary indicator for migrant status, defined as living in a country other than one's country of birth. This variable serves as a proxy for minority status in the European context, where race and ethnicity data are typically not collected. Finally, $\delta_{k,t}$ denotes a set of either country fixed effects to account for institutional and linguistic differences in test administration, or interviewer-fixed effects, to account for the fact that interviewers with more experience may be assigned to participants with lower cognitive abilities (*this equation is used to estimate Table 5*).

Next, to study how time response at one wave predicts either the Cognitive Score, or an alternative health dimension, at next wave, we estimate the following equation:

$$Y_{i,t+1} = \alpha_0 + \alpha_1 Time_{it} + \alpha_2 X_{it} + \alpha_3 Y_{it} + \gamma_{kt} + \epsilon_{i,t} \tag{2}$$

where $Y_{i,t+1}$ is an outcome variable in wave $t+1$ (e.g., cognitive score or a health outcome), $Time_{it}$ is the standardized response time in wave 8, X_{it} is a set of individual controls in wave t (same as described above), γ_{kt} denote country/interviewer fixed effects in wave t. All controls are set at baseline i.e. at wave t (i.e. Wave 8). Importantly, we control for the lagged outcome Y_{it}, i.e. either the cognitive score or another health variable, in wave 8, which is crucial for ensuring that the estimated effect of response time Z_{it} on future outcomes $Y_{i,t+1}$ is not confounded by pre-existing differences in cognitive ability or health status. Without this control, the coefficient α_1 on response

[6] See the SHARE Release Guide 9.0.0. for an explanation of the fully conditional specification (FCS) method used to compute imputed values.

time could capture the simple persistence of cognitive or health trajectories rather than the specific role of response time in predicting changes. Furthermore,if response time is correlated with past cognition or health (which is highly likely), failing to condition on Y_{it} would result in an over- or underestimation of α_1. When the outcome is mortality, we additionally control for self-assessed health at baseline, since lagged mortality status must be 0 for everyone. This allows us to partially account for baseline health status and mitigate potential bias arising from the fact that response times at t may reflect contemporaneous health deterioration.

Tables 6-8 are based on this specification.

5.2 Response Times and Wealth Accumulation

Building on Banks et al. (2010) and Smith et al. (2010), in which wealth trajectories are shown to differ between low and high-cognition individuals, we turn to estimating how response times impact future wealth trajectories, using the following equation:

$$\Delta W_{i,t} = \beta_0 + \beta_1 Time_{i,t} + \beta_2 X_i + \beta_3 Z_{it} + \psi_c + \epsilon_{i,t} \tag{3}$$

where the outcome $\Delta W_{i,t}$ is the difference in wealth from wave t to $t+1$. i.e. from 8 to wave 9, $Time_{i,t}$ is the response time corresponding to the 26-point cognitive score questions in wave 8, X_i is a set of time-invariant characteristics, such as sex, educational attainment, and migrant status, $Z_i t$ is a set of time-varying control variables such as age, age squared, labor force status, wealth and the 26-point cognitive score, all measured at baseline t, i.e. here in Wave 8. ψ_c denote country fixed effects.

Second, we introduce the degree of awareness of cognitive decline in the last specification, following Mazzonna and Peracchi (2024):

$$\Delta W_{i,t} = \beta_0 + \beta_1 Time_{i,t} + \beta_2 Aware_{it} + \beta_3 Unaware_{it} + \beta_4 Pessimist_{it} + \beta_5 X_i + \beta_6 Z_{it} + \psi_c + \epsilon_{i,t}$$

$Aware_{it}, Unaware_{it}, Pessimist_{it}$ are indicators for the corresponding perception of cognitive decline, the omitted category being “No cognitive decline”. $Z_i t$ is the same as before.

Finally, we examine whether response times can help identify individuals who are unaware of their cognitive decline. To this end, we estimate a multinomial logit model where the outcome variable captures the four mutually exclusive categories of perceived cognitive change between waves: (i) no objective or subjective decline (reference), (ii) aware (objective and perceived decline), (iii) unaware (objective decline but no perceived decline), and (iv) pessimist (no objective decline but self-reported decline). We model the probability of belonging to each perception category as a function of the same covariates used in equation (3): standardized response time, individual controls X_i and Z_{it}, including wealth and cognitive score at t. This approach allows us to test whether longer response times are predictive of being unaware of one's cognitive deterioration, conditional on cognitive performance and other background characteristics.

6 Results

6.1 Response Times and Cognitive Decline

Table 5 presents estimates from Equation 1, assessing the association between response times and cognitive performance. In line with Sanders et al. (2025), we find that longer response times are significantly associated with lower cognitive scores across all specifications. This confirms that response latency captures meaningful variation in processing speed—an important, yet often overlooked, component of cognitive functioning in survey-based assessments.

The negative relationship between response times and cognitive scores is robust to the inclusion of controls for age (centered), gender, and migrant status, as well as country fixed effects, and interviewer fixed effects (FE), suggesting that neither observable demographics, nor cultural/national specificities, nor interviewer-specific pacing, drive the observed correlation.

To benchmark the magnitude of the response time effect, we compare it to the coefficients on key demographic controls in columns (3) and (4) of Table 5. A one standard deviation increase in standardized response time (Z-time) -approximately 38 seconds- is associated with a 0.515-point reduction in cognitive score (column 4). For comparison, the coefficient on age (centered around the sample mean) in column (3) is -0.167, implying that a one standard deviation increase in response time has an effect equivalent to aging by approximately 3 years.

The estimated effect of being female (relative to male) is $+0.685$, while the effect of being a migrant—defined as living in a country other than one's country of birth—is -0.381. These comparisons indicate that the association between response time and cognitive score is substantial: it is two-thirds as large as the gender gap in cognitive functioning at older ages and even larger than the migrant gap. This highlights the predictive value of response times as a proxy for cognitive functioning, capturing meaningful variation in cognition that aligns with well-established social gradients.

We then estimate Equation 2, predicting cognitive score at Wave 9 based on baseline cognitive performance and response times in Wave 8. As shown in Table 6, response time remains a significant predictor of future cognitive decline, even after controlling for cognitive score at Wave 8. In Column (1), with no additional controls, a one standard deviation increase in response time is associated with a 0.207-point lower cognitive score at follow-up. This estimate remains stable as we sequentially add controls: age in Column (2), interviewer fixed effects in Column (3), and finally additional demographic controls—age squared, gender, and migrant status—in Column (4), where the effect size is

–0.177.

To benchmark this effect, we compare it to the estimated coefficient on age in Column (3), which suggests that one additional year of age is associated with a 0.104-point decline in cognitive score. Based on this, the effect of a one standard deviation increase in response time is equivalent to the effect of approximately 1.6 years of aging.

To interpret the strength of the association between response times and cognitive deterioration more concretely, we examine how response speed predicts the probability of experiencing a clinically meaningful decline. Columns (2) and (3) of Table A.4 use binary indicators for a 20% or greater drop in global cognitive score or in memory recall, respectively. The results suggest that a one standard deviation increase in response time is associated with a 2.3 percentage point increase in the probability of a 20% drop in overall cognitive score, and a 1.9 percentage point increase in the probability of experiencing substantial memory loss. These magnitudes are notable given the relatively short time span between waves (approximately two years), and they highlight that slower response speed is not only associated with continuous cognitive decline (as shown in Table 6), but also with meaningful shifts across clinical or functional thresholds.

Table A.1 explores whether the predictive power of response times for future cognitive decline varies with respondents' baseline cognitive health status. Column (3) replicates the full specification from Table 6, Column (4). Column (2) restricts the sample to individuals classified as cognitively normal at baseline (i.e., excluding those with MCI or dementia) and shows that the coefficient on response time remains significant, though slightly attenuated (-0.136 vs. -0.177), suggesting that response times retain predictive power even among cognitively healthy individuals. This implies that response times also capture early signals of decline, even before deficits are formally detected. Column (1) provides further evidence through interaction terms between response time and cognitive status categories. We find that the association between slower response times and future cognitive decline becomes stronger as baseline cognitive impairment worsens.These results reinforce the idea that response speed is particularly predictive among those already exhibiting signs of cognitive vulnerability, but also retains value among the cognitively unimpaired.

Table A.2 examines heterogeneity in the predictive power of response times across demographic groups. Column (1) shows that the association between slower response times and future cognitive decline is more pronounced for women (-0.211) than for men (-0.131). Column (2) further indicates that the predictive strength of response times is notably higher for migrants (-0.345) compared to natives (-0.159).

