MAYNOOTH UNIVERSITY

DOCTORAL THESIS

When Time Matters Most - Procrastination and Its Impact in Older Adulthood

A thesis by:
Cormac Monaghan

Under the supervision of:
Dr. Joanna McHugh Power
Prof. Rafael de Andrade Moral

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophyin the

Hamilton Institute

Maynooth University

To my younger self, who decided to go through this challenging life experience

Abstract

Background: Procrastination is a widespread and pervasive self-regulatory failure. However, research has primarily focused on younger adult populations. As the global population of individuals over the age of 65 continues to grow, understanding whether, how, and why older adults procrastinate has become increasingly important.

Methods: To address this gap, this thesis examines the mechanisms and consequences of procrastination in older adulthood using three complementary datasets. These include a nationally representative secondary dataset from the United States, a secondary dataset from Ireland, and a primary dataset collected in the United Kingdom.

STUDY 1 used data from the United States Health and Retirement Study to examine whether depressive symptomatology and loneliness mediated the association between age and procrastination. Structural equation modelling revealed a significant indirect effect via depressive symptomatology such that older adults with higher levels of depression were more likely to engage in procrastination. Subsequent exploratory analysis revealed that this relationship was primarily driven by fatigue, loneliness, and lack of motivation.

STUDY 2 investigated the social aspects of procrastination by examining whether differences were present between younger and older adults in their perceptions of procrastination as a violation of social norms. Using data collected from 200 adults in the United Kingdom, multilevel modelling revealed that both financial and health procrastination were perceived more negatively than general procrastination. However, there was little evidence that these perceptions differed between younger and older adults.

STUDY 3 examined the temporal aspects of procrastination by investigating the associations between temporal orientation, subjective remaining life, and procrastination. Using secondary data from adults in Ireland, latent class analysis and Bayesian regression demonstrated that while no moderating role for subjective remaining life was present, both subjective remaining life and temporal orientation were independently associated with procrastination.

STUDY 4 examined whether procrastination affected engagement in health preventive behaviours among older adults. Using cross sectional data from the United States Health and Retirement Study, this study used generalised additive models to show that procrastination was negatively associated with a range of health preventive behaviours, including prostate exams, mammograms, cholesterol screenings, and dental visits.

STUDY 5 involved using longitudinal data from the United States Health and Retirement Study to test if procrastination could be an early marker of cognitive decline. Using discrete time Markov models this study showed that procrastination scores were significantly higher among individuals with MCI or dementia than those with normative cognitive function. Furthermore, procrastination was associated with cognitive impairment and predicted subsequent transitions from normative cognitive functioning to mild cognitive impairment

Conclusions: Collectively, the findings demonstrate that procrastination remains a meaningful phenomenon in older adulthood and cannot be fully understood using theories developed primarily via younger populations. Instead, procrastination appears to reflect a dynamic developmental process shaped by interacting affective, motivational, social, temporal, and cognitive factors. Beyond its theoretical significance, procrastination was associated with poorer engagement in preventive health behaviours and emerged as a potential early behavioural marker of cognitive decline. These findings highlight the importance of adopting a lifespan perspective to better understand the causes, consequences, and practical implications of procrastination in older adulthood.

Declaration of Authorship

I, **Cormac Monaghan**, declare that this thesis titled, **“When Time Matters Most - Procrastination and Its Impact in Older Adulthood”** and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

The thesis work was conducted from September 2022 to October 2026 in the Hamilton Institute, Maynooth University, under the supervision of Dr. Joanna McHugh Powerand Prof. Rafael de Andrade Moral

Cormac Monaghan

Maynooth University

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Taighde Éireann
Research Ireland

Publications

At the time of writing, three chapters of this thesis have been published in peer-reviewed journals. Specifically, Chapters 3, 6 and 7 have appeared in *Aging & Mental Health*, *Preventive Medicine*, and *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, respectively.

Peer-reviewed journal articles

- Monaghan, C., Avila-Palencia, I., Han, S. D., & McHugh Power, J. (2024). Procrastination, depressive symptomatology, and loneliness in later life. *Aging & Mental Health*, *28*(9), 1270–1277. 10.1080/13607863.2024.2345781.

- Monaghan, C, de Andrade Moral, R., & McHugh Power, J. (2025). Procrastination and preventive health-care in the older U.S. population. *Preventive Medicine*, *190*, 108185. 10.1016/j.ypmed.2024.108185.

- Monaghan, C., de Andrade Moral, R., Kelly, M., & McHugh Power, J.. (2026). Procrastination as a Marker of Cognitive Decline: Evidence from Longitudinal Transitions in the Older Adult Population. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, *18*(1), e70245. 10.1002/dad2.70245.

In addition to these published articles, both Chapter 5 and a subsection of Chapter 2 are currently under review. Moreover, Chapter 4 forms part of a broader programme of ongoing research that is currently being prepared for publication.

Articles under review or in writing

- Monaghan, C., de Lara, I. A. R., de Andrade Moral, R., & McHugh Power, J. (Under review). Goodness of fit diagnostics for discrete time Markov models of cognitive transitions Preprint available here.

- Monaghan, C., Gartlan, C., de Andrade Moral, R., & McHugh Power, J. (Under review). Do Perceptions of Remaining Life Shape Procrastination? Evidence from Latent Class and Bayesian Models. Preprint available here.

- Sirois, F., Markham, H., Monaghan, C., de Andrade Moral, R, & McHugh Power, J. (In writing). Does personality influence how we see others?

Alongside these scholarly outputs, the methodological work undertaken during this PhD resulted in the development of an R package.

Software and technical outputs

</> Monaghan, C., de Andrade Moral, R., & McHugh Power, J. (2024). *LWC2022: Langa-Weir Classification of Cognitive Function for 2022 HRS Data*.
R package version 1.0.0. Package available here.

Conference Proceedings

During the course of this PhD, findings from the thesis were disseminated via presentations at national and international conferences in the fields of gerontology, health psychology, statistics, and procrastination research.

- Monaghan, C., & McHugh Power, J. (2023). Age, procrastination, depressive symptomatology, and loneliness: a structural equation modelling approach. *Irish Gerontological Society 70th Annual and Scientific Meeting*. Galway, Ireland. Presentation available here.

- Monaghan, C., de Andrade Moral, R., & McHugh Power, J. (2024). Procrastination as a risk factor for poor health in older adults. *38th Annual Conference of the European Health Psychology Society*. Cascais, Portugal. Presentation available here.

- Monaghan, C., de Andrade Moral, R., & McHugh Power, J. (2024). Modelling the Non-linear Associations between Age and Health: Implications for Care. *Irish Gerontological Society 71st Annual and Scientific Meeting*. Athlone, Ireland. Presentation available here.

- Monaghan, C, de Andrade Moral, R., & McHugh Power, J. (2025). The Statistical Power of Alcohol Consumption Measures. *45th Conference on Applied Statistics in Ireland*. Galway, Ireland. Presentation available here.

- Monaghan, C., Gartlan, C., de Andrade Moral, R., & McHugh Power, J. (2025). The Role of Temporal Orientation and Subjective Remaining Life in Procrastination. *12th International Conference on Procrastination Research*. Utrecht, The Netherlands. Presentation available here.

Open Access Statement

In the spirit of open science principles, all materials associated with this thesis have been made publicly available wherever possible. Code, analysis scripts, and supplementary materials can be accessed via the repositories listed below.

Discrete time Markov models: Assessing goodness of fit

Repository: c-monaghan/hopeful-hornet

Procrastination, depressive symptomatology, and loneliness in later life

Repository: c-monaghan/earth-eagle

Do perceptions of remaining life shape procrastination?

Repository: c-monaghan/fearless-leader

Analysis notebook: c-monaghan.github.io/fearless-leader/

Procrastination and preventive health-care in the older U.S. population

Repository: c-monaghan/foolish-commander

Procrastination as a marker of cognitive decline

Repository: c-monaghan/crisp-clam

Analysis notebook: c-monaghan.github.io/crisp-clam

In addition to the chapter-specific materials above, the full LaTeX source code and an online HTML version of this thesis are available at the following links below.

Thesis materials

Source code: c-monaghan/thesis

Web version: c-monaghan.github.io/thesis/

"If you only do what you can do, you'll never be better than what you are."

Master Shifu

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I know I said finally, but there's one more person that needs to be thanked. In the last month of writing this thesis, we unofficially adopted a cat named Bigsy. Bigsy doesn't belong to us; in fact, he lives down the road. But ever since we fed him one day he now comes to our house to watch us work, while mostly sleeping on the couch. Nevertheless, thank you Bigsy. Having you sleeping there next to me made writing that little bit easier.

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List of Abbreviations

AIC	**A**kaike **I**nformation **C**riterion
ANOVA	**AN**alysis **O**f **VA**riance
BIC	**B**ayesian **I**nformation **C**riterion
CBT	**C**ognitive **B**ehavioural **T**herapy
CESD	**C**entre for **E**pidemiological **S**tudies **D**epression
CFC	**C**onsideration of **F**uture **C**onsequence
CFC-I	**C**onsideration of **F**uture **C**onsequence - **I**mmediate
CFC-F	**C**onsideration of **F**uture **C**onsequence - **F**uture
CFI	**C**omparative **F**it **I**ndex
DGM	**D**ata **G**enerating **M**echanism
ELSA	**E**nglish **L**ongitudinal **S**tudy of **A**geing
FIML	**F**ull **I**nformation **M**aximum **L**ikelihood
GAM	**G**eneralised **A**dditive **M**odel
GED	**G**eneral **E**ducational **D**evelopment
HRS	**H**ealth and **R**etirement **S**tudy
JAGS	**J**ust **A**nother **G**ibbs **S**ampler
LCA	**L**atent **C**lass **A**nalysis
MCI	**M**ild **C**ognitive **I**mpairment
PPS	**P**ure **P**rocrastination **S**cale
RMSEA	**R**oot **M**ean **S**quare **E**rror of **A**pproximation
R-UCLA	**R**evised **U**niversity of **C**alifornia, **L**os **A**ngeles
SEM	**S**tructural **E**quation **M**odelling
SD	**S**tandard **D**eviation
SDT	**S**elf **D**etermination **T**heory
SOC	**S**elective **O**ptimisation with **C**ompensation
SRL	**S**ubjective **R**emaining **L**ife
SRMR	**S**tandardized **R**oot **M**ean **S**quare **R**esidual
SST	**S**ocioemotional **S**electivity **T**heory
TICS	**T**elephone **I**nterview for **C**ognitive **S**tatus
TILDA	**T**he **I**rish **L**ongitudinal **S**tudy on **A**geing
TLI	**T**ucker **L**ewis **I**ndex
TPRS	**T**hin **P**late **R**egression **S**plines
US	**U**nited **S**tates

CHAPTER 1

Literature Review

1.1 Preface

Global demographic shifts are creating unprecedented challenges for societies worldwide. Currently, the proportion of individuals aged 65 years and above is growing faster than younger age groups (World Health Organisation, 2025). This shift in demographics motivates the public health imperative of understanding and supporting behaviours that enable individuals to maintain autonomy, health, and wellbeing across the life course. Among these behaviours, the timely initiation and completion of important tasks (or the failure to do so) may hold profound significance. Failing to complete an important tasks can often be due to procrastination. Procrastination is defined as the voluntary and irrational delay of intended actions despite expecting to be worse off for the delay (Klingsieck, 2013a; Steel, 2007). Typically, procrastination is framed as an individualistic failure of self-regulation. However, in the context of an ageing population, the implications of procrastination may extend far beyond the individual, representing a critical but hitherto largely neglected public health concern.

According to prior research, approximately 15-20% of the population engage in procrastination to the point that it causes personal distress or difficulties (Harriott & Ferrari, 1996). This form of procrastination is known as chronic procrastination (Rozental & Carlbring, 2014). While extensively studied in academic contexts, where the prevalence of procrastination can reach as high as 95% among students (Abbasi & Alghamdi, 2015), this narrow empirical focus has created a critical knowledge gap.

The consequences of procrastination in later life are qualitatively different to those experienced in earlier life and carry substantially higher stakes. For older adults, delaying important tasks can have consequences just for academic performance, but for fundamental wellbeing (Kaftan & Freund, 2018). For instance, postponing health-related tasks such as health screenings can lead to late-stage disease diagnoses; delaying financial tasks could jeopardise retirement security; and avoiding advance care planning may precipitate crises for individuals and their families. These forms of delay also have the potential to compound stress, accelerate functional decline, increase healthcare costs, and ultimately threaten the very independence that public health initiatives for ageing populations seek to promote. As such, it is clear that procrastination is a critical and urgent matter for public health of older populations.

However, the current landscape of procrastination research cannot be readily applied to older adults without some considerations. The paradoxical nature of procrastination (i.e., knowingly acting against one's own best interests) has made it a topic for researchers interested in self-regulation, motivation, and decision making (J. R. Ferrari, 2001; Pychyl & Sirois, 2016; Sirois & Pychyl, 2013; Steel & König, 2006). To date, most of the dominant theoretical models of procrastination have been developed primarily through research on younger populations. As such, these models may provide limited insight into the unique motivational landscape of older adulthood. Ageing brings with it many changes, and it is through these changes that the triggers, manifestations, and consequences of procrastination may yield different effects in older than in younger adulthood. A comprehensive understanding of procrastination across the lifespan is therefore essential, not only for advancing psychological theory but for developing effective, age-sensitive interventions that support timely action on tasks critical to health, financial security, and quality of life in later years.

This thesis addresses this research gap by examining procrastination in older adulthood (adults primarily aged 60+) through a lifespan-developmental lens. While it is beyond the scope of the thesis to provide an account of procrastination across the entire lifespan, here we consider one important life stage, older adulthood. Chapter 1 establishes the foundation for this investigation. In what follows, I will (1) provide a historical context for the research topic by tracing the conceptual evolution of procrastination from a moral failing to a psychological construct; (2) critically examine dominant theoretical frameworks from a lifespan developmental perspective; and (3) synthesise existing (limited) evidence on the unique consequences and manifestations of procrastination in later life.

1.2 The conceptual history of procrastination

To understand procrastination in later life, it is first essential to delineate what the construct is and how its conceptualisation has evolved over time. This section outlines this progression, beginning from its early historical interpretations as a characterological flaw to its current status as a multifaceted psychological phenomenon of self-regulatory failure. Ultimately, this shift has fundamentally shaped how we measure, study, and interpret procrastination.

1.2.1 From moral failing to psychological construct

Procrastination has a long history as a recognised aspect of human behaviour, and it has been consistently viewed through a moral and characterological lens. Ancient Egyptian hieroglyphs associated delay with neglect and forgetfulness (DeSimone, 1993), while classical philosophers established early frameworks for understanding willpower failure. Aristotle, in his *Nicomachean Ethics*, examined the concept of *akrasia*, or weakness of will, describing *malakia* as a specific form of *akrasia* in which individuals fail to act despite knowing what should be done (Steel, 2007). This concern was echoed by other historians and statesmen. Thucydides, an Athenian general and historian, documented the catastrophic consequences of political and military delay, while Cicero, a Roman consul and philosopher, framed procrastination as a moral weakness and failure of duty (McCloskey, 2011; Steel, 2007).

This view of procrastination persisted across cultural and historical contexts. Early Christian writers frequently warned against idleness and delay (e.g., Proverbs 6:9-11), while Buddhist philosophy identified *kausidya* (spiritual sloth) as antithetical to diligence (Rinpoche et al., 1997). This perspective continued during the Renaissance and Enlightenment as procrastination became more connected to laziness and inefficiency (DeYoung et al., 2010). The rise of the Industrial Revolution further cemented this perspective, promoting both productivity and efficiency and thus casting procrastination as its antithesis (Johnson, 1840). Ultimately, this historical context shows that while interpretations have changed, procrastination has commonly been seen as a failure of will and morality.

The emergence of psychology as a discipline facilitated a critical paradigm shift, reframing procrastination from the realm of morality to the realm of empirical science. Initially, this reframing was hampered by a lack of consensus regarding what procrastination was (J. R. Ferrari et al., 1995). Early research offered varied conceptualisations, with some scholars even proposing "active procrastination" as a potentially functional form of strategic delay (Bernstein & Bernstein, 1996; Chun Chu & Choi, 2005; J. R. Ferrari, 1993). However, modern psychological research largely rejects this idea, focusing instead on procrastination's irrational and self-defeating aspects.

1.2.2 The definition of procrastination

A robust conceptual framework now underpins the field's consensus. According to Klingsieck (2013a), to be classified as procrastination, a behaviour must meet multiple criteria (see Figure 1.1): (1) it involves **voluntarily** postponing (Milgram et al., 1998) an **important** activity (Lay & Schouwenburg, 1993); (2) the individual knows this delay is **counterproductive** and will likely **lead to negative outcomes** (Steel, 2007), and (3) the individual feels some form of **negative emotions**, such as guilt, anxiety, or stress (J. R. Ferrari et al., 1995; Simpson & Pychyl, 2009). This multi-part definition leads to the widely accepted view of procrastination as:

> *The voluntary and unnecessary delay of an intended course of action despite expecting to be worse off for the delay.* (Klingsieck, 2013a; Steel, 2007)

This conceptualisation is crucial for distinguishing procrastination from similar behaviours. For instance, procrastination is not the same as strategic delay (C. J. Anderson, 2003), which represents a rational postponement to optimise outcomes (e.g., postponing starting an assignment to conduct more research). Nor is it the same as idleness, as procrastinators often engage in other tasks that offer immediate but less important rewards (H. Wu et al., 2016). The key difference is the self-defeating nature of procrastination (Sabini, 1982). The individual knows delaying is against their best interest but chooses to do it anyway.

In this sense, procrastination can be understood as a breakdown in the cognitive, emotional, and behavioural processes that align actions with intentions and long-term goals (Rozental & Carlbring, 2014). Cognitively, intentions fail to translate into effective planning or initiation. Emotionally, short-term mood regulation overrides longer-term goal pursuit. Behaviourally, an action is deferred despite awareness of its importance. It is the interaction of these processes, rather than the act of delay itself, that defines procrastination.

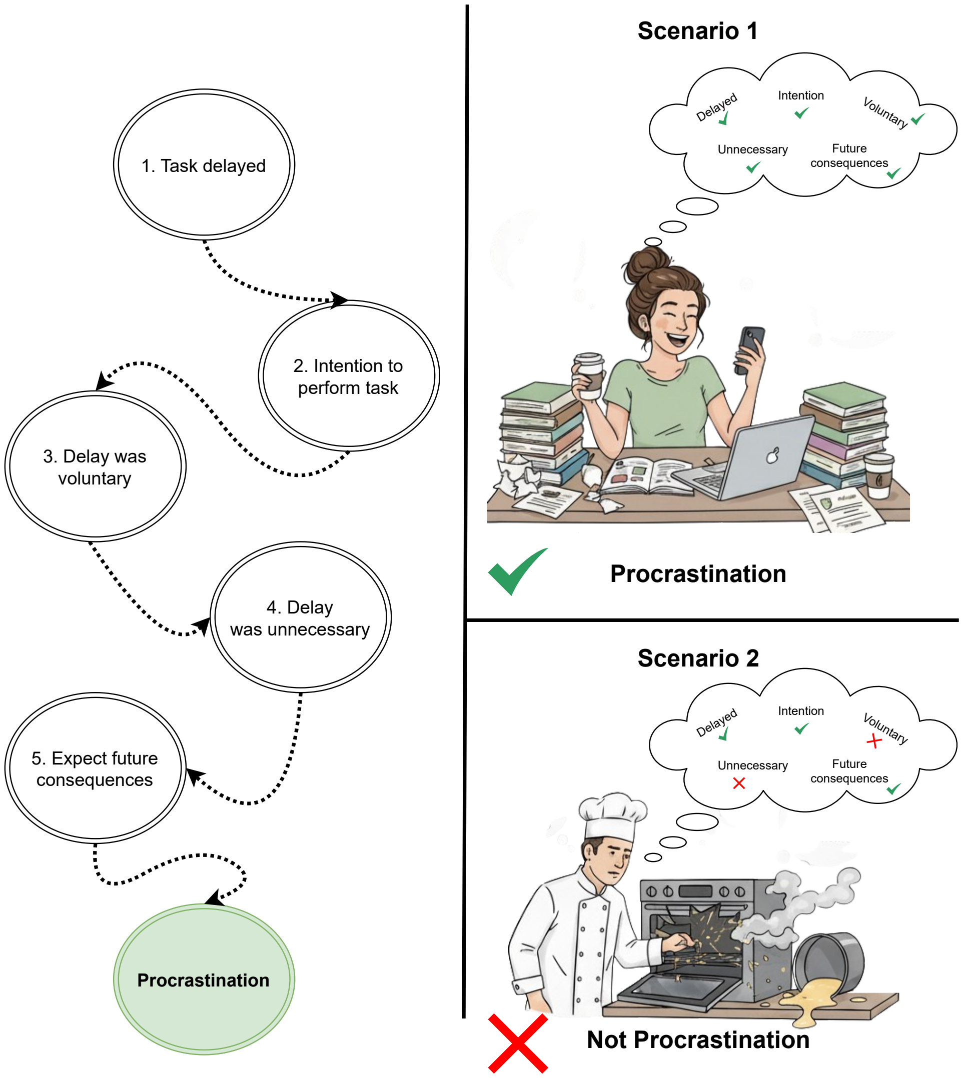

Figure 1.1: *The criteria necessary for a behaviour to be classified as procrastination. In Scenario 1, the student voluntarily delays her intended studies, knowing there will be consequences for her exam tomorrow, thus meeting all criteria for procrastination. However, in Scenario 2, the chef cannot bake the cake because the oven is broken and the batter has spilled. Since the delay is not voluntary or unnecessary, it was not caused by procrastination, but rather an unavoidable obstacle. Parts of this image were made using generative artificial intelligence (Google Gemini Nano Banana).*

This modern understanding significantly impacts how we view procrastination in later life. For older adults, tasks seen as "necessary and personally important" are quite different from that of a younger adult. They often relate to health, finances, and/or social legacy. Delaying a medical appointment, putting off financial planning, or avoiding making a will is rarely a strategic choice. Rather it is better understood as an unnecessary, voluntary delay that can have serious and lasting consequences for one's independence and wellbeing. Or more simply put, procrastination.

1.2.3 The prevalence and general consequences of procrastination

Before examining how procrastination affects older adults, it is first important to consider its prevalence and general impact in the wider population (see Table 1.1). Epidemiological studies suggest that approximately 15-20% of the adult population identify as chronic procrastinators (Harriott & Ferrari, 1996). In certain contexts, such as academia, this figure increases dramatically, with up to 95% of students reporting frequent procrastination (Abbasi & Alghamdi, 2015). Such rates underscore procrastination to be a prevalent and maladaptive behaviour.

The consequences of procrastination are equally well-documented and extend beyond productivity. A substantial body of research links chronic procrastination to significant psychological and physical morbidity. Prior research consistently associate procrastination with elevated levels of stress (Johansson et al., 2023; Sirois et al., 2003; Stead et al., 2010), negative emotional states (Nie et al., 2025; Van Eerde, 2003) and reduced overall wellbeing (Sirois et al., 2003; Tice & Baumeister, 1997; Van Eerde, 2000). Additionally, procrastination is linked to poorer academic and job performance (Abbasi & Alghamdi, 2015; Van Eerde, 2003), lower financial stability (Shah & Mukherjee, 2025), and increased interpersonal strain (J. R. Ferrari et al., 1998). Collectively, these findings establish procrastination as a significant failure of self-regulation with real-world costs across various areas of life.

Table 1.1: *Summary of the prevalence and general consequences of procrastination.*

Domain	Key Findings
Prevalence (general populations)	15–20% of adults report chronic procrastination
Prevalence (student populations)	80–95% of students report procrastination
Psychological effects	Associated with increased stress, anxiety, depression, and reduced wellbeing
Performance outcomes	Associated with poorer academic and work performance, and greater financial instability
Interpersonal effects	Associated with increased conflict and relational strain

From looking at Table 1.1, it becomes evident that while procrastination has substantial real-world costs, its expression and significance may change across the lifespan. Although most procrastination research to date has focused on younger and student populations, several studies including older adults reveal a distinctive U-shaped developmental trajectory. For instance, W. McCown and Roberts (1994) found that procrastination typically declines from early adulthood through midlife, up until approximately 60 years, after which it begins to rise again (see Figure 1.2 for an illustration of these results). A similar pattern was reported by Beutel et al. (2016) in a large sample ($n = 2,527$) ranging from adolescence (14 years) to very old age (95 years), with procrastination levels increasing again after approximately age 70. Interestingly, the authors did not elaborate on potential explanations. While the initial decline is readily explained by the maturation of self-regulatory faculties and personality traits, particularly the normative increase in conscientiousness, which happens around age 20-30 (B. W. Roberts et al., 2006), the subsequent rise presents an interesting theoretical puzzle that cannot be fully explained by the models developed using younger populations.

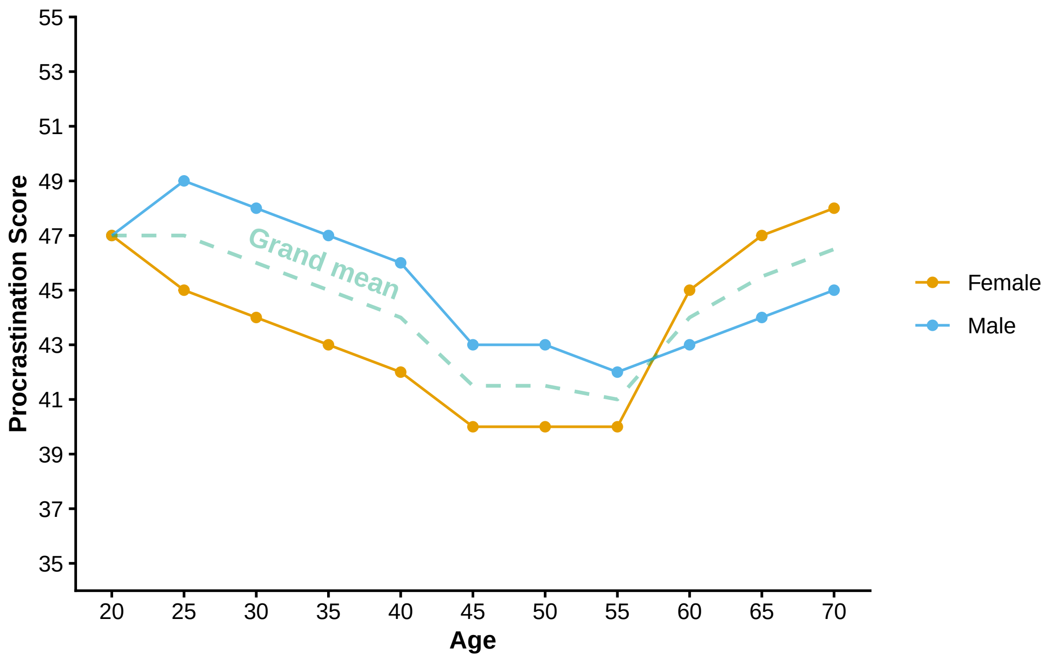

Figure 1.2: *A recreated figure from J. R. Ferrari et al. (1995) illustrating procrastination scores across age and gender from a study conducted by W. McCown and Roberts (1994). A grand mean line was added to show procrastination scores across the lifespan (irrespective of gender).*

Early explanations regarding life course trajectories in procrastination such as that depicted in Figure 1.2 pointed to cohort effects (experiences of the Great Depression and World War II) or major life transitions such as retirement and health decline (J. R. Ferrari et al., 1995). Individuals who grew up during economic hardship and wartime mobilization were likely exposed to strong norms of duty, urgency, and long-term planning, where delay carried serious consequences. However, as they aged and the structural pressures of work and family obligation receded, the behavioural expression of these norms may also have weakened.

However, cohort explanations alone are insufficient. A more complete explanation requires an integration of several likely age-specific psychological shifts: (1) a fundamental change in time perspective and motivation that devalues long-term utility (Carstensen et al., 1999; Sirois & Pychyl, 2013); (2) increased demands from complex environments that can overwhelm personal competencies (Davis, 1989; Lawton & Nahemow, 1973); and (3) the depletion of self-regulatory resources by the demands of health management (Diehr et al., 2013; Sirois, 2015). As I will argue in the following sections, what appears as a mere reduction in self-regulation may instead be a coherent, if maladaptive, re-allocation of resources away from aversive, future-oriented tasks that threaten the self-concept, and toward activities that maintain emotional equilibrium in the present.

1.3 A lifespan perspective on ageing and procrastination

Given these high stakes, it becomes essential to examine how well existing theoretical frameworks of procrastination account for the unique developmental context of ageing. The main theories in procrastination research, mostly based on studies of younger adults in schools and workplaces, offer a helpful but incomplete understanding of this self-regulatory failure in older adults.

For older adults, procrastination may manifest in unique life domains such as health, finances, and legacy planning. Additionally, procrastination can be affected by age-specific developmental factors. Such factors may include shifting time horizons, changing social roles and managing ongoing health issues (Carstensen et al., 1999; Guo et al., 2022; Sirois, 2015). These factors create a context in which the triggers, manifestations, and consequences of procrastination may be fundamentally transformed. To better understand these processes, we need to re-evaluate and adjust existing theories using a lifespan perspective that's focused on older adulthood.

As such, this section provides a critical examination of the main theories that have influenced the field of procrastination research. It starts with the basic traits related to procrastination and then moves through the key aspects of self-regulation and motivation. It also considers how situational and individual circumstances interact to impact procrastination, and how personal narratives can support procrastination. Finally, I examine how our external surroundings change the way we think about procrastination in later life. The ultimate goal of this theoretical review is not to reject existing theories but to evaluate how well they apply and what their limits are. Ultimately, this will help support the proposed lifespan-informed model of procrastination (see Figure 1.3).

1.3.1 Dispositional foundations

Trait-based approaches conceptualise procrastination as a relatively stable, cross-situational individual difference rooted in enduring personality structures (J. R. Ferrari, 2011; Steel, 2007). This perspective posits that chronic procrastination stems from enduring dispositional characteristics that systematically shape how individuals set goals, regulate impulses, and respond to task demands. Prior meta-analytic evidence robustly links procrastination to low conscientiousness, high neuroticism, impulsivity, and maladaptive perfectionism (Meng et al., 2024; Sirois, 2007; Van Eerde, 2003; Xie et al., 2018). However, a lifespan perspective suggests that the impact and expression of these traits upon procrastination may be altered in later life.

Within trait research, conscientiousness (defined as the quality of working hard and diligently) emerges as the strongest protective factor against procrastination (Meng et al., 2024), facilitating planning, behavioural regulation, and sustained goal focus (McCrae & Costa Jr, 1991; Zhao & Seibert, 2006). As such, those with higher levels of conscientiousness tend to procrastinate less. However, while the linear increase in conscientiousness across the lifespan (see B. W. Roberts et al. (2006)) could theoretically lead to less procrastination in later life, this possibility should be contextualized within the heightened stakes of the older adult task environment. The complex, self-managed tasks of later life, such as adhering to medication regimens, navigating healthcare systems, and managing retirement finances, demand a high degree of order and diligence. Unlike that of a procrastinating student, a lapse here does not result in a poor grade but rather can directly threaten health, financial security, and independent living. Thus, while the trait level of conscientiousness may be higher, the functional demand for its effective expression is simultaneously greater, creating a novel risk profile even for the relatively organized older adult.

Conversely, while neuroticism (defined as a tendency toward negative emotional states) may decline on average (B. W. Roberts et al., 2006), its behavioural impact, which typically involves negative emotional reactivity and poor stress coping, can be heightened by the existential nature of ageing-related tasks. Procrastination is frequently triggered by tasks that elicit stress or personal vulnerability (Sirois & Pychyl, 2013). With advancing age, older adults are more likely to be confronted with experiences that are direct confrontations of their own personal vulnerability and mortality, such as completing advanced directives, addressing a troubling health symptom, or experiencing the loss of a friend or loved one. For an individual with even moderate neuroticism, delaying these tasks may function as a powerful form of existential avoidance, a short-term strategy to manage the profound anxiety associated with physical decline and finitude (Fabiś & Muszyński, 2024). This creates a critical paradox: the tasks most essential for maintaining future autonomy are precisely those most likely to be postponed due to their emotional aversiveness (Pychyl & Sirois, 2016).

Furthermore, perfectionism (defined as having high standards for oneself, while also having extreme self-critical tendencies) may be reconfigured around domains central to late-life identity, such as independence and self-reliance (Yuen et al., 2007). For instance, an older adult who defines their self-concept through independence may perceive using a walking aid or accepting help with household chores as a profound personal failure (Bailey et al., 2019; Resnik et al., 2009). This perfectionistic standard can make necessary adaptive tasks feel existentially threatening, rendering them prime candidates for procrastination (Sirois et al., 2017; Xie et al., 2018). The drive to maintain a flawless front of capability, fused with the fear of being seen as a burden, may paralyse decision-making and help-seeking behaviour.

1.3.2 Core mechanisms of delay

Complementary theoretical frameworks could be considered alongside the dispositional theories to help us uncover the central explanatory mechanisms for how procrastination unfolds. The self-regulation and motivation models conceptualise procrastination as a dynamic failure in the processes that translate intentions into goal-directed action.

First, the **self-regulation framework** positions procrastination as fundamentally cognitive; a breakdown in the capacity to align thoughts, emotions, and actions with long-term objectives (Baumeister & Heatherton, 1996). In other words, a failure to translate intentions into timely action despite possessing the necessary capability (Pychyl & Flett, 2012; Sirois & Pychyl, 2013; Steel, 2007). Prior research (J. R. Ferrari et al., 1995; Rebetez et al., 2016; Schouwenburg & Groenewoud, 2001) has linked this failure to deficits in subdomains of executive functioning, particularly inhibitory control (the ability to actively ignore irrelevant stimuli) and sustained attention (the ability to maintain focus on a particular stimulus over a long period of time).

In later life, declines in these subdomains may be exacerbated by natural declines (either age-related or health-related) in processing speed and working memory (Eckert et al., 2010; O'Halloran et al., 2014). Inadvertently, these declines are also related to procrastination (S. Zhang et al., 2019). From this perspective, procrastination in later life may represent not just a self-regulatory failure, but also a partial breakdown in some of the cognitive underpinnings of self-regulation itself.

In addition, the very nature of a self-regulatory demand changes in later life. Tasks such as managing complex medication regimens, navigating healthcare systems, or organising legal affairs require not only sustained cognitive effort but also serve as reminders of declining health, dependence, or mortality (Al-Noumani et al., 2019; Maxfield et al., 2010). Within this context, procrastination may also represent a motivated avoidance of aversive tasks, ones that in this case, threaten one's self-concept as a competent, autonomous individual.

This perspective can be further extended through the concept of ego depletion, which proposes that self-control draws upon a finite set of cognitive and emotional resources (Baumeister et al., 2018). If self-regulation depends upon a finite reserve of resources, then the cumulative demands of later life may leave fewer resources available for additional tasks. Many older adults face ongoing self-regulatory demands, particularly with managing health conditions and complex care routines (Guo et al., 2022). These demands may gradually deplete the resources needed for initiating less urgent (albeit important) actions, in turn increasing vulnerability to delay.

Complementing this, **motivational frameworks** help explain *why* actions becomes harder to initiate in the first place. Temporal Motivation Theory[1] (TMT; Steel and König, 2006; Steel et al., 2018) proposes that motivation at any given moment depends on four factors: **expectancy** (how likely success feels), **value** (how worthwhile the outcome seems), **impulsiveness** (how strongly one discounts delayed rewards), and **delay** (how far away the outcome is in time).

$$\text{Motivation} = \frac{(\text{Expectancy} \times \text{Value})}{1 + (\text{Impulsiveness} \times \text{Delay})}$$

Conceptually, the numerator of the equation reflects the perceived payoff of acting (i.e., tasks tend to feel more motivating when success seems likely and the outcome is important), while the denominator reflects temporal and self-regulatory costs (i.e., motivation weakens as rewards become more distant in time, particularly for individuals who are more sensitive to delay). Thus, procrastination becomes more likely when the immediate costs of an action outweighs the anticipated future benefits (Steel & König, 2006)

When taken from a lifespan perspective, each element of this equation may undergo a systematic transformation in later life. Expectancy may weaken for novel, effortful, or technologically complex tasks as perceived competence and self-efficacy decline, even when the objective ability for the task remains (H. M. Hu, 2024; Thomas et al., 2023). Task value may be directed towards emotionally meaningful goals and away from long-term utility (Baltes & Baltes, 1990; Carstensen, 2001). Meanwhile, delay may be altered by age-related changes in temporal discounting (Green et al., 1999). Finally, while trait impulsiveness tends to decline in later life (B. W. Roberts et al., 2006), the desire to avoid negative emotional states and minimise immediate distress may serve a comparable role (Wolfe et al., 2022).

Self-Determination Theory (SDT) adds a further layer of understanding by emphasising the quality of motivation (Deci & Ryan, 2009). SDT distinguishes between autonomous motivation (i.e., acting out of personal endorsement or intrinsic value) and controlled motivation (i.e., acting due to external pressure or obligation). Tasks perceived as externally imposed are more likely to elicit controlled motivation. Within

[1]The constant 1 is added to the TMT equation to prevent it from approaching infinity when the denominator is close to 0 (Steel et al., 2018).

younger adult and student samples, controlled motivation has been associated with higher levels of procrastination, likely because externally regulated tasks evoke resistance and reduced internal commitment (Kljajic et al., 2022). In contrast, relatively little is known about how motivational quality shapes procrastination in later life. Despite this, given the importance of autonomy in later life (Carstensen & Hartel, 2006), it is plausible that externally imposed demands is later life may be particularly vulnerable to delay.

When taken together, these perspectives reveal an interesting facet to self-regulation in older adulthood. In general, older adulthood is associated with selective goal prioritisation (Carstensen, 2001), a process that is generally adaptive. However at the same time, these adaptive shifts may have unintended consequences. The stronger focus on maintaining emotional well-being and preserving autonomy that comes with getting older might make it more appealing to avoid tasks that feel stressful, externally imposed, or threatening to one's sense of independence. In this sense, the difficulty does not necessarily stem from weaker self-control, but from how that self-control is directed (i.e., prioritising short-term emotional comfort over longer-term outcomes).

1.3.3 Interplay of state and context

While self-regulation and motivation provide the core mechanisms of procrastination, context-based frameworks are essential for understanding how procrastination is triggered in daily life. This framework conceptualises procrastination not as a static trait but as a dynamic outcome between an individual's resources and the specific demands of their context (A. K. Blunt & Pychyl, 2000; Klingsieck, 2013a; Steel, 2007). It helps explain why even typically punctual individuals sometimes delay, and why habitual procrastinators occasionally act decisively.

Evidence from general populations supports this perspective. Situational factors such as task ambiguity, task aversiveness, and long deadlines have all been associated with greater likelihood of delay (Abbasi & Alghamdi, 2015; A. K. Blunt & Pychyl, 2000). In addition, internal states such as stress, fatigue, and negative mood can make procrastination more likely (Meng et al., 2024; Nie et al., 2025; Sirois, 2023). Together, these findings suggest that procrastination is more than just a stable dispositional tendency, but also context-sensitive and can be shaped by the interaction between situational pressures and momentary psychological resources.

For older adults, these situational determinants are likely to be reconfigured by changes in time perspective. Socioemotional Selectivity Theory (SST; Carstensen, 2001) proposes that individuals continuously monitor their future time. When time is perceived as limited, individuals tend to prioritise emotionally meaningful experiences over long-term goals (Carstensen & Hartel, 2006). Prior evidence supports this by demonstrating that older adults tend to show a stronger preference for emotionally meaningful social interactions and tendency to allocate attention and memory toward emotionally salient information (Lang & Carstensen, 2002).

If motivational priorities do indeed shift in this way, the situational determinants of procrastination may also take on qualitatively different meanings in later life. For instance, task aversiveness may become less about boredom in later life and more related to ego threat (Bailey et al., 2019; Resnik et al., 2009). Accordantly, a task like learning a new digital health platform or navigating an online banking system is not merely inconvenient but can feel like a high-stakes test of cognitive competence (Thomas et al., 2023). Similarly, completing an advanced care directive[2] is not a simple administrative task but a direct confrontation with one's own mortality (Sneddon, 2020). In such contexts, procrastination may function as a protective psychological barrier, allowing the individual to avoid an immediate threat to their self-concept (J. R. Ferrari & Díaz-Morales, 2007a). In addition, the perceived value of a task is filtered through an emotional meaning lens. An older adult may diligently plan a family reunion (an activity high in emotional meaning and social connection) while indefinitely postponing pension and/or health-care paperwork (an activity with high long-term utility but low immediate emotional payoff). From an SST perspective, this "neglect" may not reflect a self-regulatory failure, but simply re-prioritisation, blurring the line between maladaptive delay and adaptive selectivity.

Additionally, the daily enactment of these dynamics is further mediated by another state consideration: physiological ageing. Experience sampling studies suggest that procrastination is highly sensitive to transient states like mood and fatigue (Prem et al., 2018; Wieland et al., 2022). Individuals in later life may be more likely to experience health challenges which themselves can deplete the resources needed for self-regulation (Beauregard et al., 2015; Sirois, 2015). For instance hypertension, which is more prevalent in older adulthood (Mancia et al., 2013; Tsao et al., 2022), necessitates consistent self-care. Yet hypertension itself can deplete the resources needed for such behaviours (Artinian et al., 2010). Consequently, an older adult may delay a complex decision due to resource-based exhaustion, not laziness. Moreover, the "tempting alternatives" that trigger delay also evolve from active distractions (e.g., social media) toward activities offering cognitive or physical relief (e.g., rest), aligning with both reduced energy and the SST-driven preference for low-conflict emotional states (Cho et al., 2018; Scheibe et al., 2015).

[2] a legally recognized, written document that allows adults with capacity to outline specific medical treatment decisions for a future time when they may lose the ability to communicate, such as during serious illness or dementia.

1.3.4 Internal narrative of delay

However, the core mechanisms of both self-regulation and motivation are not merely cognitive calculations. Rather, they are sustained by a rich internal narrative of thoughts and emotions (Balkis & Duru, 2018; Ellis & Knaus, 1977). For older adults, this internal dialogue may likely be shaped by concerns about identity, competence, and legacy, making it a critical maintaining factor for procrastination.

Cognitive-behavioural models posit that our emotional and behavioural responses (e.g., anxiety and avoidance) are not determined by situations themselves, but by our interpretations of those situations (Beck, 1979). According to this perspective, procrastination is sustained by a series of maladaptive, task-related cognitions (Burka & Yuen, 2024; Ellis & Knaus, 1977; Steel, 2007). In later life, these cognitions are likely to become profoundly age-specific and identity-laden (Nieuwenhuis et al., 2018; Teo et al., 2022). A task like asking for help with finances or healthcare might be interpreted in the context of one's ageing as for example, "asking for help proves I'm no longer as capable as I once was", directly threatening a core aspect of one's self-concept. These cognitive distortions (which could include catastrophising, overgeneralisation, and personalisation) may transform neutral or beneficial tasks into profound psychological threats, driving avoidance and self-neglect (M. Zhang & Zhang, 2025). These distortions could then provide the "script" for the ego threat discussed in state-based models.

Meanwhile, Self-Worth Theory (Covington, 1984) provides an additional layer of understanding by explaining why this self-handicapping strategy is so compelling. The theory suggests that individuals are motivated to protect their global sense of self-worth. For an older adult who may value independence and cognitive sharpness (Yuen et al., 2007), the possibility of confronting limitations, whether through a formal memory assessment or the simple need for a walking aid, can be threatening to self-worth (Bailey et al., 2019). By procrastinating, a ready-made excuse is already available if potential failure arises. Should they perform poorly, failure can be attributed to not trying hard enough or not having enough time, rather than a fundamental lack of ability. This "self-handicap" allows a (for example) possible narrative, "I am still competent. I just didn't apply myself", to be maintained. The immediate emotional payoff (protecting one's self-concept) makes procrastination a reliable (if costly) short-term strategy.

