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 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 and country, with stronger associations observed among male financial respondents, and in countries with higher room left for individual decision-making in wealth management.

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 dimensions of cognitive functioning that are not fully captured by accuracy-based measures. In particular, processing speed—a core aspect of fluid intelligence—has been shown to decline earlier in life than other cognitive abilities such as memory (Salthouse (1985); Horn and Cattell (1967); Salthouse (1996)), yet it remains 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. Throughout the paper, response times refer exclusively to those recorded for cognitive test items.

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 the case of immediate and delayed memory tests. 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 response times in predicting (un)awareness of cognitive decline. 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 a decline in wealth. 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 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), the long-run effects of education (compulsory schooling reforms (Glymour et al. (2008); Crespo et al. (2014); Lövdén et al. (2020))), or early life conditions (Case and Paxson, 2009) on later-life cognitive functioning. 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. Early work by Smith et al. (2010) demonstrates 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. Complementing this evidence, Jappelli (2010) documents substantial cross-country heterogeneity in economic literacy, and Boyle et al. (2025) show that financial literacy itself declines with age, reinforcing concerns about late-life financial vulnerability.

More recent 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. In particular, longer and more variable RTs during standard cognitive tasks forecast lower MoCA scores up to five years later—an effect comparable in magnitude to several additional years of aging—and capture dimensions of processing speed not reflected in accuracy-based measures.

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 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, longitudinal, 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 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 18,766 individuals. As shown in Table 2, individuals in our working sample are on average 72 years old at Wave 8, 55% are female, and 8.5% were born in a country different from the one in which they currently reside (hereafter referred to as "migrants").

For the wealth analysis, following (Mazzonna and Peracchi, 2024), we restrict the sample to respondents aged between 60 and 80. This restriction helps address issues related to mortality and institutionalization at older ages. Moreover, since wealth information is collected from only one respondent per household, we retain a single observation per household—specifically, the individual identified as "the one most able to answer questions about [their] finances," hereafter referred to as the financial respondent. This approach follows Smith et al. (2010), who demonstrate that the cognitive skills of this individual are the most relevant for household financial outcomes. The resulting analytical sample comprises 11,910 individuals.

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 difference 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). As a robustness check, we will also consider an alternative 27-point version of the cognitive score in which backwards counting will count for 2 points instead of 1.

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: indi-

[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.

viduals 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 overall response time 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 also 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 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 may reflect either 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 backward-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 among 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 responses, as individuals do not engage with the task at all. Following their guidance, we perform several robustness checks: (i) modeling RTs non-linearly, (ii) verifying that our main results hold when excluding the fastest 5

Figure A.1 confirms these patterns in more detail. It displays the full distribution of RTs by task, separately for respondents with normal cognition and those with cognitive impairment. For most tasks—particularly numeracy and

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

backward counting—the distribution for cognitively impaired individuals is clearly shifted to the right, indicating slower responses. The only exceptions are the recall tasks, where impaired respondents tend to have shorter RTs, consistent with early task abandonment or lower engagement.

Finally, moving from the sub-tasks to the aggregate measure, we examine how 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 about 130 seconds, and respondents in the dementia range need roughly 144 seconds. Equally informative is the growing spread of response times, with the standard deviation widening 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. Appendix Figure A.5 complements these cross-sectional patterns by plotting within-person changes in standardized response time and cognitive score between Waves 8 and 9. Both variables show roughly symmetric distributions centered near zero, indicating broad stability for most respondents but sizable individual heterogeneity in the direction and magnitude of change. Some respondents improve in one dimension but not the other, underscoring that processing speed and accuracy-based performance capture related yet distinct aspects of cognitive dynamics.

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 2 (Panel A) displays the estimated density of the word-recall memory score in both levels and differences. Extremely similar to what Mazzonna and Peracchi (2024) show 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 that many respondents actually improve their score from one wave to the next. This pattern likely reflects the presence of "re-testing" effects—respondents may recall some words from one wave to the next or simply become more familiar with the testing procedure.[4]

Panel B of Figure 2 extends this analysis to the total 26-point Langa–Weir cognitive score, offering a broader view of cognitive change beyond memory alone. The distribution again exhibits a mild leftward shift between Waves 8 and 9, indicating that, on average, overall cognitive functioning remains relatively stable over the two-year period, with notable declines concentrated in the lower tail. This motivates our subsequent focus on a measure of global cognitive decline: while the 20% drop in recall scores serves as a well-established indicator of meaningful memory loss, the literature has not yet converged on an equivalent standard for composite cognition scores.

We therefore define global cognitive decline as a drop of at least 20% in an individual's total Langa–Weir score. This definition maintains symmetry with our validated memory-loss measure, facilitates direct comparison across the two dimensions of cognition, and identifies a substantively large deterioration corresponding to the lower tail of the distribution of cognitive change in our sample.

Figure 3 plots average age profiles for objective and subjective measures of cognition. Triangles represent the standardized memory (recall) score, blue squares the standardized 26-point Langa–Weir cognitive score, and the line with circles the share of respondents reporting that their memory has improved since the previous wave. Both objective indicators show a steady age-related decline, with the recall score falling more sharply than the global cognitive score. In contrast, the share of respondents perceiving their memory as better also decreases with age, but at a much slower rate and with occasional upticks, even at older ages. This divergence in slopes indicates that subjective perceptions only weakly reflect the underlying cognitive deterioration, pointing to a systematic disconnect between actual and perceived cognitive functioning.

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,

[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, thereby limiting potential re-testing effects.

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.

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.

Table 5 shows how respondents rate their memory change since last wave, and how this translates 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. 26.2% according to the 20% drop threshold (Panel A), and 12.8% 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] Appendix Table A.16 replicates this comparison using the total 26-point Langa–Weir score instead of recall, showing nearly identical proportions across self-assessment categories, which confirms that our awareness classification is robust to the chosen measure of cognitive loss.

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 4 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. Unlike Mazzonna and Peracchi (2024), who exploit the longer HRS panel to identify the first occurrence of severe memory loss over the life course, our awareness classification is only available from Wave 8 onward. We therefore restrict attention to respondents who experienced a severe loss between Waves 8 and 9, and plot the age distribution of these individuals according to their awareness status. The figure shows that aware and unaware individuals differ mainly in age composition: the aware tend to be

[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.

somewhat older, whereas the unaware are more concentrated at younger ages.

Appendix Figure A.4 confirms that this pattern is robust to alternative definitions of cognitive loss. Whether loss is defined in relative or absolute terms, or based on the global 26-point Langa–Weir cognitive score instead of the recall measure, the shape of the age distributions remains broadly similar—aware individuals are on average older than unaware ones. These complementary figures reinforce the idea that the awareness gradient is not specific to the recall-based definition but holds across different measures of cognitive deterioration.