6.2 Response Times and Health Decline

The next question we examine is whether response times in cognitive tests contain predictive information about future physical health—beyond what is captured by standard cognitive scores. Cognitive impairment is well established as a correlate of physical decline and increased mortality risk, particularly in the presence of dementia (Nguyen et al., 2003;

Sachs, 2009). Numerous studies have highlighted strong links between cognitive deterioration and the onset of frailty, a multidimensional syndrome encompassing weight loss, exhaustion, weakness, slow walking speed, and reduced physical activity. Importantly, cognition and frailty appear to be connected in a bidirectional cycle: cognitive decline raises the risk of frailty, while frailty itself may hasten cognitive deterioration (Robertson et al., 2013). Although frailty may act as a mediator in this relationship, prior work such as Cano et al. (2012) has shown that cognitive impairment independently predicts mortality.

In light of this literature, we investigate whether processing speed—measured through standardized response times—can help predict subsequent changes in health. Specifically, we regress a set of health outcomes measured at Wave 9—including ADL limitations, IADL limitations, chronic disease burden, depression symptoms (EURO-D), mobility restrictions, and the frailty index, defined continuously as number of symptoms, conditions, or limitations —on cognitive scores and response times from Wave 8. The corresponding multi-item definitions are detailed in Table 1.

Table 7 presents estimates controlling for Wave 8 cognitive function, demographic characteristics, and interviewer fixed effects. We find that longer response times are significantly associated with worse outcomes in IADLs, mobility, and frailty. These domains involve complex physical or executive functioning, suggesting that slower response speed may reflect broader physiological vulnerability. No significant associations are observed for chronic disease burden or depression, where cognitive score appears to remain the more salient predictor. Cognitive performance at baseline is consistently protective across all outcomes, particularly in domains such as depression and mobility.

Table 8 introduces an even more stringent specification by additionally controlling for health status at baseline. This allows us to interpret coefficients as associations with health deterioration between waves. Under this setup, response time remains significantly associated with subsequent increases in IADL limitations and frailty, while the effect on mobility becomes statistically insignificant—indicating that earlier results may have been driven by baseline mobility constraints. Cognitive scores continue to predict changes across all outcomes robustly.[7]

When we replicate the analyses using binary indicators of health outcomes—based on standard clinical thresholds—we find that some associations lose statistical significance (see Appendix Figure A.2).. This attenuation is expected, as dichotomizing continuous health measures (e.g., EURO-D scores or mobility indices) compresses variability and discards valuable within-category information, reducing statistical power. Nonetheless, the direction and magnitude of the effects are generally consistent, suggesting that the underlying relationships remain robust even if harder to detect in threshold-based models.

Together, these results suggest that processing speed and cognitive function each capture distinct dimensions of health risk. The persistent association between slower response times and worsening frailty, in particular, aligns with the view that processing speed may reflect underlying systemic decline that is not fully captured by standard cognitive

[7]Figure 2 shows the same results graphically.

assessments.

6.3 Response Times and Wealth Accumulation

Table 12 examines whether cognitive processing speed, proxied by response times, can predict changes in financial wellbeing—specifically, changes in net worth (wealth accumulation or depletion) between Waves 8 and 9. In Columns (1) to (3), we reproduce a result consistent with prior findings by Banks et al. (2010) and Smith et al. (2010): individuals with higher cognitive scores at baseline tend to accumulate more wealth over time. The coefficient remains stable when we account for country fixed effects (Column 2), addressing potential compositional biases due to cross-country heterogeneity in both wealth and cognitive ability, if for instance some countries exhibited both poorer cognitive functioning and lower wealth at older ages (e.g. Southern Europe). It becomes stronger when interviewer fixed effects are included (Column 3), suggesting that interviewer behavior may partly confound the observed relationship.

In Column (4), we include response time (Z-time) alongside the cognitive score. The coefficient on cognitive score remains virtually unchanged, while the coefficient on Z-time is negative and statistically significant at the 10% level. This suggests that slower response times predict wealth decumulation independently of baseline cognitive score, and hence add predictive power beyond what is captured by standard cognitive tests.

To better understand the relative contributions of cognitive performance and response speed across domains, we benchmark the standardized coefficients of each. In Table 6 (Column 4), a one standard deviation increase in cognitive score (3.644 points) is associated with a 2.10-point increase in the subsequent cognitive score, while a one standard deviation increase in response time (Z-time) predicts a 0.18-point decline. This implies that the predictive power of response time for future cognitive functioning is approximately 8% that of cognitive score.

In contrast, Table 12 (Column 4) shows that a one standard deviation increase in cognitive score is associated with an \$82,121 increase in net wealth, while a one standard deviation increase in response time predicts a \$58,112 decrease in wealth. Thus, in the financial domain, the effect of response time is around 70% the magnitude of that of cognitive score.

These comparisons show that while response times are less predictive than accuracy-based cognitive scores in both domains, they remain strong predictors of future outcomes. Notably, response times carry relatively greater weight in predicting financial outcomes than in forecasting cognitive trajectories, with an effect size that reaches nearly 70% of that of the cognitive score. This suggests that response speed captures dimensions of cognitive functioning—such as processing fluency, executive efficiency, or task engagement—not fully reflected in standard performance measures, and which may be especially relevant for complex financial decision-making.

6.4 How does awareness of cognitive decline affect wealth (de-)accumulation, and is there a role for response times in predicting unawareness?

Our analysis first confirms a critical finding from Mazzonna and Peracchi (2024), replicating their US-based results in a European context. As shown in Table A.15, severe memory loss is indeed associated with significant declines in net worth. Crucially, these financial losses are almost entirely concentrated among individuals who are unaware of their cognitive decline. This powerful result holds regardless of whether the cognitive decline is measured narrowly through recall tests or more broadly using the 26-point cognitive score (Table **??**). This establishes that the link between financial vulnerability and the unawareness of cognitive decline is a robust phenomenon, not merely an artifact of a specific test. The pivotal question is whether response times (RTs) add further predictive power. The results in Table 13 and Table 14 are striking: even after accounting for objective cognitive decline and a person's awareness of it, slower response times remain a strong, independent predictor of wealth loss. While the statistical significance of the "unaware" category itself diminishes in one specification (Table 13), this is due to reduced statistical power in a smaller sample (when we re-estimate the regressions in Table A.15 using the smaller sample from Table 13, awareness also loses significance.); the underlying pattern remains. Indeed, in the larger sample using the broader cognitive score, both unawareness and slower RTs are significant predictors of financial decline (Table 14). This demonstrates that RTs capture a dimension of cognitive vulnerability—perhaps related to processing speed or executive function—that is not fully encapsulated by standard cognitive scores or self-reported awareness, yet has tangible financial consequences.

Tables 15 and 16 show that response times also help predict awareness of cognitive decline—a particularly meaningful result in light of prior findings on the financial risks associated with being unaware of cognitive deterioration. In both tables, we estimate multinomial logits where the baseline category is those who experience no significant cognitive loss. The dependent variable captures three mutually exclusive outcomes: experiencing cognitive decline and being aware of it ("Aware"), experiencing decline without awareness ("Unaware"), and being cognitively stable but reporting memory problems ("Pessimist").

In both the 26-point cognitive score specification (Table 15) and the recall-based specification (Table 16), slower response times significantly increase the probability of being unaware of one's cognitive decline. The magnitude of the association is robust and consistent across definitions. In contrast, response times do not predict awareness or "pessimism." These patterns suggest that RTs capture a latent dimension of cognitive functioning that contributes to unawareness—a cognitive state with substantial economic consequences, as shown in Tables 13 and **??**.

Importantly, these results reinforce our earlier finding that unawareness is a critical mechanism linking cognitive health to wealth loss. RTs—beyond predicting decline and wealth deaccumulation—also serve as a signal of this unobserved vulnerability. They are thus triply informative.

7 Conclusion

This study reveals the powerful and multifaceted potential of response times (RTs) as indicators of cognitive vulnerability and its broader socioeconomic and health consequences. Using rich longitudinal data from SHARE, we document three key findings:

1. Slower response times predict subsequent declines in cognitive functioning, including both overall cognitive score and memory loss, as well as future health deterioration, frailty, and even mortality. These associations persist even after controlling for baseline cognitive performance, suggesting that RTs capture dimensions of cognitive efficiency or resilience not fully reflected in traditional test scores.

2. RTs also strongly predict wealth deaccumulation, capturing financial vulnerability that is not fully explained by cognitive scores or memory recall. Individuals with slower response times tend to lose significantly more wealth between waves, even when controlling for initial cognition, awareness of decline, and other socioeconomic factors.

3. Most strikingly, RTs are predictive of unawareness of cognitive deterioration—a particularly high-risk state in which individuals do not perceive their own decline yet are exposed to steep financial losses. This capacity to flag individuals who are both cognitively impaired and unaware makes RTs a valuable early-warning signal for deteriorating decision-making capacity.