Furthermore, the role of dysfunctional perseverative cognitions, such as rumination and worry, becomes more potent and damaging with age (Morse et al., 2024). For instance, fear of a serious diagnosis is a well-established predictor of delay in seeking help for potentially cancerous symptoms (Basch et al., 2016; Miles et al., 2008; Moser et al., 2014). However, this ruminative process ("What if they find cancer?") consumes working memory and attentional resources, leaving fewer cognitive reserves available for actual problem-solving and task initiation (Bruning et al., 2023). Moreover, this sustained negative focus amplifies anxiety and low mood (Constantin et al., 2018), which in turn makes the task seem even more aversive. This creates a feedback loop wherein, procrastination triggers rumination, which depletes resources and increases negative affect, which makes initiating the task feel even more impossible, leading to further delay.

1.3.5 External architecture of delay

This internal narrative of delay is likely to be shaped by an external architecture comprising environmental demands, technological systems, and social contexts. For older adults, this external architecture can create a series of barriers that systematically transform procrastination from an individual failure into a predictable response to their surroundings. This perspective reframes procrastination as a coherent, if maladaptive, adaptation to an environment misaligned with the individual's competencies and motivations.

At the broadest level, Environmental Press Theory provides the foundational framework, positing that behaviour emerges from the fit between personal competence and environmental demands (Crist et al., 2019; Lawton & Nahemow, 1973). According to this model, an individual's adaptive behaviour and positive affect are maximized when their competencies (e.g., sensory, motor, cognitive skills) align with the "press" (e.g., demands) of their environment. An environment with high "press" (e.g., one that is complex, confusing, or overly demanding) can overwhelm an older adult's adaptive capacities. When this occurs, what may appear as a failure of self-regulation can be more accurately understood as a behavioural manifestation of this person-environment mismatch.

Consider a highly conscientious older adult facing a new, complex, and poorly designed online portal for managing their prescriptions. The environmental demand (e.g., deciphering confusing jargon, navigation online platforms, remembering passwords) may exceed their current cognitive processing speed or technological fluency (Becker, 2004; Thomas et al., 2023). In this context, procrastination is not a simple failure of character but a rational (if maladaptive) response to an environment where the perceived cost of engagement (in terms of cognitive effort, time, and potential frustration) is prohibitively high. In this scenario, the individual withdraws from the task, and delay becomes a form of adaptive withdrawal.

This dynamic is not unique to the ageing context. Prior research on academic environments has explicitly documented how "procrastination-friendly" factors can foster unnecessary delay (Nordby et al., 2017; Svartdal et al., 2020), mirroring the principles of Environmental Press Theory. In academic settings, structural and organisational factors (e.g., long deadlines, lack of feedback, insufficient direction) have been identified that increase the probability of procrastination for students, independent of their personal traits (Svartdal et al., 2020). Just as a poorly designed academic environment can overwhelm a student's self-regulatory capacity, a "high press" environment can overwhelm an older adult's competencies, leading to the same outcome: procrastination.

In the modern world, this environmental press is increasingly mediated by digital systems. The Technology Acceptance Model specifies the psychological pathway through which the environment creates a motivational barrier (Davis, 1989). When an older adult perceives a digital platform as lacking *perceived usefulness* ("A video call isn't as good as a face-to-face visit") or *perceived ease of use* ("I'll never figure out how to log in"), it directly undermines their self-efficacy (Jokisch et al., 2022). This undermined confidence can negatively impact the expectancy component of TMT, drastically lowering their perceived likelihood of a successful outcome. Consequently, the motivational decline makes procrastination the path of least resistance. The digital environment, therefore, does not just present a cognitive challenge, but rather may actively dismantle the motivational prerequisites for task engagement.

Finally, the social environment completes this architecture by either reinforcing or mitigating these barriers. When an older adult's social circle normalizes delay (e.g. a friend stating "I never bother with those online forms"), this may condone and increase the likelihood of avoidance of a task. More profoundly, well-intentioned social pressures can be counterproductive. When a task becomes socially prescribed tasks (e.g., a general practitioner recommending a series of medical regimens) it can shift the individual's motivation from autonomous to controlled (Deci & Ryan, 2009). As per SDT (Deci & Ryan, 2009), this controlled motivation is a known precursor to procrastination (Kljajic et al., 2022), as the individual may delay as a form of psychological reactance to reassert their eroded autonomy.

1.3.6 Deeper meanings of time and task

The Selective Optimisation with Compensation (SOC) model provides the developmental context for distinguishing between adaptive and maladaptive delay in later life (Baltes & Baltes, 1990). The model posits that as resources naturally decline with age, successful adaptation involves strategically selecting fewer, more meaningful goals, optimizing remaining resources to achieve them, and compensating for losses through alternative means. From this normative perspective, disengaging from non-essential pursuits represents healthy selective disengagement. However, this disengagement can become a driver of procrastination when indiscriminately applied to goals essential for health, safety, and independent functioning (e.g., skipping medication or postponing preventative health-care behaviours). SOC thus provides a crucial benchmark for what procrastination is. Within this theoretical framework, procrastination in later life is not defined simply by delay itself, but by delay in domains that are critical for maintaining functioning.

This developmental shift in goal management interacts powerfully with evolving motivational priorities, as explained by Regulatory Focus Theory (Higgins, 1997, 1998). Ageing is frequently associated with a transition from a promotion focus (oriented toward growth and accomplishment) to a prevention focus (oriented toward safety, security, and responsibility), aligning with the principles of SST (Carstensen, 2001). While this prevention focus is generally adaptive, it creates a specific vulnerability when applied to essential but threatening tasks. For instance, an individual approaching a health screening with a prevention mindset is primarily motivated to avoid the negative outcome of a serious diagnosis. Paradoxically, this hypervigilance toward potential threat may generate such significant anxiety that it creates a self-fulfilling prophecy, fuelling the very avoidance it seeks to prevent. Thus, the prevention focus, designed to safeguard wellbeing, can inadvertently sabotage it by making engagement with essential, but slightly aversive, tasks feel overwhelmingly aversive.

The potential anxiety elicited by these tasks can further be explained in the principles of Terror Management Theory (Greenberg et al., 1986). This theory posits that a significant portion of human behaviour is driven by the unconscious need to manage the existential anxiety that arises from the awareness of our own mortality. Tasks that make mortality salient, such as drafting a will, planning a funeral, or undergoing a preventative health-care screening, pose a direct threat to these innate psychological defences by forcing a confrontation with finitude. In this light, procrastination of such tasks may be construed as not merely a failure of self-regulation but a form of death-denial.

1.3.7 Bringing it all together: Toward a lifespan-informed model

The theoretical perspectives reviewed here this chapter suggest that procrastination in later life may be understood through the convergence of multiple psychological, motivational, developmental, existential, and environmental perspectives, all nested within the developmental realities of ageing. Figure 1.3 presents a lifespan-informed conceptual framework that synthesises these perspectives into a single organising structure. Importantly, this framework does not represent a definitive causal account of procrastination in later life. Rather, the purpose of this is to organise these frameworks into a coherent conceptual structure so as to generate empirically testable hypotheses regarding the origins and maintenance of procrastination in later life.

The framework situates procrastination within the developmental reality of ageing. Lifespan and developmental theories such as SST (Carstensen, 2001), SOC (Baltes & Baltes, 1990), and Environmental Press Theory (Lawton & Nahemow, 1973) collectively suggest that older adulthood is characterised by changing motivational priorities, evolving goals, fluctuating resources, and increasing interactions between individual competencies and environmental demands.

Within this developmental reality, several motivational theories provide complementary perspectives as to the psychological processes that may accompany procrastination. TMT (Steel & König, 2006; Steel et al., 2018) explains how changes in motivational factors (expectancy, value, delay, and impulsiveness) may shape the motivation to initiate action. Meanwhile, SDT (Deci & Ryan, 2009) emphasise the differences between autonomous and controlled motivation and how this difference can affect sustained behavioural engagement. Finally, Regulatory Focus Theory (Higgins, 1997, 1998) highlights how promotion focused goals and prevention focused goals can shape the manner in which individuals approach important tasks. When considered together, these theories suggest that procrastination in later life may be viewed within a broader motivational landscape rather than reflecting a single deficit in self-regulation.

The framework also incorporates existential processes that may hold relevance in later life. Terror Management Theory (Greenberg et al., 1986) proposes that increased awareness of mortality may shape responses to certain future-oriented tasks. Consequently, procrastination may also sometimes represent an attempt to regulate emotionally threatening situations rather than simply a failure of self-control.

Beyond these individual psychological processes, the framework also recognises that procrastination occurs within environmental and social contexts. Accordingly, procrastination in later life may be understood not only as an individual phenomenon but also as one that is embedded within the environments in which older adults live and make decisions.

Overall, this conceptual framework suggests that procrastination in later life is best understood as a multidimensional phenomenon situated within the developmental context of ageing. By integrating perspectives from lifespan psychology, motivation, self-regulation, existential psychology, and environmental gerontology, the framework provides a theoretical foundation for understanding procrastination beyond the traditional view of it as a simple self-regulatory failure.

1.4 The consequences of procrastination in later life

As established from the previous synthesis, procrastination in older adulthood may appear as more than just a character flaw or bad habit. Rather it can emerge as a coherent, if ultimately self-defeating, psychological adaptation to the distinct developmental and existential challenges of ageing. However, this nuanced understanding underscores the consequences of procrastinating in later life. Whereas procrastination in youth typically results in reversible consequences, such as a poor academic grade, in later life, it can disrupt essential aspects of well-being, including physical health, financial security, and personal independence. Therefore, what might

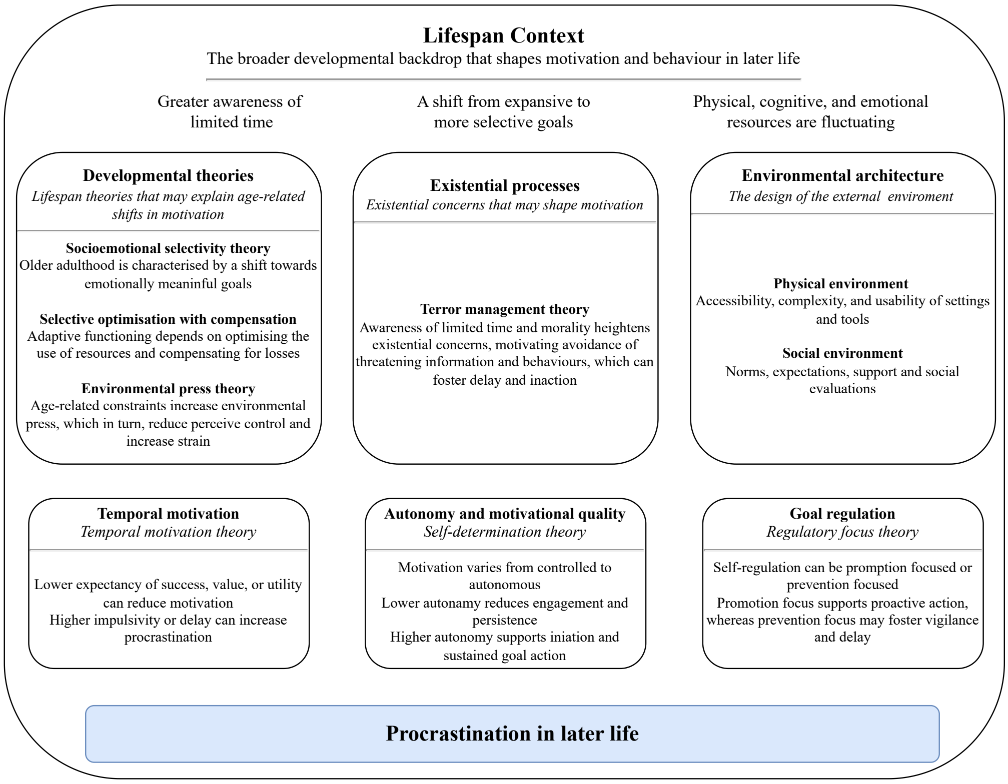

Figure 1.3: *A lifespan-informed conceptual model of procrastination in later life. The model synthesises major lifespan, motivational, existential, and environmental perspectives to provide an integrated conceptual framework for understanding procrastination in older adulthood. Rather than representing a single causal pathway, the model illustrates how age-related changes in motivational priorities, emotional regulation, environmental demands, and self-regulatory processes may collectively shape the experience of procrastination in later life.*

be seen as a common self-regulatory failure in younger adulthood becomes transformed into a significant risk factor in older adulthood. Within this context, procrastination's costs accumulate quickly against a backdrop of limited opportunities for recovery, making its impact a crucial area for understanding and promoting successful ageing. It is worth considering the areas in which procrastination may yield considerable adverse effects for older adults.

1.4.1 Health and healthcare utilisation

One of the most immediate and serious effects of procrastination in older adults is its impact on physical and mental health. Health-related procrastination can manifest in a series of detrimental outcomes. A substantial body of research links chronic procrastination to heightened stress (G. L. Flett et al., 2012; T. Jackson et al., 2003; Sirois, 2007; Sirois et al., 2003; Stead et al., 2010; Tice & Baumeister, 1997) increased depressive symptoms (Johansson et al., 2023; Nie et al., 2025; Shi et al., 2019; Stead et al., 2010), the adoption of unhealthy lifestyle behaviours (Johansson et al., 2023;

S. M. Kelly & Walton, 2021; Licata et al., 2024; Sirois, 2007), and a greater incidence of physical illnesses and somatic complaints (Johansson et al., 2023; Sirois, 2007, 2015; Sirois et al., 2003; Tice & Baumeister, 1997). These findings reveal a connected process where delaying actions and psychological distress reinforce each other. For example, putting off healthy habits like exercise or dietary changes can worsen existing health issues, while the stress of these unmet goals further increases anxiety and fatigue. In turn, each of these factors contributes to further avoidance.

This self-perpetuating cycling is conceptually explained by the procrastination-health model (Sirois, 2007; Sirois et al., 2003), which posits that procrastination contributes to health problems through both a behavioural and psychological pathway. The behavioural pathway involves the direct postponement of health-promoting actions (e.g., skipping medical appointments) and an increase in health-compromising behaviours (e.g., overeating). Meanwhile, the psychological pathway reflects the chronic stress and negative affect generated by these delays, which can lead to physiological dysregulation (e.g., elevated cortisol, inflammation) and diminished capacity for self-regulation. Importantly, these two pathways work together, creating a feedback loop that links avoidance, stress, and poor health management.

For older adults, this self-perpetuating cycle becomes particularly damaging because of age-related changes in the body and limited chances to recover (Shen et al., 2024). Delays that might be reversible in youth (e.g., postponing a health screening) can in later life, lead to irreversible outcomes. For instance, delaying a cancer screening may result in discovering the disease at a more advanced stage (Stage IV rather than Stage I). Meanwhile inconsistent care for conditions like hypertension or diabetes can raise the risk of serious complications. Adding to this risk is the reduced capacity to recover from stress or neglect, which tends to decrease with age (Shen et al., 2024). Consequently, the short-term avoidance that might have helped manage distress earlier in life can lead to physical decline and increased dependency in older adulthood.

1.4.2 Financial security and estate planning

Parallel to the health domain, the financial consequences of procrastination in later life carry significant and often lasting implications. This is because financial procrastination intersects with a non-negotiable requirement of (almost) all people: retirement. As such, while deferring financial decisions in youth may lead only to temporary hardship, similar delays in older adulthood can directly compromise long-term security, autonomy, and quality of life (Shah & Mukherjee, 2025).

At its core, financial procrastination stems from the tendency to prioritize immediate gratification over future benefits (Brown & Previtero, 2014). This "present-bias" often leads individuals to defer complex and/or unpleasant financial tasks, even when that delay is harmful. For older adults, this bias can be amplified by the motivational shifts that occur with ageing (Carstensen, 2001). As people age and focus more on emotionally meaningful goals, complex or aversive financial decisions (e.g., retirement budgeting or estate planning) may become increasingly unpleasant, as they confront issues of mortality and decline. In this context, procrastination serves as an emotionally protective but ultimately self-defeating strategy to deal with existential anxiety.

The financial environment of later life further magnifies these risks. The shift from accumulating money to preserving and spending it leaves little room for error. Empirical studies show that procrastinators are more likely to enter retirement without enough savings, have delayed pension contributions, and feel unsatisfied with their financial readiness (Börsch-Supan et al., 2023; Brown & Previtero, 2014; Shah & Mukherjee, 2025). These outcomes not only harm material well-being but also reduce feelings of perceived control and self-efficacy, which are crucial for mental health as people age (H. M. Hu, 2024).

The architecture of modern-day financial systems complicates this situation even further. The growing use of digital platforms for managing investments, retirement benefits, and bank accounts can overwhelm those with limited tech skills (Thomas et al., 2023). When engaging with these tools feels mentally taxing or frustrating, withdrawal may seem like a reasonable short-term choice. Yet, over time, such avoidance reinforces feelings of inefficacy and loss of control, which under the TMT framework (Steel & König, 2006; Steel et al., 2018), undermines the expectancy belief, thus increasing the likelihood of continued inaction.

In some cases, this withdrawal can also be seen as a subtle form of death denial. For example, avoiding financial tasks like drafting a will can symbolically postpone facing mortality (Sneddon, 2020). Creating a will is a clear example of a task that is high in utility but offers little immediate reward. It requires confronting death, managing emotions, and abstract reasoning (Sneddon, 2020). Through the lens of Terror Management Theory (Greenberg et al., 1986), procrastination in this case acts as a covert means of denying death. People symbolically extend their psychological continuity by avoiding officially addressing their eventual passing. However, this avoidance can lead to serious and often irreversible consequences.

Dying intestate (i.e., without a valid will) forces the distribution of assets according to default legal rules, which may not align with what an individual wanted. This can leave bereaved families with additional hardships (Schneiderman & Kirsh, 2001) and, in some cases, may even trigger lengthy and costly legal battles among heirs. Beyond the financial loss, such outcomes signify a loss of control and continuity, as one's final chance to establish order and provide for loved ones is forfeited.

In sum, financial procrastination in later life, whether delaying retirement planning, neglecting investments, or postponing making a will, brings together emotional, cognitive, and structural challenges. What begins as a way to manage discomfort can ultimately damage both financial stability and personal independence.

1.4.3 Psychological well-being and social connection

In addition to its measurable costs, procrastination has significant psychological and social effects that become more serious with age. While younger adults may view procrastination as a threat to performance or self-esteem, older adults may find that it harms key psychological resources like self-efficacy, perceived control, and social connections (again, key determinants of healthy ageing). In this way, procrastination is not just a failure to act but also a behaviour that weakens the psychological foundation needed for resilience and independence in older adulthood.

At the individual level, chronic procrastination is closely linked to diminished self-regulation and self-worth (Baumeister & Heatherton, 1996; Steel, 2007). Repeated failure to act on intentions creates a cycle of guilt, shame, and self-criticism (Steel, 2007), which over time undermine confidence in one's ability to initiate and sustain action. For older adults, who may already be adjusting to physical, cognitive, or social losses (Hsieh, 2013), these feelings can deepen a sense of decline and helplessness.

Emotional distress often accompanies this erosion of control. Numerous studies link procrastination with elevated stress, anxiety, depressive symptoms, and guilt (Giguère et al., 2016; Johansson et al., 2023; Sirois, 2007; Sirois et al., 2003; Van Eerde, 2003). The combination of guilt and avoidance can reduce participation in activities that support mental health, like exercise, volunteering, or social interactions (Hajek et al., 2025; S. M. Kelly & Walton, 2021). Such activities are crucial for maintaining mental and emotional wellbeing as people grow older. Thus, as participation in them declines, individuals may gradually restrict their life experiences, leading to lower life satisfaction and a diminished sense of purpose (J.-H. Park & Kang, 2023). When viewed from the framework of SOC (Baltes & Baltes, 1990) this represents a failure to adaptively select and pursue attainable goals.

On a social level, procrastination can also strain interpersonal relationships (J. R. Ferrari et al., 1998). Delays in communication, planning and shared decision-making, may create frustration and misunderstanding among family and friends. In care giving or community situations, avoiding responsibility can lead to added strain or social withdrawal. Since social networks tend to shrink in older adulthood (J.-H. Park & Kang, 2023), the relational effects of chronic procrastination can have an outsized impact on well-being.

Ultimately, procrastination in later life harms not only self-regulation but also self-connection, which weakens the sense of continuity with the future self and the bond with meaningful social circles. In this way, procrastination can be viewed as a gradual disengagement from the psychological and social aspects that give later life coherence, purpose, and connection.

1.4.4 Across the domains

Taken together, one can argue that the consequences of procrastination in later life are not independent of each other. Rather, they interact in a synergistic manner that can accelerate a decline in autonomy. For instance, consider the following cascade presented in Figure 1.4: financial procrastination (e.g., delaying retirement planning) leads to economic strain and heightened daily stress. This chronic stress, a core component of the procrastination-health model (Sirois, 2007; Sirois et al., 2003), exacerbates health problems (e.g., uncontrolled hypertension) and depletes the self-regulatory capacity needed for diligent health management. As functional health declines, the individual may experience a loss of social connection due to an inability to participate in social activities and/or potential shame about their health situation. This social withdrawal then reduces a vital source of emotional support and practical help, decreasing their sense of control and increasing feelings of helplessness. In turn, this drives more procrastination, as the individual feels less capable of addressing their growing challenges. This negative cycle creates a feedback loop where delays in one area contribute to delays in others, trapping the person in a downward spiral of avoidance, loss of resources, and worsening well-being.

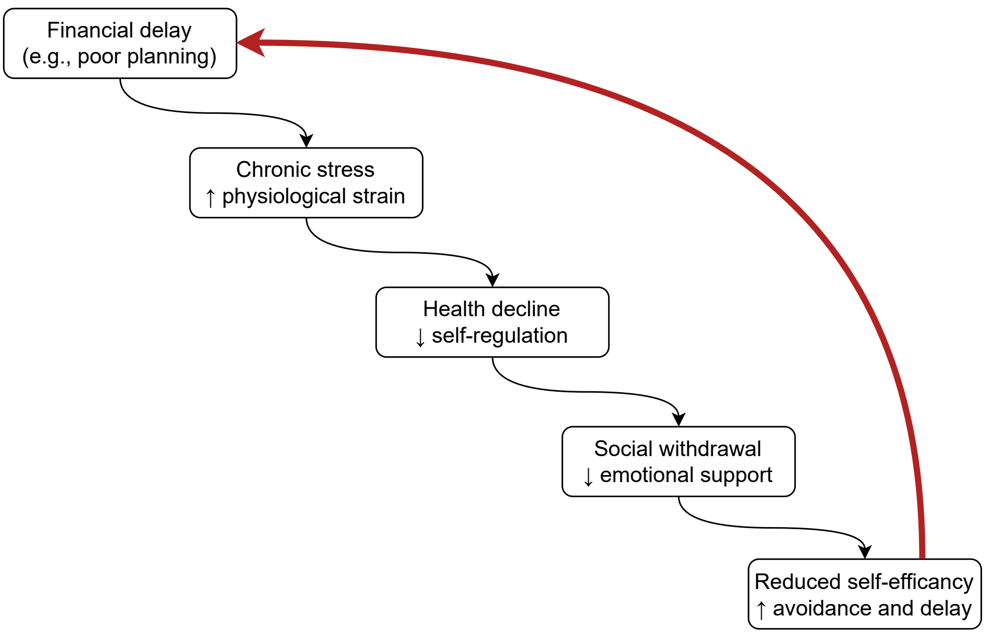

Figure 1.4: *An example of the cascading effects of procrastination in later life.*

1.5 Thesis roadmap

This thesis addresses the critical gap in understanding procrastination in later life through a series of interconnected empirical studies that progress from foundational theory to real-world implications. Each chapter builds upon the lifespan framework established in this review by examining the social context, motivational mechanisms, and overall consequences of procrastination in older adulthood, while additionally integrating advanced and interdisciplinary methodological approaches.

Chapter 2 begins by establishing the methodological foundation for the thesis. Given the interdisciplinary nature and focus on data-science for this PhD, several studies employ statistical techniques that extend beyond conventional psychological methods. This chapter outlines these analytical frameworks, while additionally introducing the development of a novel statistical methodology.

Following this, Chapter 3 examines the affective mechanisms that may explain the U-shaped trajectory of procrastination as described in Figure 1.2. Using longitudinal data and structural equation modelling, this chapter tests a mediation model positing that procrastination in later life can be explained by age-related changes in depression and loneliness. In doing so, it establishes affective vulnerability as a potential proximal mechanism underpinning age-related differences in self-regulatory failure.

Building upon this affective foundation, Chapter 4 situates procrastination within its socio-motivational context. If, as SST suggests, older adults are motivated by emotionally meaningful goals, how then do they perceive the act of procrastination itself? Using both an experimental design and multi-level modelling, this study investigates whether age-related differences exist in the social judgment and acceptance of procrastination behaviours. This chapter therefore extends the affective account by examining how social norms and perceived acceptability shape the expression and legitimisation of delay.

Chapter 5 then examines subjective time perspective as a central driver of delay. Using a combination of latent class analysis and Bayesian regression, this study tests whether perceiving one's remaining lifetime as limited predicts greater everyday procrastination. This chapter provides a focused empirical test of Socioemotional Selectivity Theory by showing how perceived time perspectives may shape self-regulatory behaviour.

Having established contextual and motivational mechanisms, the thesis then shifts to consequences. Chapter 6 investigates whether procrastination translates into reduced engagement with preventative health behaviours. Using cross-sectional data and generalised additive models, this study tests whether higher procrastination predicts lower uptake of health screening among older adults. This chapter moves the empirical investigation from the *why* of procrastination to a more concrete *so* *what*, providing empirical evidence for the public health concerns raised in this review.

Our empirical investigation culminates with Chapter 7, which examines a more severe potential consequence of procrastination: whether rising procrastination may signal emerging cognitive decline. Utilising both large-scale longitudinal data and Markov models, this study tests whether increases in procrastination predict transitions from normal cognition to mild cognitive impairment or dementia. This final chapter connects behavioural self-regulation to neurological health, positioning procrastination not only as a risk factor but potentially as an early behavioural marker of neuropathology.

Collectively, these studies advance a lifespan-developmental understanding of procrastination by integrating theory, mechanism, and consequence. Substantively, the thesis clarifies how procrastination manifests and operates in older adulthood. Methodologically, it demonstrates how statistical innovation can strengthen psychological research. Together, they portray a research programme that is not only conceptually and empirically rigorous but also methodologically innovative.

CHAPTER 2

Methodology

2.1 Methodological background

The work presented in this thesis sits at the intersection of psychology and data science. On a conceptual level, it is concerned with understanding the motivational processes and consequences of procrastination in older adult populations. Methodologically, it reflects a deliberate effort to engage with, adapt, and in some cases extend, statistical approaches that go beyond those traditionally employed in psychological research. The analytical choices made throughout the thesis therefore reflect a guided principle of both pushing data science forward and working with state of the art approaches when formulating, answering, and interpreting research questions.

As such, two overarching goals guided the methodological development of this research. First, I aimed to address important psychological research questions about procrastination using models that respect the structure, complexity, and in some cases, the longitudinal nature of the available data. Second, I sought formal training in modern statistical techniques. As a result, several chapters employ techniques that may be considered complex relative to standard practice in psychology, but which offer clear advantages in terms of validity, interpretability, and inferential robustness.

The goal of this chapter is to provide a methodological framework for the empirical components of the thesis. Rather than reproducing the technical details already presented in the later chapters, the aim of this chapter more specifically is: (i) to highlight the interdisciplinary nature of this work, (ii) to justify the use of specific modelling frameworks and explain why they were preferred over more conventional alternatives, and (iii) to provide a conceptual bridge to the development of a novel statistical technique that is presented at the end of this chapter (see Section 2.3).

2.2 Overview of methods used across the thesis

Diverse research questions and data structures necessitate different modelling approaches. Across the empirical chapters of this thesis, the following statistical techniques are used:

- Chapter 3: **Structural equation models** for studying latent factors.
- Chapter 4: **Multilevel models** for clustered data.
- Chapter 5: **Latent class analysis** combined with **Bayesian regression** to capture unobserved heterogeneity and address classification uncertainty.
- Chapter 6: **Generalised additive models** to model non-linear associations.
- Chapter 7: **Discrete-time Markov models**, implemented via multinomial logistic regression, to study transitions between cognitive states.

The following sections begin with a reminder of the research question guiding each chapter's work, before I outline each modelling framework, highlight their advantages over conventional methods, and situate them within the broader methodological trajectory of the thesis.

2.2.1 Chapter 3: Structural equation modelling

> **Research question:** Within older adult populations, is the relationship between age and procrastination mediated by loneliness and depressive symptomology?

Chapter 3 employed structural equation modelling (SEM) to examine the relationship between age and procrastination, and to test whether this association was mediated by depression and loneliness. Rather than treating these constructs as directly observed variables, procrastination, depression, and loneliness were modelled as latent variables defined by multiple observed indicators.

A common approach in mediation analysis is the use of regression based path models, such as those implemented in the `PROCESS` macro (Hayes, 2017). While accessible, these methods rely on composite scale scores and therefore assume the constructs are measured without error. In contrast, SEM explicitly separates measurement error from the latent constructs of interest by jointly estimating measurement and structural components within a single model. More specifically, SEM combines a *measurement model*, which links latent variables to their observed indicators, with a *structural model*, which specifies the directional associations among latent variables. This framework permits the simultaneous estimation of multiple direct and indirect pathways, allowing mediation processes to be evaluated within a single analytic model. Additionally, SEM provides greater flexibility for modelling correlated residuals among indicators, handling incomplete data using full-information estimation procedures, and accommodating variables measured at different levels using alternative estimators.

Firstly, the *measurement model* relates latent variables, both endogenous (η) and exogenous (ξ), to their observed indicators and can be expressed as

$$\mathbf{y} = \boldsymbol{\tau}_y + \boldsymbol{\Lambda}_y \eta + \boldsymbol{\varepsilon}_y \qquad\qquad \mathbf{x} = \boldsymbol{\tau}_x + \boldsymbol{\Lambda}_x \xi + \boldsymbol{\varepsilon}_x.$$

Here $\mathbf{y}$ $(p_y \times 1)$ and $\mathbf{x}$ $(p_x \times 1)$ are vectors of observed indicators for both the endogenous and exogenous latent variables, respectively. Both $\boldsymbol{\tau}_y$ and $\boldsymbol{\tau}_x$ are $p_y \times 1$ and $p_x \times 1$ intercept vectors for these observed indicators, respectively. Additionally, the matrices $\boldsymbol{\Lambda}_y$ $(p_y \times q)$ and $\boldsymbol{\Lambda}_x$ $(p_x \times r)$ are factor loading matrices, which quantify the strength of the relationships between each latent variable and its corresponding observed indicators. Here, q and r denote the number of endogenous and exogenous latent variables, respectively, and the vectors η $(q \times 1)$ and ξ $(r \times 1)$ represent the latent variables themselves. Finally, $\boldsymbol{\varepsilon}_y$ and $\boldsymbol{\varepsilon}_x$ are $p_y \times 1$ and $p_x \times 1$ vectors of measurement errors associated with the observed indicators.

Secondly, the *structural model* specifies relationships among latent variables and observed covariates:

$$\eta = \alpha + \mathbf{B}\eta + \boldsymbol{\Gamma}\xi + \zeta$$

where α $(q \times 1)$ is a vector of intercept terms for the endogenous latent variables. The matrix $\mathbf{B}$ $(q \times q)$ contains regression coefficients describing relationships among endogenous latent variables and $\boldsymbol{\Gamma}$ $(q \times r)$ contains regression coefficients linking exogenous latent variables to those endogenous latent variables. Finally, ζ $(q \times 1)$ captures the unexplained variation in the endogenous latent variables which is typically assumed to follow a multivariate normal distribution.

This unified framework allows mediation effects to be estimated while accounting explicitly for measurement error and correlations among mediators. Relative to regression-based approaches, structural equation modelling offers improved construct validity, formal model fit evaluation, and a natural foundation for extensions such as multiple-group or longitudinal mediation models (Gunzler et al., 2013).

2.2.2 Chapter 4: Multilevel modelling

Research question: Do perceptions of social norms related to procrastination vary across general, health, and financial domains, and do these perceptions differ between younger and older adults?

Chapter 4 employed multilevel modelling to analyse data from a mixed-factorial experimental design examining perceptions of procrastination across life domains and age groups. Specifically, the study investigated whether imagining oneself as a procrastinator versus a non-procrastinator influenced evaluations of socially normative adjectives, and whether these evaluations differed between younger adults and older adults across three life domains. The design comprised two between-subjects factors (vignette condition and age group) and one within-subjects factor (life domain), with each participant providing repeated evaluations across domains.

Consequently, this design induces a hierarchical data structure in which multiple observations are nested within individuals. Everyone responded to all three vignettes, meaning that observations were not independent, but correlated within the individuals themselves, and thus these data violate the independence assumption underlying the classical ANOVA. Analysing such data using multiple separate ANOVAs (e.g., one per domain) would (i) ignore this dependency structure, (ii) inflate the number of statistical tests, and (iii) fragment inference across models.

In contrast, multilevel modelling provides a more flexible framework by explicitly accounting for the nested, non-independent structure of the data. Domain-level responses are modelled as being nested within individuals, allowing within-person variation across domains to be separated from between-person differences Crucially, individual heterogeneity is treated as a substantive feature of the data rather than a "statistical nuisance" (Leyland & Groenewegen, 2020).

At a general level, a standard multilevel model for individual i can be expressed as:

$$y_i = \mathbf{X}_i \beta + \mathbf{Z}_i \mu_i + \varepsilon_i,$$

where y_i $(n_i \times 1)$ is a vector of observed outcomes for individual i, with n_i denoting the number of repeated observations contributed by that individual. The matrix $\mathbf{X}_i$ $(n_i \times p)$ is a design matrix for the fixed-effects associated with the $p \times 1$ vector of population-level regression coefficients β. Similarly, the matrix $\mathbf{Z}_i$ $(n_i \times q)$ is a random-effects design matrix associated with the $q \times 1$ vector of participant-specific random effects μ_i, which are assumed to follow a multivariate normal distribution. Finally, ε_i represents the within-person residual errors and are assumed to follow a normal distribution.

This general formulation allows between-subjects factors, within-subjects factors, and any of their potential interactions to be incorporated simultaneously as fixed effects within a single model framework. Additionally, multilevel models permit the use of random intercepts and slopes to account for individual differences in baseline responses and patterns of change. As a result, the full mixed-factorial design of the study can be analysed without decomposing it across multiple ANOVAs or relying on restrictive assumptions about variance and covariance structures.

2.2.3 Chapter 5: Latent class analysis and Bayesian regression

Research question: Does subjective remaining life (how long you believe you have left to live) moderate the association between temporal orientation and procrastination?

Chapter 5 combined latent class analysis and Bayesian regression to examine whether subjective remaining life (SRL) moderates the association between temporal orientation and procrastination. The key methodological challenge addressed in this chapter was that temporal orientation was not directly observed, but inferred from individual response patterns, introducing uncertainty that must be accounted for in subsequent analyses.

A standard approach in psychological research is to derive a single continuous score from multi-item scales and then subsequently dichotomise/trichotimise this score using a median split or some similar rule. While easy to implement, these strategies discard information, impose arbitrary thresholds, and treat class membership as being known with certainty (McClelland et al., 2015; Rucker et al., 2015).

Latent class analysis provides an alternative by modelling unobserved heterogeneity probabilistically. Let $\mathbf{y_i} = (y_{i1}, \ldots, y_{iJ})$ denote the vector of item responses for individual i. Latent class analysis assumes the existence of a discrete latent variable $R_i \in \{1, \ldots, K\}$ indicating membership in one of K latent classes. Conditional on R_i, the observed responses are assumed to be locally independent, such that the marginal likelihood for individual i is denoted:

$$P(\mathbf{y_i}) = \sum_{k=1}^{K} \lambda_k \prod_{j=1}^{j} P(y_{ij} \mid R_i = k),$$

where λ_k denotes the prior proportion of the population belonging to class k.

A latent class model typically yields posterior probabilities of class membership $P(R_i = k \mid \mathbf{y_i})$, or more simply π_k. For instance, for a two class model (class A versus class B) the posterior probabilities for individual i could be $\{\pi_A; \pi_B\} = \{0.65; 0.35\}$, representing a 65% probability that individual i belongs to class A and a 35% probability that they belong to class B.

However, a common limitation of applied latent class analysis is that individuals are typically assigned to their most likely class. In the above example, individual i would belong to class A. However, this approach assumes that class membership is observed without error. This deterministic approach ignores classification uncertainty and can lead to biased parameter estimates and overstated precision in subsequent models (Asparouhov & Muthén, 2014).

To avoid this limitation, rather than assigning individuals to a single class, these posterior probabilities can be incorporated directly into a Bayesian regression model via a latent Bernoulli indicator,

$$Z_i \sim \text{ Bernoulli } (p_i), \qquad p_i = P(R_i = 1 \mid \mathbf{y_i}),$$

which can be included in the linear predictor as additive and as part of a higher-order interaction. For instance, an initial linear predictor could be written as

$$g(\mathbb{E}[Y_i]) = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \beta_3 (Z_i \otimes X_i),$$

where X is a general predictor. This approach incorporates classification uncertainty into the regression model, avoids overconfident inference, and provides a coherent alternative to frequentist two-step procedures.

2.2.4 Chapter 6: Generalised additive models

Research question: Is procrastination associated with poorer health care utilisation in older adult populations?

Chapter 6 used generalised additive models to examine the association between procrastination and engagement in preventative health behaviours. A central feature of this research question was that age is known to relate **non-linearly** to health behaviours, largely due to age-based screening policies and eligibility thresholds (US Preventive Services Task Force, 2018a, 2018b, 2024). Standard generalised linear models, including logistic regression, require the analyst to specify the shape of the relationship between predictors and outcomes a priori, typically assuming linear or polynomial effects. In contrast, generalised additive models relax this assumption by allowing predictors to enter the model through smoothing functions estimated directly from the data. These non-linearities are then modelled using splines, which can be controlled, so as to smooth the "wiggliness" of the trajectories.

In general form, a generalised additive model specifies the relationship between an outcome Y_i and a set of predictors through

$$g(\mathbb{E}[Y_i]) = \eta_i,$$

where $g(\cdot)$ is a link function and the linear predictor η_i is specified as an additive combination of smooth and parametric components,

$$\eta_i = \beta_0 + \sum_{k=1}^{K} f_k(x_{ik}).$$

Within this equation, $f_k(\cdot)$ denotes a smooth function of a covariate x_{ik}, with the degree of smoothness controlled through penalisation rather than fixed parametric assumptions (Wood, 2011).

Beyond modelling non-linear main effects, generalised additive models also provide a flexible framework for representing interactions between predictors. Rather than assuming that interactions are linear or of a specific polynomial form, interactions can be modelled using smooth functions of multiple covariates. In this thesis, interactions between covariates were represented using *tensor product smooths*, which are well suited to variables measured on different scales or with different smoothness properties (Wood, 2017). Generally, such models can be written as

$$\eta_i = \beta_0 + \sum_{k=1}^{K} f_k(x_{ik}) + \sum_{(k,l)\in\mathcal{I}} f_{kl}(x_{ik}, x_{il})$$

where $f_{kl}(\cdot,\cdot)$ represents a smooth bivariate function estimated using tensor product smooths, allowing flexible interaction surfaces and $\mathcal{I}$ denotes the set of covariate pairs for which tensor product interaction smooths were included in the model.

Compared to standard regression models with linear interaction terms, this approach allows complex, non-linear effect modification to be identified without imposing restrictive assumptions. Overall, the use of generalised additive models provides a flexible alternative to conventional regression approaches.

2.2.5 Chapter 7: Markov modelling

Research question: Does procrastination predict longitudinal cognitive decline in older adulthood?

Finally, Chapter 7 employs discrete-time Markov models to examine how procrastination influences transitions between cognitive states over time. In contrast to methods that focus on cognitive status at a single time point, Markov models explicitly characterise change by modelling the probability of moving between states across successive time points.

Markov models are widely used in ageing research because they provide a flexible framework for studying progression, stability, and recovery within longitudinal processes. A defining feature of these models is the Markov property (Y. F. Zhang et al., 2010), which assumes that the probability of occupying a given state at time $t+1$ depends only on the state at time t, conditional on relevant covariates.

Let $S_{i,t} \in \{1, \ldots, K\}$ denote the cognitive state of individual i at time t. A discrete-time Markov model specifies transition probabilities of the form

$$P(S_{i,t+1} = k \mid S_{it} = j, \mathbf{x}_{it}),$$

where $\mathbf{x}_{it}$ denotes a vector of covariates that may influence transition behaviour. In this thesis, transition probabilities are modelled using a regression-based formulation, in which the conditional distribution of $S_{i,t+1}$ given S_{it} is represented via multinomial logistic regression. In general form, this can be written as

$$P(S_{i,t+1} = k \mid S_{it} = j) = \frac{\exp(\eta_{ijkt})}{\sum_{k' \neq j} \exp(\eta_{ijk't})},$$

where the linear predictor η_{ijkt} captures the effect of covariates on transitions from state j to state k.

More generally, this linear predictor may be expressed as

$$\eta_{ijkt} = \alpha_{jk} + \mathbf{x}_{it}^{\top} \beta_{jk},$$

where α represents the intercept term, x_{it} is a vector of covariates for individual i measured at time t, and β is the corresponding vector of regression coefficients specific to the transition from state j to state k. This general representation allows both baseline transition tendencies and covariate effects to vary by transition type. Compared to simpler longitudinal regression approaches, discrete-time Markov models offer several advantages. They respect the categorical and ordered nature of cognitive states, avoid treating change as a continuous outcome, and allow distinct covariate effects for different transition pathways.

Diagnostic tools for Markov models

Despite their substantive appeal and widespread use, discrete-time Markov models (particularly those involving multiple states and covariate-dependent transitions) lack well-developed tools for assessing model adequacy (Araripe et al., 2024). While diagnostics and goodness-of-fit measures are routine for many regression-based models, analogous procedures for Markov transition models remain limited, especially in the presence of polytomous outcomes and complex transition structures.

This methodological limitation motivated the statistical contribution of the thesis: the development of a new goodness-of-fit framework for discrete-time Markov models. Although motivated by longitudinal cognitive ageing research, the proposed framework is broadly applicable to transition-based models used throughout the behavioural and health sciences. The following section introduces this diagnostic approach in detail and evaluates its performance through simulation experiments designed to reflect realistic longitudinal transition processes observed in ageing research.

2.3 Discrete time Markov models: Assessing goodness of fit

Authors
Cormac Monaghan, Idemauro Antonio Rodrigues de Lara
Rafael de Andrade Moral, and Joanna McHugh Power

Many processes in ageing research are naturally characterised by movement between a finite set of discrete states over time. These may include changes in cognitive functioning, health status, or behavioural risk profiles. Such dynamics are typically represented as sequences of categorical outcomes $S = \{1, 2, \ldots, K\}$ observed repeatedly over time, where interest lies not in a single state, but in how individuals transition between states longitudinally.