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.

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: functional health, chronic disease burden, mental health, frailty, and mortality.

Functional health is measured with a mobility score that ranges from 0 (no limitations) to 10, as well as the number of limitations in activities of daily living (ADLs), and instrumental activities of daily living (IADLs).

Chronic disease burden is proxied by the number of conditions for which the individual has been diagnosed by a physician, including a heart attack, hypertension, high blood cholesterol, a stroke, diabetes, a cancer, etc. 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 model health outcomes as continuous variables to retain full information and improve precision under standard linear specifications. 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.

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 6).

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:

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

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

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 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 instead 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 7-9 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:

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

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_it 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. $\psi_{c(i)}$ denote country fixed effects.

Second, we introduce the degree of awareness of cognitive decline, following Mazzonna and Peracchi (2024), and examine whether response times can help identify individuals who are unaware of their cognitive deterioration. To this end, we estimate a multinomial logit model where the outcome variable captures 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.

The corresponding multinomial logit specification can be written as:

$$\log!\left(\frac{\Pr(D_{it}=k)}{\Pr(D_{it}=N)}\right) = \alpha_k + \gamma_k Time_{i,t} + \beta_k X_i + \delta_k Z_{it} + \psi_{c(i),k}, \quad k \in A, U, P. \tag{4}$$

$D_{it} \in A, U, P, N$ denotes the perception category of cognitive decline (Aware, Unaware, Pessimist, No decline). N is the reference category. $Time_{i,t}$ is the standardized response time; X_i and Z_{it} include the same controls as in equation (3); $\psi_{c(i),k}$ are country fixed effects.

6 Results

6.1 Response Times and Cognitive Decline

Table 6 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.

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 6. A one standard deviation increase in standardized response time (Z-time)—approximately 38 seconds—is associated with a 0.506-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 $+0.686$, while the effect of being a migrant—defined as living in a country other than one's country of birth—is -0.381. These two gaps operate in opposite directions: women perform better, whereas migrants perform worse in cognitive tests, conditional on age and interviewer fixed effects. This pattern is consistent with Sanders et al. (2025), who also find that women exhibit higher MoCA scores than men, while Black respondents perform significantly worse than White respondents in the U.S. NSHAP sample. Together, these results suggest that the demographic gradients in cognition—by gender, migration, or race—are robust across very different institutional contexts.

The magnitude of the response-time effect is substantial: it is roughly two-thirds as large as the gender gap in cognitive functioning and even larger than the migrant gap. This underscores the predictive value of response times as a proxy for cognitive functioning, capturing meaningful variation in cognition that parallels well-established social gradients in later-life cognitive health.

As shown in Table A.10, re-estimating the model for Wave 9 yields coefficients on response time and demographic controls that are almost identical to those obtained for Wave 8, confirming the stability of the RT–cognition relationship across waves. The negative association between standardized response time and cognitive score remains strong and highly significant, while the direction and magnitude of the gender and migrant effects are unchanged.

Tables A.11 and A.12 further demonstrate that these findings are not driven by the balanced-panel restriction. When the analysis is repeated using the full Wave 8 and Wave 9 samples—thus including individuals who were not re-interviewed in both waves—the results remain virtually unchanged in both magnitude and significance. The consistency of the estimates across survey waves and sample definitions reinforces the robustness of the negative link between response times and cognitive performance, suggesting that the relationship is neither wave-specific nor driven by selective attrition.

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 7, response time remains a significant predictor of future cognitive decline even after controlling for baseline cognitive score. In Column (1), with no additional controls, a one–standard-deviation increase in response time is associated with a 0.206-point lower cognitive score at follow-up. This estimate remains remarkably stable as controls are added sequentially: –0.182 when adjusting for age in Column (2), –0.167 when adding interviewer fixed effects in Column (3), and –0.175 once full demographic controls (age squared, gender, and migrant status) are included in Column (4). Despite the strong persistence of cognitive performance across waves (the coefficient on the lagged score is about 0.57), response time continues to provide significant additional predictive power, and the overall fit of the model is high ($R^2 = 0.54$).

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 comparison, a one–standard-deviation increase in response time has the same effect on subsequent cognition as approximately 1.6 years of aging.

Table A.2 explores heterogeneity in the predictive power of response times and cognitive scores across demographic groups. In Column (1), we interact both variables with gender indicators. The coefficients show that response times are slightly more predictive of future cognitive decline among women (-0.197) than among men (-0.147), while the cognitive score itself has similar predictive strength across genders. Column (2) highlights a more striking pattern when distinguishing migrants from natives: the coefficient on the RT–migrant interaction is large and highly significant (-0.334 vs. -0.160 for natives), indicating that response times carry considerably more predictive information for migrants. By contrast, the heterogeneity in the predictive power of the cognitive score is minimal—its coefficients are nearly identical across the two groups.

These results suggest that processing speed may reveal aspects of cognitive vulnerability that are particularly salient among migrant respondents, perhaps reflecting linguistic or contextual challenges that amplify the informational content of response times. This pattern mirrors the findings of Sanders et al. (2025), who report stronger RT–cognition gradients for disadvantaged demographic groups (notably Black respondents in the U.S. NSHAP), while the predictive role of accuracy-based scores remains comparatively uniform across populations.

To interpret the strength of the association between response times and cognitive deterioration more concretely, we turn to Table A.3. Column (1) replicates the continuous specification from Table 7 (Table 6) and confirms that a one–standard-deviation increase in response time is associated with a 0.175-point lower cognitive score at follow-up, reinforcing the consistency of the estimates across models. Columns (2) and (3) then translate this association into clinically meaningful terms by using binary indicators for a 20% or greater decline in total cognitive score or in memory recall, respectively. The results indicate that a one–standard-deviation increase in response time raises the probability of a 20% drop in global cognitive performance by about 2.3 percentage points, and the probability of a comparable memory loss by 1.9 percentage points.

These magnitudes are substantial given the relatively short interval between survey waves (approximately two years) and demonstrate that slower processing speed is not only associated with continuous cognitive decline (as shown in Table 7) but also with discrete transitions across clinically meaningful thresholds of impairment.

Table A.1 examines whether the predictive power of response times for future cognitive decline varies with respondents' baseline cognitive health status. Column (3) reproduces the full specification from Table 7, Column (4), and yields an almost identical coefficient on response time (-0.175), confirming internal consistency. Column (2) restricts the sample to individuals classified as cognitively normal at baseline—excluding those with MCI or dementia—and shows that the coefficient on response time remains negative and highly significant (-0.134), though slightly attenuated relative to the full sample. This demonstrates that response times continue to predict future cognitive performance even among cognitively healthy individuals, capturing early signals of decline before formal deficits emerge.