Crucially, response times are already recorded in most large-scale surveys that include cognitive testing. This makes them a costless, non-intrusive, and scalable tool for identifying individuals at elevated risk of cognitive, financial, and health decline. Our results suggest that what was previously considered a technical byproduct of survey design—response latency—should instead be viewed as a rich behavioral signal.

These findings open several promising avenues for future research. First, the cross-national design of SHARE allows us to explore country-level heterogeneity in how RTs and cognitive unawareness relate to financial and health outcomes. These associations may vary depending on institutional context—for instance, the importance of third-pillar pensions and the extent to which financial autonomy is required in later life. Second, given the strong gender differences we observe in both response times and awareness classifications, future work should examine how gender norms and social roles condition these patterns across countries.

Finally, in line with our goal of demonstrating the practical value of RTs, we are currently using machine learning algorithms to identify which time stamps are most predictive, focusing in particular on items commonly included in household surveys beyond cognitive tests. If RTs to such general survey items can predict meaningful declines in health and wealth, this would further enhance the applicability of response times as a diagnostic tool, particularly in datasets that lack formal cognitive assessments.

Table 1. Health Indicators Definitions

Indicator	Definition
ADLs (Activities of Daily Living)	Number of difficulties in: 1. Dressing, including putting on shoes and socks 2. Walking across a room 3. Bathing or showering 4. Eating, such as cutting up food 5. Getting in or out of bed 6. Using the toilet, including getting up or down
IADLs (Instrumental Activities of Daily Living)	Number of difficulties in: 1. Using a map to figure out how to get around in a strange place 2. Preparing a hot meal 3. Shopping for groceries 4. Making telephone calls 5. Taking medications 6. Doing work around the house or garden 7. Managing money (paying bills, tracking expenses) 8. Leaving the house independently and accessing transportation
Multimorbidity (2+ Chronic Diseases)	Indicator for having at least two of the following: 1. Heart attack, including myocardial infarction or coronary thrombosis 2. High blood pressure or hypertension 3. High blood cholesterol 4. Stroke or cerebral vascular disease 5. Diabetes or high blood sugar 6. Chronic lung disease (bronchitis, emphysema) 7. Cancer or malignant tumor (excluding minor skin cancers) 8. Stomach or duodenal ulcer, peptic ulcer 9. Parkinson's disease 10. Cataracts 11. Hip fracture 12. Other fractures 13. Alzheimer's disease, dementia, or other serious memory impairment 14. Other emotional disorders (e.g., anxiety, psychiatric issues) 15. Rheumatoid arthritis 16. Osteoarthritis or other rheumatic conditions
EURO-D Depression Scale (0-12)	Count of depressive symptoms: 1. Feelings of depression or sadness 2. Any hopes for the future 3. Would rather be dead 4. Feelings of guilt 5. Trouble sleeping 6. Less interest in things 7. Irritability 8. Loss of appetite 9. Fatigue 10. Trouble concentrating 11. No enjoyment 12. Tearfulness
Mobility Score (0-10)	Score based on number of limitations (0 = no limitations) in: 1. Walking 100 meters 2. Sitting for about two hours 3. Getting up from a chair after sitting for long periods 4. Climbing several flights of stairs without resting 5. Climbing one flight of stairs without resting 6. Stooping, kneeling, or crouching 7. Reaching or extending arms above shoulder level 8. Pulling or pushing large objects (e.g., living room chair) 9. Lifting or carrying weights over 5 kg (e.g., heavy grocery bag) 10. Picking up a small coin from a table

Indicator	Definition
Frailty Index (0–5)	Sum of five binary indicators for: 1. weak grip strength 2. exhaustion 3. Unintentional weight loss or appetite reduction 4. Slowness in walking or climbing stairs 5. Low frequency of moderate physical activity

Table 2. Summary Statistics

	(1)	(2)	(3)
	Wave 8	Wave 9	Both
Female	0.554	0.554	0.554
	(0.497)	(0.497)	(0.497)
Age	71.653	73.815	72.734
	(7.140)	(7.166)	(7.234)
Migrant	0.085	0.085	0.085
	(0.280)	(0.280)	(0.280)
Observations	18,766	18,766	37,532

Notes: The data come from SHARE. Summary statistics of the respondents who completed the cognitive module in waves 8 and 9.

Table 3. Descriptive Statistics for the Score, Langa-Weir Classification

	Wave 8		Wave 9	
	Mean	St. Dev.	Mean	St. Dev.
Cognitive Score	15.295	3.643	14.909	3.920
Fraction normal	0.854	0.353	0.817	0.386
Fraction with CIND	0.134	0.341	0.159	0.365
Fraction with Dementia	0.012	0.108	0.024	0.153

Notes: The data come from SHARE. Summary statistics for the cognitive score of the 18,766 respondents who completed the cognitive module in waves 8 and 9. The scale and classification are based on Langa et al. (2020).

Table 4. Descriptive Statistics for Response Times, Langa-Weir classification, Wave 8

	Mean	St.dev.	Min	Max	N
Overall	121.784	37.140	19	577	18,766
With normal Cognition	120.214	35.843	19	577	16,024
With CIND	129.823	42.131	19	432	2,522
With Dementia	143.918	48.437	49	274	220

Notes: The data come from SHARE. Summary statistics for response time in wave 8 of the respondents who completed the cognitive module in waves 8 and 9. The scale and classification are based on Langa et al. (2020).

Table 5. Cognitive Health and Response Time at Wave 8

	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.568***	-0.472***	-0.491***	-0.506***
	(0.028)	(0.026)	(0.027)	(0.027)
Age		-0.155***	-0.167***	-0.005
		(0.004)	(0.003)	(0.039)
Age^2				-0.001***
				(0.000)
Female				0.686***
				(0.046)
Migrant				-0.381***
				(0.093)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	18,766	18,766	18,766	18,766
R^2	0.024	0.116	0.355	0.364

Notes: The data come from the SHARE. The dependent variable is the cognitive score, and the variable of interest is the standardized time needed to answer the questions. Other controls include age squared, sex, and migration status.

Figure 1. Response Time and Performance at each Test

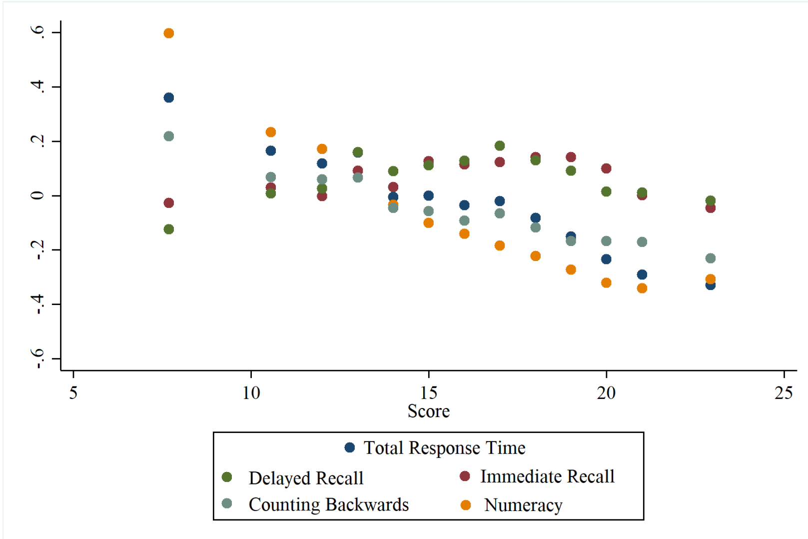


Table 6. Predicting Cognitive Score in Wave 9 using Response Time in Wave 8

	(1)	(2)	(3)	(4)
	F.Score	F.Score	F.Score	F.Score
Z-time	-0.206***	-0.182***	-0.167***	-0.175***
	(0.023)	(0.022)	(0.025)	(0.025)
Score	0.688***	0.633***	0.577***	0.571***
	(0.006)	(0.007)	(0.008)	(0.008)
Age		-0.091***	-0.104***	0.006
		(0.003)	(0.003)	(0.036)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	18,766	18,766	18,766	18,766
R^2	0.422	0.447	0.540	0.542

Notes: The data come from the SHARE. The dependent variable is the cognitive score, and the variable of interest is the standardized time needed to answer the questions. Other controls include age squared, sex, and migration status.