Because these processes unfold over time, Markov models provide a widely used framework for studying state transitions in longitudinal data (Costa et al., 2023; Sanz-Blasco et al., 2022; Tahami Monfared et al., 2023; Yu et al., 2013). Within this framework, the state of individual i at time t, denoted $Y_{i,t} \in S$, is represented as a stochastic process governed by the Markov property (Y. F. Zhang et al., 2010):

$$\begin{aligned} p_{jk}(t, t+1) &= P(Y_{i,t+1} = k \,|Y_{i,t} = j, Y_{i,t-1} = j_{t-1}, \ldots Y_{i,0} = j_0) \\ &= P(Y_{i,t+1} = k \mid Y_{i,t} = j). \end{aligned} \tag{2.1}$$

This property asserts that the probability of transitioning from state j to state k depends only on the current state $Y_{i,t}$ and not on the full history of preceding states $\{Y_{i,t-1}, \ldots, Y_{i0}\}$. Under this assumption, Markov models offer a flexible framework for estimating transition probabilities $p_{jk}(t, t+1)$ (or simply p_{jk}), describing the likelihood of movement from state j to state k over a fixed time interval.

Despite their widespread use, an important methodological challenge remains in the application of Markov models. This challenge being, how to assess whether a fitted Markov model adequately represents the transition dynamics observed in the data. This is particularly important in longitudinal studies, where Markov models are often used for forecasting, intervention evaluation, and understanding dynamic risk processes (Sanz-Blasco et al., 2022; Spackman et al., 2012). Misspecification of the transition structure can lead to biased estimates of transition probabilities and misleading substantive conclusions.

In many practical settings, observations are collected at discrete time points (e.g., annually or biennially), making discrete-time Markov models a natural choice. While continuous-time Markov models are well supported in existing software frameworks (C. H. Jackson, 2011; Ucar et al., 2019), dedicated tools for discrete-time Markov models are less developed. Existing packages such as `DTMCPack` (William, 2013) and `markovchain` (Spedicato, 2017) are useful but do not support covariate-dependent discrete-time transitions. Consequently, a common approach is to estimate the transition probabilities using a multinomial logistic regression model (see Spackman et al. (2012) as an example), treating the state at time $t+1$ as a categorical outcome conditional on the state at time t, which is entered as an additional covariate in the model. Within this framework, we can model p_{jk} as a linear function of covariates such that:

$$log\left(\frac{p_{jk}(\mathbf{z_{i,t}})}{p_{j1}(\mathbf{z_{i,t}})}\right) = \alpha_{jk} + \mathbf{z}_{i,t}^{\top}\beta_{jk} \qquad k = 2, \ldots, K, \tag{2.2}$$

where p_{j1} is the reference probability (e.g., remaining in state j), α_{jk} is a state-pair specific intercept, and β_{jk} is a vector of coefficients for covariates $\mathbf{z}_{i,t}$ (of which $Y_{i,t}$ is inclusive).

The resulting transition probabilities are obtained from the multinomial link function such that the transition probabilities from state j are given by:

$$p_{jk}(\mathbf{z}_{i,t}) = \frac{\exp(\eta_{i,t}^{(k)})}{1 + \sum_{k=2}^{K} \exp(\eta_{i,t}^{(k)})}, \qquad \text{for } k = 2, \ldots, K \tag{2.3}$$

and for the reference category by:

$$p_{j1}(\mathbf{z}_{i,t}) = \frac{1}{1 - \sum_{j=1}^{J-1} \exp(\eta_{i,t}^{(j)})} \tag{2.4}$$

Within this framework, the fitted model produces a set of transition probabilities rather than direct predictions of observed outcomes. For a system with K states, these probabilities are represented by a $K \times K$ transition probability matrix $\mathbf{P}$, where each element p_{jk} represents the probability of transitioning from state j at time t to state k at time $t+1$:

$$\mathbf{P(t, t+1)} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1K} \\ p_{21} & p_{22} & \cdots & p_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ p_{K1} & p_{K2} & \cdots & p_{KK} \end{pmatrix}.$$

Unlike standard regression models, evaluating goodness-of-fit in this setting is not straightforward (Araripe et al., 2024). Since an observed transition is a stochastic realization from this probability distribution, there is no direct analogue to prediction error or residuals that links observed transitions to model-implied transition mechanisms. In other words, we observe only the state that actually occurred, rather than the full set of probabilities assigned to all possible transitions. As a result, diagnostic tools based on residuals are not directly applicable. Existing methods, such as deviance/likelihood-ratio tests, information criteria, or simulation envelopes, provide only partial insights into the fitted model (Araripe et al., 2024). They often fail to provide a comprehensive, quantitative measure of how well the aggregate transition structure of the fitted transition probability matrix replicates the empirical transition matrix observed within the data.

Distance metrics

A natural alternative is to compare the empirical transition structure in the observed data with the model-implied transition structure. Let $\mathbf{P}$ denote the empirical transition matrix obtained directly from the observed transitions, and let $\hat{\mathbf{P}}$ denote the corresponding transition matrix estimated by fitting a Markov model. The central question then becomes: "How different is $\hat{\mathbf{P}}$ from $\mathbf{P}$?". In univariate models, a simple way of measuring this difference is by calculating a residual, which typically relies on the signed unidimensional distance between an observation and a fitted value (e.g., $y - \hat{y}$). However, determining the best way to measure a distance between two matrices is less trivial.

Distance-based metrics provide a principled way to quantify discrepancies between two transition matrices. These metrics treat the transition matrix as a $K \times K$ object whose structure can be assessed globally, rather than focusing on individual probabilities in isolation (Legendre & Legendre, 2012). Let $\mathbf{D} = \mathbf{P} - \hat{\mathbf{P}}$ denote the matrix of element-wise differences ($d_{jk} = p_{jk} - \hat{p}_{jk}$)). Several matrix norms and divergence measures can then be used to summarize the magnitude of discrepancy, each emphasizing different structural features of the transition process.

In this chapter, we evaluated six distance-based metrics and compared to standard model selection criteria (AIC and BIC) using simulation experiments motivated by longitudinal state transition processes in ageing research. The goal is to assess how effectively these measures identify models that recover the underlying transition dynamics under varying sample sizes and degrees of model misspecification. The metrics considered are summarised in Table 2.1.

Table 2.1: *Distance metrics and information criteria used in simulation study.*

Metric	Formula
Frobenius norm	$\|\|\mathbf{D}\|\|_F = \sqrt{\sum_{j=1}^K \sum_{k=1}^K d_{j,k}^2}$
Manhattan distance	$\sum_{j=1}^K \sum_{k=1}^K \|d_{j,k}\|$
Maximum absolute error	$\max_{j,k} \|d_{j,k}\|$
Root mean squared error	$\sqrt{\frac{1}{K^2} \sum_{j=1}^K \sum_{k=1}^K d_{j,k}^2}$
Correlation dissimilarity	$1 - \text{corr}(\text{vec}(\mathbf{P}), \text{vec}(\hat{\mathbf{P}}))$
Kullback–Leibler divergence	$\sum_{j=1}^K \sum_{k=1}^K (p_{jk} + \epsilon) \log\left(\frac{p_{jk}}{\hat{p}_{jk}}\right)$
Akaike information criterion	$-2\ln(\hat{\ell}) + 2\psi$
Bayesian information criterion	$-2\ln(\hat{\ell}) + \psi \ln(n)$

Note. K represents the total number of categories; $\text{corr}(x, y) = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}$ is the Pearson correlation function; $\text{vec}(\cdot)$ is an operator that converts a matrix into a vector by stacking its columns; ψ is the number of model parameters; ℓ is the model's log-likelihood; n is the sample size. Additionally, for the Kullback–Leibler divergence, a small constant $\epsilon = 1 \times 10^{-10}$ is added to each matrix entry to avoid undefined logarithms when probabilities are zero.

Methods

Simulation study aims

We designed a simulation study to evaluate the performance of different matrix-based distance metrics in assessing the goodness-of-fit of discrete-time Markov models, using dementia progression as a motivating real-world setup. The primary aim was to determine whether these metrics can reliably detect misspecification in multinomial logistic regression models used to estimate transition probabilities. The study follows best practices for simulation reporting using the ADEMP framework (Morris et al., 2019; Siepe et al., 2024).

Data generating mechanisms

Markov process structure

We simulated data for $N = 10{,}000$ individuals across $t = 3$ waves. Consistent with typical dementia progression, the data was simulated for a process with $K = 3$ mutually exclusive states such that $S \in \{1, 2, 3\}$, representing a pre-clinical state (1), mild cognitive impairment (2), and dementia (3). For each individual $i \in \{1, \ldots, N\}$ and discrete time point $t \in \{1, \ldots, T\}$, the true state at time t is denoted as $Y_{i,t} \in S$. Under a first-order Markov process, transitions between states satisfy the Markov property (see Equation (2.1)).

Covariate specification

We generated a set of time-invariant and time-varying covariates designed to mimic plausible risk factors observed in ageing cohort studies (Sonnega et al., 2014). Each covariate was chosen to reflect either a common demographic factor, behavioral, or psychological factor that may influence cognitive transitions (Monaghan et al., 2026).

- $\mathbf{x_1}$: A binary covariate drawn from a Bernoulli distribution with probability of success 0.5. Within the simulation, this variable represents a binary demographic attribute such as gender.
- $\mathbf{x_2}$: A continuous covariate drawn from a normal distribution $\mathcal{N}(70, 25)$ and then rounded to the nearest whole number. Within the simulation, this variable represents age.
- $\mathbf{x_3}$: A rounded continuous covariate from a normal distribution $\mathcal{N}(25, 225)$, truncated to the interval $[0, 60]$ such that values above or below the interval are set to the nearest value within the interval (i.e., 0 or 60) and then rounded to the nearest whole number. Within the simulation, this variable represents psychological or behavioural assessments (e.g., memory tests or psychosocial scales) with fixed bounded scores.
- $\mathbf{x_4}, \mathbf{x_5}$: Continuous noise variables, drawn from a uniform distribution $\mathcal{U}(0, 1)$.

Four of these covariates evolved over time to introduce time-varying confounding:

$$
\begin{aligned}
x_{2i,t} &= x_{2i0} + (t-1) \times 2 & & \\
x_{3i,t} &= \min\left(60, \max\left(0, x_{3i,(t-1)} + \epsilon_{i,t}^{(3)}\right)\right) & \qquad \epsilon_{i,t}^{(3)} &\sim N(5, 4) \\
x_{4i,t} &= \min\left(1, \max\left(0, x_{4i,t-1} + \epsilon_{i,t}^{(4)}\right)\right) & \qquad \epsilon_{i,t}^{(4)} &\sim \mathcal{U}(0, 0.062) \\
x_{5i,t} &= \min\left(1, \max\left(0, x_{5i,t-1} + \epsilon_{i,t}^{(5)}\right)\right) & \qquad \epsilon_{i,t}^{(5)} &\sim \mathcal{U}(0, 0.062),
\end{aligned}
$$

where $t \in \{1, 2, 3\}$ indexes follow-up waves. The full covariate vector for individual i at time t was $\mathbf{x}_{i,t} = (x_{1i,t},\ x_{2i,t},\ x_{3i,t},\ x_{4i,t},\ x_{5i,t})$.

Simulation scenarios

We evaluated three data-generating mechanisms (DGMs) of increasing complexity. In all scenarios, transition probabilities were governed by a multinomial logistic model (Equation (2.2)) with state 1 as the reference category. The corresponding transition probability for each non-reference category was calculated using Equation (2.3) and for the reference category using Equation (2.4). Additionally, all true value parameters vectors for scenarios S1, S2, and S3 ($\boldsymbol{\theta}_{S1}, \boldsymbol{\theta}_{S2}, \boldsymbol{\theta}_{S3}$, respectively) were derived from prior empirical research investigating behavioral correlates of dementia transitions (Monaghan et al., 2026).

In scenario 1, transitions depended solely on a set of individual covariates $\mathbf{X}_{i,t} = (x_{1it}, x_{2it}, x_{3it})$, with no effect of the previous state. Within this scenario, the linear predictor was defined as:

$$\eta_{i,t}^{(k)} = \alpha_k + \mathbf{X}_{it}^{\top}\boldsymbol{\beta}_k,$$

with true value parameters set as:

$$\begin{aligned}
\boldsymbol{\theta}_{S1} &= (\alpha_k,\ \beta_{1k},\ \beta_{2k},\ \beta_{3k}),\ k = 2, 3) \\
\boldsymbol{\alpha} &= (-5.152, -5.402) \\
\boldsymbol{\beta} &= (0.008, -0.034, 0.036, 0.017, 0.028, 0.045).
\end{aligned}$$

In scenario 2, transitions depended additively on both the covariates $\mathbf{X}_{i,t} = (x_{1it}, x_{2it}, x_{3it})$ and the individual's previous state Y_{it}. Within this scenario, the linear predictor was defined as:

$$\eta_{i,t}^{(k)} = \alpha_k + \mathbf{X}_{it}^{\top}\boldsymbol{\beta}_k + \mathbf{S}_{it}^{\top}\gamma_k,$$

where $\mathbf{S}_{it}$ is an indicator variable. The true value parameters were set as:

$$\begin{aligned}
\boldsymbol{\theta}_{S2} &= (\alpha_k,\ \beta_{1k},\ \beta_{2k},\ \beta_{3k}, \gamma_{1k},\ \gamma_{2k}),\ k = 2, 3 \\
\boldsymbol{\alpha} &= (-5.370, -7.907) \\
\boldsymbol{\beta} &= (0.02, -0.011, 0.036, 0.039, 0.022, 0.016, 1.711, 2.790) \\
\boldsymbol{\gamma} &= (-0.776, 20.914).
\end{aligned}$$

Finally, in scenario 3, transitions depended both on the covariates $\mathbf{X}_{i,t} = (x_{1it}, x_{2it}, x_{3it})$ and the individual's previous state Y_{it} along with their corresponding interactions. Within this scenario, the linear predictor was defined as:

$$\eta_{i,t}^{(k)} = \alpha_k + \mathbf{X}_{it}^{\top}\boldsymbol{\beta}_k + \mathbf{S}_{it}^{\top}\boldsymbol{\gamma}_k + (\mathbf{X}_{it} \otimes \mathbf{S}_{it})^{\top}\boldsymbol{\delta}_k,$$

with true value parameters defined as:

$$
\begin{aligned}
\boldsymbol{\theta}_{S3} &= (\alpha_k,\ \beta_{1k},\ \beta_{2k},\ \beta_{3k}, \gamma_{1k},\ \gamma_{2k},\ \delta_{1k},\ \delta_{2k},\ \delta_{3k},\ \delta_{4k},\ \ \delta_{5k},\ \delta_{6k}, : k = 2, 3) \\
\boldsymbol{\alpha} &= (-5.885, -10.613) \\
\boldsymbol{\beta} &= (0.102, 0.615, 0.043, 0.076, 0.019, -0.002) \\
\boldsymbol{\gamma} &= (3.845, 7.901, -0.638, 12.753) \\
\boldsymbol{\delta} &= (-0.292, -1.019, -0.474, -1.268, -0.031, -0.072, 0.093, 0.1, 0.008, 0.029, -0.082, -0.021).
\end{aligned}
$$

Estimation methods

Model fitting

For each simulated dataset, we first partitioned the data into training (80%) and test (20%) sets. Model parameters were estimated exclusively on the training data, while all performance evaluations were conducted on held-out test data. This was done so as to assess the out-of-sample recovery of transition dynamics. For each training set, we fitted 15 multinomial logistic regression models using the `nnet` package (Venables & Ripley, 2002a) across 4 different sample sizes $\{100, 250, 1000, 5000\}$. These models were grouped into three "families", corresponding to the level of model misspecification relative to the true DGM, presented below using the simplified notation of the form "response $\sim$ predictors" (where "1" represents an intercept-only model and "$\otimes$" represents an interaction between predictors):

1. Base Models (Ignoring Markov Property)

$$
\begin{aligned}
\text{Null:} &\quad Y_{t+1} \sim 1 \\
\text{Reduced 1:} &\quad Y_{t+1} \sim x1 \\
\text{Reduced 2:} &\quad Y_{t+1} \sim x1 + x2 \\
\text{True:} &\quad Y_{t+1} \sim x1 + x2 + x3 \quad \text{(Exact DGM for Scenario 1)} \\
\text{Overfit:} &\quad Y_{t+1} \sim x1 + x2 + x3 + x4 + x5
\end{aligned}
\tag{2.5}
$$

2. Additive Models (With State Dependence)

$$
\begin{aligned}
\text{Null:} &\quad Y_{t+1} \sim Y_t \\
\text{Reduced 1:} &\quad Y_{t+1} \sim x1 + Y_t \\
\text{Reduced 2:} &\quad Y_{t+1} \sim x1 + x2 + Y_t \\
\text{True:} &\quad Y_{t+1} \sim x1 + x2 + x3 + Y_t \quad \text{(Exact DGM for Scenario 2)} \\
\text{Overfit:} &\quad Y_{t+1} \sim x1 + x2 + x3 + x4 + x5 + Y_t
\end{aligned}
\tag{2.6}
$$

3.Multiplicative Models (With Interactions)

$$\begin{aligned}
\text{Null:} &\quad Y_{t+1} \sim Y_t \\
\text{Reduced 1:} &\quad Y_{t+1} \sim x1 \otimes Y_t \\
\text{Reduced 2:} &\quad Y_{t+1} \sim (x1 + x2) \otimes Y_t \\
\text{True:} &\quad Y_{t+1} \sim (x1 + x2 + x3) \otimes Y_t \quad \text{(Exact DGM for Scenario 3)} \\
\text{Overfit:} &\quad Y_{t+1} \sim (x1 + x2 + x3 + x4 + x5) \otimes Y_t
\end{aligned} \tag{2.7}$$

Model-based transition probabilities

To evaluate how well each fitted model $\mathcal{M}$ captured the underlying transition dynamics, we generated model-based transition probability matrices via a two step procedure. In the first step, an augmented version of the test dataset was created enabled the model to predict transitions from all possible previous states. For each individual i at each time point t, three augmented rows were created corresponding to the three possible previous states $j \in \{1, 2, 3\}$. This ensured that the fitted model could generate predicted probabilities

$$P(Y_{t+1} = k \mid Y_t = j, \mathbf{z}_{i,t})$$

for every j, regardless of the individual's actual previous state in the data.

In the second step, we derived the transition behaviour implied by each model by predicting next-state transitions using the model's estimated parameters. For each model $\mathcal{M}$, the estimated coefficients vector $\hat{\boldsymbol{\theta}}^{\mathcal{M}}$ were used to compute predicted probabilities for all possible state transitions $(j \to k)$.

Performance measures

The core of our evaluation involved comparing the empirical transition matrix from the test dataset to the model-implied transition matrix. Let $\mathbf{P}_{i,t}$ be the empirical transition matrix for individual i at time t obtained by tabulating state transitions $(Y_{i,t}, Y_{i,t+1})$ from the test dataset. Additionally, let $\hat{\mathbf{P}}_{i,t}$ be the model-implied transition matrix. For individual i at time t with a covariates pattern $\mathbf{z}_{i,t}$ this is a $K \times K$ matrix where the entry j, k is the model's predicted probability $P(Y_{t+1} = k \mid Y_t = j, \mathbf{z}_{i,t})$. We defined the difference matrix as $\mathbf{D}_{i,t} = \mathbf{P}_{i,t} - \hat{\mathbf{P}}_{i,t}$ and quantify the discrepancy using the distance metrics defined in Table 2.1.

Results

Initially we present an exploratory analysis of the data from each scenario using contingency tables. Table 2.2 summarizes the unconditional transitions and transition probabilities between each cognitive state across the scenarios.

To evaluate the ability of each distance metric to identify the true data-generating model, we examined the proportion of simulation repetitions in which each model $\mathcal{M}$ was ranked as the best-fitting (Figure 2.1).

Small sample sizes

For the smallest sample size ($n = 100$) clear differences emerged between distance-based metrics and likelihood-based information criteria. Across both additive and multiplicative generative scenarios, the Manhattan distance and the Kullback–Leibler divergence identified the true model at rates comparable to, and in several cases exceeding, those of AIC and BIC. As shown in Figure 2.1 both metrics maintained a non-trivial probability of selecting the true model even under increased model complexity, whereas the information criteria frequently favoured simpler alternatives. This relative robustness at small n suggests that the Manhattan distance and KL divergence are less sensitive to the sampling variability that destabilises likelihood-based criteria in sparse data settings. In contrast, the remaining metrics (e.g., Frobenius norm, RMSE, correlation dissimilarity) showed mixed performance, often favouring over fitted or reduced models.

At $n = 250$, AIC showed modest improvement, particularly for simpler generative mechanisms. However, it continued to misidentify the true model under increased complexity, most notably in the multiplicative scenarios. BIC remained unreliable across all scenarios, strongly penalizing model complexity and frequently selecting the null model. In contrast, the Manhattan distance continued to demonstrate comparatively stable recovery of the true model across repetitions, and most clearly outperformed AIC in the more complex additive and multiplicative settings. The Kullback–Leibler divergence similarly outperformed both AIC and BIC up to, but not including, the most complex multiplicative scenario.

Moderate sample sizes

With a further increase in sample size ($n = 1000$), the performance of AIC improved substantially. As shown by Figure 2.1 AIC correctly identified the true model in over approximately 90% of repetitions across all generative scenarios. However, BIC continued to exhibit systematic under fitting, performing well only in the simplest generative scenario and frequently favouring the null model in both the additive and multiplicative scenarios.

Table 2.2: *Unconditional transitions and transition probabilities across scenarios.*

	Current state (t)			
Previous state (t-1)	1	2	3	Total
Base simulation				
1	12856 (0.64)	2456 (0.12)	847 (0.04)	16159
2	2155 (0.11)	498 (0.02)	204 (0.01)	2857
3	750 (0.04)	167 (0.01)	67 (0.003)	984
Additive simulation				
1	13817 (0.69)	1996 (0.10)	192 (0.01)	16005
2	1657 (0.08)	2606 (0.04)	162 (0.01)	2606
3	120 (0.01)	55 (0.003)	1214 (0.06)	1389
Multiplicative simulation				
1	14030 (0.70)	1921 (0.10)	166 (0.01)	16117
2	1602 (0.08)	712 (0.04)	167 (0.01)	2481
3	102 (0.01)	61 (0.003)	1239 (0.06)	1402

The distance-based metrics displayed a more gradual improvement with increasing sample size. Most notably, the Kullback–Leibler divergence performed nearly equivalently to AIC across all scenarios, indicating strong sensitivity to discrepancies in the underlying transition structure. The Manhattan distance also remained informative, ranking the true model as best fitting in approximately half of all repetitions across scenarios. Although this performance was weaker than that of AIC, it did not deteriorate with increasing model complexity, suggesting that this metric captures aspects of model misspecification that are not fully reflected in likelihood-based criteria. The remaining distance measures continued to show heterogeneous behaviour, alternating between overfitting and instability across repetitions.

Large sample sizes

At the largest sample size ($n = 5000$), both AIC and BIC exhibited near-perfect performance, identifying the true model in essentially all simulation repetitions across all generative scenarios. This convergence confirms that, when sufficient data are available, traditional likelihood-based information criteria are adequate for reliable model recovery. In contrast, the relative performance of the distance-based metrics was largely comparable to that observed at $n = 1000$ showing limited additional gains with further increases in sample size. Notably, however, the Kullback–Leibler divergence mirrored the behaviour of AIC and BIC, identifying the true model in nearly all repetitions even under the most complex multiplicative generative scenario.

Case study

We illustrate the proposed goodness-of-fit assessment framework using data from the United States Health and Retirement Study (HRS; Sonnega et al., 2014). The HRS is a nationally representative longitudinal panel study administered by the Institute for Social Research at the University of Michigan, which follows American adults aged 50 years and older. Since its inception in 1992, the HRS has collected biennial data on participants' health, socioeconomic circumstances, and cognitive functioning, making it a widely used resource for studying cognitive ageing and dementia trajectories. For the purpose of this illustration, we focus on three of these biennial waves from 2018 - 2022, yielding a sample of $n = 10{,}895$ respondents.

Cognitive function in the HRS is measured using a battery of assessments adapted from the Telephone Interview for Cognitive Status (TICS; Fong et al., 2009), which is based on the Mini-mental State Examination (Folstein et al., 1975). These assessments include immediate and delayed noun free-recall tasks to evaluate episodic memory, a serial sevens subtraction task to assess working memory, and a backward counting task to capture mental processing speed. Based on these assessments, Crimmins et al. (2011) developed a validated 27-point cognitive scale along with established cut-off points to classify respondents' cognitive status. Following this classification scheme, respondents scoring between 12 and 27 were classified as having normal cognition, scores between 7 and 11 indicated mild cognitive impairment (MCI), and scores between 0 and 6 were classified as dementia.

From the available HRS covariates, we selected three predictors that are commonly examined in studies of cognitive decline (Livingston et al., 2024): sex (x_1), age (x_2), and a five-point ordinal self-rating of memory (x_3). To mirror the design of the simulation study and to assess the ability of the proposed distance metrics to distinguish informative predictors from noise, we additionally simulated two non-informative covariates from a Uniform distribution, such that $\{x_4; x_5\} \sim \mathcal{U}(0, 1)$. In addition, we included the respondent's cognitive status Y_t when necessary (i.e., Equation (2.6) and Equation (2.7)).

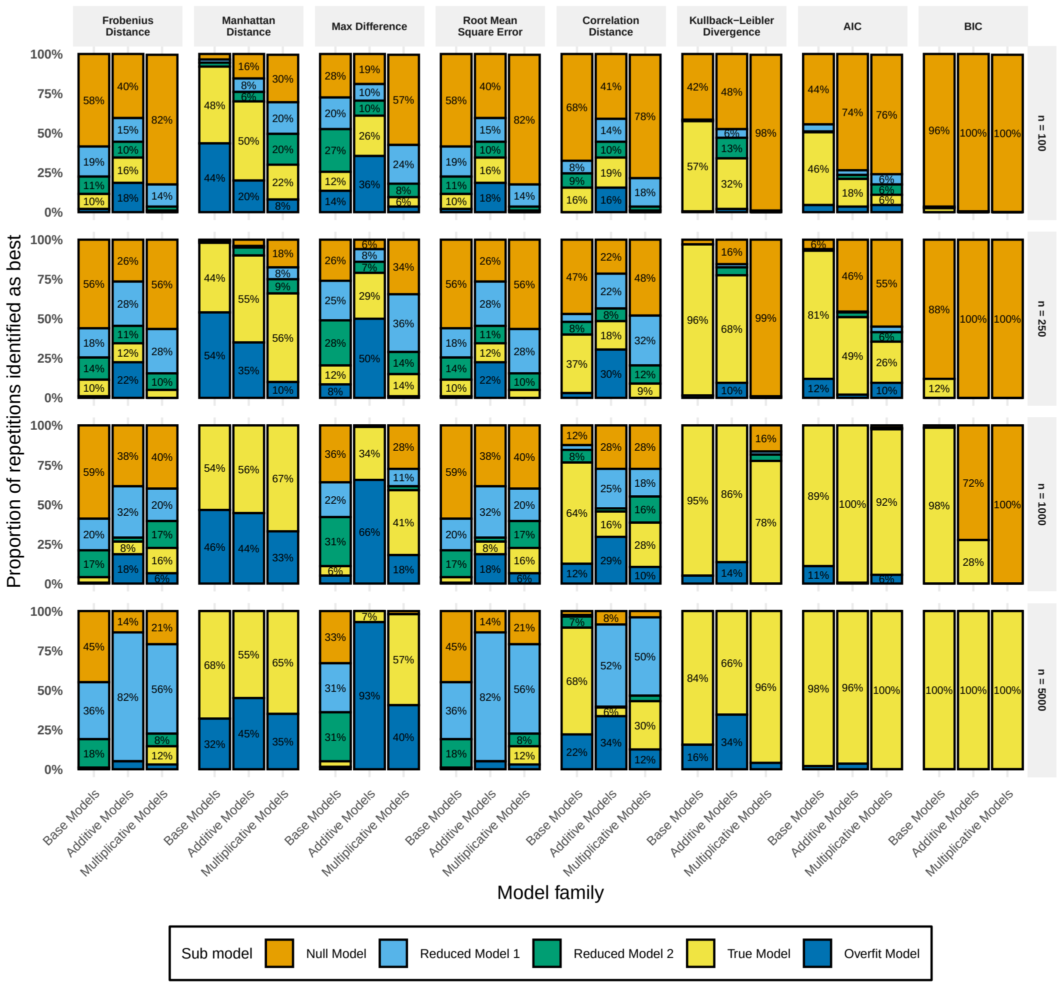

Figure 2.1: *Proportion of simulation repetitions in which each candidate model was ranked as best fitting across distance metrics and information criteria. Each stacked bar corresponds to a model class, with segment heights representing the percentage of repetitions in which each sub-model was selected as the best fitting. AIC = Akaike information criterion; BIC = Bayesian information criterion.*

Using this covariate set, we followed the same model-fitting and evaluation procedure as in the simulation study. Specifically, the data were split into training (80%) and test (20%) sets, the 15 multinomial logistic regression models defined in Equations (2.5) to (2.7) were fitted, and observed transition probabilities $\mathbf{P}_{i,t}$ were compared to predicted probabilities $\hat{\mathbf{P}}_{i,t}$. Figure 2.2 summarises the relative performance of each model across the different goodness-of-fit measures.

Consistent with the simulation results (see Figure 2.1), both the Manhattan distance and the Kullback–Leibler divergence most frequently identified the model containing the three substantively meaningful predictors (x_1, x_2, x_3) in approximately 50% of repetitions in both the base and additive scenarios. In the more complex multiplicative scenario, differences between the distance metrics became more pronounced. While the Manhattan distance increasingly favoured the model excluding the simulated noise covariates as sample size grew, the Kullback–Leibler divergence required substantially larger samples ($n = 1000$) before consistently identifying the model containing only the non-simulated predictors (mirroring that of the simulation study).

Figure 2.2: *Proportion of case study repetitions in which each candidate model was ranked as best fitting across distance metrics and information criteria. Each stacked bar corresponds to a model class, with segment heights representing the percentage of repetitions in which each sub-model was selected as the best fitting. Base models ignore first-order state dependence, whereas additive and multiplicative specifications incorporate Yt directly (with or without interactions), thereby modelling the Markov transition structure explicitly. AIC = Akaike information criterion; BIC = Bayesian information criterion*

Goodness of fit for discrete time Markov models: a discussion

This study evaluated a set of matrix-based distance metrics as tools for assessing goodness-of-fit in discrete-time Markov models estimated via multinomial logistic regression, with particular emphasis on applications to dementia progression modelling. Through a combination of simulation experiments and an empirical case study using HRS data, we demonstrate that distance-based comparisons of observed and model-implied transition matrices provide information that is complementary to, and in some settings (e.g., $n \in \{100, 250\}$) more reliable than, traditional likelihood-based information criteria.

Across the simulation study, two distance metrics consistently exhibited strong performance: the Manhattan distance and the Kullback–Leibler divergence. Both exhibited strong and comparatively stable performance across a range of sample sizes and data-generating mechanisms, particularly under increased model complexity. Most notably, the Manhattan distance frequently outperformed AIC and BIC in small samples and in settings involving interaction effects or strong state dependence. This finding suggests that the Manhattan distance is comparatively robust to the sampling variability that can destabilise likelihood-based criteria in finite samples (Emiliano et al., 2014).

The Kullback–Leibler divergence displayed a complementary pattern. While less robust than the Manhattan distance in the smallest samples and most complex scenarios, its performance improved rapidly with increasing sample size. By moderate to large samples, Kullback–Leibler closely mirrored the behaviour of AIC, and at the largest sample sizes it achieved near-perfect recovery of the true model even under the most complex multiplicative data-generating mechanisms. This aligns with the theoretical interpretation of Kullback–Leibler divergence as a measure of information loss between true and fitted transition distributions (Kullback & Leibler, 1951).

As expected, the performance of traditional information criteria improved substantially with increasing sample size. In large samples, both AIC and BIC demonstrated near-perfect recovery of the true data-generating model, consistent with their well-established asymptotic properties. These results confirm that likelihood-based approaches remain appropriate and effective when data are abundant and model complexity is well supported.

However, the more gradual convergence of the distance-based metrics highlights an important conceptual distinction. Distance metrics do not aim to optimise predictive likelihood. Instead, they assess how well a fitted model reproduces the empirical transition structure itself. Their continued sensitivity to structural discrepancies, even in larger samples, should therefore be viewed as a strength rather than a limitation. In applied settings, particularly in disease progression modelling, a model that fits well in likelihood terms may still produce implausible or distorted transition dynamics, a form of misspecification that distance-based diagnostics are well positioned to detect.

The empirical case study using HRS data further corroborated the simulation findings. Both the Manhattan distance and Kullback–Leibler divergence tended to favour models containing substantively meaningful predictors of cognitive decline (sex, age, and self-rated memory), while remaining comparatively insensitive to the inclusion of simulated non-informative covariates. This behaviour is consistent with the intended role of the distance metrics: to distinguish meaningful signal in transition dynamics from noise introduced by irrelevant predictors.

Taken together, these findings suggest that matrix-based distance metrics, in particular the Manhattan distance and Kullback-Leibler divergence, provide a valuable addition to the model evaluation toolkit for discrete-time Markov models. Rather than serving as replacements for AIC or BIC, these measures are best viewed as complementary diagnostics that foreground structural fidelity of transition dynamics. Their use is especially well suited to applied research contexts, such as dementia progression modelling, where the realism and interpretability of implied transitions are at least as important as predictive likelihood.

Limitations and future directions

Several limitations of the present study suggest directions for future research. First, although the proposed goodness-of-fit framework captures discrepancies in transition structure that are not reflected in likelihood-based criteria, the choice of distance metric remains context dependent. Different distance metrics emphasize different aspects of the transition matrix (e.g., global versus state-specific discrepancies, absolute versus distributional differences), and no single metric can be considered universally optimal. Future work could explore principled strategies for selecting or combining distance measures, potentially informed by substantive theory or decision-analytic considerations (A. R. Lee et al., 2025; L. Wu et al., 2021).

Secondly, this simulation framework is restricted to discrete-time, first-order Markov processes estimated using generalized logit models. While this specification covers a broad and widely used class of state transition models, it does not encompass more complex forms of dependence.

Several extensions therefore represent promising avenues for future work. These include higher-order Markov processes, (i.e., where transitions depend on multiple previous states) and continuous-time formulations. In addition, hidden Markov models, which incorporate latent state dynamics, would provide a natural extension for settings with measurement error or unobserved heterogeneity (Zeng et al., 2010). Beyond the generalized logit framework used here, other important classes of categorical outcome models, such as ordinal transition models and alternative link specifications, could also be investigated to assess whether the proposed goodness-of-fit framework performs similarly across modelling paradigms.

Final remarks

Matrix-based distance metrics offer a principled and interpretable complement to likelihood-based criteria for assessing discrete-time Markov models. By directly comparing empirical transition matrices to those implied by fitted models, these measures provide diagnostic information that is particularly sensitive to structural misspecification. The strong finite-sample performance of the Manhattan distance and the favourable asymptotic behaviour of the Kullback–Leibler divergence highlight their practical utility, especially in applied longitudinal settings where accurate representation of transition dynamics is central to substantive inference.

CRediT authorship contribution statement

Cormac Monaghan: Conceptualisation, Methodology, Data curation, Formal analysis, Visualisation, Writing – original draft. Writing – review & editing. **Idemauro Antonio Rodrigues de Lara:** Conceptualisation, Methodology, Formal analysis, Visualisation, Supervision, Writing - review & editing,. **Rafael de Andrade Moral** Conceptualization, Methodology, Formal analysis, Visualisation, Supervision, Writing – review & editing. **Joanna McHugh Power:** Supervision, Writing – review & editing.

CHAPTER 3

Procrastination, Depressive Symptomatology, and Loneliness in Later Life

Cormac Monaghan, Ione Avila-Palencia, S. Duke Han, and Joanna McHugh Power

Abstract: Procrastination is an almost universal behaviour and yet little research to date has focused on procrastination among older adults. The purpose of this study was to explore the potential association between age and procrastination, and the potential mediating roles of depressive symptomatology and loneliness. Structural equation modelling was applied to data from 1309 participants (aged 29-92) from two waves United States Health and Retirement Study (2016 – 2020). Within the model, sex, education, marital status, and job status were added as covariates. There was no statistically significant direct effect between age and procrastination (β = 0.06, p = 0.106). However, an indirect effect was present via depressive symptomatology (β = - 0.40, $p < 0.001$). No mediating effect of loneliness was observed (β = - 0.01, p = 0.371). Subsequent analysis revealed that the symptoms, fatigue, loneliness, and lack of motivation significantly predicted procrastination. While age was not directly associated with procrastination, increasing age was associated with a decreased likelihood of depressive symptomatology, which was in turn associated with an increased likelihood of procrastination. Such findings indicates that age demonstrates no association with procrastination because of the suppressing effect of depressive symptomatology. Results are discussed in relation to potential implications for procrastinatory behaviours in later life.

3.1 Introduction

Procrastination is an intentional delay of an intended course of action, despite potential negative consequences (Steel, 2007), such as stress, reduced productivity, missed opportunities, and potential compromised performance. While there is no reason to believe that procrastinatory behaviour disappears with age, to date research has predominantly focused on student and younger adult populations, with little attention given to procrastination behaviours among older adults.

Procrastination and procrastinatory behaviour are influenced by a multitude of factors. Previous studies on younger populations have identified psychological factors such as perfectionism, fear of failure, lack of motivation, individual differences, and maladaptive cognitive thinking as predictors of procrastination (Abbasi & Alghamdi, 2015; Balkis & Duru, 2007; Steel, 2007). Additionally, environmental factors such as task aversiveness, temporal delay, and lack of structure can also predict likelihood of procrastinatory behaviours (Klingsieck et al., 2013; Steel, 2007). Furthermore, studies have linked procrastination to heightened stress and depression levels, noting that the distress it causes can intensify the emotions leading to more procrastination (Fernie & Spada, 2008; A. L. Flett et al., 2016; G. L. Flett et al., 2012). This self-perpetuating cycle can be particularly detrimental to wellbeing, as it may lead to a decline in self-esteem and a sense of personal efficacy.

However, to gain a more comprehensive and holistic understanding of procrastination, research also needs to take into consideration procrastination in later life and examine its predictors among older adults. Procrastination in older adults can lead to a range of negative outcomes, including poor health management, delayed financial planning, and the exacerbation of social isolation. For instance, procrastination on health-related decisions can result in more severe health consequences for older adults compared to younger individuals due to the cumulative effects of aging and the potential for rapid health deterioration (Diehr et al., 2013; Stolcis & McCown, 2018). Postponing medical appointments or treatment adherence can escalate manageable conditions into critical emergencies. Furthermore, procrastination in financial decision-making related to retirement savings and asset management can lead to economic hardship.

Some studies on procrastination have gathered data from older adults, without focusing specifically on this age group. For instance, in a study of adults aged 18-77, procrastination was found to decrease with age up to the age of 60, whereupon it began to increase again (W. McCown & Roberts, 1994). This increase was attributed, by others, to retirement or health decline (J. R. Ferrari et al., 1995). A similar pattern, with a later inflection point of aged 70, was reported by Beutel et al. (2016) based on a sample of individuals aged 14-95. However, the potential reasons for this increase were not discussed in the study.

While these two studies did not focus specifically on procrastination in later life, the pattern of results they report suggests that there is a shift in procrastination at some point beyond the age of 60. As mentioned, J. R. Ferrari et al. (1995) attributed this shift to retirement or health decline. Retirement can be a challenging adjustment for some individuals, leading to uncertainty, loss of identity, and reduced social interaction, which may impact motivation and productivity (Henning et al., 2016; Heybroek et al., 2015; Wang, 2007). Furthermore, Sirois et al. (2003) proposed that procrastination is associated with declining health through increased stress and a reduction in health seeking behaviours. However, Johansson et al. (2023) suggests a bi-directional relationship with declining physical and mental health also contributing to increased procrastination due to reduced energy and motivation.

Additionally, neurobiological studies have linked variations in grey matter volume within the brain to procrastination. This association particularly highlights specific regions of the brain such as the dorsolateral prefrontal cortex, orbital frontal cortex, and ventromedial prefrontal cortex (Z. Chen et al., 2020; Y. Hu et al., 2018). These specific areas govern executive functions, such as decision-making, impulse control, and the ability to prioritize tasks. However, these areas of the brain are known to undergo changes overtime due to neuro-cognitive aging. For example, the dorsolateral prefrontal cortex, which is crucial for working memory and planning shows a decline in neural efficiency overtime (Rajah & D'Esposito, 2005). Similarly, the orbital frontal cortex, involved in the evaluation of risks and rewards, and the ventromedial prefrontal cortex, associated with emotional regulation, also undergo significant changes (Cohen et al., 2019).

Moreover, older adults are more likely to experience a range of uncontrollable life factors which may also contribute to increased in procrastinatory behaviours. Such factors include the above-mentioned declining health and cognition and retirement, along with the loss of loved ones and reduced social connections (Okun & Keith, 1998). Loneliness is commonly associated with these declines and has been linked to higher prevalence rates among older adults (Ekwall et al., 2005; Lim & Australian Psychological Society, 2018; Surkalim et al., 2022). Loneliness is described as a perceived discrepancy between one's actual and desired levels of social relationships (Peplau & Perlman, 1982) and can lead to individuals feeling demotivated (Perlman & Peplau, 1981). This perceived discrepancy, along with social isolation and a lack of meaningful connections often results in individuals feeling demotivated (Perlman & Peplau, 1981). As noted by Weiss (1975), tasks can lose their purpose and significance for lonely individuals, consequently increasing the likelihood of procrastination. Furthermore, loneliness can negatively affect cognitive functioning and in turn, decision-making processes (Lara et al., 2019), further exacerbating procrastination tendencies.

As well as loneliness, depression may also be a causal factor in determining procrastination behaviour in later life. Symptoms such as reduced pleasure in activities, low levels of energy, and difficulties concentrating (American Psychiatric Association, 2013) are noted as common reasons for procrastination in student populations (Strongman & Burt, 2000). While depression is less prevalent in older adults (Fiske et al., 2009) and can be understood though frameworks such as selective optimization with compensation (Baltes & Baltes, 1990) and socioemotional selectivity theory (Carstensen et al., 1999) its effects and symptoms can still be profoundly detrimental. Previous research (Beutel et al., 2016; A. L. Flett et al., 2016; Van Eerde, 2003) has established a link between depression and procrastination, suggesting that cognitive factors such as ruminative brooding and a lack of mindfulness may exacerbate procrastination (A. L. Flett et al., 2016). These cognitive patterns can lead to a vulnerability to depression, characterized by a high frequency of procrastination-related automatic thoughts and a deficit in self-compassion (A. L. Flett et al., 2016).

With regard to procrastination in older adults, research is limited. However, a recent study by Biella et al. (2020) found that higher levels of depressive symptoms were correlated with two maladaptive decision-making profiles: an "avoidance profile" where individuals rely on external sources for decision making, and a “procrastination profile” involved individuals who consistently delay decision-making processes for as long as possible.

Overall, loneliness and depression may, as such, predict procrastination. However, the existing body of research primarily focuses on younger student populations (Anam & Hitipeuw, 2022; Beutel et al., 2016; A. L. Flett et al., 2016) with limited research focusing on older adults. As such, the objectives of this study were twofold: (i) investigate the direct effect of age on procrastination and, (ii) investigate the indirect effects of loneliness and depressive symptomology on procrastination tendencies among older adults.