Column (1) provides further evidence using interactions between response time and baseline cognitive categories. The association between slower RTs and subsequent cognitive decline becomes progressively stronger with the severity of baseline impairment: the coefficient on response time is -0.326 for those with normal cognition, -0.366 for individuals with MCI, and -0.480 for those already classified as demented. This monotonic pattern suggests that response speed is especially informative among those already exhibiting cognitive vulnerability, while still retaining predictive value for the unimpaired.

Before turning to the analysis of health outcomes, we assess the robustness of these results to alternative specifications and definitions of the response-time measure. Appendix Tables A.4–A.8 present a series of checks confirming that our main findings are not sensitive to either functional form or to the inclusion of recall tasks in the RT definition.

Table A.4 shows that using the logarithm of RTs or adding a quadratic term yields virtually identical results, indicating that the relationship between response time and cognition is well captured by a simple linear specification.

In a related robustness test (Table A.5), we exclude the fastest 10 percent of respondents to verify that the results are not driven by implausibly short completion times that may reflect task abandonment or interviewer effects. The estimated coefficients on RT remain almost unchanged in magnitude and significance, confirming that the main association is not an artifact of extreme observations. This exercise mirrors the approach of Sanders et al. (2025), who similarly trim very short response times in their NSHAP analysis to account for respondents who disengage from complex cognitive tasks or answer too quickly for RTs to capture genuine processing.

Tables A.6–A.8 then employ an alternative RT measure that excludes recall tasks—where the link between time and performance is less clear—and instead aggregates only numeracy and backward-counting items, which directly capture processing speed. The results become even stronger: longer RTs on these speed-based tasks are more strongly associated with lower cognitive scores both cross-sectionally and over time.

Last, the results are virtually identical when we use the 27-point version of the cognitive score, in which we assign 2 points to the backwards counting task instead of only 1, in order to get closer to the original Langa-Weir scale (Appendix Table A.21), confirming that our findings are not sensitive to this alternative scoring scheme.

Together, these robustness checks confirm that the predictive power of RTs is driven by tasks that measure processing speed and executive functioning, reinforcing their interpretation as an early indicator of cognitive vulnerability rather than as an artifact of functional form, recall performance, or extreme observations.

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, the frailty index, and self-assessed health, on cognitive scores and response times from Wave 8. The corresponding multi-item definitions are detailed in Table 1.

Table 8 reports estimates controlling for Wave 8 cognitive function, demographic characteristics, and interviewer fixed effects, but not yet for baseline health. We find that longer response times are significantly associated with worse outcomes in ADLs, IADLs, mobility, frailty, and self-assessed health. In contrast, no significant associations are observed for chronic disease burden or depression, where cognitive score remains the more salient predictor. Cognitive performance at baseline is consistently protective across all outcomes, particularly in domains such as depression and mobility.

Table 9 introduces a stricter specification by additionally controlling for baseline health status, so that coefficients can be interpreted 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 effects on ADLs, mobility, and self-perceived health become statistically insignificant—suggesting that earlier associations partly reflected pre-existing functional limitations. Cognitive scores continue to robustly predict changes across all outcomes. Figure 5 (Panels A and B) illustrates these patterns graphically, confirming that only IADLs and frailty remain significantly related to slower response times once baseline health is taken into account.

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, thereby reducing statistical power. Nonetheless, the direction and magnitude of the effects remain largely consistent with those in the main specifications, indicating that the underlying relationships are robust even if harder to detect in threshold-based models.

Importantly, the differential results for ADLs and IADLs shed light on the mechanisms linking response times to health. While ADLs primarily capture physical limitations in basic self-care tasks, IADLs require higher-order cognitive and executive functioning—such as planning, problem-solving, and decision-making. The fact that response times predict changes in IADLs but not in ADLs once baseline health is accounted for strongly suggests that slower processing speed reflects cognitive rather than purely somatic decline. This interpretation is reinforced by the persistent association between longer response times and worsening frailty, which points to processing speed as an early signal of broader physiological or neurocognitive vulnerability not fully captured by standard cognitive scores.

Figure A.3 (in the Appendix) further confirms that these findings are not sensitive to the precise definition of response time. When we recompute the RT measure excluding recall tasks—where the relationship between time and performance is less clear—the associations with later-life health outcomes become noticeably stronger. In particular, longer response times on tasks that directly capture processing speed (numeracy and backward counting) are significantly more predictive of subsequent deterioration in IADLs and frailty, and to a lesser extent in mobility.

Overall, this robustness check strengthens our interpretation that the predictive content of response times operates primarily through cognitive and executive pathways. By excluding tasks in which response duration may reflect hesitation or disengagement rather than processing efficiency, the RT measure isolates the dimension most relevant to cognitive functioning. The sharper associations with IADLs and frailty thus confirm that slower processing speed signals a higher risk of complex functional decline rather than general physical limitations.

Finally, we examine whether response times also predict short-term mortality. Table 10 reports estimates from regressions where the dependent variable equals one if the respondent died between Waves 8 and 9. Since all individuals are alive at baseline, we include self-assessed health in Wave 8 as baseline health control. Across all specifications, longer response times are significantly associated with a higher probability of death within the two-year period: the coefficient on standardized response time ranges from 0.003 to 0.004 and remains highly significant after adding interviewer fixed effects and full demographic controls. By contrast, higher cognitive scores and better self-assessed health at baseline are strongly protective.

The magnitude of the effect, though small in absolute terms, is meaningful given the short observation window. A one–standard-deviation increase in response time—roughly 38 seconds—is associated with a 0.3–0.4 percentage-point higher probability of dying before the next survey wave, even after conditioning on age, cognition, and perceived health. This finding supports the view that slower processing speed captures underlying physiological or neurological frailty that elevates near-term mortality risk, consistent with evidence linking cognitive slowing to systemic aging processes.

6.3 Response Times and Wealth Accumulation

Table 12 examines whether cognitive processing speed, proxied by response times (RTs), predicts changes in financial well-being—specifically, changes in net worth (wealth accumulation or depletion) between Waves 8 and 9.[7] Columns (1)–(3) 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 country fixed effects are included (Column 2), addressing cross-country heterogeneity in both wealth and cognitive ability, and becomes slightly larger once interviewer fixed effects are added (Column 3), suggesting that interviewer behavior may partly confound the observed relationship.