Table 7. Predicting Health Outcomes in Wave 9 using Response Times in Wave 8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	F.Adl limitations	F.IADL	F.Chronic diseases	F.Depression	F.Mobility	F.Frailty	F.Self-perceived health
Z-time	0.014**	0.038***	0.008	0.022	0.053***	0.041***	0.018**
	(0.006)	(0.010)	(0.013)	(0.017)	(0.017)	(0.009)	(0.007)
Score	-0.014***	-0.041***	-0.036***	-0.058***	-0.075***	-0.047***	-0.038***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)	(0.003)	(0.002)
Observations	18,766	18,766	18,766	18,766	18,766	18,766	18,766
R^2	0.138	0.224	0.209	0.246	0.274	0.277	0.254

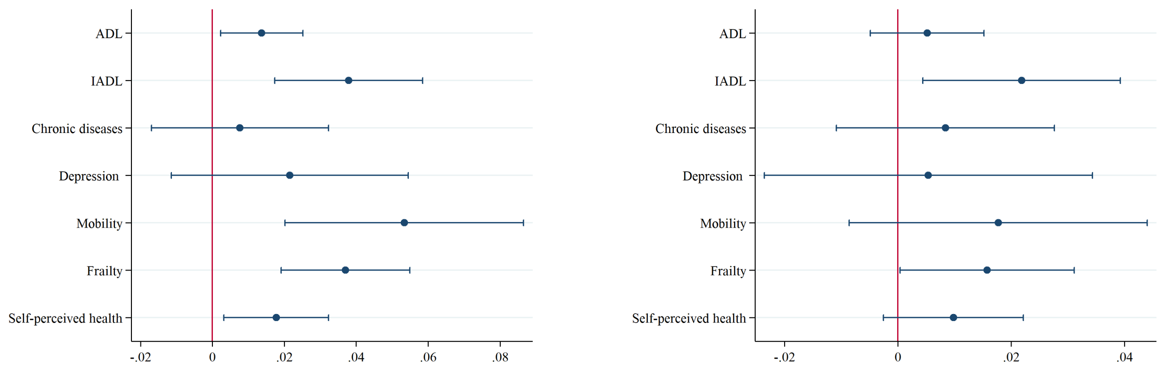
Notes: The data come from SHARE. The dependent variables in columns one to three are the number of ADL, limitations with instrumental activities of daily living (IADL), and chronic diseases; in columns four and five are the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations); and column six denotes frailty index. All the regressions control include the full set of controls and interviewer fixed effects.

Table 8. Predicting Health Outcomes in Wave 9 using Response Times and Controlling for Health Outcomes in Wave 8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	F.Adl limitations	F.IADL	F.Chronic diseases	F.Depression	F.Mobility	F.Frailty	F.Self-perceived health
Z-time	0.005	0.021**	0.008	0.005	0.018	0.015**	0.010
	(0.005)	(0.009)	(0.010)	(0.015)	(0.013)	(0.008)	(0.006)
Score	-0.009***	-0.024***	-0.009***	-0.026***	-0.029***	-0.023***	-0.014***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)
Observations	18,766	18,766	18,766	18,766	18,766	18,766	18,766
R^2	0.310	0.435	0.526	0.426	0.552	0.454	0.471

Notes: The data come from SHARE. The dependent variables in columns one to three are the number of ADL, limitations with instrumental activities of daily living (IADL), and chronic diseases; in columns four and five are the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations); and column six denotes frailty index. All the regressions control include the full set of controls and interviewer fixed effects.

Figure 2. Predicting Health Outcomes in Wave 9 using Response Times - With and without health controls at baseline.



(a) Panel A: No Health$_t$ **(b) Panel B: Health$_t$**

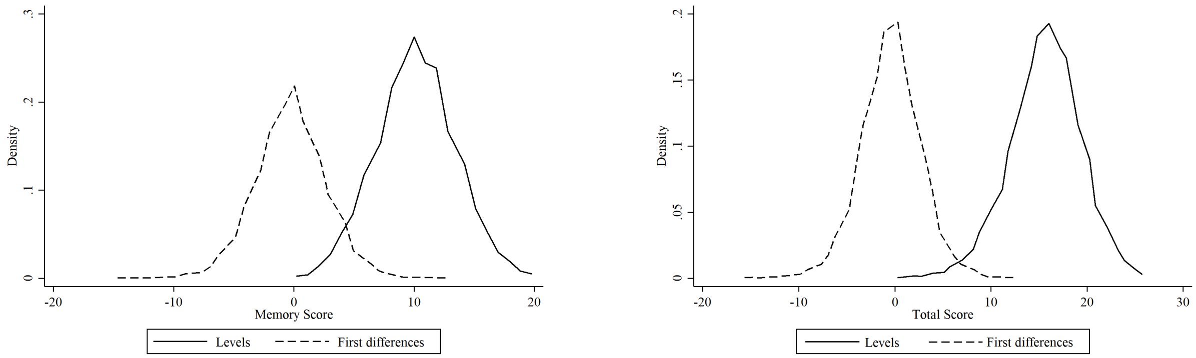
Notes: The data come from SHARE. The dependent variables are the number of ADL, limitations with instrumental activities of daily living (IADL), and chronic diseases; the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations); and the frailty index. All the regressions include the full set of controls and interviewer fixed effects. Regressions in Panel A do not control for health in Wave 8, while the regressions in Panel B control for health in Wave 8.

Table 9. Predicting Mortality between Waves 8 and 9 Using RT in Wave 8

	(1)	(2)	(3)	(4)
	F.Deceased	F.Deceased	F.Deceased	F.Deceased
Z-time	0.004***	0.003**	0.003**	0.003*
	(0.001)	(0.001)	(0.002)	(0.001)
Score	-0.006***	-0.004***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Age		0.003***	0.003***	-0.042***
		(0.000)	(0.000)	(0.004)
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	22,993	22,993	22,993	22,993
R^2	0.021	0.038	0.108	0.128

Notes: The data come from the SHARE. The dependent variable is the indicator variable, which is coded as one if the respondent is deceased in wave 9, and the variable of interest is the standardized time needed to answer the questions in wave 8. Other controls include age squared, sex, migration status, and self-assessed health.

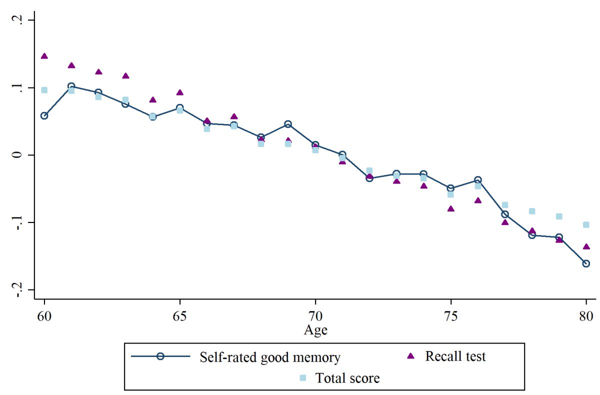
Figure 3. Memory and Total Score



(a) Panel A: Memory Score **(b) Panel B: Total Score**

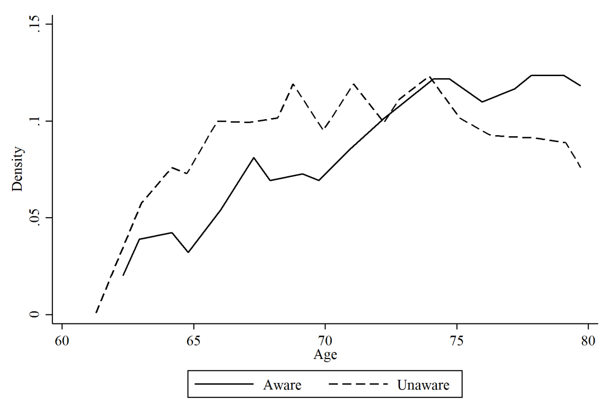
Notes: Based on SHARE. Density of memory scores in levels and first differences.

Figure 4. Assessed versus self-rated memory by age



Notes: Based on SHARE. The figure presents the average age profile for the total memory score (solid line), and the share of respondents rating their memory as better (dashed line). Both indexes are standardized.

Figure 5. Age at Memory Loss



Notes: Based on SHARE. The figure shows the distribution of age among respondents who experienced a memory loss of at least 20%.

Table 10. Self-Rated versus Assessed Memory

Self-Rated Memory Change	No	Yes	Total
	A. Severe Relative Memory Loss		
Better now	0.71	0.24	0.94
About the same	53.90	18.00	71.91
Worse now	19.15	8.00	27.15
Total	73.76	26.24	100.00
	B. Severe Absolute Memory Loss		
Better now	0.80	0.14	0.94
About the same	63.19	8.72	71.91
Worse now	23.19	3.96	27.15
Total	87.18	12.82	100.00

Notes: Based on SHARE. The table compares self-rated memory changes across waves with two different measures of memory loss: severe relative memory loss (panel A), defined as a decline of 20% or more in the memory score, and severe absolute memory loss (panel B), defined as a memory score change of 1 standard deviation or more.