3.2 Methods

3.2.1 Design and participants

This study utilised a longitudinal dataset known as the United States Health and Retirement Study (HRS; Juster and Suzman, 1995). The HRS, administered by the Institute for Social Research at the University of Michigan, is a longitudinal panel study that predominantly focuses on adults over the age of 50. The study collects, biennially, detailed information pertaining to respondent's physical, cognitive, financial, employment, family, and psychosocial conditions. In each wave of the HRS, methods of data collection vary for each respondent. The core sample is split into two distinct subsamples, distinguished as "subsample A" and "subsample B". In each wave subsample A undergoes an enhanced face-to-face interview, which encompasses physical and biomarker assessments, along with the administration of a psychosocial and lifestyle questionnaire. In contrast, subsample B undergoes a telephone interview without the administration assessments or the psychosocial and lifestyle questionnaire. These two subsamples alternate during each data collection wave. Similarly, in each wave, experimental modules are administered at the end of the core interview. These modules consist of concise questionnaires designed to explore new topics or supplement existing core survey data. However, each respondent only receives one experimental module, and the sample sizes for each module constitute approximately 10% of the core sample.

For our analysis, we utilised data from two waves of the HRS (2016 and 2020), focusing on respondents who were selected to complete an experimental module termed "long-term care insurance procrastination" during the 2020 wave. This module was split into two parts with the second half incorporating a procrastination measure with the aim of investigating how procrastination influences decision-making in later life.

3.2.2 Measures

Outcome: Procrastination

Procrastination was measured using the Pure Procrastination Scale (PPS; Steel, 2010). This scale was developed by combining the 12 highest loading items from 3 other measures of procrastination (Lay, 1986; Mann, 1982; W. G. McCown et al., 1989). The items within the PPS specifically measure dysfunctional delay, with each being measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Combining the item scores gives rise to a composite score from 12 to 60, with higher scores indicating higher levels of procrastination. The PPS conducted in 2020 (wave 2) was measured by Cronbach's alpha ($\alpha = 0.91$), showing high internal consistency. An example of a question from the scale includes, "even after I make a decision I delay acting upon it".

Mediator: Depression

Depressive symptoms were measured using a shortened 8-item version of the Centre for Epidemiological Studies – Depression (CESD-8) scale. The shortened scale is increasingly employed in large international studies such as the European Social Survey (Van de Velde et al., 2010) and the HRS (Zivin et al., 2010). Within the HRS, items on the scale are scored as either 1 (yes) or 5 (no), with items 4 and 6 being reversed scored. However, to facilitate consistent scoring with other measures, we modified the scoring system for our analysis. Responses were recoded as 1 (no) and 2 (yes), with items 4 and 6 remaining reversed scored. Combining the item scores gives rise to a composite score from 8 to 16, with higher scores indicating more depressive symptoms. The CESD-8 conducted in 2016 (wave 1) was measured by Cronbach's alpha (α = 0.81), showing high internal consistency. An example of a question from the scale includes, "how much of the time during the past week did you feel everything you did was an effort".

Mediator: Loneliness

Within the HRS, loneliness is measured using an 11-item version of the Revised University of California, Los Angeles (R-UCLA) Loneliness Scale (J. Lee & Cagle, 2017). However, for the purposes of our analysis, we utilised the first 3 items, which form the shortened 3-item version of the scale. Each item on this scale measures 3 dimensions of loneliness: relational connectedness, social connectedness, and self-perceived isolation. Each of the three items are scored on a three-point Likert scale ranging from 1 (often) to 3 (hardly ever or never) with all of them being reversed scored. Combining the item scores gives rise to a composite score from 3 to 9, with higher scores indicating higher levels of loneliness. The 3-item R-UCLA conducted in 2016 (wave 1) was measured by Cronbach's alpha (α = 0.80), showing high internal consistency. An example of a question from the scale includes, "how often do you feel left out".

Covariates

The potential covariates sex, education, marital status, and job status were chosen based on a priori knowledge of their associations with procrastination (Beutel et al., 2016; Steel & Ferrari, 2013). Education was initially categorised into several levels: no degree (0), general educational development (1), high school diploma (2), college degree (2 years) (3), college degree (4 years) (4), master's degree (5), doctorate (6). However, to facilitate the analysis, this ordinal scale was collapsed into a binary scale based on the presence college degree: does not possess a college degree (0), possesses a college degree (1). Marital status was categorised into several levels: married (1), separated/divorced (2), widowed (3), never married (4). Again, for the purpose of analysis, a binary scale was adopted based on the current marital status of being: not currently married (0), currently married (1). Job status was categorised into several levels: currently working (1), unemployed (2), laid off (3), disabled (4), retired (5), home-maker (6), other (7), on sick leave (8). Once again, for the purpose of analysis, a binary scale was adopted based on retirement status: not retired (0), retired (1).

3.2.3 Data Analysis

All data analysis was carried out in R (R Core Team, 2024). Within the final dataset, 7.45% of the data was missing across the entire dataset, though a significant proportion of this missingness was contained within the R-UCLA loneliness items. These missing values were missing at random and as such were handled using Full Information Maximum Likelihood (FIML) from the R package `Lavaan` (Rosseel, 2012). FIML is based on the maximum likelihood estimation principle and allows for the estimation of parameter values that are most likely to be true given the available data. Unlike traditional imputation methods, FIML provides better flexibility by allowing for maximal use of existing data relative to other missingness approaches and has been shown to perform equivalently to multiple imputation in handling missing data (Lee & Shi, 2021).

Prior to modelling, preliminary analyses were run to ensure that there was no violation of model assumptions. A structural equation model was applied to the data to assess the direct association between age and procrastination with both depressive symptomatology and loneliness being assessed as potential mediators. Structural equation modelling is a comprehensive statistical technique that utilizes regression models for the analysis of complex relationships between measured (observed) and latent (unobserved) variables. It provides a framework for constructing and testing models that hypothesize the directional influence of certain variables on others, including potential indirect effects through mediators. The proposed model consisted of multiple indicator factors, with the distinct items from each scale serving as indicators of their respective factor.

Model parameters were estimated using the Maximum Likelihood Method, with the null hypothesis being rejected for the hypothesized direct and indirect effects if $p < .05$. To assess model fit absolute fit indices, such as the chi-square test, root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR), along with incremental fit indices such as, the comparative fit index (CFI) and the Tucker-Lewis index (TLI) were used. Due to the chi-square test's sensitivity to large sample size (Bentler & Bonett, 1980) a greater focus was placed on the other fit metrics. Following established literature, a model was considered well fitted when the CFI and TFI values were greater than 0.90, RMSEA below 0.08, and SRMR below 0.05 (L. Hu & Bentler, 1999; Joreskog & Sorbom, 1993).

3.3 Results

The initial analysis included a total of 1320 respondents. However, we excluded respondents who had missing values in key covariates, specifically job status ($n = 8$) and marital status ($n = 3$). As a result, our final analytic sample consisted of 1309 respondents. Of this sample, 63.18% of respondents were female ($n = 827$) and were predominantly aged 50+ years: 20 - 29 years ($n = 2$), 30 - 39 years ($n = 5$), 40 - 49 years ($n = 45$), 50 - 59 years ($n = 428$), 60 - 69 years ($n = 437$), 70 - 79 years ($n = 273$), and 80+ years ($n = 119$). Descriptive statistics for all continuous variables were generated and are presented in Table 3.1.

Table 3.1: *Descriptive statistics of all continuous variables*

	Mean (95% CI)	SE	Median	SD	Range
Age	64.3 (63.70 - 64.81)	0.28	63	10.29	28 - 92
Procrastination	28.4 (27.78 - 29.04)	0.32	27	11.62	4 - 60
Depressive Symptomatology	1.49 (1.39 - 1.61)	0.06	1	2.03	0 - 8
Loneliness	4.37 (4.21 - 4.52)	0.08	4	1.60	1 - 9

3.3.1 Structural equation model

To assess the indirect effects of depressive symptomatology and loneliness on procrastination, a structural equation model was applied to the data (see Figure 3.1). The model was run for 138 iterations and converged normally. Model fit was acceptable (CFI = .931, TLI = .923, χ^2_{330} = 11520, RMSEA = .042, SRMR = .047). Latent variable loadings were all above 0.56 for procrastination, 0.46 for depressive symptomatology, and 0.74 for loneliness.

The results show that age did not have a significant direct (β = 0.060, p = 0.106) or total (β = 0.010, p = 0.782) effect on procrastination. However, an indirect effect was present for depressive symptomatology (β = - 0.04, $p < 0.001$). While age was not directly associated with procrastination, age was associated with a decreased likelihood of depressive symptomatology (β = -0.13, $p < 0.001$). The presence of depressive symptomatology was in turn associated with an increased likelihood of procrastination (β = 0.31, $p < 0.001$). Age was similarly associated with a decreased likelihood of loneliness (β = -0.16, p = 0.003) however this decrease was not associated with procrastination (β = 0.06, p = 0.343). No mediating effect of loneliness was observed (β = -0.01, p = 0.371).

Furthermore, the results of the model showed that education was significant associated with procrastination (β = - 0.16, $p < 0.001$). The additional model covariates, sex (β = 0.01, p = 0.864), marital status (β = 0.01, p = 0.805), and job status (β = - 0.02, p = 0.609) did not show significant associations with procrastination.

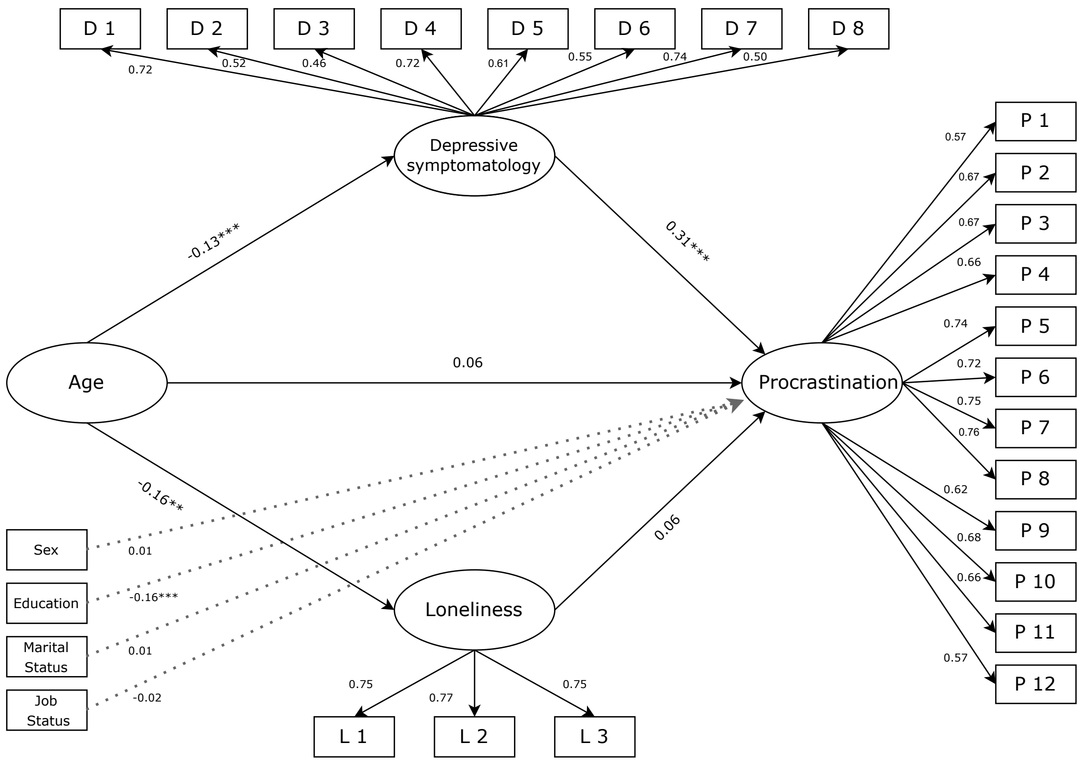

Figure 3.1: *Structural equation model of the relationship between age, procrastination, depression, and loneliness. In the following structural equation model, we have employed a set a measured constructs (D1 - D8, P1 - P12, and L1 - L3) each of which corresponds to specific survey questions designed to gauge the underlying latent construct (depressive symptomatology (D), procrastination (P), and loneliness (L)). The numerical values (beta values) represent the strength and direction of the relationship between the variables. Statistically significant pathways are represented as ** $p < .01$; *** $p < .001$. The total effect of age on procrastination is ($\beta = 0.010$, $p = 0.782$).*

3.3.2 Symptom analysis

To gain a deeper insight into the relationship between depressive symptomatology and procrastination additional supplementary analyses were carried out. Based off their CESD-8 scores respondents were categorized into two groups: having no depressive symptoms ($n = 596$) and having depressive symptoms ($n = 713$). Initially, an independent samples t-test was conducted to compare mean procrastination scores between each group. There was a statistically significant difference in scores ($t(1302) = -9.30, p < 0.001$) with respondents who had depressive symptoms ($M = 31.06, SD = 11.80$) scoring higher than respondents with no depressive symptoms ($M = 25.25, SD = 10.60$). The magnitude of difference in the means was medium (Cohen's $d = 0.52$).

Following this, a standard multiple regression analysis was performed to determine how well mean procrastination could be explained by each measure on the CESD-8. The model as a whole explained 10.9% of variance in procrastinatory behaviour ($F(8, 1276) = 19.32, p < 0.001$). It was found that fatigue ($\beta = 0.13, p < 0.001$) significantly predicted procrastination, along with loneliness ($\beta = 0.07, p = 0.033$) and lack of motivation ($\beta = 0.13, p < 0.001$). The remaining measures, depression ($\beta < 0.001, p = 0.928$), restlessness ($\beta = 0.06, p = 0.058$), lack of happiness ($\beta = 0.03, p = 0.482$), lack of enjoyment ($\beta < 0.001, p = 0.912$), and sadness ($\beta = 0.07, p = 0.063$) did not significantly predict procrastination. See Table 3.2 for full details.

Table 3.2: *Multiple regression model of CESD-8 items predicting procrastination.*

	R^2	β (95% CI)	B (95% CI)	sr^2	r
Model	.108***				
Depression		.00 (-.07 - .07)	-.01 (-.22 - .20)	.00	.19***
Fatigue		.13*** (.07 - .19)	.30 (.16 - .43)	.01	.25***
Restlessness		.06 (.00 -.11)	.12 (.00 - .24)	.00	.18***
Lack of happiness		.03 (-.05 - .10)	.07 (-.13 - .28)	.00	.19***
Loneliness		.07* (.01 - .13)	.18 (.01 - .34)	.00	.21***
Lack of enjoyment		.00 (-.06 - .07)	.01 (-.20 - .22)	.00	.15***
Sadness		.07 (.00 - .14)	.16 (-.01 - .34)	.00	.22***
Lack of motivation		.13*** (.07 - .19)	.33 (.18 - .47)	.01	.24***

Note. R^2 = R-squared; β = standardized beta value; B = unstandardized beta value; sr^2 = semi-partial correlation squared; r = zero-order correlation. A significant β indicates the unstandardized beta value and semi-partial correlation are also significant. Brackets are used to enclose the lower and upper limits of a confidence interval. Statistical significance is represented as: * p < .05; *** p <.001.

3.4 Discussion

The objective of this study was to investigate the potential association between age and procrastination, with a particular focus on the potential mediating roles of loneliness and depressive symptomatology. It was hypothesised that (i) age would have a direct effect on procrastination and (ii) loneliness and depressive symptomatology would act as mediating variables between age and procrastination. The findings of the study did not support the initial hypothesis, with age having no direct effect on procrastination. However, the subsequent hypothesis received partial support, revealing that depressive symptomatology serves as a partial suppressing mediator between age and procrastination.

The results imply that while age may not directly influence procrastination, the presence of depressive symptoms among older adults can contribute to variations in procrastinatory behaviours. In other words, being older is associated with a decreased risk of depressive symptoms, which in turn are associated with procrastination. As such, older adults are indirectly less likely to procrastinate because they are less likely to experience the depressive symptoms typically associated with procrastination. These results are in line with theoretical frameworks and may be linked to protective factors such as their ability to adapt and compensate for age-related challenges, as well as focusing on emotional well-being and meaningful experiences (Baltes & Baltes, 1990; Carstensen et al., 1999). At the same time, the link between depressive symptoms and procrastination coincides with previous research findings (Beutel et al., 2016; Biella et al., 2020; Fiske et al., 2009; Rozental et al., 2015; Steel, 2007) and can be understood through the lens of how depression affects both an individual's motivation and cognitive functioning.

The results of the model showed that having more depressive symptoms was associated with an increased likelihood of procrastination. Supplementary analysis revealed that respondents who met the cut off for depression had higher levels of procrastination. For those older adults the symptoms of depression may manifest differently compared to their younger counterparts. As highlighted by Fiske et al. (2009), older adults are less likely to experience cognitive-affective symptoms and more likely to experience fatigue, sleep disturbances, reduced interest in activities and concentration, and cognitive decline. This is in line with the results of the regression analysis which showed that fatigue and lack of motivation significantly predicted procrastination. These depressive symptoms can inadvertently hinder one's ability to initiate and complete tasks (Rozental et al., 2015). The interplay between depression and procrastination is evident in the way depressive symptoms can lead to a cycle of delayed actions and increased stress (A. L. Flett et al., 2016; G. L. Flett et al., 2012). The lack of motivation and diminished interests can contribute to a sense of apathy and a reduced enthusiasm to engage in productive behaviours. Similarly, low levels of energy and difficulties concentrating can further impede effective task management and hinder progress toward completing necessary activities.

As mentioned, advancing age brings with it a range of uncontrollable life factors, ranging from declining health, cognitive impairment, and retirement, along with the potential repeated deaths of friends and loved ones. Moreover, older adults face unique societal and cultural challenges, most notably ageism. In the absence of protective factors, the cumulative effect of these stressors can significantly contribute to the development of depressive symptoms among older adults and potentially cumulate into late-life depression (Husain-Krautter & Ellison, 2021). The development of these symptoms and depression itself could potentially shed light on the increase in later-life procrastination scores noted in both W. McCown and Roberts (1994) and Beutel et al. (2016) studies. Both studies revealed an increase in procrastination scores beyond the approximate age threshold of 60, which coincides with the onset of late-life depression (Aziz & Steffens, 2013; Fiske et al., 2009).

To effectively support older adults, interventions must be tailored to their unique experiences and challenges, such as coping with ageism, health decline, and bereavement. Support groups and therapy that focus on these life factors can provide the necessary tools to manage depressive symptoms more effectively (Eimontas et al., 2021; Krishna et al., 2011). Moreover, by tackling the underlying causes of depression, such interventions can help reduce procrastination, as they regain a sense of self control (Sirois & Pychyl, 2013). Furthermore, incorporating physical activity programs can combat fatigue and improve cognitive function, thereby reducing the tendency to procrastinate (Paterniti et al., 2002).

This tendency to procrastinate can have detrimental consequences for older adults, particularly in relation to their physical and mental well-being. Procrastination is frequently linked to heightened levels of stress and a decline in self-care behaviours (Sirois et al., 2003; Steel, 2007). Such decline can have profound ramifications for the lives of older adults. For instance, when older adults postpone medical appointments and check-ups, the effects can be far more catastrophic compared to their younger counterparts. Age-related health conditions tend to progress more rapidly and can have more severe implications for older individuals (Diehr et al., 2013). Similarly, with age the body's ability to recover and respond to medical treatments may decrease. As such, delaying appointments and check-ups can potentially lead to the exacerbation of health conditions, missed opportunities for early intervention, and increased risks to overall well-being. Additionally, the consequences of procrastination can also extend to critical financial decision-making processes. By procrastinating important financial tasks such as managing retirement disbursements or planning for healthcare and other expenses older adults risk facing financial difficulties and may struggle to maintain a stable and secure lifestyle in their later stages of life.

No mediating association was found between loneliness and procrastination. These results are not in line with previous research on loneliness and procrastination (Anam & Hitipeuw, 2022; Beutel et al., 2016). However, such research has focused predominately on younger populations and in some cases, has operationalised procrastination differently, often centering around academic procrastination. Interestingly, the results of the regression analysis showed that loneliness when measured as a symptom of depression did significantly predict procrastination. Again, this discrepancy may be a result of a difference in operationalisation with the CESD-8 measuring a general feeling of loneliness within the past week and the R-UCLA scale measuring specific aspects of loneliness in general. Overall, the results of this study provide a deeper insight into the relationship between loneliness and procrastination, specifically within the context of older adults. It suggests that the experience of loneliness in older adults may differ from that of younger adults and, consequently, may not exert the same influence on procrastination tendencies.

Furthermore, the results of the model also showed that education had a negative impact on procrastination at β= - 0.16 ($p < 0.001$). This association is consistent with previous studies that have found a similar relationship (Fiske et al., 2009; Steel & Ferrari, 2013) and suggests that older adults with higher levels of education tended to procrastinate less than those with lower levels of education. One possible explanation for this link is that higher education may, in later life, enhance cognitive functioning and mental health in older adults, which in turn may reduce the tendency to delay tasks. For instance, higher education has been shown to be associated with better cognitive functioning (Wilson et al., 2009) and lower levels of depressive symptoms (Koster et al., 2006) in later life. Therefore, higher education may act as a protective factor against procrastination in older adults by improving their cognitive and emotional well-being.

Finally, while this study does suggest that depressive symptomatology serves as a partial mediator between age and procrastination, procrastination is a complex behaviour with multiple influential factors (see Steel, 2007). These potential mediators could serve as a plausible explanation for the absence of a direct association between age and procrastination in the study's findings. For instance, while depressive symptomatology indirectly influences age and procrastination, increasing age may also be associated with risk factors such as, physical and cognitive decline (Einstein et al., 2000; D. C. Park et al., 2002; Penninx et al., 2000), along with increased sleep disturbances and bereavement (Cole & Dendukuri, 2003). The gradual development and occurrence of these event may be linked to increased fluctuations in procrastinatory behaviours. By not accounting for these potential factors, the original model may have overlooked potentially significant roles in the overall relationship between age and procrastination. As such, further investigation is warranted to comprehensively understand how age truly impacts procrastination tendencies.

3.4.1 Limitations

As previously mentioned, a significant proportion of missing data was contained within the R-UCLA loneliness items. This missingness can be attributed to the nature of the HRS "psychosocial and lifestyle questionnaire", the questionnaire the R-UCLA loneliness items are contained in. As mentioned, the HRS core sample is divided into two distinct subsamples, referred to as "subsample A" and "subsample B". In alternating waves of data collection, subsample A undergoes an enhanced face-to-face interview, which includes the psychosocial and lifestyle questionnaire, while subsample B undergoes a telephone interview without these assessments. This subsample rotation is a key feature of the HRS methodology. However, the 10% of respondents that were selected to complete the procrastination module consisted of respondents from both subsamples. Consequently, it is plausible that the majority of these respondents belonged to the opposing subsample of that year and as such did not complete the R-UCLA loneliness questionnaire. While this missingness was imputed using FIML, future research should take into account this unique subsample distribution in their methodology and when analysing and interpreting results.

Additionally, the measures employed in this study may have failed to capture the complexity of both loneliness and depression. For example, loneliness can be experienced in a variety of different forms, such as social, emotional, or existential loneliness (Ward et al., 2019). Likewise, the symptoms of depression can oftentimes have different causes and manifestations. These complexities may influence how individuals manage such negative emotional states and in turn how they initiate and complete tasks. Future research should explore how specific nuances may moderate or mediate the effects of loneliness and depression on procrastination.

Finally, this study was based on a sample from the US, which may limit the generalizability of the findings to other populations and cultures. For instance, cultural differences in time orientation, individualism-collectivism, or uncertainty avoidance may affect how people perceive and deal with procrastination (Lu et al., 2022). Therefore, it is important to replicate this study in other parts of the world to determine how robust and universal these findings are.

3.4.2 Conclusion

Procrastination is a complex behaviour that can have detrimental effects for older adults. However, the existing body of literature on procrastination in older adults remains relatively limited. The present findings suggest that the presence of depressive symptoms mediates the relationship between age and procrastination, absent of a direct effect. In other words, while age alone may not directly impact procrastination, the development of depressive symptoms among older adults acts as a pathway through which age influences procrastination behaviours. Consequently, older adults who experience depression may be particularly susceptible to procrastination. Conversely, loneliness did not play a significant mediating role. However, when considered in synergy with depression, did significantly predicted procrastination. This suggests that the experience of loneliness in older adults may differ from that of younger adults. By addressing underlying emotional factors and managing procrastination older adults may be able to retain greater control over their lives. Similarly, future research should consider the importance of exploring procrastination in later life and addressing the current knowledge gap within the literature.

CRediT authorship contribution statement

Cormac Monaghan: Conceptualisation, Methodology, Data curation, Formal analysis, Visualisation, Writing – original draft. Writing – review & editing. **Ione Avila-Palencia:** Conceptualisation, Writing – review & editing. **S. Duke Han:** Conceptualisation, Writing – review & editing. **Joanna McHugh Power:** Conceptualisation, Methodology, Formal analysis, Visualisation, Supervision, Writing – review & editing.

CHAPTER 4

Procrastination as a Social Norm Violation: The Role of Domain and Age in Evaluative Judgments

Cormac Monaghan, Fuschia Sirois, Rafael de Andrade Moral, and Joanna McHugh Power

Abstract: Although often conceptualised as an individual self-regulatory failure, procrastination may also function as a social norm violation by conflicting with expectations surrounding productivity, responsibility, and self-regulation. The present study examined whether evaluations of procrastination vary across behavioural domains and age groups. Using a mixed-factorial experimental design, 200 UK adults (18–30 years; 60+ years) recruited through Prolific were randomly assigned to evaluate either procrastination or non-procrastination vignettes across three domains: general, health, and financial. Participants rated each vignette using a negative productivity index and four bipolar adjective pairs reflecting social and self-evaluative judgments. Financial procrastination was judged as more negatively productive and more shameful than general procrastination, while health procrastination was evaluated as more negatively productive and more self-critical than general procrastination. Contrary to expectations, there was little evidence that age moderated these domain-specific evaluations. Overall, the findings indicate that procrastination is perceived as a social norm violation, but that the severity of this evaluation depends on the domain in which the behaviour occurs.

4.1 Introduction

Procrastination involves the voluntary delay of an intended course of action despite expecting negative consequences (Klingsieck, 2013a; Steel, 2007). Although often conceptualised as an individual self-regulatory failure, procrastination also has important interpersonal and social dimensions (J. R. Ferrari et al., 1998; Giguère et al., 2016). Procrastination frequently occurs in socially embedded contexts such as education, employment, and health management (Abbasi & Alghamdi, 2015; Sirois, 2007), where performance is observable and carries implications for others. Consequently, delays in these settings can carry interpersonal implications that extend beyond the individual, shaping how others evaluate the appropriateness, reliability, and responsibility of one's behaviour (Giguère et al., 2016).

One framework for understanding these evaluations is social norms. Social norms are cognitive representations of how others would typically think, feel, or act in a given situation (Giguère et al., 2016). Social norms are oftentimes seen as unwritten rules or expectations. Examples include, saying "please" and "thank you", returning shopping carts, or queuing in lines. However, social norms are not universal and can vary substantially across cultures, social groups, and contexts (Chen-Xia et al., 2023; Filippidis et al., 2026). Behaviours that are considered normative in one setting may be less expected or even absent in another. For instance, norms surrounding queuing in lines or standing on a particular side of an escalator may be more strongly enforced in one country but not another (Filippidis et al., 2026). As such, social norms are not fixed behavioural rules, but rather context-dependent. Nevertheless, across contexts, social norms play a fundamental role in shaping human behaviour by providing standards against which actions are evaluated.

Social norms influence behaviour through several interrelated mechanisms. One important mechanism is social comparison (Giguère et al., 2016). Social comparison theory (Festinger, 1954) posits that individuals evaluate their own behaviour relative to that of others, using perceived norms as benchmarks for what is appropriate. However, norm adherence is not solely driven by comparative processes. They also operate through broader regulatory mechanisms, including perceptions of what most people do (i.e., descriptive norms) and perceptions of what most people approve of (i.e., injunctive norms) (Cialdini & Trost, 1998; Cialdini et al., 1990). Taken together, these processes motivate individuals to align their behaviour with group expectations in order to avoid social disapproval (Cialdini & Trost, 1998). Consequently, behaviours which fall outside these norms are more likely to be noticed and may be perceived as socially incongruent.

Within this framework, procrastination can be conceptualised as a behaviour that frequently violates social norms. Delaying important tasks often conflicts with widely endorsed expectations surrounding productivity, reliability, and effective self-regulation.

However, not all forms of procrastination are equally socially consequential. Norm-based evaluations are most likely to arise in situations where delays disrupt interpersonal expectations or have implications for others (Giguère et al., 2016). For example, an individual who delays completing a work assignment until after the deadline, despite having sufficient time to do so, may be perceived not only as inefficient but also as inconsiderate or unreliable if their delay affects colleagues or collaborators. Over time, repeated violations of such interpersonal expectations may contribute to negative social evaluations and social devaluation by others (J. R. Ferrari et al., 1998; Giguère et al., 2016; Schouwenburg & Lay, 1995).

However, the perception and evaluation of these norm violations are unlikely to be uniform across individuals or cultures and may vary across the lifespan. Younger adults tend to be more responsive to social comparison processes and peer-based evaluation (Koppenborg & Klingsieck, 2022; Nordby et al., 2017). Moreover, procrastination frequently occurs in contexts such as education and early career development (Abbasi & Alghamdi, 2015; Koppenborg & Klingsieck, 2022), where performance and competence are highly visible to others (Bursztyn & Jensen, 2015). As a result, procrastinatory behaviours may be particularly likely to attract social scrutiny among younger adults and consequently carry greater evaluative significance.

In contrast, later life is generally characterised by a more stable sense of self and age-related shifts in motivational priorities (Buunk et al., 2020). According to Socioemotional Selectivity Theory, as we age we increasingly prioritise emotionally meaningful goals and long-term well-being (Carstensen, 2001). Consequently, evaluations of procrastination may become less influenced by peer-based comparison and more influenced by the perceived consequences of delay. This suggests that age differences in evaluations of procrastination may be particularly evident across domains that differ in their relevance to long-term well-being.

These considerations suggest that the relationship between social norms and procrastination is inherently domain-specific. While much research has focused on "general procrastination", procrastination is particularly consequential within the health (Johansson et al., 2023; Monaghan et al., 2025; Sirois, 2007; Sirois et al., 2003, 2023) and financial (Brown & Previtero, 2014; Gamst-Klaussen et al., 2019; Shah & Mukherjee, 2025) domains, where delays can carry meaningful and often long-term consequences. For instance, procrastinating health screenings could result in undetected issues increasing in severity, especially as we get older (Monaghan et al., 2025). Importantly, each of these domains are embedded within distinct normative contexts. In general task contexts, norms emphasising productivity and timely completion are reinforced through social expectations and peer-based evaluation (Cialdini et al., 1990). In contrast, health-related behaviours are guided by social norms that emphasise self-care and taking care of one's health for the future (Ball et al., 2010; Dean & Kickbusch, 1995), while financial behaviours are shaped by norms surrounding personal responsibility (Samuel et al., 2023).

Beyond shaping the domains that individuals prioritise, age-related differences in social comparison and motivational processes may also influence the overall evaluation of procrastination. Younger adults are generally more sensitive to peer evaluation and social comparison (Koppenborg & Klingsieck, 2022; Nordby et al., 2017), whereas older adults tend to report greater emotional regulation and self-compassion (Buunk et al., 2020; Carstensen, 2001). Consequently, procrastination may carry different psychological meanings across age groups, even when it occurs in the same context. Younger adults may be more likely to interpret procrastination as reflecting some form of personal inadequacy or failure, whereas older adults may adopt a less self-critical perspective.

Building on this framework, we propose that procrastination is not uniformly perceived as a norm violation, but that its evaluation depends jointly on the domain in which it occurs and the age of the individual evaluating the behaviour. Specifically, we expect procrastination to be i) evaluated more negatively in domains associated with long-term responsibility and consequential outcomes (i.e., health and finance) than in more general task contexts. Furthermore, we expect that ii) these domain effects will be moderated by age, such that older adults will judge both health and financial procrastination more harshly than younger adults. Finally, we expect that iii) in general older adults and younger adults will differ in their evaluations of the procrastination scenarios.

4.2 Methods

4.2.1 Study design

This study employed a mixed-factorial experimental design to elicit norms relating to traits across three life domains (general, health, financial). Specifically, the norms were elicited using vignettes to enable participants to imagine themselves as either a procrastinator or a non-procrastinator. The full text of all vignettes is provided in Appendix A. The study employed a 2 (vignette condition: procrastination vs. non-procrastination; between-subjects) × 2 (age group: younger adults $18 - 30$ vs. older adults $60+$; between-subjects) × 3 (domain: general, health, financial; within-subjects) mixed factorial design.

Participants were randomly assigned to read either the procrastination or non-procrastination vignettes, with allocation balanced across conditions (vignette condition, age group, and gender). Each participant read the three vignettes in order to facilitate within-person comparisons of the ratings of each of the three domains. The general vignette was always presented first, while the health and financial vignettes were then presented in randomized order to control for sequence effects. Additionally, two attention checks (i.e., "please select strongly agree") were randomly presented within the study to ensure data quality. Participants remained blind to the study's hypotheses and to the between-subjects manipulation (i.e., age).

4.2.2 Participants

Data were collected via the crowdsourcing platform Prolific, targeting two age groups of UK-based adults: younger adults (18–30 years) and older adults (60+ years). A total of 200 participants were recruited, yielding 600 vignette evaluations (3 evaluations per participant). Of these 200 participants 51% ($n = 101$) were female. Participants were compensated £2 for on average 10 minutes of participation, consistent with Prolific's fair payment guidelines.

Participants who failed the attention checks or had excessive missing data (i.e., $>$ 80% missing) were excluded from analyses and additional participants were gathered until the target quota was met. Ethical approval for the study was obtained from Institutional Research Ethics Boards at Durham University.

4.2.3 Materials and procedure

Vignette stimuli

Participants were presented with three short, domain-specific vignettes wherein they were instructed to imagine themselves as the type of person described in the vignettes. In the procrastination condition, participants imagined themselves as someone who *often unnecessarily delays* important tasks despite negative consequences. In the non-procrastination condition, they imagined themselves as someone who *rarely delays* tasks and typically acts promptly. Each vignette included realistic examples (e.g., booking a medical check-up or paying a bill) to encourage vivid and self-relevant mental simulation. Following the presentation of each vignette, participants were first asked to rate how "easy or difficult it was to imagine themselves" in the scenario (1 = very easy; 5 = very difficult) and secondly asked to self-rate how "they would feel about themselves" using a set of bi-polar adjectives (described below).

Social norm evaluations

Participants rated each vignette using ten bipolar adjective pairs reflecting social and productivity-related norms (e.g., *careful–careless*, *industrious–lazy*), which were selected from both a study by Robinson et al. (2016) and an unpublished undergraduate thesis conducted by a student of the second author (Markham & Sirois, n.d.). Each of the adjective scores ranged from 1 - 7, with higher scores indicating a greater evaluation of the negative adjective. Six of these adjectives formed a negative productivity index (Markham & Sirois, n.d.), averaged such that higher scores indicated a stronger evaluation of negative productivity. The remaining four adjective pairs were analysed separately (*future-oriented - present-oriented*, *anxious–relaxed*, *admirable-shameful*, and *self-compassionate – self-critical*).

4.2.4 Data analysis

All data analysis was carried in R (R Core Team, 2025). Given that multiple vignette ratings were nested within participants, we used multilevel models with random intercepts included to account for within-participant variability. Let $i = 1, \ldots, N$ represent participants and $j = 1, \ldots, n_i$ represent observations within participant. For each outcome, the linear predictor was defined as:

$$\eta_{ij} = \mathbf{x}_{ij}^\top \boldsymbol{\beta} + u_i$$

where $\mathbf{x}_{ij}$ is a vector of fixed-effect predictors (in this case, vignette scenario, vignette domain, and age group), $\boldsymbol{\beta}$ is the corresponding vector of regression coefficients, and $u_i \sim \mathcal{N}(0, \sigma_u^2)$ represents participant-specific random intercepts.

Outcome 1: Negative productivity index

The negative productivity index was measured by averaging six of the adjective pairs and as such was on a continuous scale bounded between 1 – 7. Because standard linear models assume unbounded normally distributed residuals, applying a Gaussian model to bounded data may lead to biased estimates and spurious predictions (S. Ferrari & Cribari-Neto, 2004). To address this, the index was rescaled to an open unit interval ($y_{ij} \in \{0, 1\}$) and modelled using a beta distribution, with the `glmmTMB` package (McGillycuddy et al., 2025). Such formulation allows for both the modelling of the mean μ_{ij} and dispersion ϕ_{ij} such that:

$$\begin{aligned} y_{ij} &\sim \text{Beta}(\mu_{ij}, \phi_{ij}) \\ \text{logit}(\mu_{ij}) &\sim \eta_{ij} \\ \log(\phi_{ij}) &= \mathbf{z}_{ij}^\top \boldsymbol{\gamma} \end{aligned}$$

where $\mathbf{z}_{ij}$ is a vector of predictors (in this case, vignette domain) and $\boldsymbol{\gamma}$ are regression coefficients.

Outcome 2: Adjective ratings

In contrast, the individual adjectives were measured on an ordinal Likert scale ranging from 1 – 7. Rather than treating these ordinal responses as continuous, cumulative link mixed models were fitted using the `ordinal` package (Christensen, 2025), which appropriately accounts for the ordered nature of the data without assuming equal spacing between scale points. Let $Y_{ij} \in \{1, \ldots, 7\}$ denote the ordinal response. A cumulative link mixed model was specified such that:

$$\Pr(Y_{ij} \leq k) = \text{logit}^{-1}(\theta_k - \eta_{ij}), \quad k = 1, \ldots, 6$$

where θ_k are ordered threshold parameters.

Model interpretation and follow-up analyses

To facilitate interpretation, estimated marginal means and pairwise contrasts were derived from the fitted models using the `emmeans` package (Lenth & Piaskowski, 2026). Additionally, to account for the multiple comparisons, all resulting p-values were adjusted using a Hochberg correction (S. Y. Chen et al., 2017).

For the negative productivity index (beta regression model) both the estimated marginal means and resulting pairwise contrasts were likewise computed on the response scale, allowing for the effects to be interpreted as differences in predicted scores between conditions. For the cumulative link models, estimated marginal means and resulting pairwise contrasts were back-transformed from the logit scale to the original 1 – 7 response scale. As such, reported values represent predicted mean ratings and differences on the original Likert scale.

4.3 Results

Participants ($N = 200$) were evenly distributed across age groups, with 100 younger adults and 100 older adults. The mean age for the younger adults was $M = 24.49$ ($SD = 3.49$) while for older adults the mean age was $M = 65.1$ ($SD = 4.53$). Additionally, mean ratings for both the negative productivity index and individual adjective pairs are presented in Figure 4.1. Finally, full demographic information for the study sample is presented in Table A.1.

4.3.1 Negative productivity index

The negative productivity index was analysed using a beta mixed-effects regression model with a logit link function. The model included three factors: *scenario* (procrastination and non-procrastination), *domain* (general, health, and financial), and *age group* (younger adult and older adult). Likelihood ratio tests indicated that including both the *scenario* × *domain* interaction, ($\chi^2(2) = 42.30; p < .001$), and the *scenario* × *age group* interaction, ($\chi^2(1) = 7.79; p = .005$), significantly improved model fit, whereas the *domain* × *age group* interaction did not ($\chi^2(2) = 0.99; p = .63$). Full model results are presented in Table A.2.

H1: Domain differences in evaluations of procrastination

The results for the negative productivity index were consistent with our hypothesis that domain differences would be present between both the procrastination and non-procrastination scenarios (see Figure 4.2). Within the non-procrastination scenarios, negative productivity evaluations were generally low across all domains. Within this scenario, the financial domain ($M = 0.11$ [0.09; 0.13]) was associated with lower perceived negative productivity than both the general ($M = 0.13$ [0.11; 0.16]; $p =$

.026) and health ($M = 0.16$ [0.14; 0.18]; $p < .001$) domains. Additionally, the health domain was rated slightly more negatively than the general domain ($p = .048$).

More importantly, in the procrastination scenario, negative productivity evaluations were substantially higher across all domains. Procrastination in the financial domain ($M = 0.68$ [0.65; 0.71]) was associated with the highest levels of negative productivity, exceeding both the general ($M = 0.60$ [0.57; 0.63]; $p < .001$) and slightly the health ($M = 0.64$ [0.61; 0.67]; $p = .001$) domains. Similarly, procrastination in the health domain was evaluated as more negatively productive than the general domain ($p = .034$).

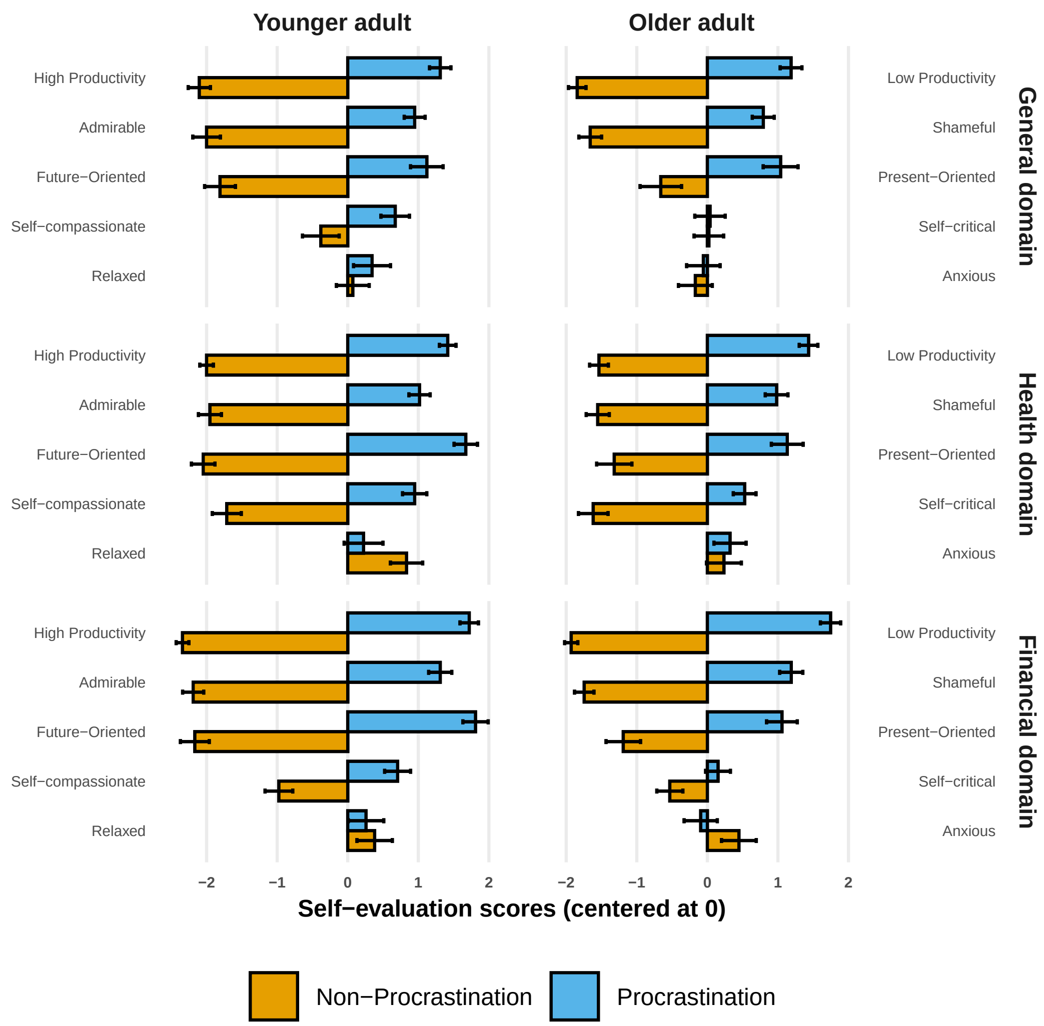

Figure 4.1: *Mean self-evaluation scores for the negative productivity index and each adjective pair in the procrastination and non-procrastination condition, across both domain and age group. Self-evaluations were made on a 1-7 point Likert scale and were rearranged on a -3 to 3 scale for illustrative purposes. Error bars represent the standard error of the mean.*

H2: Age differences in domain evaluations of procrastination

Contrary to our hypothesis that age differences would be present in the domain evaluations of procrastination, there was little evidence that evaluations of each procrastination domain differed between younger and older adults. As mentioned, the likelihood ratio tests indicated that the *domain* × *age group* interaction had no significant effect within the model and inspection of the model results revealed non-significant effects for all domains (see Table A.2).