In Column (4), we include standardized response time (Z-time) together with the cognitive score. The coefficient on cognition remains positive and highly significant, whereas Z-time is negative and significant at the 5 percent level. Quantitatively, a one-standard-deviation increase in Z-time—roughly 37 seconds (see Table 11)—is associated with an average €9 000 decrease in net worth between waves, holding constant cognitive score and other covariates. These

[7]The wealth sample exhibits cognitive distributions similar to the full sample (Appendix Table A.14), suggesting that restricting to financial respondents does not materially alter the composition of cognitive health categories.

coefficients indicate that slower response times predict meaningful wealth decumulation independently of baseline cognitive ability, adding predictive content beyond standard cognitive tests.

To benchmark magnitudes, Table 11 reports that the standard deviation of the cognitive score in Wave 8 is 3.543 points. Using this scale, a one-SD increase in cognitive score predicts approximately €4 000 greater wealth accumulation, whereas a one-SD increase in response time predicts roughly €9 000 less. In relative terms, the effect of RT is about 70 percent larger in absolute value than that of cognition.

These comparisons confirm that although RTs are weaker predictors than accuracy-based cognitive scores for cognitive outcomes (as shown in Table 7), they are powerful correlates of financial trajectories. Slower processing speed signals vulnerability that manifests not only in cognition but also in subsequent financial decumulation, potentially through multiple channels—declining cognitive health, reduced awareness, or the indirect financial costs of health deterioration.

The results are robust to several alternative specifications. As shown in Appendix Table A.13, excluding the fastest 10 percent of respondents—those whose very short completion times may reflect superficial engagement or interviewer irregularities—leaves the coefficients on both cognitive score and response time virtually unchanged. The RT coefficient remains negative and significant (about –8.4, compared with –9.0 in Table 12), confirming that the observed association is not driven by outliers or measurement artifacts. This exercise parallels the earlier robustness check in the cognitive analysis (Appendix Table A.5) and reinforces that our estimates capture genuine variation in processing speed rather than spurious noise in time stamps.

When we instead employ the alternative RT measure that excludes recall tasks (Appendix Table A.17), the estimated effect of RT on wealth nearly doubles in magnitude (around –15, significant at the 1 percent level), while the coefficient on cognitive score remains positive and stable. This stronger association suggests that the predictive content of response times may stem primarily from the processing-speed components—numeracy and backward counting—rather than from recall tasks, where response durations could partly capture other factors such as retrieval effort or early task termination. Focusing on these speed-based items thus appears to sharpen the measure, helping to isolate the aspects of RT that are most consistently associated with later wealth changes.

Figure 6 illustrates cross-country heterogeneity in the associations between cognition, response times, and wealth. Panel A refers to cognitive scores and Panel B to standardized response times. Within each panel, we report results from two complementary specifications: in the first, the variable of interest (score or time) is interacted with indicators for the four regional groups of SHARE countries—Northern, Continental, Southern, and Eastern Europe—while in the second, it is interacted with an index summarizing the relative importance of the third-pillar pension system, that is, the weight of private and voluntary retirement saving. Each panel displays the corresponding coefficients and 95 percent confidence intervals.

The results show that both the positive association between cognition and wealth and the negative association between slower response times and wealth are broadly consistent across Europe but vary in magnitude. In Panel A, the cognition–wealth gradient is strongest in Northern and Continental European countries, where cognitive ability appears to translate most directly into financial accumulation. In Panel B, the wealth penalty associated with slower response times is likewise steeper in Northern and Continental Europe and weaker in Southern and Eastern countries, mirroring differences in the degree of individual responsibility for financial management. The interactions with the third-pillar index reveal the same pattern: the effects of both cognition and response times on wealth are significantly larger in countries where private pensions and voluntary savings play a greater role in retirement income.

This cross-country pattern aligns closely with previous evidence linking institutional design to the importance of cognitive and financial skills. In the United Kingdom, Banks et al. (2010) show that the shift from defined-benefit to defined-contribution schemes increased the need for numeracy and financial competence, as individuals must actively manage savings and annuitization choices. In the United States, Smith et al. (2010) find that household wealth depends strongly on the numeracy of the financial respondent, operating in a largely self-directed pension environment. More broadly, Jappelli (2010) document that financial literacy is systematically lower in countries with more generous public pensions and higher social-security contributions, where the first pillar substitutes for private financial decision-making. Taken together, these results indicate that cognitive and behavioral measures matter most in institutional contexts that rely heavily on individual initiative. The heterogeneity shown in Figure 6 thus constitutes a key contribution of this paper: it demonstrates that the strength of both the cognition–wealth and RT–wealth relationships depends on the structure of national pension systems and the extent of individual autonomy in managing financial resources.

Last, Appendix Table A.18 explores gender heterogeneity in the association between cognition, response times, and wealth. Consistent with earlier evidence, the positive link between cognitive score and wealth accumulation is considerably stronger for men than for women, suggesting that cognitive ability translates more directly into financial outcomes among male financial respondents. The negative association between slower response times and wealth is also somewhat larger for men (around –€13 000 per SD) than for women (–€6 000), though the difference is less precisely estimated. Overall, these results reinforce the view that gendered roles in household financial management condition how cognitive functioning—and to a lesser extent processing speed—affects later-life wealth trajectories.

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

We begin by replicating the main finding of Mazzonna and Peracchi (2024) using SHARE data. Appendix Table A.15 closely mirrors their HRS-based specification. Consistent with their results, we find that severe cognitive loss—defined as a 20 percent drop in either the recall or the total Langa–Weir score—is associated with substantial wealth decumulation. In column (1), a severe cognitive loss predicts an average decline of about €21 000–€22 000 in net worth between Waves 8 and 9. When we further distinguish respondents by their level of awareness, this effect is shown to be concentrated entirely among those who are unaware of their decline: they lose about €28 000–€30 000 on average, while aware or "pessimistic" individuals experience no significant change in wealth. The magnitude and pattern of these effects are remarkably similar to those reported by Mazzonna and Peracchi (2024), who find average losses of 30000–40 000 in the HRS over comparable horizons. Importantly, the results are nearly identical whether cognitive loss is defined narrowly using the memory score or more broadly using the total Langa–Weir index, indicating that the awareness gradient in financial vulnerability is robust across different measures of cognitive deterioration.

Building on this validated framework, the next step is to ask whether response times can help identify the individuals most likely to fall into this "unaware" category. Tables 13 and 14 report multinomial logit estimates where the dependent variable captures the respondent's perception of cognitive change: "aware" (objective and perceived decline), "unaware" (objective decline but no perceived decline), or "pessimistic" (no objective decline but self-reported worsening). The reference group consists of those with no objective or perceived decline.