Table 11. Means and Standard Deviations (SDs) of Key Variables

	(1) Full Sample	(2) Loss Sample
D.Wealth	466.293	429.801
	(3850.299)	(2726.298)
L.Wealth	1596.048	1256.874
	(4376.832)	(3167.904)
Aware	0.080	0.305
	(0.271)	(0.460)
Unaware	0.182	0.695
	(0.386)	(0.460)
Pessimist	0.192	0.000
	(0.394)	(0.000)
L.Memory Score	10.306	11.085
	(3.211)	(3.249)
L.Total Score	15.824	16.552
	(3.543)	(3.635)
L.Age	69.244	69.874
	(4.990)	(4.943)
Female	0.586	0.566
	(0.493)	(0.496)
L.Married	0.598	0.580
	(0.490)	(0.494)
High school	0.341	0.315
	(0.474)	(0.465)
College	0.003	0.003
	(0.054)	(0.054)
L.Employed	0.141	0.118
	(0.348)	(0.323)
Migrant	0.085	0.095
	(0.279)	(0.294)
N	11,910	3,125

Notes: Based on SHARE. Memory loss is based on the recall test. The table presents the mean and standard deviations (in parentheses) of key variables for the full sample and the sample of respondents who experienced a memory loss of at least 20%.

Table 12. Predicting Wealth (De-)accumulation from Wave 8 to Wave 9 using Wave 8 Response Times

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Score	30.885***	25.063***	21.687**	29.765***
	(11.161)	(8.979)	(8.958)	(10.796)
Z-time			-115.969***	-92.662**
			(38.924)	(38.749)
Country FE	No	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.062	0.192	0.192	0.319

Notes: Based on SHARE. The dependent variable is a change in net worth. Controls include lags of age, age squared, sex, labor force status, marital status, migration status, and wealth.

Table 13. Predicting Wealth (De-)accumulation from Wave 8 to Wave 9 using Wave 8 Response Times: Loss based on recall test.

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Z-time	-116.5167***	-115.4682***	-91.6365**	-91.5565**
	(38.9329)	(38.8967)	(38.5973)	(38.7905)
Memory loss	-62.1416		-72.5307	
	(63.4480)		(71.5291)	
L.Score	23.5187**	23.7969**	31.9004***	31.7347***
	(9.1625)	(9.2487)	(11.1880)	(11.2981)
Aware		-25.2445		-100.3499
		(100.9056)		(107.8927)
Unaware		-50.3185		-58.2793
		(70.1589)		(78.4677)
Pessimist		66.5476		3.7142
		(101.5686)		(107.3633)
Country FE	Yes	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.193	0.193	0.319	0.319

Notes: Based on SHARE. The dependent variable is a change in net worth. Memory loss and awareness classification is based on a recall test. Controls include lags of age, age squared, sex, labor force status, marital status, migration status, wealth, and cognitive score.

Table 14. Predicting Wealth (De-)accumulation from Wave 8 to Wave 9 using Wave 8 Response Times: Loss based on 26-point Score.

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Z-time	-116.2812***	-115.0558***	-90.2623**	-90.2418**
	(38.9215)	(38.8508)	(38.4128)	(38.5978)
Memory loss	-91.3168		-127.4795	
	(69.6909)		(78.1709)	
L.Score	23.5390**	24.0183***	32.3125***	32.2437***
	(9.1955)	(9.2811)	(11.1545)	(11.2715)
Aware		-4.5363		-137.8011
		(116.2351)		(121.4149)
Unaware		-113.5182		-122.8035
		(75.0645)		(83.5386)
Pessimist		44.7482		-1.9603
		(92.9593)		(98.9630)
Country FE	Yes	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.193	0.193	0.319	0.319

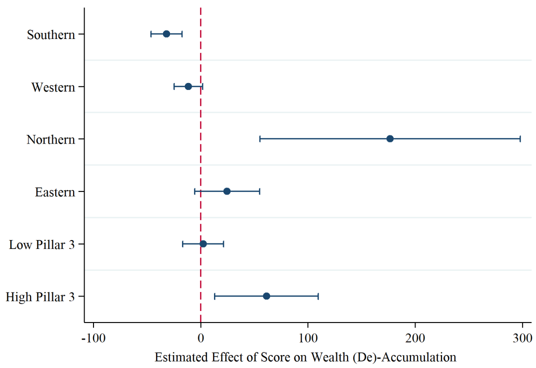
Notes: Based on SHARE. The dependent variable is a change in net worth. Memory loss and awareness classification are based on the total cognitive score. Controls include age, age squared, sex, labor force status, marital status, migration status, lagged wealth, and cognitive score

Table 15. Predicting Awareness, Multinomial logit: Based on 26-Score

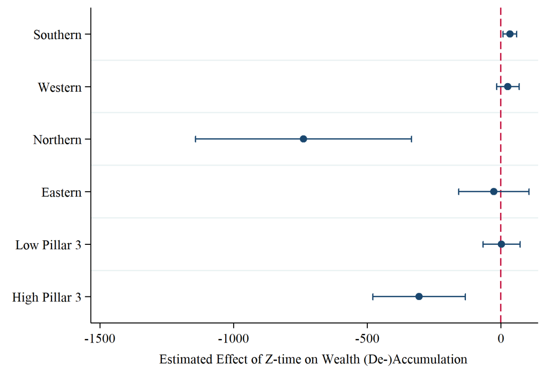
	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	0.0122	0.0345	0.0816***
	(0.0247)	(0.0440)	(0.0308)
Score	-0.0505***	0.0494***	0.1531***
	(0.0074)	(0.0138)	(0.0104)
Female	0.1488***	-0.1095	-0.2690***
	(0.0514)	(0.0905)	(0.0681)
Observation	11,910	11,910	11,910

Notes: Based on SHARE. Awareness classification is measured by memory loss based on the total score. Z-time measures standardized total time stamps. All regressions include lagged age, age squared, sex, educational attainment, labor force status, marital status, country identifiers, migration status, wealth, and lagged score.

Figure 6. Country Heterogeneity of Estimated Effects on Wealth



(a) Panel A: Score



(b) Panel B: Z-time

Notes: Based on SHARE. High pillar denotes countries which have pillar 3 above average,

Table 16. Predicting Awareness, Multinomial logit: Based on Recall Test

	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	0.0081	0.0425	0.0587**
	(0.0262)	(0.0375)	(0.0263)
Score	-0.0498***	0.0693***	0.1554***
	(0.0078)	(0.0121)	(0.0087)
Female	0.1631***	-0.2127***	-0.3344***
	(0.0543)	(0.0786)	(0.0562)
Observation	11,910	11,910	11,910

Notes: Based on SHARE. Awareness classification is measured by memory loss based on recall. Z-time measures standardized total time stamps. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

Table 17. Cognitive Health and Changes in Wealth: Heterogeneity by Sex

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Z-time*male	-181.4324**	-182.2243**	-182.1131**	-182.1838**
	(71.0400)	(71.0148)	(71.3620)	(71.0696)
Z-time*female	-38.4738	-37.9605	-38.7863	-38.2068
	(40.0864)	(40.0799)	(39.9859)	(39.9945)
Unaware*male	-111.3433	-242.0181*		
	(129.0839)	(130.0030)		
Unaware*female	-19.4462	-40.8395		
	(94.8727)	(105.4415)		
Aware*male	-277.2714	-365.3336		
	(197.7549)	(230.8009)		
Aware*female	23.0002	2.3665		
	(112.1511)	(125.3941)		
Pessimist*male	34.3328	11.4830		
	(233.3599)	(208.9257)		
Pessimist*female	-17.6593	-10.2253		
	(88.4601)	(84.8243)		
Score*male	39.2101**	40.0789**	39.7515**	40.4919**
	(16.7427)	(16.6261)	(16.7153)	(16.6097)
Score*female	27.1032**	27.9733**	27.0068**	27.8489**
	(12.0722)	(12.1753)	(12.0414)	(12.1347)
Loss*male			-169.4801	-284.8505**
			(121.6931)	(130.9016)
Loss*female			-1.1105	-22.5611
			(76.6563)	(85.0660)
Loss based on 26-Score	No	Yes	No	Yes
Loss based on Recall	Yes	No	Yes	No
Interviewer FE	Yes	Yes	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.319	0.319	0.319	0.319

Notes: Based on SHARE. Z-time measures standardized total time stamps. All regressions include lagged age, age squared, sex, educational attainment, labor force status, marital status, and wealth.