H3: Age differences in evaluations of procrastination

Finally, contrary to our hypothesis that age differences would be present in the overall evaluations of procrastination, there was little evidence that evaluations of procrastination itself differed between younger and older adults (see Figure 4.2). When evaluating the procrastination scenarios, both older adults ($M = 0.64$ [0.60; 0.69]) and younger adults ($M = 0.64$ [0.61; 0.69]) reported similar evaluations of negative productivity ($p = 0.864$). Interestingly however, when evaluating the non-procrastination scenarios, older adults ($M = 0.16$ [0.14; 0.18]) reported significantly higher levels ($p < 0.001$) of negative productivity than younger adults ($M = 0.11$ [0.09; 0.13]).

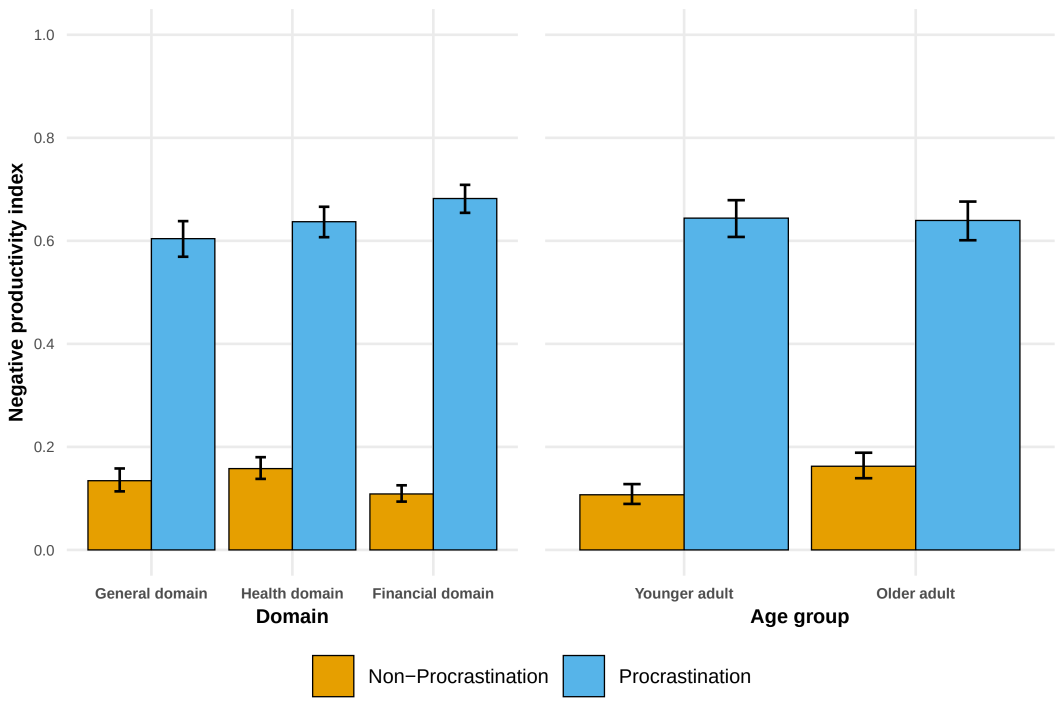

Figure 4.2: *Estimated marginal means for the negative productivity index as a function of the vignette scenario and domain (left panel), as well as the vignette scenario and age group (right panel).*

4.3.2 Adjective ratings

Each of the four individual adjective pairs were analysed using a cumulative link mixed model. Similar to the negative productivity index, the model included three factors: *scenario* (procrastination and non-procrastination), *domain* (general, health, and financial), and *age group* (younger adult and older adult). For all adjectives pairs (except *relaxed - anxious*) likelihood ratio tests indicated that both the *scenario* × *domain* interaction ($\chi^2(2) \in \{9.68 - 71.37\}; p < 0.001$) and the *scenario* × *age group* interaction ($\chi^2(2) \in \{4.00 - 13.74\}; p \in \{0.0002 - 0.045\}$) significantly improved model fit, whereas the *domain* × *age group* did not ($\chi^2(2) \in \{0.21 - 3.44\}; p \in \{0.179 - 0.912\}$). For the *relaxed - anxious* adjective pair, none of the interaction terms improved the model fit, and while an additive model was retained for interpretation, none of the adjective results were in line with our hypotheses. Full model results are presented in Table A.3.

H1: Domain differences in evaluations of procrastination

For several of the adjective pairs, significant domain effects were present depending on whether participants evaluated a procrastination or non-procrastination scenario (see Figure 4.3).

For the *admirable – shameful* adjective, non-procrastination scenarios were rated as uniformly admirable across domains (all $p \geq .244$). In contrast, the procrastination scenarios were rated as substantially more "shameful", with the financial domain receiving the most negative evaluations ($M = 5.26$ [5.03; 5.49]), followed by the health ($M = 5.01$ [4.79; 5.24]), and general ($M = 4.86$ [4.64; 5.09]) domain. Pairwise comparisons of the marginal means indicated that financial contexts were evaluated significantly more shamefully than general contexts ($p = .001$), with a marginal difference between financial and health contexts ($p = .050$).

Results for the *future-oriented – present-oriented* adjective provided weaker evidence for domain specific evaluations. Within the non-procrastination scenarios, both health ($M = 2.10$ [1.77, 2.42]) and financial ($M = 2.08$ [1.76, 2.42]) domains were rated as significantly more "future-oriented" than in the general domain ($M = 2.59$ [2.22, 2.97]; both $p = .011$). In contrast, no significant differences (all $p \geq 0.083$) were noted in the procrastination scenarios with the general ($M = 5.28$ $[4.92 - 5.65]$), health ($M = 5.61$ $[5.30 - 5.92]$) and financial ($M = 5.64$ $[5.33 - 5.95]$) domains being rated similarly.

For the *self-compassionate – self-critical* adjective, the results for the non-procrastination scenarios indicated the health domain was associated with the most "self-compassionate" evaluation ($M = 2.19$ [1.19; 2.48]), followed by the financial ($M = 3.32$ [2.92; 3.53]) and general ($M = 3.81$ [3.50; 4.12]) domains. Subsequent pairwise comparisons of the marginal means indicated that all the domains significantly differed from one another (all $p < 0.001$). In contrast, for the procrastination scenarios, the health domain was associated with the most "self-critical" evaluations ($M = 4.75$ [4.49; 5.02]), followed by the financial ($M = 4.44$ [4.18; 4.71]) and general ($M = 4.39$ [4.11; 4.66]) domains. Pairwise comparisons indicated that health domain was evaluated as significantly more self-critical than general contexts ($p = 0.043$), whereas differences between financial and general ($p = 0.703$) and between financial and health domains ($p = 0.067$) were both not significant.

Overall, the strongest domain-specific differences were present for both the evaluations of "shamefulness" and "self-criticism", with procrastination in the financial and health domains generally receiving more negative evaluations than procrastination in the general domain.

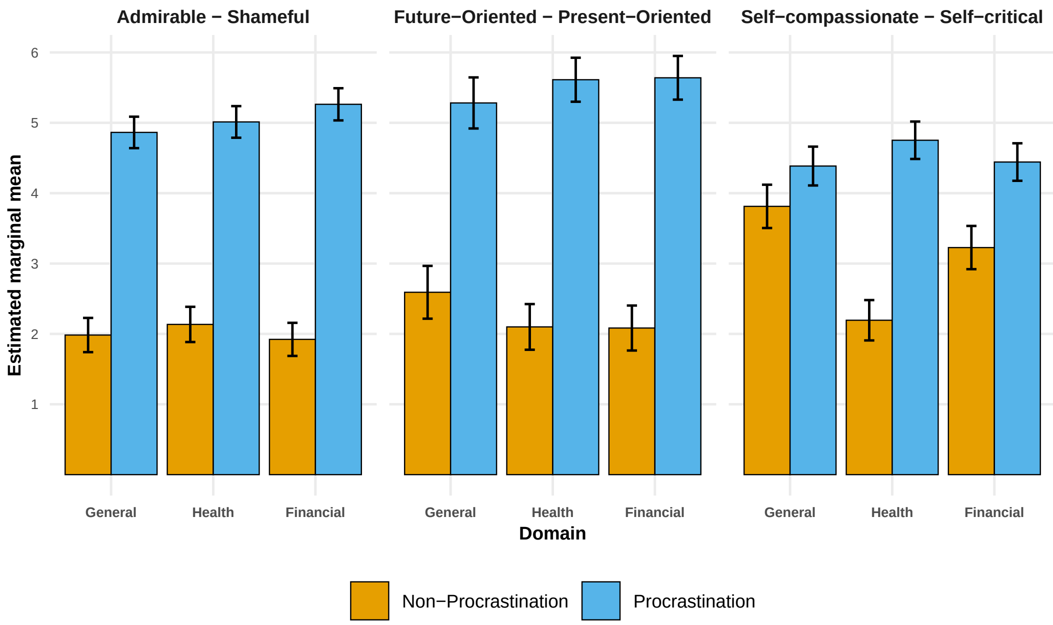

Figure 4.3: *Estimated marginal means for three of the adjective pairs as a function of the vignette scenario and domain. Error bars represent 95% confidence intervals.*

H2: Age differences in domain evaluations of procrastination

Similar to the negative productivity index, there was little evidence that adjective evaluations of each procrastination domain differed between younger and older adults. As mentioned, the likelihood ratio tests indicated that the *domain* × *age group* interaction had no significant effect within the model and inspection of the model results revealed non-significant effects for all domains (see Table A.3).

H3: Age differences in evaluations of procrastination

With regard to our hypothesis that age differences would be present in the overall evaluations of procrastination, there was weak evidence present for differences between younger and older adults (see Table A.3 and Figure 4.4).

For the *admirable – shameful* adjective, younger adults evaluated the non-procrastination scenarios as more "admirable" than older adults ($M = 1.79$ [1.51, 2.06] vs. $M = 2.24$ [1.96, 2.53]; $p = .024$). However, no age differences were observed between younger and older adults when evaluating the procrastination scenarios ($M = 5.09$ [4.83, 5.35] vs. $M = 5.00$ [4.73, 5.27]; $p = .631$).

A similar set of results were noted for the *future-oriented – present-oriented* adjective. Younger adults evaluated the non-procrastination scenarios as more "future-oriented" than older adults ($M = 1.76$ [1.43, 2.09] vs. $M = 2.76$ [2.31, 3.21]; $p < .001$). Again, no such differences were noted in the procrastination scenarios with younger and older adults reporting similar evaluations ($M = 5.75$ [5.39, 6.11] vs. $M = 5.27$ [4.86, 5.69]; $p = .089$).

For the *self-compassionate – self-critical* adjective, no such age differences were noted between younger and older adults in the non-procrastination scenario ($M = 2.90$ [2.56, 3.24] vs. $M = 3.26$ [2.93, 3.58]; $p = .134$). However, younger adults evaluated procrastination scenarios as significantly more "self-critical" than older adults ($M =$ 4.82 [4.53, 5.12] vs. $M = 4.23$ [3.93, 4.53]; $p = .005$).

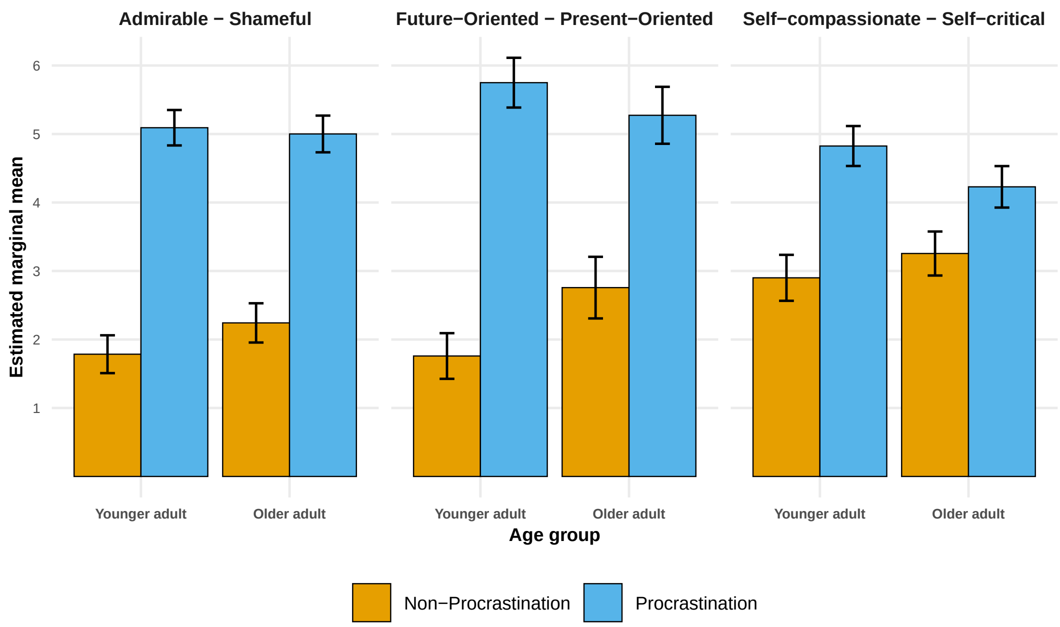

Figure 4.4: *Estimated marginal means for three of the adjective pairs as a function of the vignette scenario and age group. Error bars represent 95% confidence intervals.*

4.4 Discussion

The current study examined whether procrastination is perceived as a violation of social norms, and whether such evaluations depend on both the domain in which the behaviour occurs and the age of the individual making the evaluation. Overall, three key findings emerged from the analysis. First, procrastination was repeatedly associated with more negative self-evaluations relative to non-procrastination scenarios, supporting its conceptualisation as a norm-violating behaviour (Giguère et al., 2016). Second, these evaluations varied across domains, with procrastination in the financial and health domains generally attracting stronger negative evaluations than procrastination in the general domain. Third, contrary to expectations, there was little evidence that domain-specific evaluations differed between younger and older adults. However, younger adults viewed procrastination itself (irrespective of domain) more self-critically than older adults. Together, these findings suggest that procrastination is understood not only as a self-regulatory failure but also as a socially evaluated behaviour whose meaning depends on context.

Consistent with theoretical accounts of social norms (Cialdini & Trost, 1998; Cialdini et al., 1990; Giguère et al., 2016), procrastination was associated with more negative evaluations across nearly all the bi-polar adjectives. Participants who imagined themselves procrastinating reported significantly higher negative productivity, shamefulness, self-criticism, and present-orientation. From a social comparison perspective (Festinger, 1954), procrastination likely signals a deviation from perceived normative behaviour, thereby eliciting negative self-evaluation. Importantly, these effects were observed even though participants were asked to imagine themselves in hypothetical scenarios, suggesting that the normative meaning of procrastination is deeply internalised rather than requiring real-world consequences.

However, the perceived severity of procrastination as a norm violation depended on the domain in which it occurred. Although procrastination was evaluated negatively across all domains, its effects were strongest in the financial domain, followed by the health domain, and then weakest in the general domain. This pattern was consistent across the negative productivity index as well as key adjective pairs such as *admirable - shameful* and *self-compassionate – self-critical*.

One explanation for these domain differences is that financial and health behaviours are embedded within particularly strong normative expectations. Financial behaviours are closely tied to norms of responsibility, planning, and future-oriented decision-making (Samuel et al., 2023; Shah & Mukherjee, 2025). Procrastination in this domain may be especially salient because it signals a failure to uphold socially valued standards with clear long-term consequences. Similarly, health-related procrastination has been widely linked to adverse outcomes, such as reduced well-being and poorer health behaviours (Johansson et al., 2023; Monaghan et al., 2025; Sirois, 2007; Sirois et al., 2003, 2023). Consequently, delaying health-related actions may be viewed as particularly problematic because it conflicts with norms surrounding self-care and long-term well-being. In contrast, general procrastination may be perceived as less consequential, resulting in comparatively weaker evaluations. This may be because, norm violations are most salient when they disrupt shared expectations or carry visible consequences (Giguère et al., 2016). In the present study, financial and health scenarios likely made these consequences more explicit, thereby amplifying the perceived severity of the violation.

Contrary to our expectations however, there was no evidence that these domain evaluations of procrastination differed between younger and older adults. Across all the social norm adjectives, evaluations of each of the procrastination domains were broadly similar between younger and older adults. Despite sharing age-related differences in motivational priorities and social goals, younger and older adults appeared to share a broad consensus regarding the social undesirability of procrastination. Such results suggest that norms surrounding procrastination may be relatively stable across adulthood, even if the reasons individuals seek to avoid procrastination change with age.

One notable exception was in the evaluations of self-criticism. Younger adults viewed procrastination (irrespective of domain) as significantly more self-critical than older adults. In contrast, all other evaluations were largely comparable across both age groups. This age difference suggests that while there is shared consensus between younger and older adults regarding the external evaluation of procrastination (e.g., reduced productivity or increased shamefulness), they may differ in how they interpret its internal, self-reflective implications. Younger adults are generally more responsive to social comparison processes and peer-based evaluation (Koppenborg & Klingsieck, 2022; Nordby et al., 2017). As such, they may be more likely to internalise procrastination as a sense of failure and respond with heightened self-criticism. On the other hand, older adults may adopt a more emotionally regulated or self-compassionate perspective, which not only reduces procrastination (Sirois, 2014b) but also may reduce any internalised judgements about procrastination itself, offering an interesting avenue of future research.

Taken together, these findings extend existing understandings of procrastination by demonstrating that procrastination is not merely a private self-regulatory failure but also a socially evaluated behaviour. The results further suggest that the social meaning of procrastination depends less on the age of the individual and more on the domain or context in which the delay occurs. Behaviours that threaten long-term health or financial well-being appear particularly likely to attract negative evaluations, highlighting the importance of considering the social and contextual dimensions of procrastination alongside its individual determinants.

From an applied perspective, these findings suggest that interventions aimed at reducing procrastination may benefit from leveraging domain-specific normative cues. Highlighting the long-term consequences of procrastination in financial and health contexts at any age may strengthen its perceived normative relevance and, in turn, motivate behavioural change. At the same time, the observed age difference observed for self-criticism suggest that interventions may need to account for developmental differences in how procrastination is interpreted. For younger adults, approaches that address potential self-criticism and social comparison processes may be particularly beneficial, whereas for older adults, emphasising well-being and long-term outcomes may be more effective.

In conclusion, this study provides evidence that procrastination functions as a meaningful social norm violation, but one whose severity is not fixed. Rather than being uniformly evaluated across situations, procrastination is interpreted through the lens of the domain in which it occurs and the consequences associated with delay. Although younger and older adults showed largely similar evaluative patterns, procrastination in financial and health contexts was consistently judged more negatively than procrastination in general contexts. These findings advance our understanding of procrastination beyond an individual self-regulatory failure, highlighting its role as a socially embedded behaviour shaped by shared norms, contextual consequences, and developmental processes.

4.4.1 Limitations and future research

Several limitations to this study should be acknowledged. First, the use of vignette-based scenarios may limit ecological validity, as imagined self-evaluations may not fully reflect real-world behaviour. Second, the cross-sectional design prevents strong conclusions about developmental change, and future longitudinal work would be necessary to disentangle age and cohort effects.

Future research could build on these findings by examining individual differences in norm sensitivity, such as trait procrastination or social comparison orientation, as potential moderators of these effects. Additionally, linking these evaluative patterns to actual behavioural outcomes would provide a more comprehensive understanding of how perceived norm violations translate into real-world consequences.

4.4.2 Conclusions

In conclusion, the present study demonstrates that procrastination is widely perceived as a violation of social norms, but that the strength and nature of this evaluation depend on the domain in which it occurs, and in some unique cases, the age of the individual making the evaluation. These findings underscore the importance of adopting a context-dependent and lifespan-informed perspective when examining the social meaning of procrastination and contribute to a broader understanding of how social norms shape the evaluation of self-regulatory behaviour.

CRediT authorship contribution statement

Cormac Monaghan: Conceptualisation, Methodology, Data curation, Formal analysis, Visualisation, Writing – original draft. Writing – review & editing. **Fuschia Sirois:** Conceptualisation, Resources, Formal analysis; Data curation, Supervision. **Rafael de Andrade Moral:** Formal analysis; Writing – review & editing. **Joanna McHugh Power:** Writing – review & editing.

CHAPTER 5

Do Perceptions of Remaining Life Shape Procrastination? Evidence from Latent Class and Bayesian Models

Cormac Monaghan, Ciarán Gartlan, Rafael de Andrade Moral, and Joanna McHugh Power

Abstract: Procrastination is linked to temporal orientation, with stronger future orientation typically associated with lower procrastination. However, it remains unclear whether subjective remaining life is associated with procrastination. This study examined associations between temporal orientation, subjective remaining life, and procrastination in a sample of 140 adults aged 18–77. Latent class analysis identified two temporal profiles: a high future orientation group (46.43%) and a neutral orientation group (53.37%). Bayesian regression indicated that higher subjective remaining life was likely associated with greater procrastination, although the effect was modest. In contrast, future orientation showed a clear negative association with procrastination. These findings suggest that subjective remaining life may function as a contextual factor, whereas temporal orientation represents a more robust correlate of procrastination.

5.1 Introduction

Procrastination, the voluntary and irrational delay of intended actions despite expecting to be worse off for the delay (Klingsieck, 2013b; Sirois & Pychyl, 2013), represents a form of self-regulatory failure with well-documented costs for psychological well-being, health, and goal attainment (Sirois & Pychyl, 2016b; Stead et al., 2010). Although often studied as a relatively stable individual difference (Meng et al., 2024) procrastination is inherently temporal (Borawski et al., 2026; Sirois & Pychyl, 2013). It involves repeated decisions to prioritise the needs of the present self over the needs of the future self (Sirois & Pychyl, 2013). As such, procrastination has been previously conceptualised as a form of temporal misalignment (Díaz-Morales & Ferrari, 2015; Díaz-Morales et al., 2008; J. R. Ferrari & Díaz-Morales, 2007b).

This temporal misalignment may be particularly consequential in older adulthood. Whereas delays in youth often involve reversible costs, procrastination in later life can carry more enduring consequences for health, financial security, and autonomy (Monaghan et al., 2025; Shah & Mukherjee, 2025). Additionally, ageing coincides with systematic changes in how individuals perceive and relate to time. Chronic procrastinators report feeling less connected to their future self (Sirois, 2014a; Sirois & Pychyl, 2016b; Specter & Ferrari, 2000) and engage less in future-oriented planning (J. R. Ferrari & Díaz-Morales, 2007b), suggesting that individual differences in temporal cognition may play a central role in sustaining procrastinatory behavior.

One mechanism thought to maintain procrastination is unrealistic optimism regarding the future self. Procrastinators tend to assume that the future self will be more motivated, disciplined, or capable of completing delayed tasks (Sirois & Pychyl, 2016b). When these expectations fail to materialise, the resulting gap between intention and action generates negative affect, including guilt, frustration, and self-blame (A. Blunt & Pychyl, 2005; Fee & Tangney, 2000; B. McCown et al., 2012), reinforcing the cycle of delay. Understanding the factors that influence this temporal disconnection is therefore critical for explaining why individuals continue to delay action in ways that undermine their long-term well-being.

5.1.1 Consideration of future consequences

A central construct for measuring individual differences in temporal motivation is consideration of future consequences (CFC; Strathman et al., 1994). CFC measures the extent to which individuals weigh future rewards versus immediate rewards when making decisions (Rebetez et al., 2016). Individuals high in CFC are more likely to prioritise delayed but meaningful rewards, engage in goal-directed behavior, and invest effort in outcomes that benefit their long-term welfare (Boyd & Zimbardo, 2012; Milfont & Schwarzenthal, 2014). Conversely, those low in CFC tend to focus on short-term gratification and impulsive action (Joireman et al., 2005).

Consistent with this framework, procrastination is robustly and negatively associated with CFC (Rebetez et al., 2016; Sirois, 2004, 2014a). Individuals who place greater weight on future consequences tend to plan ahead and persist in aversive tasks, whereas those low in CFC are more prone to avoidance and delay. Meta-analytic evidence (Sirois, 2014a) across 14 independent samples, including three studies directly assessing CFC, reports a reliable negative association between procrastination and future time perspective ($\bar{r} = -0.45, p < 0.001$). These findings underscore the importance of temporal orientation as a dispositional correlate of procrastination.

However, CFC captures "*how strongly individuals value future outcomes*", not "*how much future time they believe they have*". Broader perceptions of future time may therefore provide an important contextual frame within which CFC operates. In particular, beliefs about one's remaining lifetime may shape the motivational salience of future consequences and, by extension, the extent to which future-oriented dispositions translate into action.

5.1.2 Subjective remaining life

According to Socioemotional Selectivity Theory (Carstensen, 2001), individuals continuously monitor their perceived time left to live (i.e., their subjective remaining life) and adjust their goals and motivational priorities accordingly. When individuals perceive time as expansive, they are more likely to focus on knowledge acquisition, growth, and long-term rewards. However, as this time begins to shorten individuals tend to prioritise emotionally meaningful and immediate experiences (Kaftan & Freund, 2018).

These shifts have implications for procrastination. An expansive time horizon may encourage long-term planning and investment (Kornadt et al., 2018), but it may also reduce perceived urgency for completing aversive or obligatory tasks (i.e., tasks most susceptible to procrastination). In contrast, a limited time horizon may heighten urgency and promote more efficient allocation of effort (Hasmanová Marhánková & Soares Moura, 2024), potentially reducing delay. Thus, subjective remaining life may exert both facilitating and inhibiting influences on procrastination, depending on how future outcomes are weighted.

5.1.3 Subjective remaining life and consideration of future consequences

Despite their overlap, subjective remaining life and CFC have not been examined together in the context of procrastination. Importantly, the two constructs capture distinct aspects of temporal cognition. Subjective remaining life measures "how much time is believed to remain", whereas CFC measures "the degree to which future outcomes influence present behavior". These dimensions may interact in shaping self-regulatory decisions.

For example, individuals who perceive a long remaining lifetime but place little weight on future consequences may be especially prone to procrastination, viewing delayed action as inconsequential given ample time ahead. By contrast, those with a similarly expansive time horizon but high CFC may to plan and act in accordance with long-term goals. Conversely, those who perceive a short remaining lifetime but with high CFC may reduce procrastination by amplifying both urgency and commitment to goal fulfilment. In this way, subjective remaining life may define the temporal context within which dispositional future orientation influences procrastinatory behavior.

5.1.4 The present study

The present study examines how subjective remaining life relates to procrastination and whether this association is moderated by individual differences in consideration of future consequences. We hypothesised that individuals with a longer subjective remaining life would report greater procrastination, reflecting a reduced sense of temporal urgency. Furthermore, we expected that this relationship would depend on individuals' level of CFC: those low in CFC would show a stronger positive association between subjective remaining life and procrastination, while those high in CFC would exhibit a weaker or null relationship due to their stronger future-oriented motivation.

5.2 Method

5.2.1 Design and participants

This is an analysis of cross-sectional survey data recruited through both convenience and snowball sampling methods. The initial sample comprised 229 respondents. However, 90 respondents were excluded from analysis due to either high levels of missing data across all variables ($\geq$ 80% missingness; $n = 87$) or missing data in key covariates ($n = 3$). As such, the final analytic sample comprised 140 respondents.

5.2.2 Measures

Predictor: Consideration of future consequences

Consideration of future consequences (CFC) was assessed using the CFC-14 scale (Joireman et al., 2012). This scale consists of two 7-item subscales: CFC-Future (CFC-F) and CFC-Immediate (CFC-I). Items are measured on a 7-point Likert scale ranging from 1 (not at all like me) to 7 (very much like me). Subscale scores (range: $7 - 49$) were computed by summing the respective items, and a total CFC score (range: $14 - 98$) was calculated by reverse-scoring CFC-I items and combining them with CFC-F. Within this sample, the reliability of both subscales was strong, with Cronbach's α values of 0.85 for CFC-F and 0.81 for CFC-I. An example item from the CFC-F subscale includes, "I am willing to sacrifice my immediate happiness or well-being in order to achieve future outcomes", while an example item from the CFC-I subscale includes, "I think that sacrificing now is usually unnecessary since future outcomes can be dealt with at a later time".

Predictor: Subjective remaining life

Subjective remaining life (SRL) was operationalised following established approaches in lifespan and ageing research (Kornadt et al., 2018). SRL was calculated as the difference between participants' subjective life expectancy and their current age, with higher values indicating a perception of having more remaining lifetime. Subjective life expectancy was assessed using two questions adapted from the Healthy AGeing in Scotland study (Douglas et al., 2018). Participants first estimated the average life expectancy of others their age and sex, then provided their own life expectancy.

Outcome: Procrastination

Procrastination was measured using the Pure Procrastination Scale (PPS; Steel, 2010). Each item is measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A composite procrastination score (range: $12 - 60$) is calculated by summing each item. In this sample, the PPS demonstrated strong reliability with a Cronbach's α score of 0.90. An example of an item from the scale includes "I delay making decisions until it's too late".

Covariates

Three covariates, sex, presence of a chronic illness, and self-rated general health were included in the analysis based on a priori knowledge of their associations with procrastination and self-regulatory behaviour (Sirois & Kitner, 2015; Steel & Ferrari, 2013). All covariates were dichotomized such that: sex (0 = male, 1 = female), chronic illness (0 = absent, 1 = present), and self-rated general health (0 = poor health, 1 = good health).

5.2.3 Procedure

The study was approved by the departmental review board at Maynooth University. Participation in the study was both voluntary and anonymous. Participants provided informed consent before completing the online survey, which was administered via Qualtrics, ensuring secure data handling through encryption and compliance with data protection standards.

5.2.4 Data Analysis

All data analysis was carried out using R (version 4.5.2; R Core Team, 2025).

Latent class analysis

A latent class analysis (LCA) was conducted to identify unobserved heterogeneity in respondents' temporal orientation based on their response patterns to the CFC-14 item. LCA is a model-based clustering approach for categorical data that assumes the observed multivariate distribution arises from a finite mixture of latent subpopulations, each characterised by distinct response probabilities across the observed indicators (Kaplan, 2008; Sinha et al., 2021).

To facilitate estimation and address insufficient degrees of freedom associated with the full seven-point response scale, CFC-14 items were trichotomised prior to analysis (see Equations (A.1) to (A.3) in the Appendix). Responses ranging from 1 – 3 (representing negatively worded answers) were recoded as 1. The response 4, representing neither agreement nor disagreement was recoded as 2. Finally, responses ranging from 5 – 7 (representing positively worded answers) were recoded as 3.

LCA was performed using the `PoLCA` package (Linzer & Lewis, 2011). A series of models with a number of latent classes ranging from $R \in \{1, 2, 3, 4\}$ were fit. Following recommendations to mitigate convergence on local maxima (Meijer et al., 2022), each model was estimated with a maximum of 3,000 iterations and 100 random starting values. Model fit was assessed primarily by the Bayesian Information Criterion (BIC), which has been shown to perform well in latent class settings (Linzer & Lewis, 2011; Van Lissa et al., 2024), alongside normalised entropy as an index of classification certainty. Entropy values exceeding 0.80 were interpreted as indicating adequate separation between latent classes (Meijer et al., 2022). Rather than assigning individuals to classes using modal posterior probabilities, posterior class membership probabilities were retained. This approach explicitly accounts for classification uncertainty and avoids bias associated with treating latent class membership as an observed variable (see Asparouhov and Muthén, 2014).

Bayesian regression

Associations between temporal orientation, subjective remaining life, and procrastination were examined using Bayesian regression models implemented in JAGS via the `R2jags` package (Yu-Sung & Masanao, 2024). Posterior class probabilities from the LCA were used to propagate latent class uncertainty. Specifically, each participant's class membership was treated as a Bernoulli variable with success probability equal to their posterior probability of being in the non-reference class (π_i). This allowed the model to integrate uncertainty in class assignment directly into the regression.

The regression model included latent class membership, subjective remaining life (mean-centred), and their interaction as predictors, along with sex, self-rated general health, and chronic illness status as covariates. Statistically, let Y_i be the observed response variable for individual i. We assume the following:

$$\begin{aligned} y_i &\sim \mathcal{N}(\mu_i, \sigma^2) \\ \mu_i &\sim \beta_0 + \beta_1 \text{Class}_i + \beta_2 \text{SRL}_i + \beta_3 \text{Class}_i \times \text{SRL}_i + \\ &\quad \beta_4 \text{Sex}_i + \beta_5 \text{General Health}_i + \beta_6 \text{Chronic Illness}_i \\ \text{Class}_i &\sim \text{Bernoulli}(\pi_i) \end{aligned}$$

Weakly informative normal priors were placed on all regression coefficients, and a half-t prior was specified for the residual standard deviation.

$$\beta_k \sim \mathcal{N}(0, 100^2), \quad k = 0, \ldots, 6, \quad \sigma \sim \text{half-t}(0, 100, 1).$$

5.3 Results

Our final analytic sample comprised 140 respondents with the following age distribution: 18-24 ($n = 48$), 25-44 ($n = 46$), and 45+ ($n = 46$). Of these 140 respondents, 68.57% ($n = 96$) were female, 35.00% ($n = 49$) had a chronic illness, and 92.14% ($n = 129$) rated their health as good. Descriptive statistics for all continuous variables were generated and are presented below in Table 5.1

Table 5.1: *Descriptive statistics for all continuous variables.*

Variable	Mean (95% CI)	Std. Error	Median	SD	Range
Age	36.45 (33.88 – 39.02)	1.30	28.5	15.5	18 – 77
CFC-F	32.36 (31.00 – 33.76)	0.71	33	8.28	7 – 49
CFC-I	26.17 (24.82 – 27.53)	0.69	26	8.22	6 – 49
Procrastination	34.76 (32.83 – 36.68)	0.97	35	11.57	12 – 60

5.3.1 Latent class analysis

To determine a respondent's temporal orientation, we ran four latent class models and presented model fit indices for all four models in Table 5.2. The two-class model showed lower BIC values compared to all other R-class models, indicating improved fit. Additionally, the entropy value exceeded 0.80, suggesting clear class separation. Overall, the two-class model demonstrated a strong balance between model complexity and fit and the fit metrics are highlighted in bold.

Table 5.2: *Goodness-of-fit statistics for one to four class models*

Model	k	Log(L)	BIC	Entropy	Probability of class
1 class	28	-1920.06	3978.48	NA	
2 classes	**57**	**-1728.25**	**3738.18**	**0.91**	**0.536 / 0.464**
3 classes	86	-1666.62	3758.23	0.95	0.436 / 0.421 / 0.143
4 classes	115	-1625.76	3819.81	0.96	0.143 / 0.457 / 0.271 / 0.129

Note. k = Number of free parameters; Log(L) = Log-likelihood value; BIC = Bayesian Information Criterion.

Figure 5.1 displays posterior-averaged item-response profiles for the two latent classes. For each class, mean item responses were averaged across 500 posterior draws of class membership, with shaded bands indicating 95% posterior credible intervals. One class, comprising 45.1% of respondents (n = 64), showed consistently higher responses on CFC-Future items and lower responses on CFC-Immediate items, indicating a strong emphasis on future consequences. This class was labelled the *high future, low immediate orientation group*. The second class, comprising 54.9% of respondents (n = 79), exhibited relatively flat and mid-range responses across both subscales, suggesting neither a pronounced future nor immediate oriented temporal focus. As a result, this class was labelled the *neutral orientation group*.

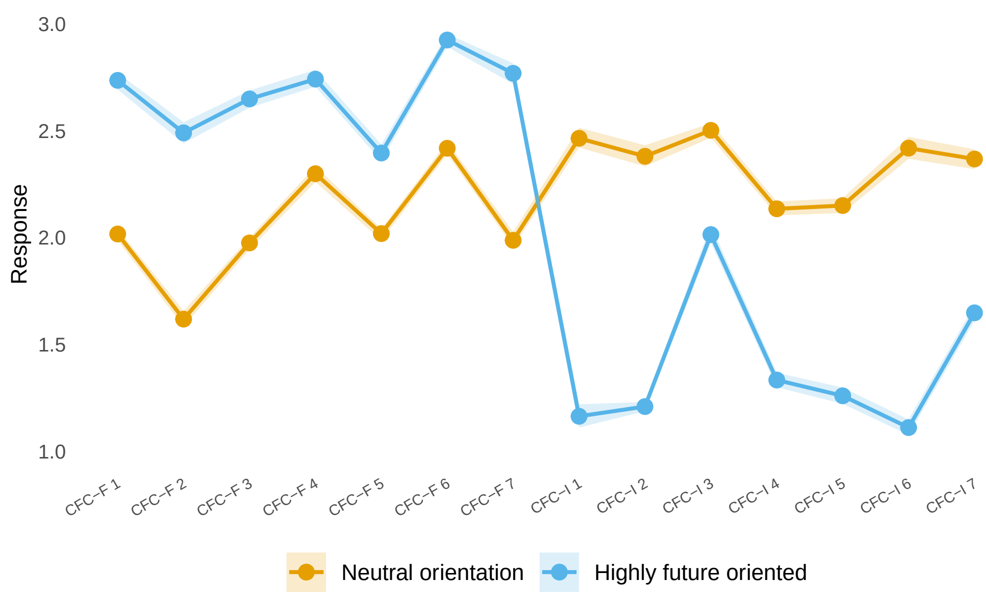

Figure 5.1: *Latent profile plot of posterior-averaged item-response profiles. Each point represents the mean item response averaged over 500 posterior draws of class membership, with shaded bands indicating 95% posterior credible intervals.*

5.3.2 Bayesian regression

Posterior distributions for all regression parameters are reported in Figure 5.2. For each parameter, the figure displays the posterior mean, 95% credible interval, and full posterior density, with estimates derived from the pooled posterior draws of the Bayesian regression model incorporating latent class uncertainty.

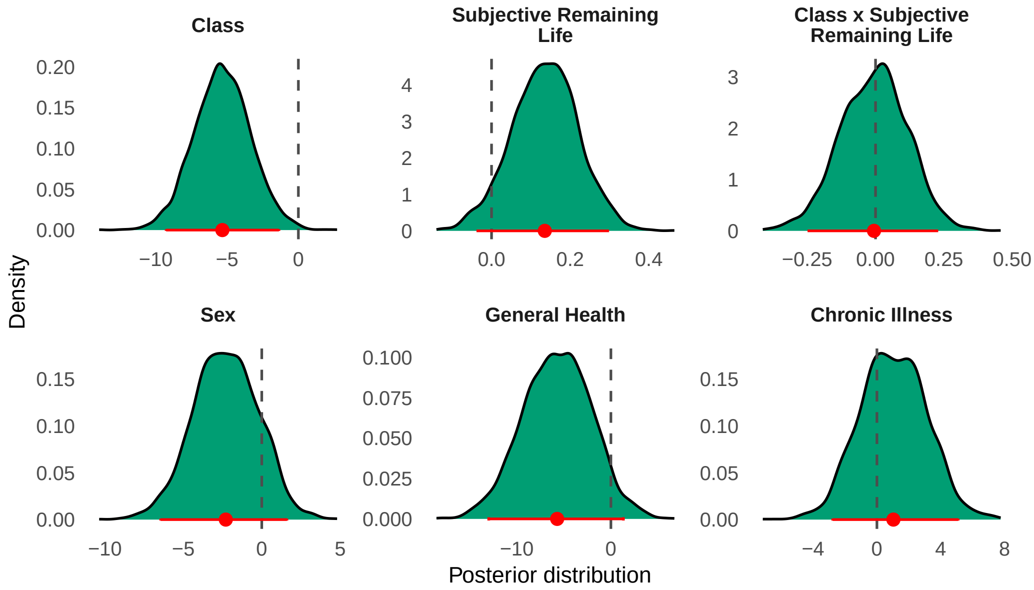

Figure 5.2: *Posterior distributions of Bayesian regression coefficients. Panels display marginal posterior densities for each predictor, with red points indicating posterior means and horizontal bars denoting 95% credible intervals. The dashed vertical line at zero represents the null value; intervals overlapping zero indicate uncertainty about the direction and magnitude of effects.*

Across most predictors, posterior estimates were modest in magnitude and characterised by substantial uncertainty. The interaction between temporal orientation class and subjective remaining life was close to zero and highly uncertain ($\beta = -0.01\ [-0.25, 0.23]$). In contrast, the main effect for subjective remaining life showed a small positive association with procrastination ($\beta = 0.14\ [-0.04, 0.30]$). Although the 95% credible interval overlapped zero, approximately 94% of posterior samples were greater than zero (see Figure 5.2), indicating moderate evidence for a positive association. Additionally, temporal orientation (i.e., class) exhibited a negative main effect on procrastination ($\beta = -5.33\ [-9.28, -1.23]$) suggesting that individuals with a stronger future orientation tended to report lower procrastination scores.

With regard to the covariates, the effects for both sex ($\beta = -2.29\ [-6.35, 1.61]$) and chronic illness ($\beta = 1.03\ [-2.78, 5.09]$ were highly uncertain. In contrast, general health showed a moderate negative association with procrastination ($\beta = -5.71\ [-13.00, 1.32]$) with approximately 95% of the posterior samples being less than zero, suggesting that those with reported good health tended to report lower procrastinations. However, the relative abundance of respondents who reported poor health 7.69%$(n = 11)$ versus good health 92.31%$(n = 129)$ warrants caution in interpretation.

Consistent with these results, Figure 5.3 presents posterior predictive distributions of procrastination scores for both temporal orientation class (left panel) and subjective remaining life (right panel). While predicted procrastination scores were lower for individuals with a stronger future orientation (left panel), this difference had no meaningful effect on procrastination scores across subjective remaining life scores (right panel).

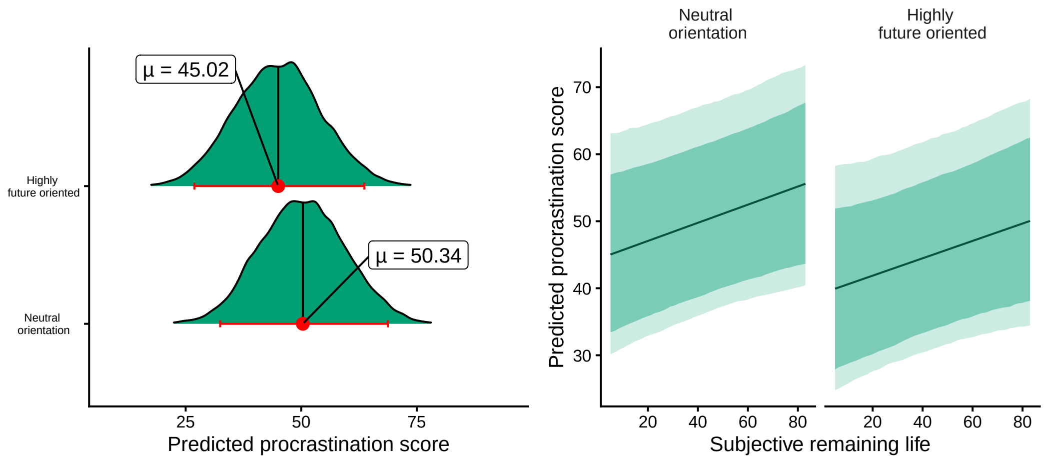

Figure 5.3: *Posterior predicted procrastination scores. The left panel shows scores stratified by temporal orientation class. The solid red points indicate the posterior mean and horizontal bars denoting the 95% credible intervals. Meanwhile, the right panel shows scores as a function of subjective remaining life. The shaded ribbons indicate the 80% and 95% credible intervals. All predictions are shown holding covariates constant at their reference levels.*

5.4 Discussion

While previous research has explored the temporal nature of procrastination (Rebetez et al., 2016; Sirois, 2004; Specter & Ferrari, 2000) no study has examined this nature across the lifespan, with a specific focus on subjective remaining life. Temporal orientation (how individuals perceive time) plays a significant role in shaping behaviour (Boyd & Zimbardo, 2012; Zimbardo & Boyd, 1999). Although studies such as those by Rebetez et al. (2016) highlight the role of future orientation in reducing procrastination, the intersection of temporal orientation and subjective remaining life (how much time one feels they have left) remains unexplored. Therefore, this study examined whether subjective remaining life was associated with procrastination, and whether it moderated the relationship between temporal orientation and procrastination.