In both specifications—using either the total Langa–Weir score or the recall-based definition—slower response times are significantly associated with a higher probability of being unaware, but not with being "aware" or "pessimistic." A one-standard-deviation increase in RT raises the likelihood of unawareness by roughly 6–8 percentage points, holding cognitive score and other covariates constant. By contrast, higher cognitive scores sharply reduce the probability of unawareness while increasing the probability of being aware, consistent with better meta-cognitive monitoring among cognitively stronger individuals. The gender pattern is also consistent with previous evidence: women are significantly less likely to be unaware, in line with their higher average self-assessment accuracy documented in the HRS and other surveys.

Appendix Tables A.19 and A.20 replicate these analyses using the alternative RT measure that excludes recall tasks. The results become even stronger: the estimated marginal effects of RT on the probability of being unaware roughly double in magnitude (to 10–13 percentage points) and remain highly significant, while associations with the other categories remain negligible. These findings confirm that the predictive power of RTs for unawareness does not hinge on the specific composition of tasks and is strongest for those measures that best capture processing speed.

Taken together, these results show that response times can help identify individuals who are both cognitively declining and unaware of their deterioration—a particularly high-risk group from a financial perspective. By flagging these individuals early, RTs provide a low-cost behavioral indicator of unobserved cognitive vulnerability that complements traditional performance-based assessments.

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 decumulation, 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 baseline cognition, demographics, and country fixed effects. The magnitude of this association varies across Europe, being strongest in Northern and Continental countries and in those with more developed third-pillar pension systems—settings where older adults retain greater autonomy over savings and investment decisions.

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.

A natural next step is to investigate the mechanisms through which slower response times translate into wealth decumulation in later life. In our European setting, these mechanisms may differ from those in the United States, where individual financial management and market exposure play a larger role. The country-level heterogeneity we document—stronger RT–wealth associations in systems with more developed third-pillar pensions—suggests that institutional arrangements shape how cognitive vulnerability affects financial trajectories. In countries where private savings and investment decisions are more central, slower processing speed may impair financial judgment and portfolio maintenance, leading to steeper declines in wealth. By contrast, in more protective welfare systems, cognitive vulnerability could manifest through different channels, such as greater health expenditure or long-term care costs associated with frailty and unrecognized cognitive decline. Exploring these alternative pathways, and how they interact with national health and pension systems, would help clarify the mechanisms underlying the link between processing speed and financial well-being in ageing societies.

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) Wave 8	(2) Wave 9	(3) 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).

Figure 1. Response Time and Performance at each Test

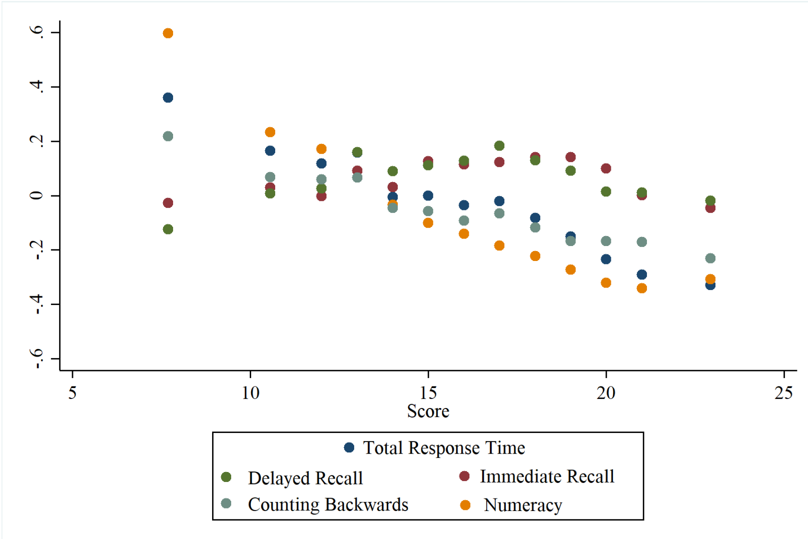
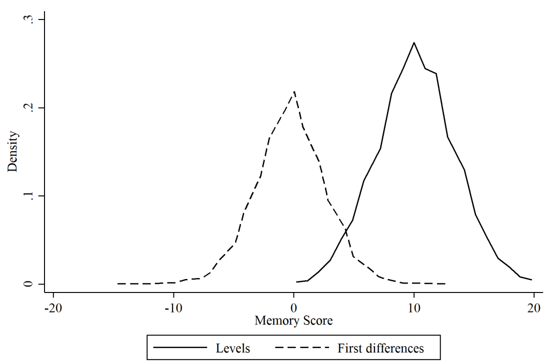
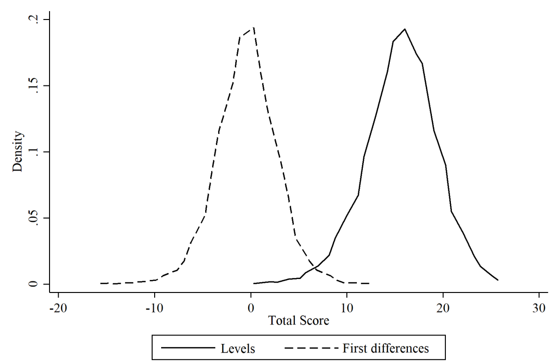


Figure 2. Memory and Total Score



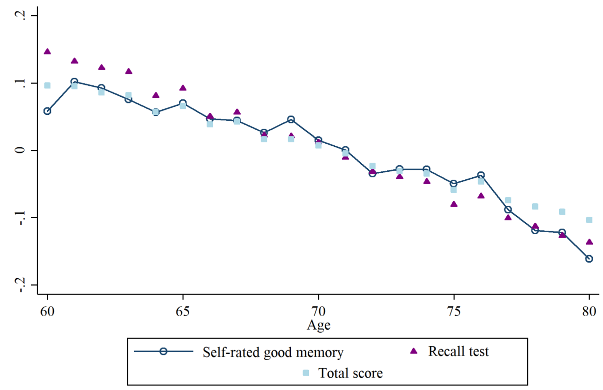
(a) Panel A: Memory Score



(b) Panel B: Total Score

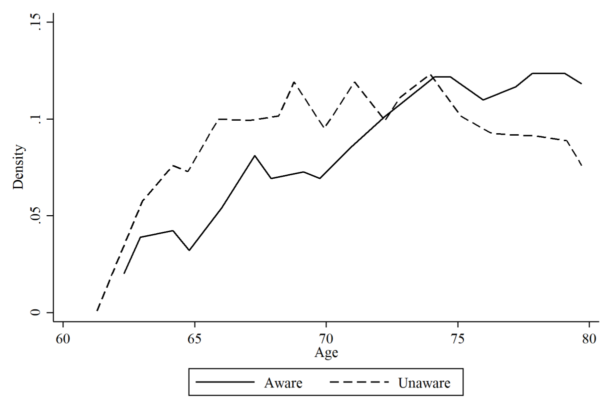
Notes: Based on SHARE. Density of memory scores in levels and first differences.