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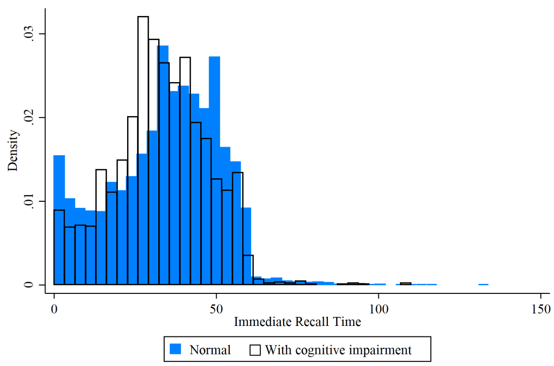
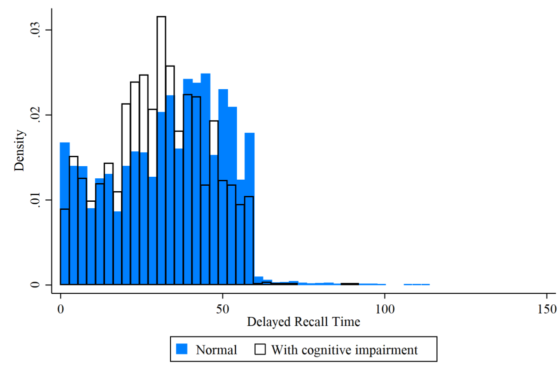
Online Appendix

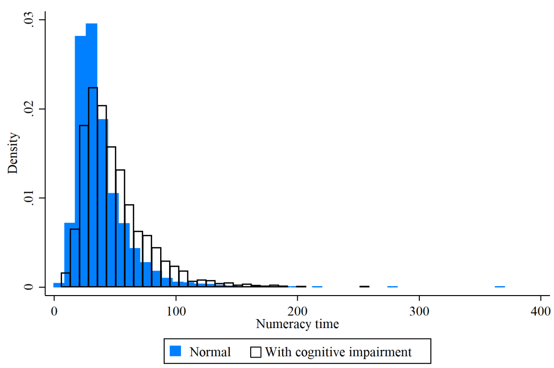
Figure A.1. Density of Response Times



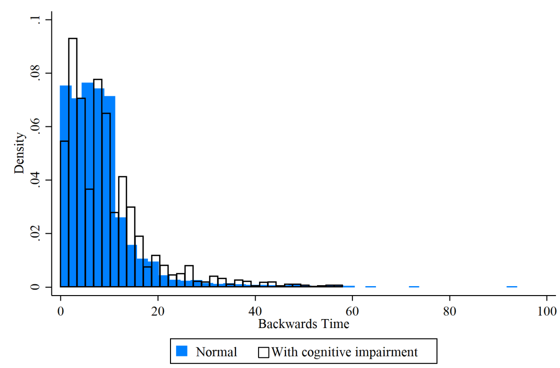
(a) Panel A: Immediate Recall



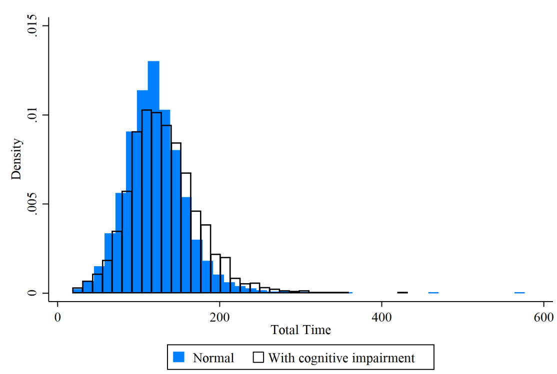
(b) Panel B: Delayed Recall



(c) Panel C: Numeracy



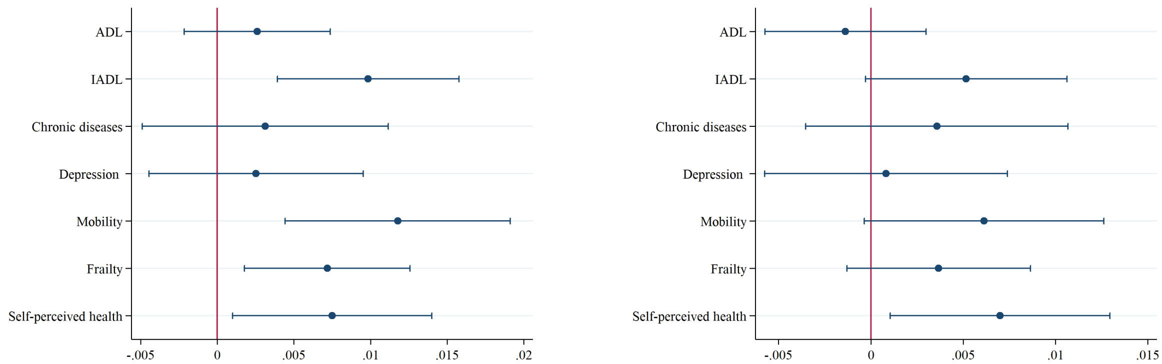
(d) Panel D: Backwards Counting



(e) Panel E: Total Time

Notes: The data come from SHARE.

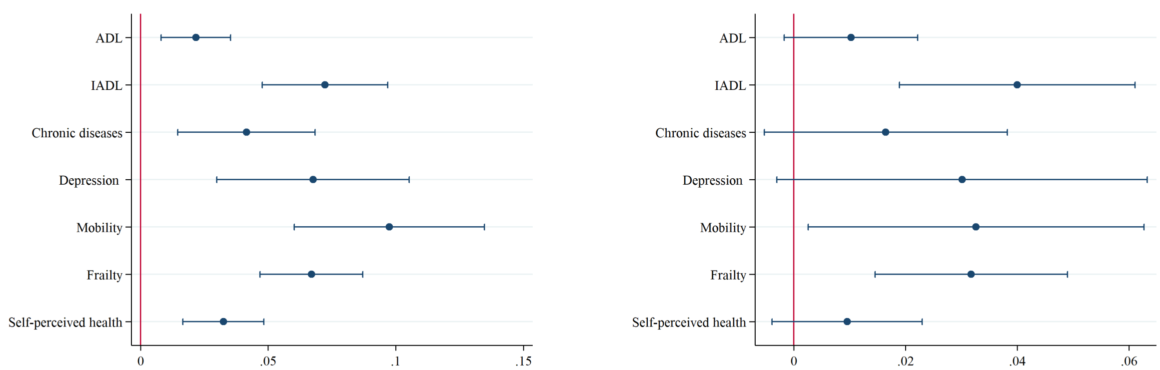
Figure A.2. Health Outcomes in Wave 9 and RT in Wave 8, Indicator Variables



(a) Panel A: No Health$_t$ **(b) Panel B: Health$_t$**

Notes: The data come from SHARE. The dependent variables are the indicator variables for having ADL, IADL, more than two chronic diseases, more than two mobility limitations, a depression scale larger than four, and a frailty index larger than three. All the regressions include the full set of controls and interviewer fixed effects. Regressions in Panel A do not control for health in Wave 8, while the regressions in Panel B control for health in Wave 8.

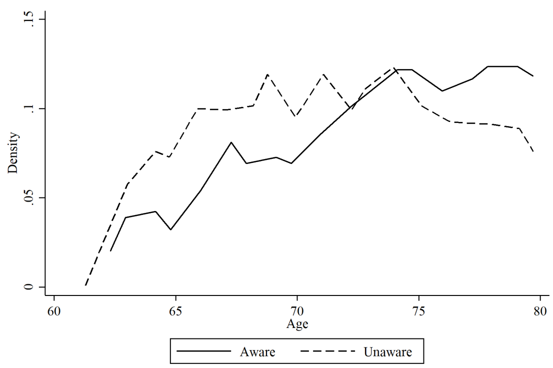
Figure A.3. Health Outcomes in Wave 9 and Alternative RT in Wave 8



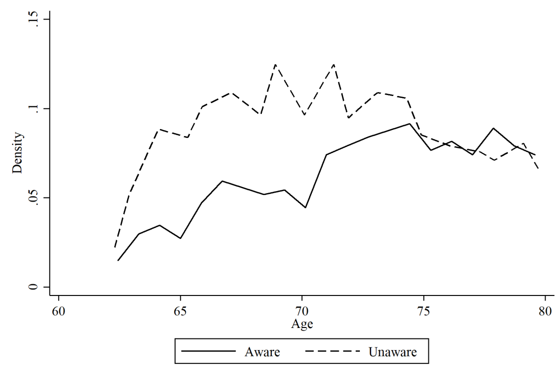
(a) Panel A: No Health$_t$ **(b) Panel B: Health$_t$**

Notes: The data come from SHARE. The alternative RT measures one standard deviation of the sum of numeracy and backwards counting response time. The dependent variables are the number of ADL, limitations with instrumental activities of daily living (IADL), and chronic diseases; the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations); and the frailty index. All the regressions include the full set of controls and interviewer fixed effects. Regressions in Panel A do not control for health in Wave 8, while the regressions in Panel B control for health in Wave 8.