Latent class analysis identified two distinct temporal orientation classes: a *high future orientation* group and a *neutral orientation* group. In line with prior research (Rebetez et al., 2016; Sirois, 2014a), temporal orientation showed a credible negative association with procrastination, such that individuals with a stronger future orientation reported lower procrastination scores (see Figure 5.3). Moreover, when it came to subjective remaining life, the results were more nuanced. Consistent with our hypothesis, the posterior mean suggested a positive association between subjective remaining life and procrastination, with approximately 94% of posterior samples indicated an effect in this direction. Although the magnitude of this association was modest and accompanied by interval uncertainty, the directional probability provides moderate evidence that perceiving more time left to live may be associated with greater procrastination.

Such results suggest that perceiving an expansive time horizon may reduce perceived urgency to act, thereby increasing susceptibility to delay. Individuals who perceive ample time remaining in life may feel less immediate pressure to act, reinforcing the tendency to defer effortful or aversive tasks to a future self. In this sense, subjective remaining life may contribute to the temporal misalignment that characterises procrastination (Borawski et al., 2026; Sirois & Pychyl, 2013). However, subjective remaining life did not appear to moderate the association between temporal orientation and procrastination. As seen from Figure 5.2, the posterior estimates for the interaction term were largely centred near zero. Moreover, predicted procrastination scores were broadly similar across levels of subjective remaining life within both temporal orientation classes (see Figure 5.3). Overall, the lack on an interaction effect and relatively small main effect size ($\beta = 0.14$) suggests that rather than acting as a dominant motivational factor, subjective remaining life may operate as a contextual factor that shapes how urgently future consequences are experienced. More broadly, procrastination be more strongly shaped by self-regulatory capacity, task characteristics, and personality traits such as conscientiousness (Meng et al., 2024; Sirois & Pychyl, 2013; Steel, 2007).

Taken together, these results tentatively suggest that perceiving a longer remaining lifetime may be associated with greater procrastination. However, from a Bayesian perspective, such an association is modest and warrants further investigation. Further research, particularly using longitudinal or experimental designs, is needed to determine whether changes in perceived remaining time translate into measurable shifts in procrastinatory behaviour. More importantly, while the present findings suggest that subjective remaining life may play a role in procrastination, this role is considerably weaker than that of stable future-oriented dispositions.

5.4.1 Limitations and future directions

Several limitations should be acknowledged. First, the cross-sectional nature of this study precludes causal inference and limits conclusions about temporal dynamics between subjective remaining life and procrastination. Longitudinal designs would be particularly valuable for examining whether changes in perceived time are associated with within-person changes in procrastination. Second, the relatively small sample size ($n = 140$) and use use of convenience sampling restricts generalisability. Although the sample spanned a wide age range $(18 - 77)$, future research should aim to replicate these findings in both larger and more representative samples.

Moreover, our usage of the Pure Procrastination Scale (Steel, 2010) does not distinguish between different procrastination processes or task domains, but rather general procrastination tendencies. Future studies may benefit from examining domain-specific procrastination or task-level behaviour, particularly in contexts where future time perspectives are more salient (e.g., health decisions, retirement planning, or emotionally meaningful goals). Finally, future work should consider the role of individual differences such as conscientiousness, emotion regulation, and self-control (Meng et al., 2024; Steel, 2007), which may mediate or overshadow the effects of temporal orientation and subjective remaining life on procrastination.

5.4.2 Conclusions

This study examined whether subjective remaining life shapes the relationship between temporal orientation and procrastination. Using latent class analysis and Bayesian regression, we found strong evidence that stronger future orientation is associated with lower procrastination. Subjective remaining life showed moderate evidence of a small positive association with procrastination but did not moderate the relationship between temporal orientation and procrastination. Overall, these findings suggest that stable temporal orientation may play a more substantial role in procrastination than subjective perceptions of remaining life time.

CRediT authorship contribution statement

Cormac Monaghan: Conceptualisation, Methodology, Formal analysis, Visualisation, Writing - Original Draft, Writing - Review & Editing. **Ciarán Gartlan:** Conceptualisation, Data Curation, Writing - Review & Editing. **Rafael de Andrade Moral:** Methodology, Formal analysis, Supervision, Writing - Review & Editing. **Joanna McHugh Power:** Conceptualisation, Methodology, Formal analysis, Supervision, Writing - Review & Editing.

CHAPTER 6

Procrastination and Preventive Health Care in the Older US Population

Cormac Monaghan, Rafael de Andrade Moral, and Joanna McHugh Power

Abstract: Maintaining health preventive behaviors throughout life reduces the risk of non-communicable diseases. However, these behaviours often require effort and discipline to adopt, and may be prone to procrastination. This study examined whether procrastination affected engagement in health preventive behaviours among older adults. We applied generalised additive models to data from the 2020 wave of the United States Health and Retirement Study. Our analytic sample consisted of adults aged $50+$ ($n = 1338$; mean $= 68.24$; range $= 50 - 95$). We focused on six health preventive behaviours: prostate exams, mammograms, cholesterol screenings, pap smears, flu shots, and dental visits. We evaluated depressive symptomatology and procrastination as predictors of these six behaviours. Procrastination was associated with less frequent engagement in mammograms and cholesterol screenings among women, though it had no significant association with pap smears or flu shots. Additionally, procrastination interacted with depression reducing the likelihood of prostate exams in men and dental visits in both men and women, such that individuals with high procrastination and low depression were associated with less frequent engagement in both preventive health behaviours. Procrastination may be a behavioural risk factor for maintaining optimal health in older adults. Given that procrastination is a potentially modifiable behaviour, interventions aimed at reducing procrastination, such as simplifying tasks or providing default appointment, could improve engagement in critical health preventive behaviours.

6.1 Introduction

Procrastination, defined as the deliberate delay of an intended course of action despite expecting negative consequences (Steel, 2007) has been the subject of extensive study over the last two decades. Procrastination can be conceptualized as both a characteristic trait and a coping strategy for dealing with the unpleasant emotions often associated with challenging tasks (Sirois & Pychyl, 2016b). While studies have demonstrated its deleterious impact on productivity (Asio, 2021; Kim & Seo, 2015), the consequences of procrastination likely extend beyond productivity and into health and well-being (Sirois et al., 2023). Notably, chronic procrastination is associated with heightened stress (G. L. Flett et al., 2012; Johansson et al., 2023; Sirois, 2007; Sirois et al., 2003; Stead et al., 2010; Tice & Baumeister, 1997), increased depression (Johansson et al., 2023; Shi et al., 2019; Stead et al., 2010), unhealthy lifestyle behaviours (Johansson et al., 2023; S. M. Kelly & Walton, 2021; Sirois, 2007) and a greater incidence of physical illnesses and symptoms (Johansson et al., 2023; Sirois, 2007, 2015; Sirois et al., 2003).

Procrastination may affect health through both direct and indirect pathways. The procrastination health model (Sirois, 2007; Sirois et al., 2003) proposes that procrastination may negatively impact health via the generation of stress, which could cause hypothalamic-pituitary-adrenal axis activation, and sympathetic activation (Bengel & Schwaiger, 2004; Jedema & Grace, 2004; Sirois & Pychyl, 2016a; Stephens & Wand, 2012), leading to health decline (Sirois et al., 2023). Moreover, procrastination can impact mental health, by leading to self-blame, criticism, and depression (G. L. Flett et al., 2012; B. McCown et al., 2012; Monaghan et al., 2024; Sirois, 2014b).

Another pathway through which procrastination might influence health is via its putative impact on engagement in preventive health behaviours - routine health check-ups and screenings, which are essential for the early detection and treatment of potential health issues. Previous research exploring predictors of preventive health behaviours has highlighted the critical role of psychosocial factors, among which procrastination may fall (Andersen, 2008; Andersen & Newman, 1973; Veazie & Denham, 2021).

It is critical to explore psychosocial predictors of preventive health behaviours, because while such behaviours are critical for maintaining health, they often require effort and discipline to adopt (S. Kelly et al., 2016; Turk & Meichenbaum, 1991), and can stimulate negative emotions. Additionally, public health messages that aim to encourage preventive health behaviours may trigger negative emotions in some people, which can lead them to procrastinate instead of acting (Sirois, 2017). Understanding such psychosocial predictors of preventive health behaviours, including procrastination, may allow us to better determine the likelihood of their uptake.

Research has to date predominantly focused on student and younger adult populations, often overlooking older adults. This is of concern as the health consequences of procrastination may become even more profound with increasing age. Ageing is a complex biological process that can weaken the body's defences against various health problems and diseases (Bandaranayake & Shaw, 2016; Ferrucci et al., 2008; Kulminski et al., 2007) making health management increasingly important as one ages. Older adults can face critical health-related decisions, such as selecting treatment options, adhering to medication regimens, or changing lifestyle habits, which may cause task overload. Procrastination may exacerbate this overload, as the effort required to manage multiple health tasks could become overwhelming.

Preventive health behaviours among older adults are further complicated by the presence of national policy recommendations (US Preventive Services Task Force, 2018a, 2018b, 2024). In the United States (U.S.), policy recommendations suggest that adults are screened for early detection of diseases like cancer, which becomes more likely with age (Rawla, 2019; Sun et al., 2017). In 2022, prostate and breast cancer caused over 38,165 and 37,841 deaths respectively among U.S. adults aged 60+ (The International Agency for Research on Cancer, 2024). However, in both the U.S. and United Kingdom, such screening is not recommended beyond a certain age, since their benefits may not outweigh associated risks or costs (Grad et al., 2019; Hugosson, 2018). As such, any exploration of preventive health behaviours in older adults must take into account the prevailing policy recommendations.

Within age ranges where screening behaviours are recommended, procrastination may interfere (Johansson et al., 2023; Sirois, 2015; Sirois et al., 2003). For older adults, procrastinating preventive healthcare, particularly those that are infrequent, such as screenings and check-ups, can have significant consequences; a delayed screening leading to an undetected disease can result in more severe deterioration with age (Diehr et al., 2013). Numerous studies have utilised and extended the procrastination health model to establish links between procrastination and health (Johansson et al., 2023; Rapoport et al., 2024; Sirois, 2007, 2017; Sirois et al., 2003; Stead et al., 2010). Within these studies, only two have a focus on older adult procrastination, but both examine specific health outcomes, namely sleep quality (Firdaus et al., 2020) and tooth loss (Shimamura et al., 2022). Notably, a recent study by Rapoport et al. (2024) highlights the relatively little studies that do focus on general health exams.

As such, this study aimed to explore the associations between procrastination and a range of preventive health behaviours, including prostate exams, mammograms, pap smears, cholesterol screenings, flu shots, and dental visits, in older US adults. Given that these behaviours typically require infrequent action, and prior research (while limited) has shown that procrastination can impact them (Rapoport et al., 2024), it was expected that high scores on measures of procrastination would be associated with lower engagement in these behaviours. Additionally, considering the multifaceted nature of proactive health management, we expected interactions between procrastination, depression, and age for certain preventive health behaviours.

6.2 Methods

6.2.1 Design and participants

This study used data from the United States Health and Retirement Study (HRS) (Juster & Suzman, 1995). The HRS is a longitudinal dataset managed by the Institute for Social Research at the University of Michigan and tracks the health, economic, and social well-being of American adults primarily aged 50 and older. Our analyses focused on data from the 2020 wave of the HRS, specifically targeting respondents who completed a “long-term care insurance procrastination" module during that period. This module comprised two parts, with the second segment incorporating a procrastination measure designed to investigate its impact on decision-making in later life.

6.2.2 Measures

Predictor: Procrastination

General procrastination tendencies were measured using the Pure Procrastination Scale (Steel, 2010). This scale consists of 12 items that were measured on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). When combined, these item scores give rise to a total procrastination score ranging from 12 to 60, with higher scores indicating higher levels of procrastination. The scale had a Cronbach’s α score of 0.91 in this sample, indicating high internal consistency. An example of a question from the scale includes “I delay making decisions until it’s too late”.

Covariate: Depressive symptomatology

Depressive symptoms were included in our model based on a priori knowledge of their associations with procrastination (Monaghan et al., 2024) and health protection (Clayborne & Colman, 2019). Depressive symptoms were measured using the CESD-8, a shortened eight item version of the Centre for Epidemiological Studies – Depression scale. This scale has been shown to be a valid and reliable measure of depressive symptoms in older adults (Briggs et al., 2018). The scale consists of 8 items that are scored as either 0 (no) or 1 (yes), with items 4 and 6 being reversed scored. The total depression score ranged from 0 to 8, with higher scores indicating higher levels of depressive symptoms. The scale had a Cronbach’s α score of 0.82 in this sample, indicating high internal consistency. An example of a question from the scale includes “how much of the time during the past week did you feel everything you did was an effort”.

Outcomes: Health preventive behaviours

The HRS systematically evaluates and gathers data on a variety of health preventive screenings and behaviours during each wave. The protective measures encompass a comprehensive range of behaviours, such as prostate exams, mammograms, cholesterol screenings, pap smears, flu shots, and visiting the dentist. For each screening, participants self-report whether they have undergone the procedure within the past two years, which is then recorded as a binary score: 0 (no) or 1 (yes). An example of one of these questions includes: "In the last two years, have you had a mammogram or x-ray of the breast, to search for cancer".

Covariates

Several covariates, chronic illness, retirement status, and Medicare health insurance were included in the analysis based on a priori knowledge of their associations with screening behaviours (Beydoun & Beydoun, 2008; Eibich & Goldzahl, 2021). Each covariate was dichotomized: chronic illness, retirement, and Medicare status were coded as 1 (presence of the condition/retirement/Medicare) and 0 (absence).

6.2.3 Data analysis

Given that the decision to delay or avoid preventive health actions can be influenced by a multitude of factors such as perceived risks and benefits, past experiences, individual differences, and policy (Werle, 2011), it was expected that the relationship between procrastination and preventative health actions would not follow a straightforward, linear relationship. As such, we applied generalised additive models (GAMs; Wood, 2017) to our data. GAMs are a powerful statistical tool for modelling complex and non-linear relationships between a response variable and one or more predictor variables making them a better choice than generalised linear models (GLMs) for this analysis. Unlike the GLM, which assumes that the response variable depends on a linear combination of the predictors ($\beta_i x_i$), GAMs allow the response variable to depend on smooth functions of the predictors ($f_i(x_i)$). These smooth functions can capture the curvature and variability of the data better than linear functions. Therefore, for participant i, the response variable Y_i is assumed to have a distribution belonging to the exponential family (in this case a binomial distribution) with a mean parameter μ_i and a dispersion parameter ϕ.

In general form, the linear predictor can be written as:

$$g(\mu_i) = \alpha + f_1(x_{1i}) + f_2(x_{2i}) + \cdots + f_p(x_{pi}) \tag{6.1}$$

where $g(.)$ is a link function chosen based on the distribution of the response variable and parametric space, α is an intercept term, and $f_1, \ldots, f_p$ are smooth functions applied to the predictor variables $x_1, \ldots, x_p$. The smooth functions used here are based on thin plate regression splines (TPRS; Wood, 2017), a method that estimates smooth curves to improve model predictions. Unlike assuming a specific functional form (e.g., linear or quadratic), TPRS approximates non-linear relationships between the response and covariates. Additionally, to prevent overfitting, a penalty is applied to limit excessive curve complexity.

To identify the most appropriate model for each response variable, we fitted three different GAMs using the `mgcv` package (Wood, 2017), including models with and without interaction terms (for full details see Table A.4). All data analysis was carried out using the statistical software R (R Core Team, 2025).

6.3 Results

The initial analysis included a total of 1,368 respondents. However we excluded respondents who had excessive missing values in the procrastination measure ($n = 7$) and those who were under the age of 50 ($n = 24$). Thus, our final analytic sample comprised 1,338 respondents, of whom 62.48% ($n = 836$) were female. Additionally, our sample were predominantly aged 60+ years, with the following age distribution: 50-59 years ($n = 299$), 60-69 years ($n = 500$), 70-79 years ($n = 308$), and 80+ years ($n = 231$). Descriptive statistics were generated and are presented below (see Table 6.1).

Table 6.1: *Descriptive statistics of all continuous variables in GAM analysis*

	Mean (95% CI)	Std. Error Mean	Median	SD	Range
Men					
Age	68.9 (68.04 - 69.82)	0.5	67	10.2	51 - 95
Procrastination	27.8 (26.78 - 28.74)	0.5	27	11.1	4 - 60
Depressive Symptomatology	1.3 (1.10 - 1.42)	0.1	1	1.8	0 - 8
Women					
Age	67.8 (67.15 - 68.50)	0.3	66	9.9	50 - 95
Procrastination	28.7 (27.85 - 29.48)	0.4	27	12.0	1 - 60
Depressive Symptomatology	1.8 (1.62 - 1.92)	0.1	1	2.2	0 - 8

6.3.1 Generalised additive models

In our analysis of each health preventive behaviour, we utilised GAMs with procrastination treated as a predictor and both depressive symptomatology and age treated as covariates. Each response variable was modelled individually with each continuous variable treated as a smooth term within the GAM framework. To ensure the accuracy of each model, we performed diagnostics checks using the *k.check* function from `mgcv`, which helped verify that an appropriate number of basis dimensions were selected for each smooth function (see Table A.5).

Health preventive behaviours

Interaction effects

Procrastination interacted significantly with depressive symptomatology to influence prostate exam likelihood ($\chi^2 = 11.0$, ref. df $= 3.8$, $p = 0.029$). Specifically, higher levels of procrastination were associated with a lower probability of obtaining a prostate exam. However, the presence of depressive symptoms modified this probability with examples such as high procrastination and high depression resulting in an increased probability of undergoing the exam, whereas low procrastination coupled with high depression resulting in a decreased probability.

Similarly, procrastination interacted significantly with depression to affect dental visit likelihood in both men ($\chi^2 = 23.0$, ref. df $= 5.8$, $p = 0.001$) and women ($\chi^2 = 10.0$, ref. df $= 3.0$, $p = 0.018$). For men, higher procrastination decreased the likelihood in attending the dentist, depressive symptoms altering this likelihood. For women, both high levels of procrastination and depression would result in a decreased likelihood in attending the dentist. For a breakdown of results see both Table 6.2 and Figure 6.1).

Table 6.2: *Estimated procrastination results from each generalised additive model.*

Preventive Behaviour	Predictor	Gender	χ^2	edf	Ref. df	p
Prostate Exam	Procrastination x Depression	Men	11.0	3.8	3.8	0.029*
Mammograms	Procrastination	Women	4.1	1.0	1.0	0.042*
Cholesterol Screenings	Procrastination	Men	2.2	1.7	2.1	0.360
		Women	4.3	1.0	1.0	0.037*
Pap Smears	Procrastination	Women	1.0	1.0	1.0	0.330
Flu Shots	Procrastination	Men	0.8	1.0	1.0	0.386
		Women	2.1	1.0	1.0	0.146
Dental Visits	Procrastination x Depression	Men	23.0	4.9	5.8	0.001***
		Women	10.0	3.0	3.0	0.018*

Note. Smooth functions do not have parametric coefficients due to the non-parametric estimate of generalised additive models. $\chi 2$ = chi-squared statistic; edf = effective degrees of freedom; ref df = reference degrees of freedom. p = a value derived from a significance test that the resulting smooth or parametric term occurred by chance. For smooth terms this value is derived from a chi-squared statistic. Statistical significance is represented as: * p < .05; ** p < 0.01.

Main effects

Additionally, the results of the GAM analysis revealed significant non-interacting associations for both mammograms ($\chi^2 = 4.1, \text{ref.df} = 1.0, p = 0.042$) cholesterol screenings ($\chi^2 = 4.3, \text{ref.df} = 1.0, p = 0.037$) in women (Figure 2). However, no significant effects were found for either pap smears ($\chi^2 = 1.0, \text{ref.df} = 1.0, p = 0.330$) and flu shots ($\chi^2 = 2.1, \text{ref.df} = 1.0, p = 0.146$) in women. Additionally for men, procrastination showed no association with either cholesterol screenings ($\chi^2 = 2.2, \text{ref.df} = 2.1, p = 0.360$) or flu shots ($\chi^2 = 0.8, \text{ref.df} = 1.0, p = 0.386$). Again, a detailed breakdown of the results can be found in Table 6.2, with full model results in Table A.6.

6.4 Discussion

The current study aimed to extend the procrastination and health literature by investigating the association between procrastination and a range of health preventive behaviours in an older U.S. population. It was hypothesised that higher levels of procrastination would be associated with less frequent engagement in health preventive behaviours. The findings of the study support this hypothesis: among older adults, higher levels of procrastination in women only were associated with less frequent engagement in undergoing both mammograms and cholesterol screenings. Additionally, procrastination significantly interacted with depression to influence engagement in prostate exams in men and dental visits in both men and women. However, procrastination was not associated with the likelihood of undergoing a pap smear or a flu shot.

While this study is the first of our knowledge to investigate the association between procrastination and health preventive behaviours of older adults, these findings are consistent with that of previous research on younger populations (S. M. Kelly & Walton, 2021; Rapoport et al., 2024; Sirois, 2007, 2017; Sirois et al., 2003, 2023; Stead et al., 2010). Consistent with the procrastination health model (Sirois, 2007; Sirois et al., 2003), the results highlight the behavioural pathways through which procrastination impacts health. Specifically for older adults, procrastination may lead to the postponement or neglect of specific health preventive behaviours. The differences in procrastination's impact across these behaviours may be partially explained by the complexity and structure of the tasks required to complete each screening (E. M. Anderson, 2001). Preventive behaviours that require multiple steps, such as scheduling appointments or travelling to health facilities, may provide more opportunities for procrastination compared to one-time, simple actions. Of course, it is important to consider these results in the context of policy recommendations. For instance, exploring the uptake of breast cancer screening among women aged 75+ in the U.S. may not be worthwhile, as any decrease in this age group is likely due to policy rather than individual factors like procrastination (US Preventive Services Task Force, 2024).

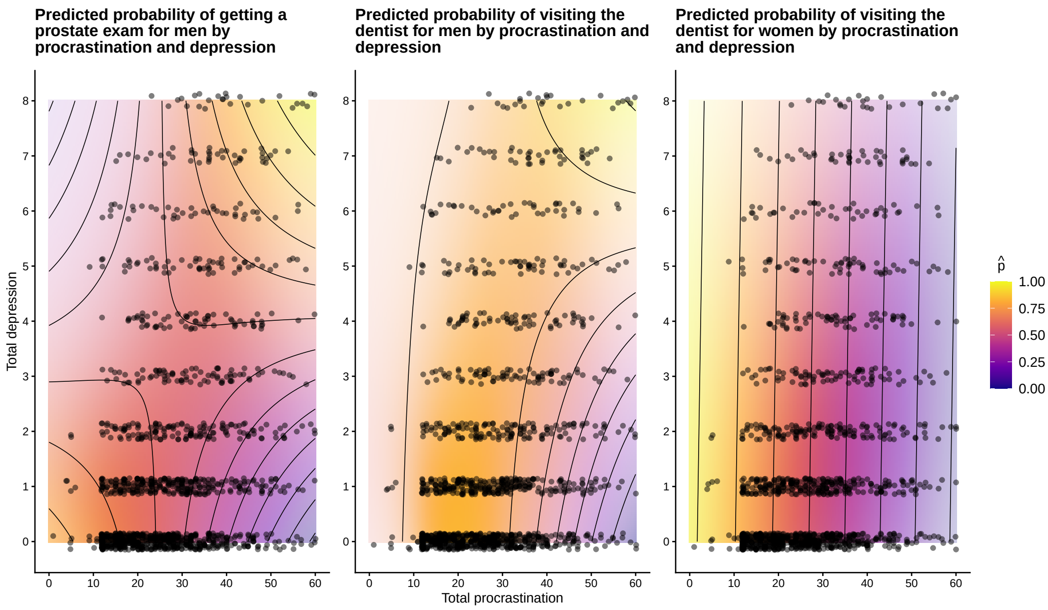

Figure 6.1: *Heat maps of predicted probabilities for health preventive behaviours estimated using tensor product smooths. Transparency was added to each heat map based on the inverse standard error of each model. Hence, areas of higher transparency indicate greater uncertainty due to larger standard errors and fewer data points within that region.* $\hat{p}$ *= estimated probability from model.*

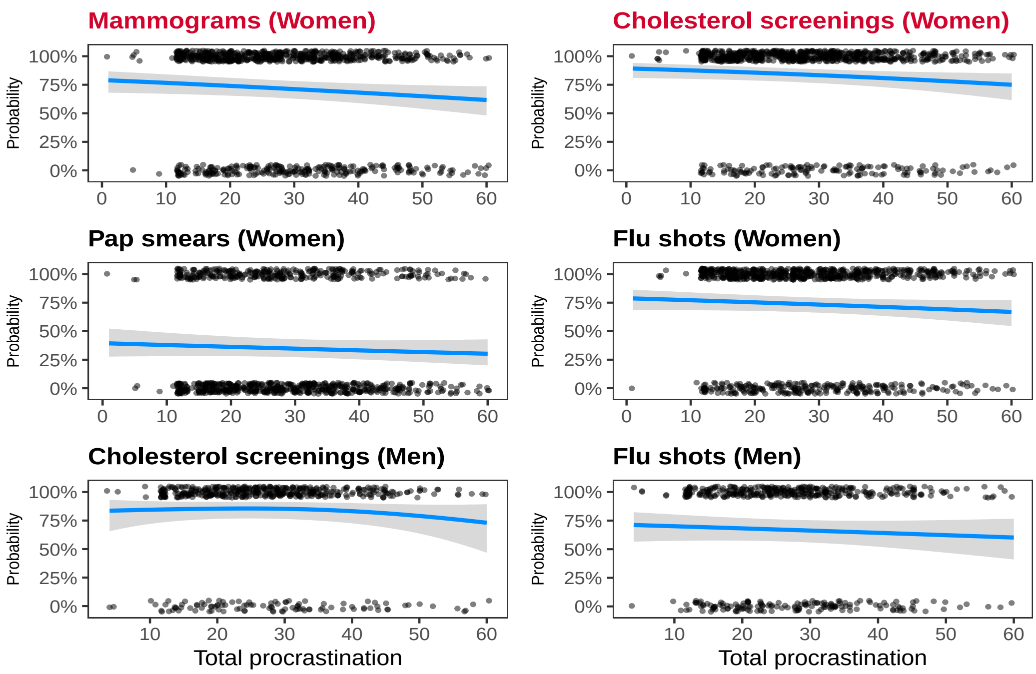

Figure 6.2: *Generalised additive model plots for procrastination and health preventive utilisation. The blue lines represent predicted probabilities obtained from the models, whereas the grey ribbon represents the 95% confidence interval for that particular health preventive behaviour. Data points are jittered for better visualization. Health preventive behaviours marked in red indicate significance at the 5% level.*

As mentioned, preventive behaviours play a crucial role in reducing the healthcare burden associated with chronic diseases (Bruhn, 2000). However, results from the GAM analysis revealed that older women with higher levels of procrastination were significantly less likely to undergo a mammogram, but not a pap smear. Moreover, the tensor product smooth results indicated an interplay between procrastination and depression with regard to prostate exams, as well as depression and age for pap smears. The predictive heat maps indicated that older men with higher levels of procrastination were less likely to get a prostate exam. While higher levels of depression seemed to increase this likelihood, the scarcity of data points within this region ($n = 13$) introduces a greater degree of uncertainty and necessitates caution due to extrapolation. Additionally, age emerges as the predominant factor in the predictive heat map for pap smears, with the probability of undergoing the procedure decreasing as age increases, regardless of depression levels.

Such results may be attributed to various factors such as, fear of the unknown, anxiety about medical procedures, financial constraints, or policy decision. The prospect of being diagnosed with a condition that has significant health implications, such as cancer can be daunting (Esbensen et al., 2008). This trepidation, coupled with the stress of confronting potentially distressing realities about one's health, often leads individuals to defer necessary screenings (Beauregard et al., 2015; Sirois, 2015). Additionally, the costs associated with healthcare, even with insurance, can be a significant barrier for many older adults (Osborn et al., 2017). Overall, the prospect of being diagnosed with a life-altering condition such as cancer is not only emotionally stressful, but also carries with it a significant financial burden. This emotional and financial stress can exhaust the psychological resources required to effectively cope with and manage emotions, thereby exacerbating procrastination (Sirois et al., 2023). This is further compounded by policy recommendations for discontinuing certain screenings among older adults (US Preventive Services Task Force, 2018a, 2018b, 2024). However, as life expectancy increases, it becomes crucial to reassess these policies to ensure they align with the evolving needs and health profiles older adults, rather than adhering strictly to age-based criteria.

Additional results can be interpreted through a similar lens. For instance, cholesterol screenings and dental check-ups are critical components of preventive healthcare and serve as vital indicators for heart disease and oral health (Greenland et al., 2010; Thomson et al., 2010). Again, the associated stress off facing such serious health conditions can perpetuate a cycle of procrastination. Furthermore, dental health is a vital aspect of overall well-being, yet dental anxiety and the costs associated with care contribute to avoidance behaviours (Armfield et al., 2007; Rapoport et al., 2024; Steinvik et al., 2023). Procrastination in attending such screenings and check-ups can result in missed opportunities for early detection and intervention, significantly increasing the risk of advanced diseases and the need for more complex treatments.

The cumulation of these stressors along with procrastination itself can also have profound psychological ramifications on older adults. Postponing or neglecting to attend health appointments or prioritize self-care can lead to an accumulation of guilt, anxiety, and stress. These emotional responses can deeply influence an individual's self-perception. Procrastination is often associated with negative self-evaluations and self-deprecating thoughts, which can exacerbate feelings of low self-worth and hopelessness (G. L. Flett et al., 2012; B. McCown et al., 2012) as well as physical health decline (Osborn et al., 2017). Consequently, understanding and addressing the psychological aspects of procrastination is crucial in the holistic health management of older adults. Moreover, the complexity of preventive behaviours, scheduling, attending, and following up on the appointment, can influence the effect of procrastination. Individuals may be more likely to delay behaviours that require more effort or planning (Andersen, 2008).

Furthermore, the procrastination in preventative health behaviours not only affects individual health outcomes but also has a cascading effect on public health and healthcare expenditure. As mentioned, delaying preventive check-ups can lead to the late diagnosis of diseases, which in turn are often more costly and difficult to treat (Reddy et al., 2022). Such diagnoses can result in increased morbidity and mortality rates, which in turn, place a heavier burden on healthcare systems.

Overall, the study's findings underscore the behavioural pathways through which procrastination affects preventive health behaviours, along with the interplay that depression plays. It is important to note, however, that the preventive behaviours examined here are primarily low-frequency activities. Research into how procrastination impacts such infrequent behaviours is limited (Rapoport et al., 2024), with most studies focusing on more routine behaviours like exercise or healthy eating, which require sustained effort and may involve different motivational processes. Future research should explore how the nature and frequency of preventive behaviours influence their predictors and outcomes, as the factors driving low-frequency actions may differ from those involved in long-term behaviour maintenance. Additionally, targeted interventions to reduce procrastination among older adults could improve health outcomes and ease the burden on healthcare systems. For example, simplifying appointment scheduling or offering default appointments may reduce procrastination and improve health by lessening the burden on individuals. Additionally, addressing the psychological, financial, and policy-related factors contributing to procrastination is crucial for ensuring effective care for older adults.

6.4.1 Limitations

Our findings are based on data from the HRS, which focuses on the health and economic dynamics of ageing in the United States. The experiences of health and the impact of stress on health outcomes can vary significantly across different countries due to a multitude of factors such as cultural differences, healthcare systems, socioeconomic status, and public health policies (Hernandez & Blazer, 2006; Schoen et al., 2005). These differences can affect health care utilisation independently of stress and procrastination, potentially confounding the results, if applied to international contexts. Additionally, our analyses are constrained by the questions, responses, and variables included within the HRS. As such, while this study focused on the general completion of preventive health behaviours, future research would benefit from examining the specific sub-behaviours involved in the preventive health process as such could reveal critical points where procrastination exerts its influence, particularly in the transition from intention to action.

Furthermore, repeated activation of the stress response system is a known factor linking procrastination and health behaviours (Sirois et al., 2023). However, stress was excluded from our analysis due to a high level of missingness (71%). As such, future research should include stress in their models to comprehensively understand the relationship between procrastination and health care utilisation.

6.4.2 Conclusions

Proactive health management can significantly mitigate the risks associated with ageing. For older adults, procrastination emerges as a significant risk factor that can undermine preventive health behaviours such as prostate exams, mammograms, cholesterol screenings, and dental visits. The tendency to postpone essential health care check-ups and wellness practices can lead to increased stress and, consequently, a greater number of health issues. Given that procrastination is a modifiable behaviour the findings of this study underscore the potential benefits of reducing procrastination, not only to enhance the quality of life, but also to mitigate the risks associated with poor health and delaying preventive health behaviours.

CRediT authorship contribution statement

Cormac Monaghan: Conceptualisation, Methodology, Data curation, Formal analysis, Visualisation, Writing – original draft. Writing – review & editing. **Rafael de Andrade Moral**: Methodology, Formal analysis, Supervision, Visualisation, Writing – review & editing. **Joanna McHugh Power**: Conceptualisation, Methodology, Formal analysis, Supervision, Writing – review & editing.

CHAPTER 7

Procrastination as a Marker of Cognitive Decline: Evidence from Longitudinal Transitions in the Older Adult Population

Cormac Monaghan, Rafael de Andrade Moral, Michelle Kelly, and Joanna McHugh Power

Abstract: Cognitive decline is a global health concern, making the identification of early, modifiable risk factors essential. While apathy is a recognized prodromal marker, procrastination may also signal early executive dysfunction. We used longitudinal secondary data from the United States Health and Retirement Study among adults aged 60+ ($n = 549; \bar{x} = 69.70; \sigma = 7.58$). Cognitive function, procrastination, depression and a proxy measure of apathy were assessed. Transitions between normative cognitive function, mild cognitive impairment (MCI), and dementia were modelled using a discrete-time first-order Markov model. Procrastination scores were higher among individuals with MCI or dementia than those with normative cognitive function. Procrastination also interacted with age, disproportionately increasing the risk of decline in the oldest participants. Procrastination was associated with cognitive impairment and predicted transitions to MCI, suggesting it may serve as both an early behavioral marker and compounding risk factor.

7.1 Introduction

Dementia involves progressive cognitive decline that impairs daily functioning (Prince et al., 2013; Sanz-Blasco et al., 2022) with cases projected to rise to 152.8 million by 2050 (Nichols et al., 2022). Identifying and addressing modifiable risk factors is crucial to mitigate this projected rise in prevalence. Two particularly vulnerable groups are older adults and those with mild cognitive impairment (MCI), of whom up to 80% progress to dementia within six years (Cooper et al., 2015; Shigemizu et al., 2020; Tschanz et al., 2006).

The Lancet Commission on Dementia identified fourteen causal risk factors including smoking, hypertension, and diabetes, which account for approximately 45% of dementia cases worldwide (Livingston et al., 2024). Prodromal markers, on the other hand, reflect early disease processes and may signal limited opportunities for prevention (Teipel et al., 2025). One such prodromal marker is apathy, or the significant loss of motivation, as distinct from depression and cognitive impairment (Fresnais et al., 2023; Richard et al., 2012). Apathy is prevalent in both MCI and dementia subgroups (Donovan et al., 2014; Fresnais et al., 2023; Salem et al., 2023; van Dalen et al., 2018), and is a robust predictor of progression from MCI to dementia (Ruthirakuhan et al., 2019; Salem et al., 2023; van Dalen et al., 2018). While apathy has been well-established as a prodromal marker and risk factor for dementia progression, emerging evidence suggests that procrastination may also relate to early cognitive decline.

Although apathy and procrastination can appear similar in that both lead to reduced engagement in everyday activities, the underlying behavioural processes are distinct. Apathy reflects reduced internal drive and emotional engagement, impairing initiation of action (Fresnais et al., 2023). In contrast, procrastination is a self-regulatory failure defined by the voluntary delay of an important and intended course of action despite expecting negative consequences (Klingsieck, 2013b; Sirois & Pychyl, 2013). This distinction suggests that individuals who procrastinate typically form intentions but fail to execute them in a timely manner. This failure can often be understood through an affective framework, where delayed action may stem from the avoidance of negative emotions (i.e., stress or anxiety) associated with the task (Sirois & Pychyl, 2013). Furthermore, while also conceptualised as a stable trait linked to specific personality factors (Meng et al., 2024), these factors can shift in later life and may interact with emerging cognitive or motivational changes to influence procrastination behaviour in older adult (Donnellan & Lucas, 2008; Oi & Frazier, 2024).

These parallels raise the possibility that procrastination could serve as an early marker of cognitive impairment or even a modifiable risk factor. Chronic procrastination may exacerbate decline by limiting engagement in cognitively stimulating activities such as physical exercise, problem-solving, and goal-setting, which build cognitive resilience and reduce dementia risk (S. M. Kelly & Walton, 2021; Livingston et al., 2024). Reduced engagement may contribute to a cycle of cognitive disengagement, accelerating decline.

Importantly, procrastination is responsive to intervention through cognitive-behavioral strategies and self-regulation training (Rozental & Carlbring, 2014; Van Eerde & Klingsieck, 2018). Crucially, procrastination may identify individuals with motivational or executive dysfunction who do not yet meet the long-term symptom threshold for apathy, offering a potentially valuable and earlier marker (and possible target) for neurodegenerative risk.

Since age remains the strongest predictor of MCI and dementia, it is important to consider how procrastination operates across the lifespan (i.e. interaction with age). Many established modifiable risk factors such as hypertension, hearing loss, smoking, and social isolation, exert age-dependent effects, with certain factors carrying more weight at midlife than in late life (Livingston et al., 2020, 2024). Understanding how procrastination interacts with age may help clarify its role in the aetiology of cognitive decline and identify windows of opportunity for targeted intervention.

To our knowledge, no studies have directly examined procrastination as a predictor of cognitive decline or dementia progression. Accordingly, the present study aimed to a) assess differences in procrastination levels across three groups: individuals with dementia, individuals with MCI, and individuals with neither dementia nor MCI, and b) test whether higher procrastination scores predict transition from normative cognition function to dementia or MCI to dementia.

7.2 Methods

7.2.1 Data and study population

Analyses were conducted using a secondary data source; a multi-wave prospective cohort study called the Health and Retirement Study (HRS; Fisher and Ryan, 2018), which tracks the health, economic, and social well-being of over 18,000 American adults primarily aged 50+. The HRS is managed by the Institute for Social Research at the University of Michigan, with data collected every two years. Initial data collection of a participant is conducted through a face-to-face interview, with follow-up biennial interviews conducted either by phone or face-to-face. The average retention rate ranges from 68.8% to 92.3% (Health and Retirement Study, 2017). At the time of writing, fifteen years of HRS data are currently archived.

We focused on four waves of HRS data from 2016 to 2022. Specifically, our study sample consisted of respondents who participated in an experimental module assessing procrastination during the 2020 wave. These experimental modules, administered at the end of the core HRS interview, consist of concise questionnaires designed to explore new topics or supplement existing core survey data (Juster &

Suzman, 1995). Each respondent receives only one experimental module, with sample sizes for each module constituting approximately 10% of the core sample. As a result, while the core HRS sample includes approximately 18,000 respondents, our inclusion criteria (i.e., having completed the experimental module) identified an initial sample of 1,368 respondents. We then applied the following exclusion criteria: respondents with missing cognitive assessment data for any wave ($n = 419$), those under 60 years of age (as cognitive symptoms typically occur around this age; $n = 398$), and those with complete missing values across the procrastination measure ($n = 2$). The application of these exclusion criteria resulted in a final analytic sample of 549 respondents, of whom 61.57%($n = 338$) were female.

7.2.2 Measures

Outcome: Cognitive Function and Cognitive Category

Cognitive function in the HRS is assessed using a series of tests adapted from the Telephone Interview for Cognitive Status (TICS; Brandt et al., 1988; Fong et al., 2009). These tests include an immediate and delayed 10-noun free recall test (to assess episodic memory), a serial seven subtraction test (to assess working memory), and a backward count from 20 test (to assess mental processing). Based on these assessments, Crimmins et al. (2011) developed both a 27-point cognitive scale and validated cut-off points to assess and classify cognitive status. Using these points, respondents who scored $12 - 27$ were classified as having normal cognition, $7 - 11$ as having MCI, and $0 - 6$ as having dementia.

Predictor: Procrastination

Procrastination was measured using the Pure Procrastination Scale (Steel, 2010), a psychometrically validated scale for evaluating procrastination when conceptualized as a dysfunctional delay. The PPS consists of 12 items rated on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In responding to the scale items, participants were asked to reflect on their general behavioural tendencies, with no specific time-frame provided. Total procrastination scores range from 12 to 60, with higher scores indicating greater tendency to procrastinate. In the HRS, the PPS was administered only in wave 3 (2020) of the respective waves. As such, we use the wave 3 measure as both a retrospective and prospective proxy for procrastination scores across all waves in the analysis. This approach assumes relative temporal stability in procrastination over the study period. In this sample, the PSS had a Cronbach's α score of 0.92, indicating high internal consistency. In responding to the scale items, participants were asked to reflect on their general behavioural tendencies, with no specific time-frame provided. An example of a question from the scale includes "I delay making decisions until it's too late".

Covariate: Apathy

While no direct measure of apathy exists within the HRS, we utilised two questions from the eight-item version of the Center for Epidemiological Studies Depression (CES-D8) scale (Briggs et al., 2018) as proxies for apathy: “You felt that everything you did was an effort" and "You could not get going”. Both items capture core features of apathy (behavioural and motivational disengagement) and, while not a comprehensive measure of apathy, provide a valid and pragmatic approximation for modelling purposes. Each item was measured on a binary “yes/no” scale with total scores ranging from 0 to 2.

Covariate: Depression

Depressive symptoms were included in our model based on their associations with both procrastination (Klingsieck, 2013b) and cognitive ageing (Livingston et al., 2020). As mentioned, the HRS uses the CESD-8 as a measure of depressive symptomatology. The scale consists of 8 items that are scored as either 0 (no) or 1 (yes), with items 4 and 6 being reversed scored. Since we used two items from this scale as proxies for apathy, we scored the remaining 6 items, giving a total score ranging from 0 to 6, with higher scores indicating higher levels of depressive symptoms. Across the waves, this 6-item scale showed reliable internal consistency ($\alpha \in \{0.81 - 0.83\}$). An example of a question from the scale includes “Much of the time during the past week, your sleep was restless”.