Figure 3. Age profiles of memory, global cognition, and self-assessed memory



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. Notes: Based on SHARE. The figure presents the average age profiles of three indicators: the standardized memory (recall) score (triangles), the standardized 26-point Langa–Weir cognitive score (squares), and the share of respondents who rate their memory as “better” than in the previous wave (line with circles).

Figure 4. 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 5. 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 6. Cognitive Health and Response Time at Wave 8

	(1) Score	(2) Score	(3) Score	(4) 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.

Table 7. 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 8. 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

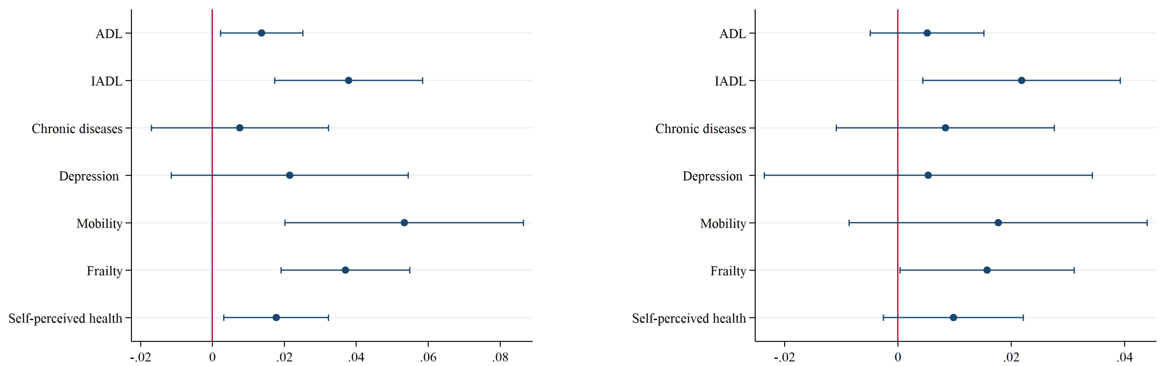
Notes: The data come from SHARE. The dependent variables in columns one to three are the number of ADL, limitations with instrumental activities of daily living (IADL), and chronic diseases; in columns four and five are the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (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 9. 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 5. Predicting Health Outcomes in Wave 9 using Response Times - With and without health controls at baseline.



(a) Panel A: Not controlling for Health$_t$ **(b) Panel B: Controlling for Health$_t$**

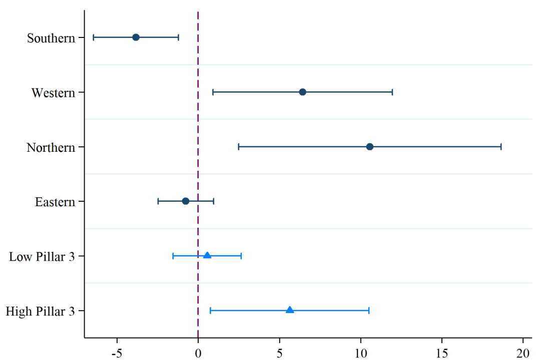
Notes: The data come from SHARE. The dependent variables are the number of limitations with ADLs, with IADLs, and chronic diseases; the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations); the frailty index, and self-perceived health (from 1 to 5, 1 is excellent and 5 is poor). 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 the corresponding health dimension in Wave 8.

Table 10. Predicting Mortality between Waves 8 and 9 Using RT in Wave 8

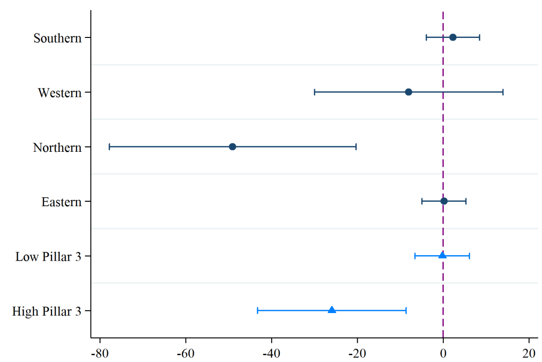
	(1)	(2)	(3)	(4)
	F.Deceased	F.Deceased	F.Deceased	F.Deceased
Z-time	0.004***	0.003**	0.003**	0.003*
	(0.001)	(0.001)	(0.002)	(0.001)
Score	-0.006***	-0.004***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Age		0.003***	0.003***	-0.042***
		(0.000)	(0.000)	(0.004)
Interviewer FE	No	No	Yes	Yes
Other 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 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 11. Means and Standard Deviations (SDs) of Key Variables

	(1) Full Sample	(2) Loss Sample
D.Wealth	43.990	32.228
	(488.420)	(398.519)
L.Wealth	333.079	301.103
	(603.313)	(564.652)
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.Z-time	121.360	122.036
	(37.069)	(37.143)
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	8.599***	4.431***	4.523***	4.182***
	(1.326)	(1.167)	(1.403)	(1.410)
L.Z-time				-8.966**
				(4.496)
Country FE	No	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.130	0.218	0.324	0.324

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 Awareness, Multinomial logit: Based on 26-Score

	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	0.0132	0.0342	0.0815***
	(0.0246)	(0.0439)	(0.0307)
Score	-0.0514***	0.0498***	0.1531***
	(0.0074)	(0.0138)	(0.0104)
Female	0.1543***	-0.1122	-0.2653***
	(0.0515)	(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.

Table 14. Predicting Awareness, Multinomial logit: Based on Recall Test

	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	0.0093	0.0423	0.0587**
	(0.0262)	(0.0375)	(0.0263)
Score	-0.0509***	0.0696***	0.1552***
	(0.0078)	(0.0121)	(0.0088)
Female	0.1701***	-0.2149***	-0.3302***
	(0.0544)	(0.0787)	(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.