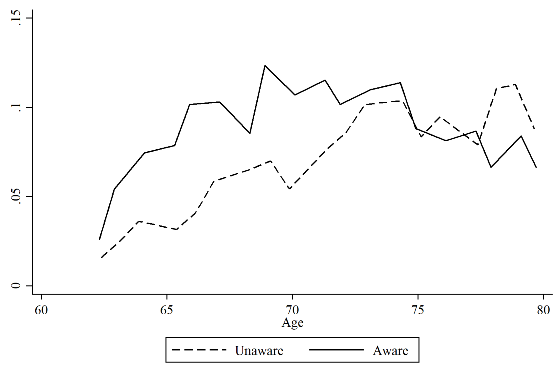
Figure A.4. Age at Loss: Alternative definitions of Loss



(a) Panel A: 1SD of Memory Score



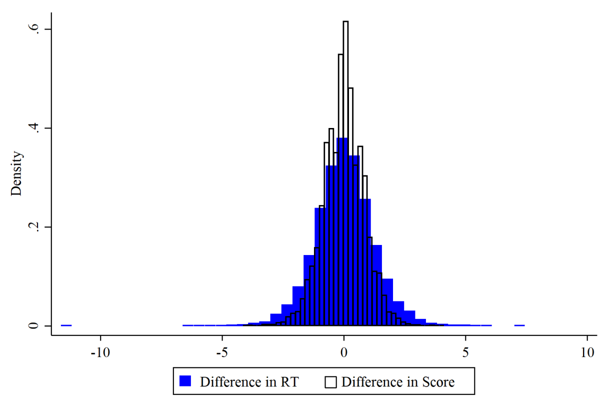
(b) Panel B: 20% of Total Score



(c) Panel C: 1SD of Total Score

Notes: The data come from SHARE. Panel A defines loss as a one-standard-deviation decrease in memory score; Panel B defines loss as a 20% decrease in total score; Panel C defines loss as a one-standard-deviation decrease in total score.

Figure A.5. Distribution of Changes in Standardized Time and Score



Notes: Based on data from SHARE. The figure plots the distribution of changes in standardized score and response time between waves 8 and 9.

Table A.1. Cognitive Health in Wave 9 and RT in Wave 8: Heterogeneity by Cognitive Health in Wave 8

	(1)	(2)	(3)
	F.Score	F.Score	F.Score
Z-time*Normal	-0.326***		
	(0.029)		
Z-time*MCI	-0.366***		
	(0.068)		
Z-time*Dementia	-0.480**		
	(0.196)		
Z-time		-0.134***	-0.175***
		(0.026)	(0.025)
Interviewer FE	Yes	Yes	Yes
Excludes with CIND and Dementia	No	Yes	No
Observations	18,766	16,024	18,766
R^2	0.438	0.461	0.542

Notes: The data come from the SHARE. The dependent variable is the cognitive score in wave 9. All the regressions include the full set of controls. Column one includes cognitive health classification in wave 8 and the interaction between standardized time and this classification. Columns two and three control for the cognitive score in wave 8. Column two excludes those with MCI and dementia, and column three is the original regression.

Table A.2. Cognitive Health in Wave 9 and RT in Wave 8: Heterogeneity by Demographic Characteristics

	(1)	(2)
	F.Score	F.Score
Z-time*female	-0.197***	
	(0.031)	
Z-time*male	-0.147***	
	(0.036)	
Score*female	0.595***	
	(0.009)	
Score*male	0.537***	
	(0.011)	
Z-time*native		-0.160***
		(0.026)
Z-time*migrant		-0.334***
		(0.077)
Score*native		0.569***
		(0.008)
Score*migrant		0.594***
		(0.021)
Interviewer FE	Yes	Yes
Observations	18,766	18,766
R^2	0.542	0.542

Notes: The data come from the SHARE. The dependent variable is the cognitive score in wave 9. All the regressions include the full set of controls and cognitive health in wave 8.

Table A.3. Cognitive Health in Wave 9 and RT in Wave 8: Sensitivity to Functional Form of RT

	(1)	(2)	(3)
	F.Score	F.Score	F.Score
Z-time	-0.175***	-0.177***	
	(0.025)	(0.026)	
Z-time^2		0.002	
		(0.011)	
Ln(RT)			-0.506***
			(0.077)
Interviewer FE	Yes	Yes	Yes
Observations	18,766	18,766	18,766
R^2	0.542	0.542	0.541

Notes: The data come from the SHARE. The dependent variable is the cognitive score in wave 9. All the regressions include the full set of controls and cognitive health in wave 8.

Table A.4. Predicting severe memory/cognitive loss between Waves 8 and 9 using RT in wave 8

	(1)	(2)	(3)
	D.Score	Cognitive loss	Memory Loss
Z-time	-0.175***	0.023***	0.019***
	(0.025)	(0.003)	(0.004)
Age	0.006	0.001	-0.002
	(0.036)	(0.005)	(0.006)
Interviewer FE	Yes	Yes	Yes
Observations	18,766	18,765	18,746
R^2	0.305	0.149	0.156

Notes: The data come from the SHARE. The dependent variables in columns one to three are changes in cognitive health between waves 8 and 9, cognitive loss of more than 20%, and memory loss of more than 20%, respectively. All the regressions include the full set of controls and cognitive health in wave 8.

Table A.5. Descriptive Statistics for Numeracy and Backwards Response Times, Langa-Weir classification, Wave 8

	Mean	St.dev.	Min	Max	N
Overall	47.386	24.136	0	428	18,766
With normal Cognition	45.466	22.542	0	428	16,024
With CIND	57.261	28.940	7	275	2,522
With Dementia	74.005	31.466	18	169	220

Notes: The data come from SHARE. Summary statistics for backwards and numeracy response time in wave 8 of the respondents who completed the cognitive module in waves 8 and 9. The scale and classification are based on Langa et al. (2020).

Table A.6. Cognitive Health and Alternative Response Time at Wave 8

	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.890***	-0.762***	-0.829***	-0.869***
	(0.030)	(0.027)	(0.031)	(0.032)
Age		-0.148***	-0.158***	-0.023
		(0.003)	(0.003)	(0.038)
Age^2				-0.001***
				(0.000)
Female				0.783***
				(0.045)
Migrant				-0.257***
				(0.091)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	18,766	18,766	18,766	18,766
R^2	0.060	0.143	0.374	0.386

Notes: The data come from the SHARE. The dependent variable is the cognitive score, and the variable of interest is the standardized time needed to answer the numeracy and backwards counting questions. Other controls include age squared, sex, and migration status.

Table A.7. Predicting Cognitive Score in Wave 9 using Alternative Response Time in Wave 8

	(1)	(2)	(3)	(4)
	F.Score	F.Score	F.Score	F.Score
Z-time	-0.336***	-0.305***	-0.307***	-0.329***
	(0.024)	(0.023)	(0.028)	(0.029)
Score	0.675***	0.621***	0.566***	0.558***
	(0.006)	(0.007)	(0.008)	(0.008)
Age		-0.090***	-0.103***	-0.002
		(0.003)	(0.003)	(0.036)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	18,766	18,766	18,766	18,766
R^2	0.427	0.451	0.542	0.544

Notes: The data come from the SHARE. The dependent variable is the cognitive score, and the variable of interest is the standardized time needed to answer the numeracy and backwards counting questions. Other controls include age squared, sex, and migration status.

Table A.8. Predicting Mortality between Waves 8 and 9 Using Alternative RT in Wave 8

	(1)	(2)	(3)	(4)
	F.Deceased	F.Deceased	F.Deceased	F.Deceased
Z-time	0.007***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.002)	(0.002)
Score	-0.006***	-0.003***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Age		0.003***	0.003***	-0.041***
		(0.000)	(0.000)	(0.004)
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	22,993	22,993	22,993	22,993
R^2	0.022	0.039	0.108	0.128

Notes: The data come from the SHARE. The dependent variable is the indicator variable, which is coded as one if the respondent is deceased in wave 9, and the variable of interest is the standardized time needed to answer the numeracy and backwards counting questions in wave 8. Other controls include age squared, sex, migration status, and self-assessed health.