Confounders

To account for potential confounding, we controlled for demographic variables with established associations with both cognitive function and procrastination (VanderWeele, 2019). These included measures of age, sex, and educational attainment (Livingston et al., 2020; Steel & Ferrari, 2013). Educational attainment was classified into three categories: no formal education, GED (General Educational Development)/high school diploma, and college/further education.

7.2.3 Data Analysis

All data analysis was carried out in R (R Core Team, 2025). To model transitions in cognitive states over time, we employed a first order discrete-time Markov model, a class of stochastic processes that satisfy the Markov property, which can be formally expressed as:

$$P(X_{t+1} = j | X_t = i, X_{t-1} = i_{t-1}, \ldots X_0 = i_0) = P(X_{t+1} = j | X_t = i)$$

This property asserts that the probability of transitioning from state $X_t = i$ to a future state $X\_t + 1 = j$ depends only on the current state X_t, and not on the full history of preceding states. Here, there are three potential states: normative cognitive function, mild cognitive impairment, and dementia. We consider dementia to be an absorbing state, i.e. once an individual reaches this state, they cannot return to the other states in a future time point.

Unlike continuous-time models, discrete-time Markov models are not readily supported by a dedicated R package for deriving transition probabilities. Therefore, we implemented the model manually using multinomial logistic regression from the `nnet` package (Venables & Ripley, 2002b). This approach estimates the log-odds of transitioning to each non-reference state as a linear function of covariates, relative to a chosen reference category. For a system with K cognitive states (with state K as the reference), the model takes the form:

$$\log \frac{P(Y = j \mid x)}{P(Y = K|x)} = \beta_0 + \beta_j^\top x \qquad \text{for } j = 1, \ldots K - 1$$

From these equations, the predicted transition probabilities for the non-reference states $j = 1, \ldots, K - 1$ are derived as:

$$P(Y = j|x) = \frac{e^{\beta_{0j} + \beta_j^\top x}}{1 + \sum_{k=1}^{K-1} e^{\beta_{0k} + \beta_k^\top x}}$$

and for the reference state K as:

$$P(Y = K \mid x) = \frac{1}{1 + \sum_{k=1}^{K-1} e^{\beta_{0k} + \beta_j^\top x}}$$

7.3 Results

Our final analytic sample comprised 549 respondents with the following age distribution: 60 - 70 ($n = 186$), 71 - 80 ($n = 203$), 81 - 90 ($n = 142$), and 90+ ($n = 18$). Descriptive statistics for the full sample, as well as data stratified by cognitive status (normative cognitive function, MCI, and dementia), are presented in Table 7.1. Both Figure 7.1 and Figure A.1 capture the unconditional transitions and transition probabilities (respectively) between wave one and two (first transition), wave two and three (second transition), and wave three and four (third transition), yielding a total of 1,647 observed transitions over time.

Table 7.1: *Baseline descriptives for the study sample and stratified by cognitive status category.*

	Full sample (n = 549)	NC (n = 452)	MCI (n = 86)	Dementia (n = 11)
Age (years)	69.70 ± 7.58	69.70 ± 7.55	69.60 ± 7.55	70.00 ± 9.89
Sex				
Male	38.43% (n = 211)	39.82% (n = 180)	32.56% (n = 28)	27.27% (n = 3)
Female	61.57% (n = 338)	60.18% (n = 272)	67.44% (n = 58)	72.73% (n = 8)
Education				
No degree	16.24% (n = 98)	10.56% (n = 47)	39.53% (n = 34)	63.64% (n = 7)
GED	51.48% (n = 279)	51.91% (n = 231)	52.33% (n = 45)	27.27% (n = 3)
Further education	32.29% (n = 175)	37.53% (n = 167)	8.14% (n = 7)	9.09% (n = 1)
Apathy	0.37 ± 0.63	0.31 ± 0.59	0.65 ± 0.76	0.36 ± 0.51
Depression	0.98 ± 1.48	0.88 ± 1.41	1.41 ± 1.71	1.09 ± 1.87
Procrastination[a]	28.60 ± 12.00	27.7 ± 11.30	32.10 ± 13.80	39.00 ± 16.00

Note. Descriptives for continuous and categorical variables are represented using means ± standard deviations and percentages and frequencies respectively. NC = Normative cognitive function; MCI = Mild cognitive impairment; GED = General Educational Development.
[a] Procrastination scores were collected in 2020 (Wave 3) and are presented here for descriptive comparison, although they were not measured at baseline.

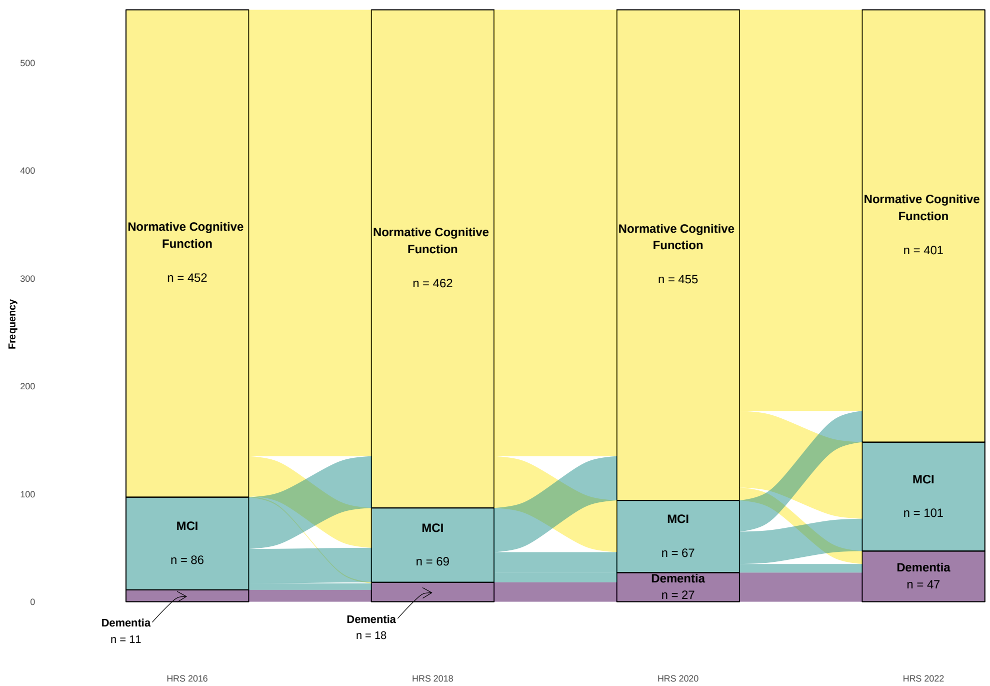

Figure 7.1: *Frequency of cognitive status transitions between HRS waves.*

7.3.1 Cross sectional differences

Initially, a Kruskal-Wallis test was conducted to examine differences in procrastination scores (measured in 2020) across three cognitive status groups after Levene's test indicated violation of homogeneity of variance ($p = 0.039$). The analysis revealed a statistically significant effect of cognitive status, ($\chi^2(2) = 17.54, p < .001$), indicating that procrastination levels differed significantly between at least two of the groups. Post-hoc analysis using a pairwise Wilcoxon rank-sum test with a Benjamini-Hochberg correction showed that participants with normal cognition ($M = 27.7, SD = 11.7$) reported significantly lower levels of procrastination than those with both MCI ($M = 32.1; SD = 11.3; p = 0.004$) and dementia ($M = 36.2; SD = 14.8; p = 0.005$). No significance difference was found between those with MCI and dementia ($p = 0.334$). Figure 7.2 displays the distribution of procrastination scores across groups, with both boxplots and dotplots showing median values and individual data points. Significance bars indicate the pairwise differences described above.

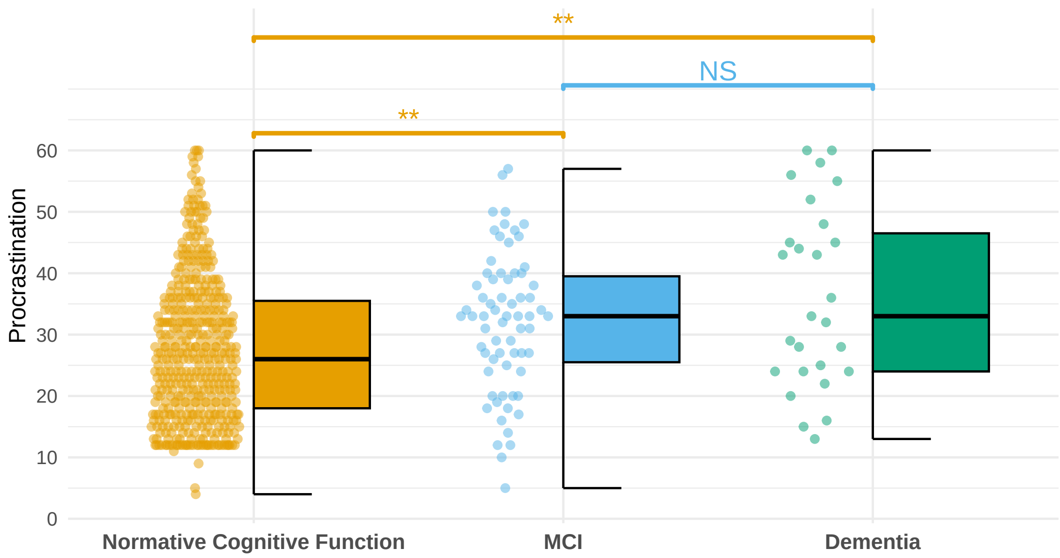

Figure 7.2: *Group differences in 2020 procrastination scores according to cognitive status.*

7.3.2 Markov analysis

Results from the discrete-time Markov analysis, showed that all covariates significantly influenced the likelihood of transitioning between cognitive states (see Figure 7.3). Notably, *procrastination* interacted significantly with *age* to affect two key transitions: increasing the likelihood of transitioning from normative cognitive function to MCI (OR $= 1.001; p < 0.001$) and decreasing the likelihood of reverting from MCI to normative cognitive function (OR $= 0.999; p < 0.001$). *Women* were significantly less likely than men to transition from both normative cognitive function to dementia (OR $= 0.67; p < 0.001$) and from MCI to dementia (OR $= 0.71; p < 0.001$).

For *education attainment*, individuals with a GED were less likely to transition from normative cognitive function to either MCI (OR $= 0.46; p < 0.001$) or dementia (OR $= 0.29; p < 0.001$) and from MCI to dementia (OR $= 0.64; p < 0.001$). They were also more likely to back transition from MCI to normative cognitive function (OR $= 2.24; p < 0.001$). Those with a college level education or higher demonstrated a significantly reduced likelihood of transitioning from normative cognitive function to either MCI (OR $= 0.31; p < 0.001$) or dementia (OR $= 0.07; p < 0.001$) and from MCI to dementia (OR $= 0.22; p < 0.001$). They were also more likely to back transition from MCI to normative cognitive function (OR $= 3.23; p < 0.001$).

Higher levels of *depression* were associated with an increased likelihood of transitioning from normative cognitive function to MCI (OR $= 1.14; p = 0.013$) and a reduced likelihood of transitioning back from MCI to normal cognition OR $= 0.88; p = 0.013$). Finally, higher levels of *apathy* were associated with an increased likelihood of transitioning from normative cognitive function to dementia (OR $= 1.20; p < 0.001$).

Figure 7.4 presents the predicted transition probabilities across varying levels of age and procrastination. These estimates illustrate how the interaction between age and procrastination influences the likelihood of progressing between cognitive states over time. Notably, while transition probabilities remain relatively stable at very low levels of procrastination, substantial shifts emerge as both age and procrastination increase. In particular, older individuals with higher procrastination scores show an elevated probability of cognitive decline transitioning from normative cognitive function to mild cognitive impairment (MCI) and a reduced likelihood of transitioning back from MCI to normative cognitive function, highlighting the compounded risk posed by these two variables in later life.

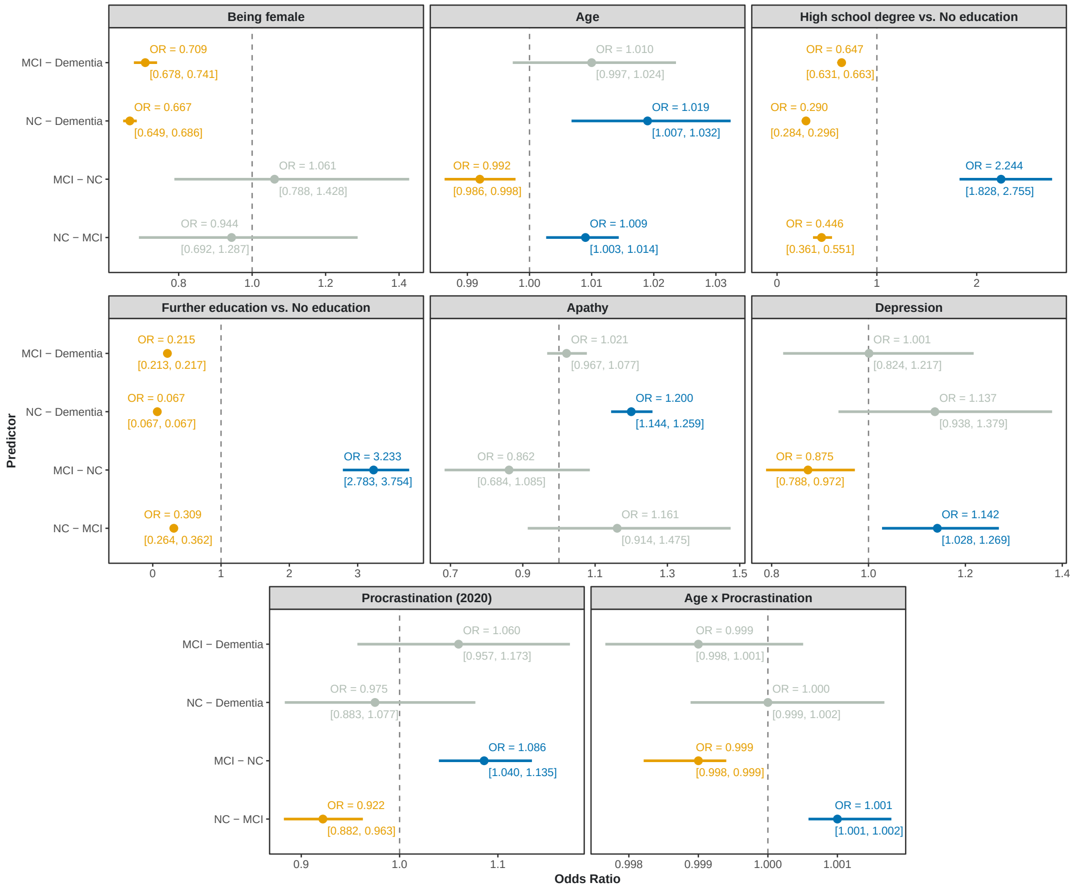

Figure 7.3: *Odds ratios (95% confidence intervals) of transitioning from one cognitive state to another calculated using generalised logit models. Odds ratios significantly different from 1 at a 5% significance level are presented in blue (positive) or orange (negative), otherwise they are presented in grey. NC = Normative cognitive function; MCI = Mild cognitive impairment.*

7.4 Discussion

Dementia poses a growing global health burden, with modifiable risk factors and prodromal markers offering important targets for intervention (Livingston et al., 2020, 2024). While apathy has been well established as a prodromal marker and predictor of dementia (Donovan et al., 2014; Fresnais et al., 2023; Salem et al., 2023; van Dalen et al., 2018), emerging evidence suggests that procrastination may also signal early cognitive dysfunction (Joseph et al., 2021; S. Zhang et al., 2019). This study examined whether procrastination, particularly in later life, could serve as a predictor of cognitive decline. We assessed both cross-sectional differences in procrastination across three cognitive groups (normative cognitive function, MCI and dementia) and longitudinal associations with transitions in cognitive status, to clarify whether procrastination functions as a novel and age-sensitive marker of emerging cognitive impairment.

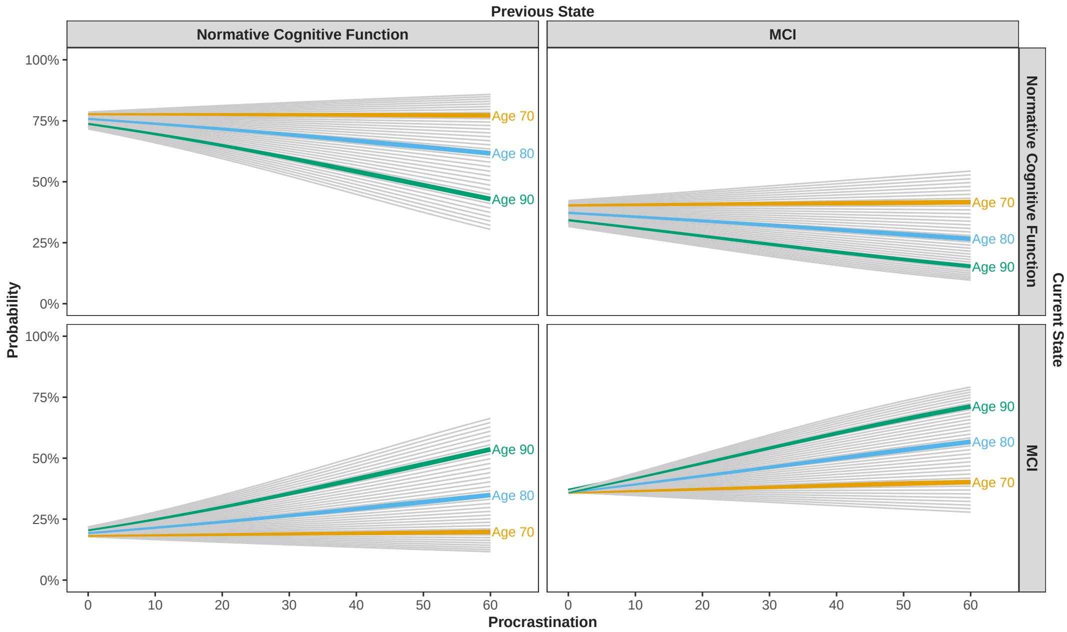

Figure 7.4: *Predicted transition probabilities by procrastination and age. Each curve represents a different age profile, ranging from the minimum (62 years) to the maximum (97 years) of the dataset. Specific ages of interest (70, 80, and 90) are highlighted.*

Our analysis revealed significant group differences in procrastination, with individuals experiencing cognitive impairment, both MCI and dementia, reporting higher procrastination scores than those with normative cognitive function. These findings support the hypothesis that procrastination may be associated with cognitive decline and aligns with emerging evidence linking procrastination to cognitive dysfunction (Joseph et al., 2021; S. Zhang et al., 2019). Interestingly, while both MCI and dementia groups exhibited elevated procrastination scores, no significant difference emerged between these two groups. This suggests that increases in procrastination may occur relatively early in the neurodegenerative process, potentially preceding or paralleling the emergence of more overt cognitive symptoms.

However, it should be noted that the number of participants classified as having MCI ($n = 67$) or dementia ($n = 27$) was relatively small compared to those with normative cognitive function ($n = 455$). This imbalance in group sizes may have limited the sensitivity of our comparisons and raises the possibility that subtle differences between MCI and dementia groups were obscured by statistical power constraints. In addition, our analytic sample contained a higher proportion of women than men (61.57% female) reflecting the demographic composition of the available HRS respondents who met eligibility criteria. Although this imbalance was not the result of a sampling decision, it may influence the generalisability of our findings, as women in older cohorts differ from men in both dementia risk profiles and health-seeking behaviours (Berve et al., 2025). Future research should aim to replicate these findings in more evenly distributed samples to better determine whether these results are consistent across men and women and whether procrastination continues to increase across progressive stages of impairment or plateaus following early decline.

Beyond these cross-sectional differences, our discrete-time Markov analysis offered insight into how procrastination alongside other demographic and psychological factors, influences the likelihood of transitioning between cognitive states over time. Notably, procrastination emerged as a dynamic predictor of cognitive change, interacting with age to significantly increase the odds of transitioning from normative cognitive function to MCI, while simultaneously decreasing the odds of moving from MCI back to normative cognitive function.

These findings imply that procrastination may serve dual roles, both as a marker of early cognitive dysfunction and, potentially, as a behavioral impediment to moving from MCI state to the normative cognitive state. One plausible pathway involves the reinforcement of maladaptive behaviors such as reduced cognitive engagement or reduced participation in cognitively protective activities, such as physical exercise, social interaction or medical adherence (Hajek et al., 2025; S. M. Kelly & Walton, 2021; Sirois, 2007; Stead et al., 2010). In parallel, procrastination has been associated with chronic stress and elevated cortisol levels (Sirois et al., 2023), which may accelerate hippocampal atrophy, β-amyloid plaque deposition, and brain inflammation (Franks et al., 2021; Wallensten et al., 2023), further undermining cognitive resilience. These behavioral and biological mechanisms align with self-regulation theories suggesting that procrastination reflects executive dysfunction (Rozental & Carlbring, 2014), an early feature of neurodegenerative progression (Clark et al., 2012). At the same time, these results align with both the affective and trait-based perspectives on procrastination. Higher procrastination in individuals with cognitive impairment may partly reflect affective dysregulation (e.g., anxiety or stress-related avoidance) (Sirois & Pychyl, 2013) or age-related shifts in stable behavioural tendencies that accompany neurodegenerative change (Oi & Frazier, 2024). While our study cannot differentiate between these frameworks, our results highlight that procrastination is a multifaceted construct encompassing motivational, affective, and self-regulatory dimensions.

The observed interaction with age (see Figure 7.4) suggests that the influence of procrastination on cognitive trajectories may grow stronger with advancing age, a period during which neuro-plasticity diminishes, and behavioral risk factors exert greater influence (Livingston et al., 2020, 2024). This effect was particularly pronounced among the oldest participants. As illustrated in Figure 7.4, the effect of procrastination is relatively modest for younger-older adults (those age 70). However, the slope of these transitions steepens considerably for individuals aged 80 and especially for those age 90. These findings indicate that procrastination is increasingly associated with a higher risk of cognitive decline and a lower likelihood of improvement in cognitive status in late old age.

This pattern underscores the possibility that procrastination functions as a compounding risk factor in older adulthood, particularly among the oldest individuals, by both reflecting emerging cognitive difficulties and potentially accelerating their progression. In younger-old adults, cognitive reserve and compensatory mechanisms (Gooijers et al., 2024) may buffer against the impact of poor self-regulation. However, as individuals reach more advanced ages, these protective systems weaken (R. O. Roberts et al., 2015). Consequently, maladaptive behavioral tendencies like procrastination can exert a disproportionate toll on cognitive function. These findings underscore the potential value of addressing behavioral regulation and self-management in older adults as part of broader dementia risk-reduction strategies, particularly for those of a much older age.

By revealing a significant interaction between age and procrastination, this study highlights the importance of broadening dementia risk models to incorporate dynamic lifestyle and psychological variables. Procrastination, as both a modifiable and measurable behavioral tendency (Van Eerde & Klingsieck, 2018), represents a promising target for low-cost, non-invasive interventions aimed at enhancing cognitive resilience in older populations. Tracking self-regulatory behavioral tendencies such as procrastination may offer an early warning system for emerging cognitive risk, opening avenues for preventative action before irreversible decline takes hold.

7.4.1 Limitations

Despite the insights offered by this study, several limitations should be considered. Most notably, although our longitudinal Markov modelling approach captured changes in cognitive status, a key constraint was the measurement of procrastination at only a single time point (2020). As a result, we assumed temporal stability in procrastination scores across time and used this measure as both a retrospective and prospective proxy for procrastination scores. However, this precluded analysis of within-person changes in this behavior over time and whether such changes affect cognitive transitions. It should be noted that this limitation is inherent to the HRS dataset rather than a methodological oversight (Juster & Suzman, 1995). Future studies should prioritise repeated assessments of procrastination to determine whether increases in procrastination precedes, accompanies, or follows cognitive decline.

A further limitation concerns the classification of cognitive status. As our analyses rely on the HRS, we are constrained by its operational definitions of MCI and dementia (Crimmins et al., 2011), which are based on threshold scores on the TICS (Brandt et al., 1988; Fong et al., 2009). Developed as a telephone-based analogue of the Mini-Mental State Examination, the TICS is a widely adopted and well validated cognitive screener (Fong et al., 2009). However, like all brief screening measures, TICS-based classifications may not fully align with more detailed clinical assessments, raising the possibility of diagnostic misclassification. Future research using more comprehensive cognitive batteries or clinical diagnoses would help validate and refine the patterns observed here.

Additionally, negative emotional states (e.g., anxiety) are important psychological factors linked to both cognitive ageing and procrastination (Livingston et al., 2020; Sirois & Pychyl, 2013). However, we were unable to robustly adjust for anxiety in our models due to substantial systematic missingness in the HRS anxiety measure (see Figure A.2 and Figure A.3). Moreover, our use of a proxy measure of apathy may not have fully captured the multidimensional nature of apathy. Additionally, it meant that only six of the original eight CESD-8 items were used for scoring depression, possibly introducing measurement error. Future research should incorporate more validated apathy assessments to strengthen the behavioral inferences drawn.

Finally, while the models adjusted for several key demographic and psychological covariates, unmeasured confounding (undiagnosed medical conditions, medication use, or sleep quality) could also have influenced cognitive outcomes. Future research should seek to replicate and extend these findings using more clinically diverse samples.

7.4.2 Conclusions

In summary, this study offers preliminary evidence that procrastination may function as an early behavioral tendency marker of cognitive decline, particularly in older age. Individuals with MCI and dementia reported higher procrastination scores, and longitudinal modelling revealed that procrastination, especially when coupled with advancing age, was predictive of increased cognitive decline. These findings underscore the importance of everyday self-regulatory behaviors in dementia risk and resilience. As a modifiable and measurable construct, procrastination holds promise as a target for early detection and preventative intervention strategies aimed at sustaining cognitive health in ageing populations.

CRediT authorship contribution statement

Cormac Monaghan: Conceptualisation, Methodology, Data curation, Formal analysis, Visualisation, Writing – original draft. Writing – review & editing. **Michelle Kelly**: Writing – review & editing. **Rafael de Andrade Moral**: Formal analysis, Visualisation, Supervision, Writing – review & editing. **Joanna McHugh Power**: Conceptualisation, Formal analysis, Supervision, Writing – review & editing.

CHAPTER 8

When Time Matters Most: A Critical Discussion

8.1 Thesis overview

This thesis aimed to address a significant and consequential gap in the psychological literature: the nature, mechanisms, and real-world implications of procrastination in older adulthood, to in part address the paucity of lifespan research concerning procrastination. Within this thesis five empirical studies were carried out. Each of these studies investigated a distinct, but theoretically interconnected part of this problem. The empirical studies began by investigating affective mechanisms (Chapter 3), before moving onto both social evaluative contexts (Chapter 4) and motivational processes (Chapter 5), and finally culminating in two respective real-world consequences, health utilisation (Chapter 6) and cognitive decline (Chapter 7). Taken together, the findings of this thesis are not merely an accumulation of evidence, but additionally speak to how and why procrastination matters in later life, and more broadly why procrastination urgently matters for public health.

The goal of this final chapter is threefold: i.) to synthesise the key findings across the studies, with the lifespan-informed model proposed in Chapter 1 in mind; ii.) to identify the theoretical and empirical contributions of the thesis as a whole, considering limitations and directions for future research; and iii.) to consider the broader real-world implications of this body of work, situating this work within the wider public health landscape of population ageing.

8.2 Revisiting the lifespan-informed model

The lifespan-informed theoretical framework proposed in Figure 1.3 drew upon several theories from the lifespan and motivational literature. These included: Socioemotional Selectivity Theory (SST; Carstensen, 2001; Carstensen et al., 1999), Temporal Motivation Theory (TMT; Steel and König, 2006; Steel et al., 2018), Self-Determination Theory (SDT; Deci and Ryan, 2009), Selective Optimisation with Compensation (SOC; Baltes and Baltes, 1990), Regulatory Focus Theory (Higgins, 1997, 1998), Environmental Press Theory (Lawton & Nahemow, 1973), and Terror Management Theory (Greenberg et al., 1986). Rather than proposing a single causal explanation for procrastination in later life, the framework brought these perspectives together to organise the developmental, motivational, affective, existential, and environmental factors that may contribute to procrastination in older adulthood.

The empirical findings presented throughout this thesis provide varying levels of support for different components of this framework (see Figure 8.1). While several conceptual domains were well supported, others required refinement, and some remain largely untested. Taken together, the findings suggest that **procrastination in later life reflects a dynamic developmental system shaped by interacting affective, motivational, social, cognitive, and contextual processes**. Each of these processes will now be considered in turn, in the context of specific model components discussed in Chapter 1, and in the context of this synthesizing claim.

8.2.1 The affective process

Evidence from Chapter 3 provided strong support for the importance of affective processes within the model. Specifically, depressive symptomatology functioned as a partial mediator in the relationship between procrastination and age. As such, depressive symptomatology may represent an important domain through which age-related challenges translate into inaction. More specifically, this relationship may be driven by symptoms such as fatigue, motivational depletion, and feelings of loneliness, as per the exploratory symptom analysis (Table 3.2). Furthermore, the findings from Chapter 6, provide an illustration of such inaction by demonstrating that depression and procrastination can interact with one another to lower the probability that older adults would engage in preventive health behaviours, such as prostate exam and dental visits (see Figure 6.1).

Critically, this affective pathway could be understood through the lens of TMT. Negative emotional states can undermine self-efficacy and motivation (Nie et al., 2025), which in turn may undermine how "likely success feels" for a given task (i.e., the *expectancy* component of the TMT equation). As such, when success feels less likely and the energy needed for completing a task is reduced, the motivational force to initiate a task (even a protective health related task) is substantially reduced (Steel et al., 2018). Additionally, from a lifespan perspective, both SDT and SOC emphasise the importance of maintaining motivational resources for adaptive functioning in later life (Baltes & Baltes, 1990; Deci & Ryan, 2009). However, negative emotional states may undermine these resources (Fiske et al., 2009) and subsequently, the initiation and maintenance of goal-directed behaviour. As such, the evidence presented in this thesis is consistent both with the synthesized claim and with existing models of procrastination.

8.2.2 The temporal motivational process

Chapter 5 provided an opportunity to evaluate one of the central conceptual assumptions of the framework. Drawing on SST, the lifespan-informed model proposed that a limited future time perspective would reconfigure task motivation. Specifically, a reduced sense of remaining time was expected to decrease procrastination by increasing the perceived importance of acting in the present.

The findings provided partial support for this assumption. As shown in the posterior distributions of Figure 5.2, there was a small positive association between subjective remaining life and procrastination. In other words, individuals who perceived more time remaining in life reported higher levels of procrastination. However, the findings also suggest that this relationship was more complex than what was originally proposed. Subjective remaining life did not moderate the relationship between temporal orientation and procrastination (Figure 5.3). In fact, the posterior distributions (Figure 5.2) showed that a stable future-oriented disposition was a stronger negative predictor of procrastination than subjective remaining life. One interpretation of this may be that future orientation and subjective remaining life capture related (albeit conceptually distinct) aspects of temporality. While subjective remaining life captures an individual's appraisal of how much time they believe remains in life, future orientation reflects broader reflects a broader dispositional tendency to consider, value, and invest in future outcomes (Zimbardo & Boyd, 1999). Individuals who place habitually place less emphasis on the future consequences of their actions develop a cognitive present-oriented temporal bias (Zimbardo & Boyd, 1999), which is known to be related to procrastination (Sirois, 2014a). Consequently, while perceiving less time remaining in life may alter motivational priorities (Carstensen, 2001), this alone may be insufficient in altering procrastination if an individual's broader temporal disposition remains unchanged.

Taken together, this suggests an important refinement to the role of SST within the lifespan model and within procrastination in later life as a whole. Rather than influencing procrastination by simply making people more aware of limited time, SST may be better conceptualised as providing a broader developmental context within which motivational priorities change, rather than specifying a direct explanation for procrastination itself.

8.2.3 Behavioural and health consequences

The final two empirical studies (Chapters 6 and 7) extended the conceptual framework by highlighting the further downstream consequences of procrastination in later life.

Chapter 6 showed that higher levels of procrastination was associated with reduced engagement in several important preventive health behaviours, including mammograms, cholesterol screenings, prostate examinations, and dental visits. In line with prior research (Johansson et al., 2023; Sirois, 2007; Sirois et al., 2003), these findings confirm that procrastination can undermine proactive health management even in later life, particularly when those health behaviours require planning, scheduling, and sustained self-regulation (S. Kelly et al., 2016; Turk & Meichenbaum, 1991).

Health screenings, by their very nature, require individuals to confront the possibility of serious illness. As per Terror Management Theory, this can elicit existential anxiety within an individual (Greenberg et al., 1986). While procrastination of such health behaviours represents a self-regulatory failure, it may also represent a subtle form of death denial. This may be especially true for cancer-related health screenings (prostate exams and mammograms). For instance, Moser et al. (2014) notes that when thinking about "cancer", 60% of people automatically think about "death".

The observed interaction with depression (Figure 6.1), further reinforces this as older adults with depression may be especially susceptible to existential distress (Fiske et al., 2009).

Meanwhile, Chapter 7 demonstrated that procrastination may also function as an early behavioural marker of cognitive decline. Individuals with MCI and dementia reported higher levels of procrastination (Figure 7.2), and additional longitudinal modelling indicated that procrastination was associated with an increased likelihood of cognitive decline and a reduced likelihood of cognitive recovery (Figure 7.4). Environmental Press Theory provides an important contextualisation for these findings. As an individual's competencies decline, the complexity and demands of the everyday environment (the "environmental press") increases (Lawton & Nahemow, 1973). Tasks that were once been routine may become "high-press" demands, exceeding one's capabilities. Within this context, procrastination may represent more than just a self-regulatory failure, but also a response to a person - environment mismatch.

8.2.4 An empirical integration

When taken together, the empirical work presented throughout this thesis supports the overall conceptual organisation of the lifespan-informed model. However, the results also suggest several important refinements (see Figure 8.1). Firstly, affective states (particularly depressive symptomatology) may be a strong domain which undermines the motivation to initiate tasks. Depression consistently accompanied higher levels of procrastination and was implicated across both psychological and behavioural outcomes. Secondly, stable motivational dispositions (such as temporal orientation) appear to be more influential in shaping procrastination than context-sensitive ones (such as subjective remaining life). This suggests that the role of SST in later life procrastination is less about temporal salience and more about emotional re-prioritisation. Finally, there are multiple downstream consequences to procrastination in later life, particularly in the health and cognitive domains. Importantly, not all theories and pathways within the lifespan-informed model could be tested within the scope of this thesis. As such, these pathways and theories remain open for further investigation.

Overall, the evidence presented throughout this thesis supports viewing procrastination in later life as a multidimensional phenomenon situated within the developmental context of ageing. Rather than being simply explained by any single theory or mechanism, procrastination appears to reflect the convergence of affective, motivational, cognitive, existential, environmental, and contextual influences. Collectively the findings reinforce the value of adopting a lifespan perspective when seeking to understand why procrastination persists in older adulthood and how it may contribute to important health and cognitive outcomes.

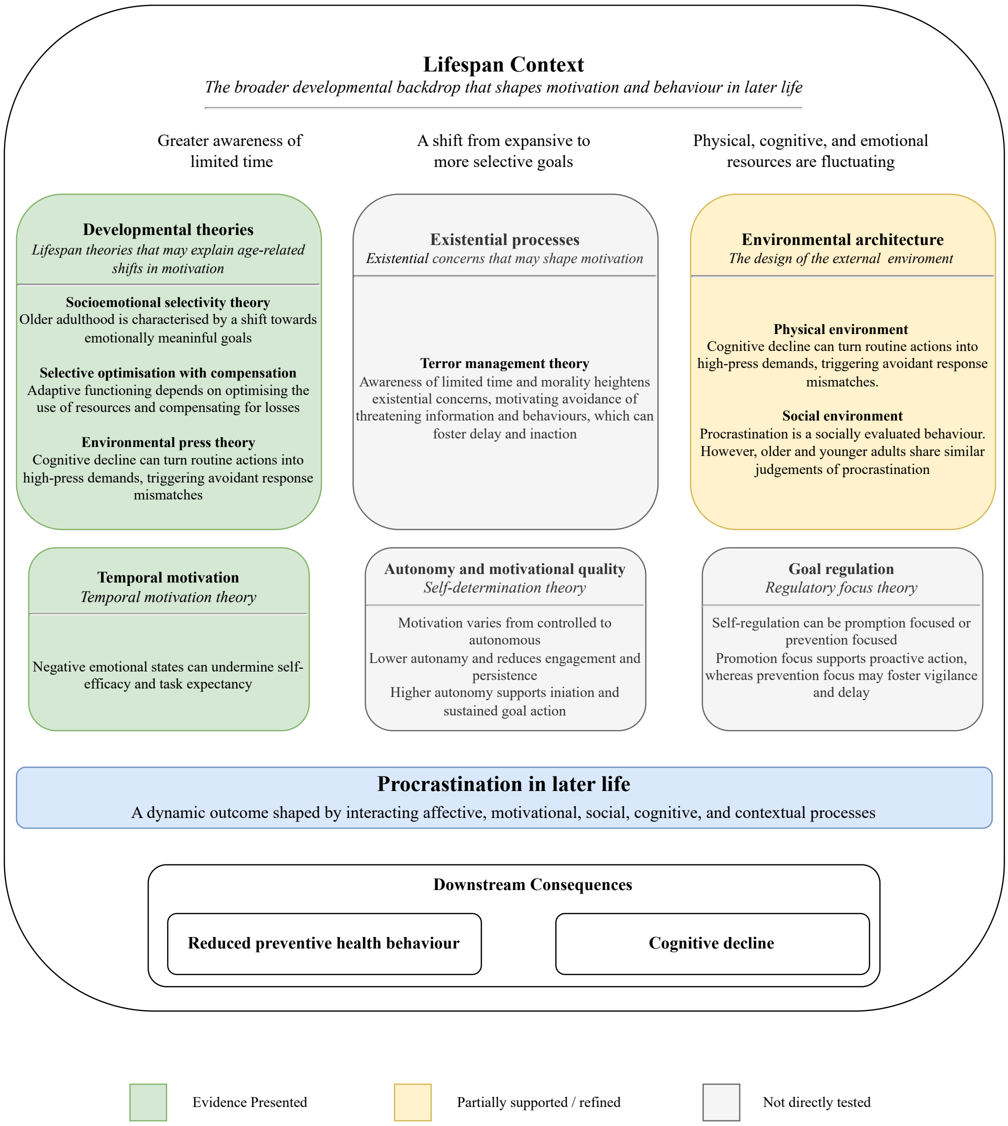

Figure 8.1: *A revised lifespan-informed model of procrastination in older adulthood after empirical investigation. Overall, the model posits that procrastination in later life reflects a dynamic developmental system shaped by interacting affective, motivational, social, cognitive, and contextual processes.*

8.3 Overarching themes

Individually, the empirical findings of each chapter address a distinct research question and provide insights into procrastination in later life. However, several broader themes emerge when these findings and insights are considered collectively. When taken together, these themes highlight the integrative contribution of this thesis and offer a more comprehensive picture of procrastination in later life than any single component alone. Overall, they suggest that procrastination is not simply about delaying an action, but rather it is a complex behavioural phenomenon embedded within emotional, social, motivational, and developmental systems.

8.3.1 Procrastination as a socially embedded behaviour

The first overarching theme concerns the social nature of procrastination. While often conceptualised as an internal self-regulatory failure (Klingsieck, 2013a; Steel, 2007), the findings of this thesis suggest that procrastination is also embedded within broader social contexts. Consistent with the work of Giguère et al. (2016), the findings of Chapter 4 suggest that procrastination was broadly perceived as a violation of social norms. This was particularly evident in areas characterised by important long-term consequences, such as health and financial decision-making. For many, delaying a simple task may be viewed as inconvenient. However, delaying an important medical exam or financial decision carries broader implications for both individual well-being and social responsibility (Bandaranayake & Shaw, 2016; Brown & Previtero, 2014; Ferrucci et al., 2008; Gamst-Klaussen et al., 2019; Kulminski et al., 2007; Mottola et al., 2024; Shah & Mukherjee, 2025).

Importantly, these findings also highlight an important distinction between the externalisation (social evaluation) and the internalisation (personal meaning) of procrastination. Between younger and older adults, there was a broad consensus present that procrastination was a problematic behaviour. However, younger adults reported a greater self-critical evaluation of procrastination. This suggests that while the overall social meaning of procrastination (i.e., "procrastination is bad") remains relatively stable throughout adulthood, the way individuals interpret and respond to their own procrastination may change with age.

When considered alongside the broader findings of this thesis, these results suggest that procrastination is not a purely private act. Rather, procrastination is shaped by shared norms, interpersonal expectations, and differences in how one self-evaluates themselves. As such, to truly understand procrastination requires not only paying attention to individual motivational processes, but also to the social contexts in which the decision to act or delay occurs.

8.3.2 The cycle of depression, procrastination, and health

A second overarching theme concerns the possibility of a self-perpetuating cycle between depression, procrastination, and health. Initially, Chapter 3 suggests that depressive symptoms mediate the relationship between age and procrastination. More specifically, older adults who experience depression are significantly more likely to procrastinate. Based off the exploratory symptom analysis presented in Table 3.2, this association is likely driven by fatigue, motivational decline, and possible feelings of loneliness, which in turn may all undermine the capacity to initiate and complete tasks. Chapters 6 and 7 then show that such procrastination translates into various health compromising behaviours and cognitive decline. However, such forms of procrastination are likely to contribute to deteriorating physical and cognitive functioning, which may subsequently exacerbate depressive symptoms and further reduce an individual's motivational capacity (much like the cascading process in Figure 1.4). Although future longitudinal research would be required to text this explicitly.

This overarching theme aligns with the procrastination–health framework (Sirois, 2007; Sirois et al., 2003), which provides a conceptual basis for how procrastination may translate into downstream health consequences (albeit with a stronger focus on the role of stress). Nevertheless, a similar framework could be used to disentangle the possible self-perpetuating cycle implied here. In fact, emerging meta-analytic evidence does suggest a possible bi-directional association between procrastination and depression (Nie et al., 2025). However, the current findings extend these accounts by situating this potential cycle within older adulthood, where the consequences of repeated delay may accumulate more rapidly. When taken together, these results highlight the need for future research to more directly disentangle the temporal ordering and reciprocal dynamics implied by this cycle, and to identify leverage points for intervention to interrupt the cycle.

8.3.3 The public health significance of procrastination

A third overarching theme concerns the significance of procrastination for healthy ageing. Procrastination represents a significant and potentially modifiable public health risk in ageing populations. The collective findings of this thesis provide substantial support for this claim.

The findings from Chapter 3 are consistent with the suggestion that depressive symptoms partially mediate the relationship between age and procrastination, highlighting the importance of mental health in shaping procrastination. Late-life depression is already a public health concern (Fiske et al., 2009; Paun, 2023). With the proportion of the population over the age of 65 growing (World Health Organisation, 2025) this means that there is likely to be growing numbers of individuals impacted by late-life depression. Given the possibility of a cyclical association between procrastination and depression, this growing increase makes procrastination a wider concern. Echoing this concern, the findings from Chapter 6 suggest that procrastination (and at the same time its interaction with depression) is associated with reduced engagement in several preventive health behaviours. Older women who reported higher levels of procrastination were less likely to undergo mammograms, cholesterol screenings, and dental visits, while older men were less likely to undergo prostate examinations and dental visits. These behaviours (mammograms, prostate exams, cholesterol screenings, and dental visits) are particularly important because they typically require an individual to plan, schedule, and act in such a way that the future version of that individual will benefit (S. Kelly et al., 2016).