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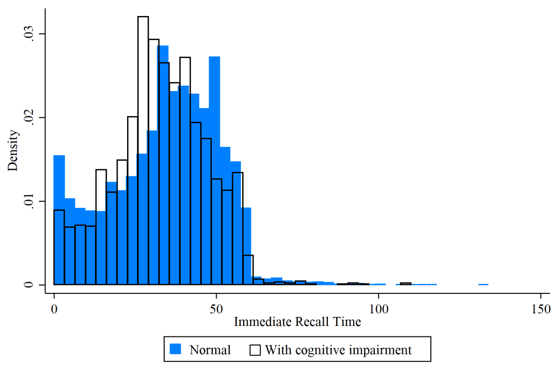
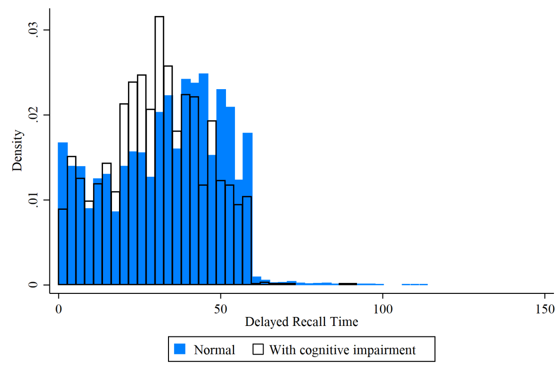
Online Appendix

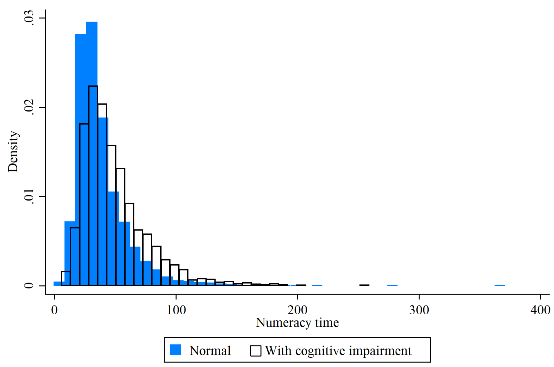
Figure A.1. Density of Response Times



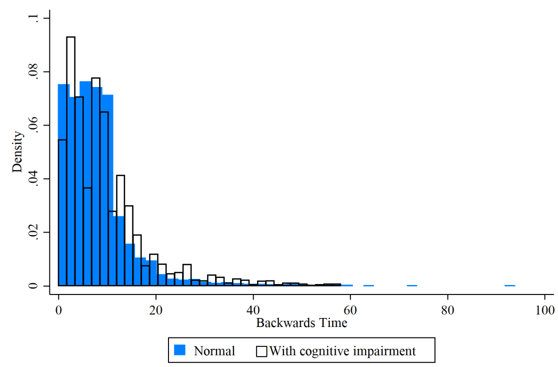
(a) Panel A: Immediate Recall



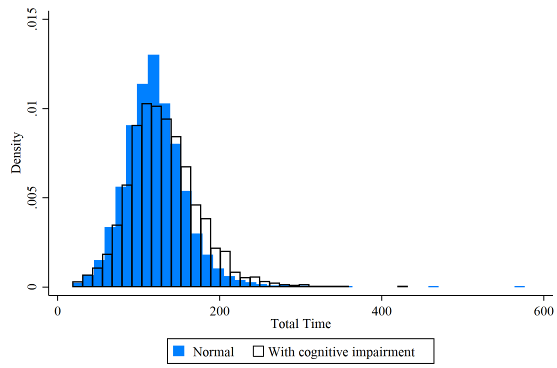
(b) Panel B: Delayed Recall



(c) Panel C: Numeracy



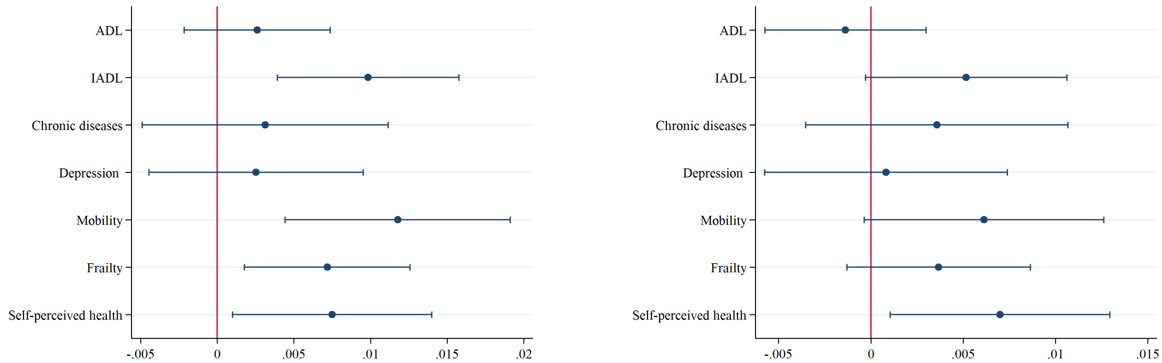
(d) Panel D: Backwards Counting



(e) Panel E: Total Time

Notes: The data come from SHARE.

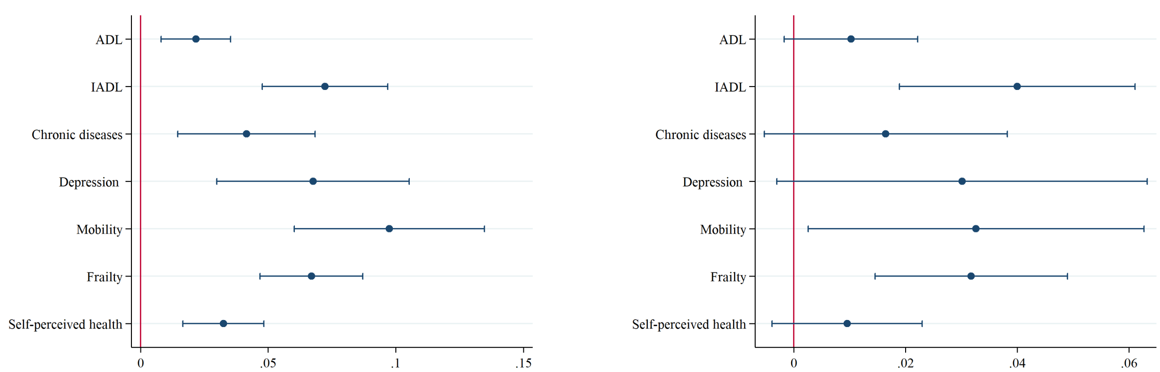
Figure A.2. Health Outcomes in Wave 9 and RT in Wave 8, Indicator Variables



(a) Panel A: Not controlling for Health$_t$ **(b) Panel B: Controlling for Health$_t$**

Notes: The data come from SHARE. The dependent variables are the indicator variables for having at least one ADL, one 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 the corresponding health dimension in Wave 8.