Table A.9. Cognitive Health and Response Time at Wave 9

	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.509***	-0.404***	-0.448***	-0.468***
	(0.029)	(0.028)	(0.029)	(0.029)
Age		-0.175***	-0.189***	-0.074*
		(0.004)	(0.004)	(0.043)
Age^2				-0.001***
				(0.000)
Female				0.781***
				(0.048)
Migrant				-0.370***
				(0.098)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	17,963	17,963	17,962	17,962
R^2	0.019	0.129	0.353	0.364

Notes: The data come from the SHARE. The dependent variable is the cognitive score in wave 9, and the variable of interest is the standardized time needed to answer the questions in wave 9. Other controls include age squared, sex, and migration status.

Table A.10. Cognitive Health and Response Time at Wave 8: Full Sample

	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.616***	-0.454***	-0.489***	-0.496***
	(0.025)	(0.024)	(0.025)	(0.025)
Age		-0.190***	-0.197***	0.075**
		(0.003)	(0.003)	(0.032)
Age^2				-0.002***
				(0.000)
Female				0.632***
				(0.040)
Migrant				-0.396***
				(0.077)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	28,242	28,242	28,242	28,151
R^2	0.024	0.163	0.362	0.371

Notes: The data come from the SHARE. The dependent variable is the cognitive score in wave 8, and the variable of interest is the standardized time needed to answer the questions in wave 8. Other controls include age squared, sex, and migration status.

Table A.11. Cognitive Health and Response Time at Wave 9: Full Sample

	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.364***	-0.238***	-0.358***	-0.367***
	(0.021)	(0.020)	(0.020)	(0.020)
Age		-0.173***	-0.189***	0.138***
		(0.002)	(0.002)	(0.027)
Age^2				-0.002***
				(0.000)
Female				0.626***
				(0.032)
Migrant				-0.489***
				(0.068)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	41,075	41,075	41,072	40,912
R^2	0.008	0.123	0.369	0.379

Notes: The data come from the SHARE. The dependent variable is the cognitive score in wave 9, and the variable of interest is the standardized time needed to answer the questions in wave 9. Other controls include age squared, sex, and migration status.

Table A.12. Predicting Cognitive Score in Wave 9 using Response Time in Wave 8: Discarding the bottom 10 percentile

	(1)	(2)	(3)	(4)
	F.Score	F.Score	F.Score	F.Score
Z-time	-0.204***	-0.185***	-0.164***	-0.171***
	(0.024)	(0.024)	(0.026)	(0.026)
Score	0.694***	0.636***	0.586***	0.580***
	(0.007)	(0.007)	(0.008)	(0.008)
Age		-0.092***	-0.103***	0.026
		(0.003)	(0.004)	(0.055)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	16,878	16,878	16,878	16,878
R^2	0.421	0.446	0.541	0.542

Notes: The data come from the SHARE. The dependent variable is the cognitive score, and the variable of interest is the standardized time needed to answer the questions. Other controls include age squared, sex, and migration status.

Table A.13. Predicting Wealth (De-)accumulation from Wave 8 to Wave 9 using Wave 8: Discarding the bottom 10 percentile

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Score	40.776***	31.620***	30.345***	31.975***
	(11.680)	(9.339)	(9.266)	(11.154)
Z-time			-51.624	-78.745**
			(32.106)	(36.295)
Country FE	No	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	10,681	10,681	10,681	10,681
R^2	0.083	0.211	0.211	0.331

Notes: Based on SHARE. The dependent variable is a change in net worth. Controls include lags of age, age squared, sex, labor force status, marital status, migration status, and wealth.

Table A.14. Descriptive Statistics for the Score, Langa-Weir Classification for the Wealth Sample

	Wave 8		Wave 9	
	Mean	St. Dev.	Mean	St. Dev.
Cognitive Score	15.824	3.543	15.408	3.833
Fraction normal	0.892	0.311	0.855	0.353
Fraction with CIND	0.101	0.301	0.128	0.334
Fraction with Dementia	0.008	0.088	0.018	0.132

Notes: The data come from SHARE. Summary statistics for the cognitive score of the 11,910 respondents who completed the cognitive module in waves 8 and 9. The scale and classification are based on Langa et al. (2020).

Table A.15. Mazzonna and Peracchi (2024) Replication

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Memory loss	-180.2964***		-113.4229*	
	(57.4516)		(66.6564)	
Aware		-76.1937		-55.6217
		(77.7317)		(111.2018)
Unaware		-171.5796***		-133.3921*
		(63.5917)		(72.6186)
Pessimistic		153.7661*		24.9289
		(81.9338)		(89.0980)
L.recall	39.5215***	40.9935***		
	(11.5878)	(11.7130)		
L.Score			28.5458***	29.0058***
			(8.8665)	(9.0050)
Based on Recall Test	Yes	Yes	No	No
Based on 26-Score	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	18,355	18,355	12,549	12,549
R^2	0.471	0.471	0.187	0.187

Notes: Based on SHARE. The dependent variable is the change in net worth. All regressions include age, age squared, sex, educational attainment, labor force status, marital status, migration status, country fixed effects, and lagged wealth.

Table A.16. Self-Rated versus Assessed Memory: Based on Total Score

Self-Rated Memory Change	No	Yes	Total
	A. Severe Relative Memory Loss		
Better now	0.78	0.16	0.94
About the same	60.65	11.26	71.91
Worse now	21.32	5.84	27.15
Total	82.75	17.25	100.00
	B. Severe Absolute Memory Loss		
Better now	0.78	0.16	0.94
About the same	61.74	10.17	71.91
Worse now	22.19	4.96	27.15
Total	84.71	15.29	100.00

Notes: Based on SHARE. The table compares self-rated memory changes across waves with two different measures of memory loss: severe relative memory loss (panel A), defined as a decline of 20% or more in the 26-score, and severe absolute memory loss (panel B), defined as a 26-score change of 1 standard deviation or more.

Table A.17. Predicting Wealth (De-)accumulation from Wave 8 to Wave 9 using Wave 8 Alternative Response Times

	(1)	(2)	(3)	(4)
	ΔW	ΔW	ΔW	ΔW
Score	30.885***	25.063***	20.043**	26.922**
	(11.161)	(8.979)	(9.011)	(10.826)
Z-time			-122.247***	-119.320**
			(45.750)	(48.423)
Country FE	No	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.062	0.192	0.192	0.319

Notes: Based on SHARE. The dependent variable is a change in net worth. Controls include lags of age, age squared, sex, labor force status, marital status, migration status, and wealth.

Table A.18. Predicting Awareness, Multinomial logit: Based on 26-Score and Alternative Time

	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	-0.0140	0.1065**	0.1338***
	(0.0274)	(0.0444)	(0.0306)
Female	0.1527***	-0.1261	-0.2823***
	(0.0515)	(0.0908)	(0.0682)
Observation	11,910	11,910	11,910

Notes: Based on SHARE. Awareness classification is measured by memory loss based on the total score. Z-time measures standardized total time stamps. All regressions include lagged age, age squared, sex, educational attainment, labor force status, marital status, country identifiers, migration status, wealth, and lagged score.

Table A.19. Predicting Awareness, Multinomial logit: Based on Recall Test and Alternative Time

	(1) Pessimistic	(2) Aware	(3) Unaware
Z-time	-0.0095	0.0773**	0.0960***
	(0.0290)	(0.0390)	(0.0272)
Female	0.1659***	-0.2213***	-0.3436***
	(0.0545)	(0.0788)	(0.0563)
Observation	11,910	11,910	11,910

Notes: Based on SHARE. Awareness classification is measured by memory loss based on recall. Z-time measures standardized total time stamps. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

Table A.20. Predicting Cognitive Score in Wave 9 using Response Time in Wave 8: Using 27-Score

	(1) F.Score	(2) F.Score	(3) F.Score	(4) F.Score
Z-time	-0.208***	-0.183***	-0.170***	-0.177***
	(0.023)	(0.023)	(0.025)	(0.025)
Score	0.694***	0.639***	0.582***	0.575***
	(0.007)	(0.007)	(0.008)	(0.008)
Age		-0.091***	-0.105***	0.007
		(0.003)	(0.003)	(0.036)
Age	No	Yes	Yes	Yes
Interviewer FE	No	No	Yes	Yes
Other controls	No	No	No	Yes
Observations	18,766	18,766	18,766	18,766
R^2	0.422	0.446	0.540	0.541

Notes: The data come from the SHARE. The dependent variable is the 27-score, and the variable of interest is the standardized time needed to answer the questions. Other controls include age squared, sex, and migration status.