Finally, and perhaps most notably, the findings of Chapter 7 suggest that procrastination may have implications for cognitive ageing. Older adults who reported higher levels of procrastination were more likely to experience transitions towards cognitive impairment. Additionally, the association between procrastination and cognitive impairment became more consequential with advancing age, such that the oldest-old (those 90+ years old) were most at risk. Even though the effect sizes for these results were quite small, the interaction between procrastination and age makes these results of concern as the oldest-old adults are already at the most risk of dementia (R. O. Roberts et al., 2015).

Collectively, these findings suggest that procrastination in later life should not be viewed as a simple bad habit or problem related to productivity. Rather, procrastination in later life appears to overlap with several domains related to successful ageing, including emotional well-being, preventive health management, and cognitive functioning. When considered from this perspective, procrastination emerges as a behaviour with meaningful public health implications.

8.4 Theoretical contributions

From a theoretical standpoint, this thesis makes several contributions to the theoretical understanding of procrastination, self-regulation, and ageing.

Firstly, to the best of the author's knowledge, this thesis is the first to i.) develop a lifespan-informed model of procrastination in older adults and ii.) empirical evaluate parts of that model across multiple studies with a core focus on older adulthood. For the most part, research into the area of procrastination has been dominated by studies and theoretical frameworks that focus on younger adults. As always, there are exceptions with some studies investigating specific aspects of procrastination in older adulthood (Biella et al., 2020; Shah & Mukherjee, 2025; Stolcis & McCown, 2018) or including older adults as a subset of a broader sample (Beutel et al., 2016; J. R. Ferrari et al., 1995; Firdaus et al., 2020; Harriott & Ferrari, 1996). However, no previous program of research has attempted to evaluate the mechanisms, social context, motivational reasoning, behavioural consequences, and potential cognitive implications of procrastination in older adulthood. While much work still needs to be done in this field, this thesis extends the field of procrastination beyond its traditional focus on younger adults.

Secondly, this thesis contributes to the theoretical understanding of procrastination. Procrastination is typically seen as a self-regulatory failure (Rozental & Carlbring, 2014). However, the findings presented here suggest that procrastination in later life may represent something more complex. Drawing on several lifespan developmental theories, this thesis proposes that procrastination may reflect dynamic response changes in an older adult's motivational resources and priorities, the environment they live in, as well as their overall health, emotional wellbeing, and cognitive function. Rather than viewing procrastination as an individual deficit in self-regulation, the thesis broadens the understanding of procrastination by situating procrastination within the developmental realities of ageing.

Thirdly, this thesis contributes to the growing recognition that procrastination is socially evaluated. The findings from Chapter 4 demonstrate that procrastination is more negatively evaluated in the health and financial domains. Typically, these domains are characterised by long-term consequences; procrastinating a doctor's appointment or paying a bill has more notable consequences than procrastinating starting an essay. This suggests that the social meaning of procrastination is shaped by the context in which delay occurs (Giguère et al., 2016), and that certain forms of procrastination may carry greater social and psychological significance than others.

Finally, this thesis situates procrastination as a meaningful determinant of healthy ageing. Procrastination has long been associated with health and wellbeing (see Sirois (2017) for review). However, like most studies in this field the focus has been on the health and wellbeing over the younger population. The findings from Chapter 6 suggest that procrastination in later life is associated with reduced engagement in numerous preventive health behaviours, including prostate exams, mammograms, cholesterol screenings, and dental visits. These findings tentatively build on the procrastination-health framework (Sirois, 2007; Sirois et al., 2003) by demonstrating that procrastination may have particularly important implications in later life.

This is further emphasised by the findings of Chapter 7, perhaps one of the most novel theoretical contributions of this thesis. The findings from this chapter suggest that procrastination may function not only as a determinant of healthy ageing but also as a potential determinant of cognitive decline. By cross-situating procrastination with established theories of executive function, self-regulation, and health engagement (S. M. Kelly & Walton, 2021; Rozental & Carlbring, 2014; Sirois et al., 2003) and neurobiological pathways implicated in dementia such as, chronic stress, cortisol and hippocampal atrophy (Franks et al., 2021; Sirois, 2023; Wallensten et al., 2023), this thesis opens a potentially novel gap in the crosshairs of behavioural psychology, gerontology, and cognitive neuroscience.

8.5 Methodological contributions

In addition to the theoretical contributions, this thesis makes several methodological contributions to the fields of statistics and data science. Each of the contributions reflects an attempt to resolve an issue that emerged as the result of a challenge in the applied questions behind the empirical work of this thesis.

First and foremost, this thesis addresses a fundamental difficulty in the evaluation of discrete-time Markov models. As noted in the methodological overview presented in Chapter 2, determining if a fitted Markov model accurately represents the transition structure of the real data is a difficult challenge and subject of ongoing research. Unlike most standard regression techniques, where residuals can be calculated and subsequently analysed, Markov models do not provide residuals in the same sense (Araripe et al., 2024). Rather they provide transition probabilities which may be converted to multivariate residuals. This makes model diagnostics and goodness-of-fit assessments challenging since they are not available by working with univariate residuals directly.

To address this, a large-scale simulation study (as outlined in Section 2.3) was conducted. Rather than relying on a global fit statistic (such as the AIC or BIC), the study developed a novel procedure for directly comparing the transition structure implied by the fitted model against the observed transition structure of the raw data. Overall, this approach provides researchers with an alternative and more nuanced diagnostic tool for longitudinal data analysis, moving beyond simple likelihood comparisons. This is especially true for research studies involving smaller sample sizes as we obtained favourable results for the distance-based diagnostics in this case, when compared to the information criteria (as per Figures 2.1 and 2.2).

Moreover, this thesis demonstrates the value of applying more flexible and advanced statistical approaches to the study of procrastination and ageing. Across the empirical chapters, a range of statistical techniques were used, including mediation analysis, multilevel modelling, Bayesian estimation, generalised additive modelling, and longitudinal transition modelling. As outlined in Chapter 2, many of these methods offer several advantages (modelling of non-linear relationships, probabilistic uncertainty, and complex temporal transitions) and extend beyond what may be traditionally used in psychological procrastination research.

Nevertheless, the complexity of procrastination in later life suggests that there remains considerable scope for further methodological development. As mentioned previously, many of the relationships examined within this thesis are likely to be dynamic, reciprocal, and interdependent rather than strictly unidirectional. Consequently, future research may benefit from using statistical approaches capable of simultaneously estimating multiple pathways and temporal dependencies. For instance, multivariate models (fitted under either the frequentist or Bayesian paradigms) would allow for the joint modelling of procrastination, depressive symptomatology, health behaviours, and cognitive functioning while explicitly accounting for any potential correlations between these outcomes. Similarly, dynamic structural equation models or cross-lagged panel models when applied to repeated measures of procrastination across time would allow for future researchers to disentangle the relationships between procrastination, affective functioning, and health over time.

8.6 Limitations

As with any body of work, several limitations should be considered when interpreting the findings of this thesis. Although each of the individual chapters have their own specific limitations (which have already been discussed), a number of broader methodological considerations apply for the thesis as a whole. Firstly, while meaningful associations were demonstrated between procrastination, depression, social norms, subjective remaining life, health behaviours, and cognitive functioning, the direction of these relationships cannot be determined. Indeed, several of the theoretical pathways proposed throughout this thesis are likely to be reciprocal. For example, procrastination may contribute to poorer health and cognitive outcomes, while declining health and cognitive functioning may themselves increase procrastinatory behaviour (Johansson et al., 2023). Additionally, while Chapter 7 did employ longitudinal data, the procrastination variable itself was measured only at a single time point, largely due to the nature of the HRS experimental modules. Consequently, it was not possible to examine within-person changes in procrastination or determine whether changes in procrastination precede, accompany, or follow changes in cognitive functioning.

A second overarching limitation concerns the extensive use of secondary data. Several chapters of this thesis (namely, Chapters 3, 6 and 7) utilised data from the HRS. While the HRS provides a rich and nationally representative data source for the study of ageing, it was not originally designed with procrastination as i.) a primary construct of interest and ii.) a repeatedly measured construct. Consequently, the scope of this thesis was limited by the variables available within the dataset, as well as both the nuances of those variables and the design of the HRS itself.

In addition, the use of the HRS data introduces several important contextual and generalisability limitations. The HRS is based entirely on a US population. As such, the findings may not fully generalise to other national, healthcare, and cultural contexts. This is especially relevant for the findings of Chapters 6 and 7, where procrastination was examined in the context of preventive health care usage and cognitive ageing. The health care system in the US is quite different from many of the European systems, particularly with respect to accessibility, insurance, and financial costs (Marchildon, 2022). Such differences may influence not only the consequences of procrastination but also the reasons behind why one may procrastinate. For example, in health care systems where access is largely universal and financial barriers are relatively low, delaying a medical appointment may be more directly attributable to procrastinatory tendencies. However, in health care systems where access is more costly or difficult to attain, procrastination of such care may be partly due to such structural barriers rather than purely because of an individual's self-regulatory processes.

Overall, the constraints of the HRS had several implications for the analyses conducted throughout the thesis. First, certain important psychological constructs could not always be included into statistical models. For instance, stress was excluded from the generalised additive models used in Chapter 6 due to 71% of the data being missing, despite stress being a key component in the relationship between procrastination and health care utilisation (Sirois, 2007, 2023; Sirois et al., 2003, 2023). Similarly, alternative affective states (e.g., anxiety) could not be sufficiently examined in both Chapters 3 and 7 due to high levels of systematic missingness across the waves of data collection. Finally, and as mentioned before, data from the HRS are drawn from a US population, which limits the generalisability of findings to other national, healthcare, and cultural contexts. Nevertheless, the HRS made it possible to investigate procrastination within a large, nationally representative ageing cohort that would otherwise be difficult to gather through primary data collection alone.

Finally, the results of this thesis are mostly observational in nature. While a compelling theoretical and empirical case is made for the significance of procrastination in older adulthood, this thesis does not provide direct evidence that interventions targeting procrastination in older adults improve health behaviour engagement, reduce cognitive risk, or attenuate the affective consequences of procrastination. Prior research has shown procrastination to be responsive to intervention (Ferreira et al., 2025; Rozental et al., 2018; Van Eerde & Klingsieck, 2018) however, the majority of these interventions have been developed and evaluated using younger adult populations. Consequently, it remains unclear whether existing interventions approaches are appropriate for older adults.

8.7 Directions for future research

When considered together, the findings and limitations of this thesis open up a number of important and interesting avenues for future research.

To the best of the authors knowledge, the HRS is the only longitudinal cohort study that i.) collects data on older adults and ii.) has a measure of procrastination, albeit only a single wave measure of procrastination. However as noted in the above limitations section, the HRS has its own strengths and limitations. While the HRS made it possible to examine procrastination within a large scale, nationally representative ageing population, the absence of a repeated procrastination measure limited the ability to within-person changes in procrastination over time or disentangle the temporal ordering of many of the relationships observed throughout this thesis. As such, perhaps one of the most important priorities for future research is the development of longitudinal studies that repeatedly assess procrastination across later life. Throughout this thesis, procrastination was shown to be associated with depressive symptomatology, subjective remaining life, preventive health behaviours, and cognitive decline. However, due to the observational (and mostly cross-sectional) nature of these findings, the temporal ordering of these relationships could not be fully determined.

Longitudinal study designs with repeated measures of procrastination would enable researchers to examine within-person changes in procrastination, especially as individuals experience major life events such as retirement, bereavement, declining health, or simply very old age. In addition, such studies would enable direct testing of casual claims that could not be fully disentangled within this thesis. For instance, whether increases in depressive symptoms precede and cause increases in procrastination, or whether there is a bi-directional relationship between procrastination and health care utilisation in older adulthood, or whether procrastination predicts, accompanies, or follows cognitive decline.

One important thing to note is that this would not necessarily require the creation of new longitudinal cohort studies. In fact, a practical next step would be the incorporation of a brief, validated measure of procrastination, such as the short General Procrastination Scale (Sirois et al., 2019) into existing large scale longitudinal ageing datasets. Possible studies could include The Irish Longitudinal Study on Ageing (TILDA) or the English Longitudinal Study of Ageing (ELSA). While it would also be beneficial to recommend this for the HRS, the fact that the procrastination measure was included within an "experimental module" means that it wont ever be included in the HRS again, albeit unless an administrative change is made within the study itself. Overall, integrating a measure of procrastination into established studies such as these would provide an efficient means of examining the longitudinal development of procrastination in older adults across a range of diverse healthcare systems, cultural contexts, and ageing trajectories.

In addition, the observational findings established in this thesis require complementary experimental and intervention research. Several of the findings within this thesis suggest that procrastination may be associated with depressive symptomatology, reduced engagement in preventive health behaviours, and cognitive decline. Collectively, these findings suggest that procrastination may be a risk factor for health ageing. However, whether reducing procrastination would improve these outcomes is still an unanswered question.

Existing evidence suggests that procrastination is responsive to intervention (Ferreira et al., 2025; Rozental et al., 2018; Van Eerde & Klingsieck, 2018). However, the majority of intervention studies have focused on younger adults, particularly university students, and typically revolve around academic performance or general self-regulation. Relatively little is known about whether these approaches would be equally effective in older adulthood. According to Van Eerde and Klingsieck (2018), procrastination is particularly responsive to cognitive behavioural therapy (CBT). However, such approaches may need to be modified for older adults to account for age-related physical and cognitive changes (Skosireva et al., 2025). Future research should therefore evaluate whether established interventions can be successfully adapted for older adult populations. In addition, health care systems may benefit from external changes, that reduce opportunities for delay. For instance, having default appointment scheduling, automated reminders, or more simplified booking procedures.

8.8 Applied and clinical implications

The findings of this thesis suggest that procrastination in later life may have implications extending beyond productivity and everyday self-regulation. Over multiple studies, procrastination was associated with emotional well-being, preventive health behaviours, and cognitive functioning. Overall, procrastination may represent an important determinant in healthy ageing. As such, the findings of this thesis collectively point toward several practical implications for clinicians, public health practitioners, and policy-makers working with older populations.

One of these implications is that procrastination may warrant greater attention during routine health and wellbeing assessments. The findings of this thesis suggest that procrastination may be associated with depressive symptomatology, reduced engagement in preventive health behaviours, and may be considered a marker of cognitive decline. Incorporating brief measures of procrastination into health and wellbeing assessments may help identify individuals who are at increased risk of delaying important health related actions. Given the prior mediating role of depression noted in Chapter 3, this would be particularly useful if late life depression was also being screened for at the same time. A simple procrastination screening tool, such as the shortened General Procrastination Scale (Sirois et al., 2019), could help identify older adults at risk of both health behaviour avoidance and potential early cognitive impairment. Such older adults could be given additional support, monitoring, or intervention.

A second implication concerns the design of environments in which older adults make important health and life decisions. As mentioned in Chapter 1, procrastination in later life may arise from a mismatch between the external environment (healthcare portals, financial platforms, appointment scheduling systems) and an older individual's current competencies and self-regulatory resources (Becker, 2004; Thomas et al., 2023). The results from Chapter 6 suggested that the association between procrastination and preventive health care usage may be because of the structural complexity of health behaviours, echoing this proposition. Consequently, making some simplified structural and environmental changes may help in reducing the procrastination driven avoidance. One such notable change could include default appointment scheduling. Rather than requiring an individual to proactively decide when to book an appointment for a preventive health check-up, practitioners could schedule the appointment automatically and inform the individual as of the date (with the option to cancel or reschedule if necessary). In fact, prior research has shown such practice to increase uptake in influenza vaccinations (Chapman et al., 2016). Other changes could include more accessible digital systems or proactive health practitioner outreach would likely help in reducing the procrastination-driven avoidance. Perhaps the most important aspect of this would be that such changes wouldn't require individuals to change their dispositional tendencies. Rather, these changes would seek to modify the environment in ways that make desired behaviours easier to initiate and maintain.

Finally, a larger implication would be to reframe procrastination in later life as more than just a "bad habit", but rather as a marker of healthy ageing. Reframing procrastination in this way has the advantage of shifting the explanation of procrastination away from individualised explanations toward a more integrated biopsychosocial explanation. One that could incorporate both not only person level, but also and contextual influences.

8.9 When time matters most

Procrastination has traditionally been studied as though time were an abundant resource. A resource to be managed, optimised, and occasionally wasted without any real lasting consequence. For a younger adult, this is oftentimes true. A missed deadline or a delayed decision can usually be revisited, repaired, or simply forgotten. However, this thesis suggests that later life does not afford the same margin of error. A postponed mammogram, an unmade will, or a delayed conversation about care are not simply inconvenient. They are decisions made against a backdrop of genuinely diminishing time, where the capacity to recover from delay, be it physically, financially, and cognitively, is itself in decline. While procrastination, on the surface, may look like the same across the lifespan; underneath, it is a fundamentally different wager.

Simply put, it is this shift in stakes that makes procrastination in older adulthood an urgent concern rather than a curious one. The mechanisms uncovered across this thesis, depressive symptomatology, social evaluation, temporal orientation, health disengagement, and cognitive decline, are not unique to old age. A younger adult may experience all these things too. However, what is unique is how little room later life leaves before these decisions harden into irreversible outcomes. As the global population continues to age, this margin will matter to a growing number of people and the oftentimes invisible act of putting something off may increasingly determine whether that time is spent well or lost. Recognising when time matters most, and building the psychological, social, and environmental supports that help people act while it still does, may be one of the most consequential, and most overlooked, challenges of supporting healthy ageing.

APPENDIX A

Supplementary Material

Supplementary Material - Chapter 4

Procrastination as a Social Norm Violation: The Role of Domain and Age in Evaluative Judgments

Procrastination vignettes

General procrastination
Imagine yourself as someone **who often procrastinates**, that is you often unnecessarily delay tasks you said you would do **despite knowing that this may harm to yourself or others**. You rarely start unpleasant or difficult tasks right away and instead put them off for another time, and you often miss deadlines. Even with small tasks that you find inconvenient, stressful or frustrating, you often say that you will do them later, but then don't follow through. When you do start tasks and encounter a difficulty, you often find yourself putting that task off for another time even though it is not in your best interest to do so.

Health procrastination
Imagine yourself as someone who often **procrastinates health tasks**, that is you often unnecessarily delay tasks you said you would do even though **you know this may harm your wellbeing**. You rarely book recommended check-ups or health tests right away and instead put them off for another time, and you sometimes miss appointments.

Even with small health tasks you find inconvenient, stressful or frustrating (e.g., arranging a routine screening, picking up a prescription, or doing home exercises) you often say you'll do them later but then don't follow through. When you do start a health task and encounter a difficulty (e.g., a long NHS phone queue, an online form that takes time, or soreness from an exercise), you set it aside for another time even though it's not in your best interest to do so.

Financial procrastination
Imagine yourself as someone who **often procrastinates financial tasks**, that is you often unnecessarily delay tasks you said you would do even though **you know that this may harm the financial well-being of yourself or others**. You rarely spend time budgeting or reviewing your bank statements right away and instead put them off for another time, and you often miss payment due dates.

Even with small financial tasks that you find inconvenient, stressful or frustrating (e.g., paying a utility bill, or reviewing your monthly spending), you often say that you will do them later, but then don't follow through. When you do start a financial task and encounter a difficulty (e.g., problem cancelling a subscription, can't find a receipt for a refund, or a long phone queue to speak to the bank/a problem with the online banking system), you often find yourself putting that task off for another time even though it is not in your best interest to do so.

Non-procrastination vignettes

General non-procrastination
Imagine yourself as someone **who rarely procrastinates**, that is you rarely unnecessarily delay tasks you said you would do, because you know that this may cause harm to yourself or others. You almost always start unpleasant or difficult tasks right away and don't put them off for another time, and you rarely miss deadlines.

Even with small tasks that you find inconvenient, stressful or frustrating, you try to get on with them right away. When you encounter difficulty on the task you are working on, you keep going because it is in your best interest to do so

Health non-procrastination
Imagine yourself as someone who **rarely procrastinates health tasks**, that is you rarely unnecessarily delay tasks you said you would do because **you know this harms your well-being**. You almost always book recommended check-ups or tests right away and don't put them off, and you rarely miss appointments.

Even with small health tasks you find inconvenient, stressful or frustrating (e.g., arranging a routine screening, picking up a prescription, or doing home exercises) you try to get on with them right away. When you encounter a difficulty (e.g., a long NHS phone queue, an online form that takes time, or soreness from an exercise), you keep going because it is in your best interest to do so.

Financial non-procrastination
Imagine yourself as someone **who rarely procrastinates financial tasks**, that is you rarely unnecessarily delay tasks you said you would do because **you know that this may harm the financial well-being of yourself or others**. You almost always spend time budgeting or reviewing your bank statements right away and don't put them off, and you rarely miss payment due dates.

Even with small financial tasks that you find inconvenient, stressful or frustrating (e.g., paying a utility bill, or reviewing your monthly spending), you try to get on with them right away. When you encounter a difficulty (e.g., problem cancelling a subscription, can't find a receipt for a refund, or a long phone queue to speak to the bank/a problem with the online banking system), you keep going because it is in your best interest to do so.

Table A.1: *Full demographic information by age group.*

	Younger adult (18–30)	**Older adult (60+)**	**Total**
Sample size	100	100	200
Female (%)	51%	50%	51.00%
White (%)	68%	97%	82.50%
Education level			
High school	25%	35%	30.99%
College / University	56%	41%	48.50%
Post graduate	19%	24%	21.50%
Relationship status			
Married	30%	78%	54.00%
Never married	69%	8%	38.50%
Separated / Divorced	1%	12%	6.50%
Widowed	0%	2%	2.00%

Table A.2: *Full model results from the beta mixed-effects model predicting negative productivity index.*

Parameter	Coefficient	SE	95% CI	p
Fixed effects				
Intercept	-2.08	0.13	[-2.33, -1.82]	< .001
Scenario (Procrastination)	2.54	0.15	[2.24, 2.84]	< .001
Domain (Health)	0.16	0.11	[-0.06, 0.39]	.162
Domain (Financial)	-0.29	0.12	[-0.52, -0.07]	.012
Age group (Older)	0.43	0.16	[0.12, 0.73]	.006
Scenario × Domain (Health)	-0.05	0.12	[-0.28, 0.18]	.676
Scenario × Domain (Financial)	0.58	0.12	[0.35, 0.81]	< .001
Scenario × Age group (Older)	-0.50	0.18	[-0.85, -0.15]	.005
Domain (Health) × Age group (Older)	0.06	0.11	[-0.15, 0.27]	.600
Domain (Financial) × Age group (Older)	0.10	0.11	[-0.11, 0.31]	.343
Dispersion model				
Intercept	2.59	0.11	[2.37, 2.82]	< .001
Domain (Health)	0.64	0.19	[0.27, 1.01]	< .001
Domain (Financial)	0.80	0.18	[0.44, 1.16]	< .001
Random effects				
SD (Intercept: ID)	0.54	–	[0.48, 0.62]	–

Note. All coefficients are reported on the logit scale. The outcome variable was rescaled to the open unit interval $(0, 1)$ and modelled using a beta distribution.
Reference categories: scenario = non-procrastination, domain = general, age group = younger.
Confidence intervals are computed using a Wald z-distribution approximation.

Table A.3: *Full model results from the cumulative link mixed models predicting the individual adjective ratings.*

Parameter	Coefficient	SE	95% CI	*p*
Admirable - Shameful				
Scenario (Procrastination)	7.52	0.66	[6.21, 8.82]	< .001
Domain (Health)	0.27	0.38	[-0.48, 1.02]	.483
Domain (Financial)	-0.23	0.39	[-0.98, 0.53]	.561
Age group (Older)	1.03	0.56	[-0.07, 2.13]	.067
Scenario × Domain (Health)	-0.02	0.40	[-0.80, 0.77]	.968
Scenario × Domain (Financial)	1.09	0.41	[0.29, 1.89]	.007
Scenario × Age group (Older)	-1.35	0.68	[-2.67, -0.03]	.046
Domain (Health) × Age group (Older)	0.19	0.40	[-0.58, 0.97]	.627
Domain (Financial) × Age group (Older)	0.13	0.40	[-0.65, 0.91]	.746
Random effects				
SD (Intercept: ID)	2.04	–	–	–
Future-oriented - Present-oriented				
Scenario (Procrastination)	5.11	0.58	[3.96, 6.25]	< .001
Domain (Health)	-0.48	0.38	[-1.22, 0.26]	.200
Domain (Financial)	-0.50	0.38	[-1.25, 0.24]	.184
Age group (Older)	2.18	0.56	[1.07, 3.28]	< .001
Scenario × Domain (Health)	1.36	0.40	[0.56, 2.15]	< .001
Scenario × Domain (Financial)	1.43	0.40	[0.64, 2.22]	< .001
Scenario × Age group (Older)	-2.56	0.70	[-3.93, -1.20]	< .001
Domain (Health) × Age group (Older)	-0.63	0.40	[-1.41, 0.15]	.115
Domain (Financial) × Age group (Older)	-0.64	0.40	[-1.42, 0.14]	.105
Random effects				
SD (Intercept: ID)	2.07	–	–	–
Self-compassionate - Self-critical				
Scenario (Procrastination)	1.75	0.45	[0.86, 2.63]	< .001
Domain (Health)	-2.68	0.38	[-3.42, -1.94]	< .001
Domain (Financial)	-1.02	0.35	[-1.71, -0.34]	.003
Age group (Older)	0.57	0.46	[-0.33, 1.47]	.214
Scenario × Domain (Health)	3.31	0.41	[2.50, 4.12]	< .001
Scenario × Domain (Financial)	1.05	0.38	[0.31, 1.79]	.005
Scenario × Age group (Older)	-1.59	0.54	[-2.66, -0.53]	.003
Domain (Health) × Age group (Older)	-0.03	0.38	[-0.78, 0.71]	.929
Domain (Financial) × Age group (Older)	0.13	0.37	[-0.60, 0.86]	.736

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Table A.3 (continued): *Full model results from the cumulative link mixed models predicting the individual adjective ratings.*

Parameter	**Coefficient**	**SE**	**95% CI**	*p*
Random effects				
SD (Intercept: ID)	1.55	–	–	–
Relaxed - Anxious				
Scenario (Procrastination)	-0.03	0.32	[-0.66, 0.59]	.913
Domain (Health)	0.44	0.19	[0.08, 0.81]	.017
Domain (Financial)	0.23	0.18	[-0.13, 0.59]	.213
Age group (Older)	-0.43	0.32	[-1.05, 0.19]	.173
Random effects				
SD (Intercept: ID)	1.94	–	–	–

Note. All coefficients are reported as log-odds from the cumulative link mixed models. References categories include: scenario = non-procrastination, domain = general, age group = younger. The relaxed–anxious model includes only main effects. Confidence intervals are computed using a Wald z-distribution approximation.

Supplementary Material - Chapter 5

Do Perceptions of Remaining Life Shape Procrastination? Evidence from Latent Class and Bayesian Models

Trichotomising the consideration of Future Consequences scale

`PoLCA` (Linzer & Lewis, 2011) represents degrees of freedom (DF) as the difference between the number of unique parameters (N) and the number of independent parameters, given the number of classes R, the number of questions J, and the number of individual items per question K_j. We can represent this difference as:

$$DF = N - \big((R-1) + \sum_{j=1}^{J}(K_j - 1) \times R\big) \tag{A.1}$$

Therefore, in an R-class model with $N = 140, J = 14$, and $K_j = 7$ the resulting degrees of freedom can be represented as:

$$\begin{aligned} DF &= N - \big((R-1) + \sum_{j=1}^{14}(7 - 1) \times R\big) \\ &= 140 - (R - 1 + 84R) \\ &= 141 - 85R \end{aligned} \tag{A.2}$$

Substituting in any value $R > 1$ where $R \in \mathbb{N}$ results in negative degrees of freedom and an unidentifiable model. However, by trichotomizing the individual items such that $K_j \rightarrow 3$, our degrees of freedom can be represented as:

$$\begin{aligned} DF &= N - \big((R-1) + \sum_{j=1}^{14}(3 - 1) \times R\big) \\ &= 140 - (R - 1 + 28R) \\ &= 141 - 29R \end{aligned} \tag{A.3}$$

Under this new formulation, we are now able to fit multiple latent class models with varying degrees of R.

Supplementary Material - Chapter 6

Procrastination and Preventive Health-Care in the Older U.S. Population

Selection of each GAM

To identify the most appropriate model for each response variable, we fitted three different GAMs:

- A simple model with separate smooth terms for procrastination, depression, and age.
- An interaction model using a tensor product smooth for the interaction between procrastination and depression, along with a smooth term for age.
- An interaction model using a tensor product smooth for the interaction between procrastination and age, along with a smooth term for depression.

The models were fitted using the `mgcv` package (Wood, 2017) in R, using the logistic link function and restricted maximum likelihood estimation. For each model, we computed the Akaike Information Criterion (AIC) to compare relative fits. These scores were then compared, and the model with the lowest AIC was selected as the best-fitting model for each response variable (Table A.4). Model 1 was selected for mammograms, cholesterol screenings, pap smears, and flu shots, while model 2 was selected for prostate exams and dental visits.

Table A.4: *Akaike Information Criterion (AIC) for each generalised additive model.*

Outcome	AIC: Model 1	AIC: Model 2	AIC: Model 3
Prostate Exam	650.2	**648.0**	651.2
Mammogram	**970.4**	972.8	973.0
Cholesterol Screening	**1274.5**	1276.3	1278.8
Pap Smear	**1008.2**	1009.4	1010.7
Flu Shot	**1565.6**	1567.3	1566.8
Dental Visits	1697.8	**1695.3**	1699.6

Note. This table reports the Akaike Information Criterion (AIC) values for three different generalized additive models fitted for each preventive health behavior. The model with the lowest AIC for each behavior is highlighted in bold.

Table A.5: *Diagnostic check for smooth terms in the generalized additive model.*

Response	Gender	Predictor	*k*	edf	*k*-index	p-value
Prostate Exam	Men	Procrastination x Depression	24	3.5	1.0	0.230
		Age	9	3.0	1.1	0.958
Mammograms	Women	Procrastination	9	1.0	1.0	0.735
		Depression	8	1.0	1.0	0.920
		Age	9	3.3	1.0	0.430
Cholesterol Screenings	Men	Procrastination	9	1.7	1.0	0.620
		Depression	8	1.0	1.0	0.890
		Age	9	2.5	1.0	0.400
	Women	Procrastination	9	1.0	1.0	0.970
		Depression	8	1.0	0.9	0.088
		Age	9	2.5	1.0	0.940
Pap Smears	Women	Procrastination	9	1.0	1.0	0.205
		Depression	8	1.0	1.0	0.325
		Age	9	2.1	1.0	0.818
Flu Shots	Men	Procrastination	9	1.0	1.0	0.815
		Depression	8	1.4	1.0	0.753
		Age	9	1.0	0.9	0.003
	Women	Procrastination	9	1.0	0.9	0.015
		Depression	8	1.0	1.0	0.303
		Age	9	1.0	1.0	0.515
Dental Visits	Men	Procrastination x Depression	24	4.9	1.1	0.963
		Age	9	2.2	1.0	0.493
	Women	Procrastination x Depression	24	3.0	1.0	0.753
		Age	9	1.0	1.0	0.305

Note: This table provides diagnostic information from the `k.check()` function used to assess the adequacy of the basis dimension k for each smooth term in the model. k = the specified number of basis functions for the smooth term; edf = effective degrees of freedom; k-index = a diagnostic value that assesses whether k is adequate. Values close to 1 indicate that k is sufficient, while values near or below 0 suggest that k may need to be increased; p-value = a value derived from a likelihood ratio test for the null hypothesis that the current k is adequate. A small p-value indicates that a larger k may be required for a better model fit.

Table A.6: *Full estimated results from each generalised additive model.*

Response	Gender	Predictor	χ^2	edf	ref df	estimate	p-value
		Procrastination x Depression	11.0	3.4	3.8	-	0.029*
		Age	10.8	3.0	3.8	-	0.025*
Prostate Exam	Men	Chronic Illness	-	-	-	0.7	0.004**
		Retirement Status	-	-	-	0.4	0.144
		Medicare Insurance	-	-	-	- 0.7	0.02*
		Procrastination	4.1	1.0	1.0	-	0.042
		Depression	1.0	1.0	1.0	-	0.311
Mammograms	Women	Age	41.9	3.3	4.1	-	<0.001***
		Chronic Illness	-	-	-	0.0	0.952
		Retirement Status	-	-	-	0.5	0.022*
		Medicare Insurance	-	-	-	- 0.4	0.120
		Procrastination	2.1	1.7	2.1	-	0.360
		Depression	0.1	1.0	1.0	-	0.718
Cholesterol Screenings	Men	Age	4.5	2.5	3.1	-	0.221
		Chronic Illness	-	-	-	1.5	<0.001***
		Retirement Status	-	-	-	- 0.2	0.942
		Medicare Insurance	-	-	-	- 0.7	0.080

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Table A.6 (continued): *Full estimated results from each generalised additive model.*

Response	Gender	Predictor	χ^2	edf	ref df	estimate	p-value
Cholesterol Screenings	Women	Procrastination	4.3	1.0	1.0	-	0.037*
		Depression	0.4	1.0	1.0	-	0.519
		Age	7.4	2.5	3.2	-	0.071
		Chronic Illness	-	-	-	0.5	0.018*
		Retirement Status	-	-	-	0.7	0.004**
		Medicare Insurance	-	-	-	0.1	0.649
Pap Smears	Women	Procrastination	0.9	1.0	1.0	-	0.330
		Depression	0.3	1.0	1.0	-	0.598
		Age	43.4	2.1	2.7	-	<0.001***
		Chronic Illness	-	-	-	0.0	0.962
		Retirement Status	-	-	-	0.4	0.038*
		Medicare Insurance	-	-	-	- 0.2	0.294
Flu Shots	Men	Procrastination	0.8	1.0	1.0	-	0.386
		Depression	0.2	1.4	1.7	-	0.876
		Age	13.6	1.0	1.0	-	<0.001***
		Chronic Illness	-	-	-	1.0	<0.001***
		Retirement Status	-	-	-	0.4	0.156
		Medicare Insurance	-	-	-	- 0.2	-0.475

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Table A.6 (continued): *Full estimated results from each generalised additive model.*

Response	Gender	Predictor	χ^2	edf	ref df	estimate	p-value
Flu Shots	Women	Procrastination	2.1	1.0	1.0	-	0.146
		Depression	0.0	1.0	1.0	-	0.965
		Age	5.4	1.0	1.0	-	0.02**
		Chronic Illness	-	-	-	0.1	0.451
		Retirement Status	-	-	-	0.1	0.543
		Medicare Insurance	-	-	-	0.6	0.016*
Dental Visits	Men	Procrastination x Depression	23.0	4.9	5.8	-	0.001***
		Age	5.8	2.2	2.8	-	0.116
		Chronic Illness	-	-	-	- 0.3	0.187
		Retirement Status	-	-	-	0.0	0.696
		Medicare Insurance	-	-	-	- 0.2	0.586
	Women	Procrastination x Depression	10.0	3.0	3.0	-	0.018*
		Age	6.0	1.0	1.0	-	0.015*
		Chronic Illness	-	-	-	- 0.3	0.080
		Retirement Status	-	-	-	0.2	0.306
		Medicare Insurance	-	-	-	- 0.1	0.710

Note. This table presents the full estimated results from the generalized additive models for each response variable. Smooth functions do not have parametric coefficients due to the non-parametric estimate of generalized additive models. χ^2 = chi-squared statistic; edf = effective degrees of freedom; ref df = reference degrees of freedom. Estimate = beta values for non-smooth predictors; p-value = a value derived from a significance test that the resulting smooth or parametric term occurred by chance. For smooth terms (procrastination, depression, and age) this value is derived from a chi-squared statistic, while for non-smooth terms (chronic illness, retirement status, and Medicare insurance) this value is derived from a t statistic. Statistical significance is represented as: * $p < .05$; ** $p < 0.01$ *** $p < .001$.

Supplementary Material - Chapter 7

Procrastination as a Marker of Cognitive Decline: Evidence from Longitudinal Transitions in the Older Adult Population

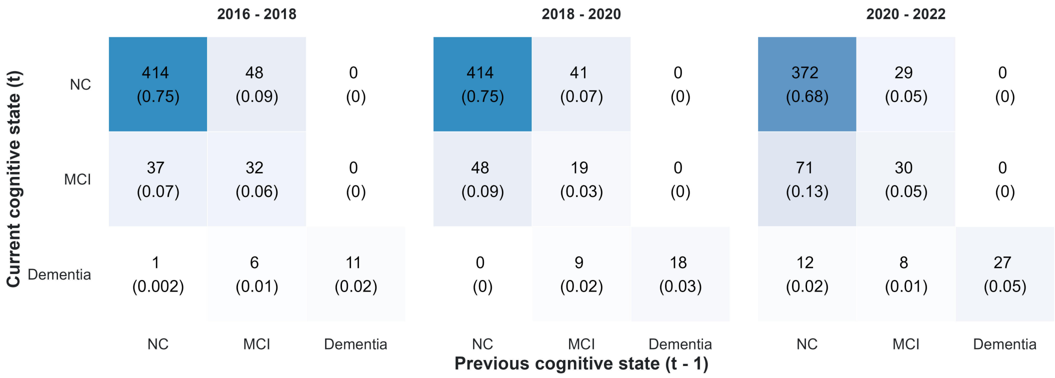

Figure A.1: *Unconditional transitions and transition probabilities between wave one and two (2016- 2018), wave two and three (2018-2020), and wave three and four (2020-2022).*

Model instability when including anxiety as a covariate

The Health and Retirement Study (HRS) includes a brief anxiety measure (five items from the Beck Anxiety Inventory) administered as part of the psychosocial and lifestyle questionnaire. However, this questionnaire is given to only half of the cohort in each wave, resulting in systematic rotating missingness. As such, participants with anxiety data in one wave do not have data in the next, and vice versa. Consequently, anxiety data are missing for approximately 61% of participants in our analytic sample. In addition, no anxiety data are available for the 2016 wave.

Consequently, including anxiety as a covariate would require substantial case wise exclusion, reducing the analytic sample from 549 to 214 individuals and limiting longitudinal coverage from four waves (2016, 2018, 2020, 2022) to two (2018, 2022). This degree of attrition resulted in a particularly sparse transition matrix, especially for our ages on interest (Figure A.2), with most remaining individuals showing very few cognitive transitions across waves. Under these conditions, model estimation became unstable, and several predicted transitions were based on interpolation rather than observed data patterns (Figure A.3). For instance, all model predictions for the ages of interest (70, 80, and 90) from the bottom right panel of Figure A.3 (i.e., remaining in MCI) are interpolations as the observed data (Figure A.2) shows no individual within these ages remaining in MCI.

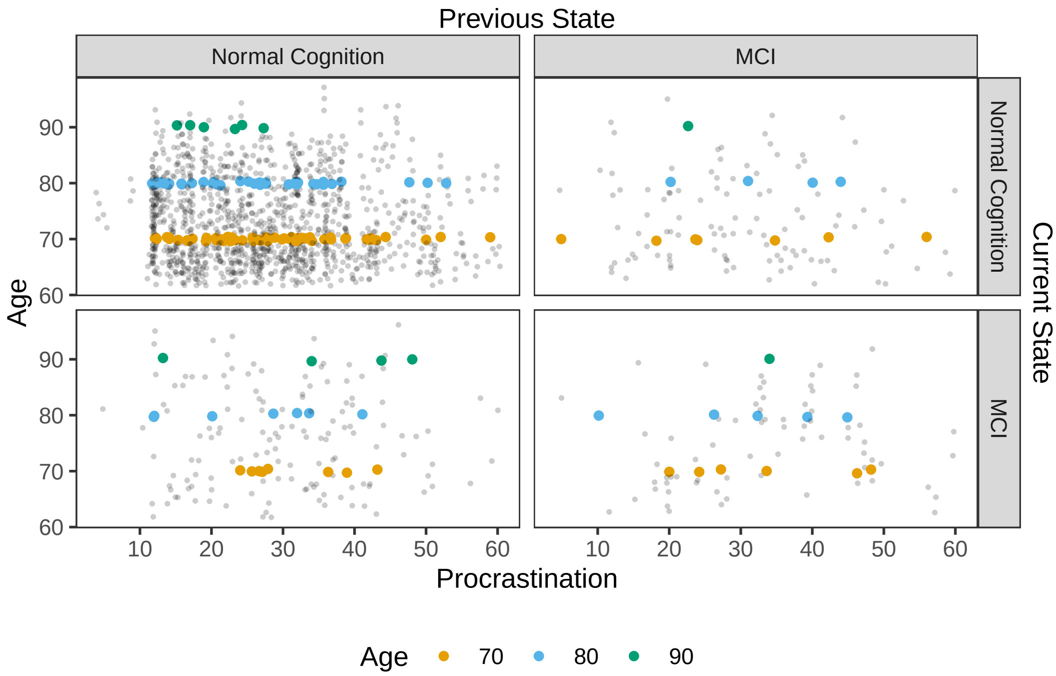

Figure A.2: *Observed transitions by procrastination and age within the reduced dataset (n = 214). Each data point shows an observed transition for person of a particular age and a particular procrastination score, with particular ages of interest (70, 80, 90) highlighted. From the illustration, we note that only 2 individuals of age-interest transitioned from mild cognitive impairment back to normal cognitive function (top right panel), both with procrastination scores below 25. As such, any model predictions for an individual aged 70 or 80 beyond these procrastination scores are interpolations. Additionally, no individuals of age-interest remained in mild cognitive impairment (bottom right panel). Any resulting predictions from remaining in this cognitive state for these ages are again interpolations.*

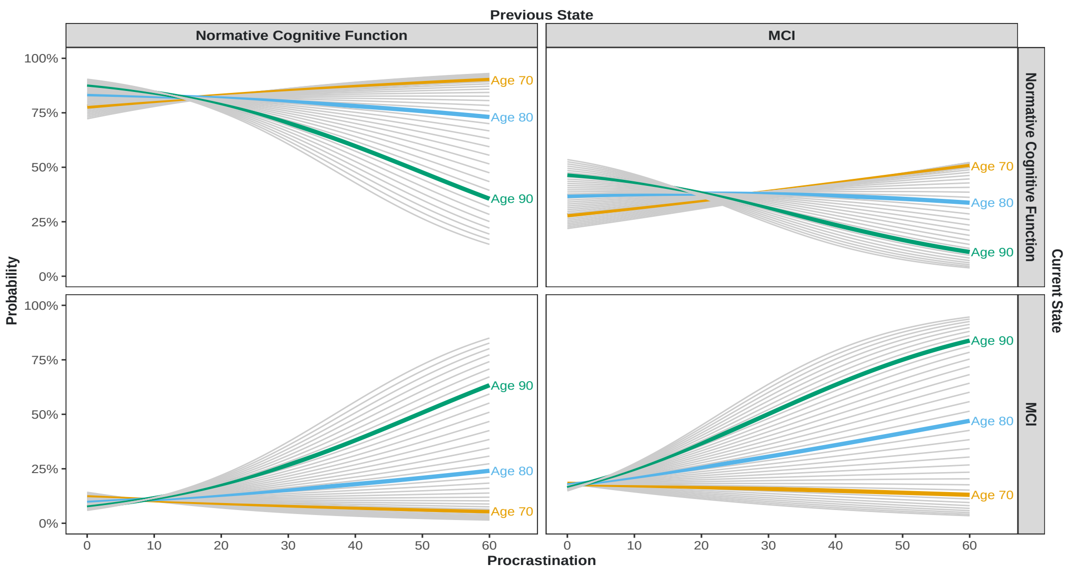

Figure A.3: *Predicted transition probabilities by procrastination and age in the reduced dataset after the case wise deletion. The resulting sparseness of the observed transition matrix (Figure A.2) led to interpolation and model instability.*

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