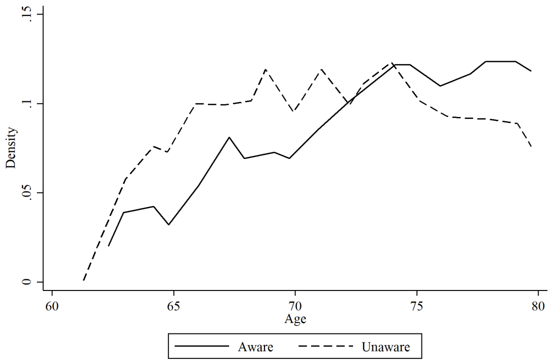
Figure A.3. Health Outcomes in Wave 9 and Alternative RT in Wave 8



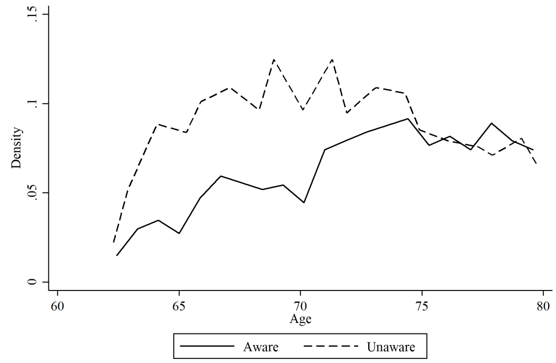
(a) Panel A: Not controlling for Health$_t$ **(b) Panel B: Controlling for Health$_t$**

Notes: The data come from SHARE. The alternative RT measures one standard deviation of the sum of numeracy and backwards counting response times (i.e. discarding recall tasks). The dependent variables are the number of ADL limitations, IADL limitations, 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); the frailty index, and self-assessed health. 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 the corresponding health dimension in Wave 8.

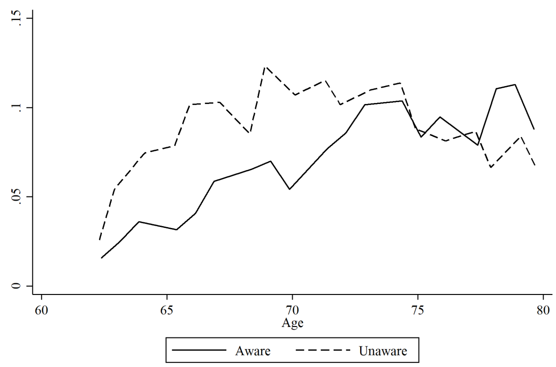
Figure A.4. Age at Loss: Alternative definitions of Loss



(a) Panel A: 1SD of Memory Score



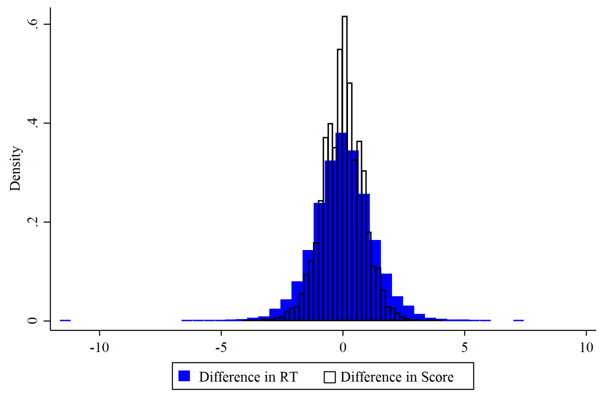
(b) Panel B: 20% of Total Score



(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. 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.4. 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.5. 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.6. 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.7. 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.8. 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.9. 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.10. 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.11. Cognitive Health and Response Time at Wave 8: Full Sample

	(1) Score	(2) Score	(3) Score	(4) 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.12. Cognitive Health and Response Time at Wave 9: Full Sample

	(1) Score	(2) Score	(3) Score	(4) 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.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	7.862***	4.368***	4.231***	3.969***
	(1.372)	(1.230)	(1.472)	(1.486)
L.Z-time				-8.403*
				(4.500)
Country FE	No	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	10,681	10,681	10,681	10,681
R^2	0.121	0.206	0.325	0.325

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	-21.8072***		-21.1394**	
	(8.3218)		(8.4568)	
L.recall	5.4431***	5.3872***		
	(1.3551)	(1.3656)		
L.Score			4.2504***	4.2165***
			(1.0993)	(1.1055)
Aware		-18.6274		-12.7486
		(12.4032)		(12.8932)
Unaware		-27.7918***		-30.1736***
		(10.0334)		(10.4375)
Pessimist		-12.3308		-12.0887
		(10.4519)		(9.9351)
Based on Recall Test	Yes	Yes	No	No
Based on 26-Score	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	12,540	12,540	12,540	12,540
R^2	0.209	0.209	0.208	0.208

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	8.599***	4.431***	4.523***	3.724**
	(1.326)	(1.167)	(1.403)	(1.450)
Z-time				-15.022***
				(4.615)
Country FE	No	Yes	NA	NA
Interviewer FE	No	No	Yes	Yes
Observations	11,910	11,910	11,910	11,910
R^2	0.130	0.218	0.324	0.324

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. Cognitive Health and Changes in Wealth: Heterogeneity by Sex

	ΔW
Z-time*male	-12.9759*
	(7.8332)
Z-time*female	-6.6498
	(4.7240)
Score*male	6.6081***
	(2.2307)
Sore*female	2.7044*
	(1.5717)
Interviewer FE	Yes
Observations	11910
R^2	0.324

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.

Table A.19. Predicting Awareness, Multinomial logit: Based on 26-Score and Alternative Time

	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	-0.0119	0.1059**	0.1330***
	(0.0273)	(0.0444)	(0.0307)
L.Score	-0.0524***	0.0535***	0.1558***
	(0.0075)	(0.0137)	(0.0104)
Female	0.1580***	-0.1283	-0.2780***
	(0.0516)	(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.20. Predicting Awareness, Multinomial logit: Based on Recall Test and Alternative Time

	(1)	(2)	(3)
	Pessimistic	Aware	Unaware
Z-time	-0.0071	0.0768**	0.0958***
	(0.0289)	(0.0390)	(0.0273)
L.Score	-0.0516***	0.0716***	0.1572***
	(0.0079)	(0.0120)	(0.0088)
Female	0.1727***	-0.2232***	-0.3391***
	(0.0545)	(0.0789)	(0.0564)
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.21. Predicting Cognitive Score in Wave 9 using Response Time in Wave 8: Using 27-Score

	(1)	(2)	(3)	(4)
	F.Score	F.Score	F.Score	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.