how ict use and time fragmentation shape well being

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How ICT Use and Time Fragmentation Shape Well-Being

Final Thesis

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Abstract

Digital technology is embedded in almost every part of daily life. Most adults carry a connected device from morning to night, and activities that used to be tied to a fixed time and place can now happen anywhere and at any moment. Research links heavy ICT use to lower well-being, but the measured effects are small and depend on context. One possible pathway has received little direct attention. ICT changes the structure of the day itself. Connectivity allows activities to be performed in shorter pieces and switched at any moment, so days become fragmented into more and shorter episodes. Three links matter here: ICT use and well-being, fragmentation and well-being, and ICT use and fragmentation. They form a triangle, and each side has been studied on its own. The understudied link is fragmentation as the channel that ties ICT use to well-being.

The study uses episode level diary data from the 2021 American Time Use Survey and its Well-Being Module (6,902 respondents). Two ICT predictors are constructed from the diary. ICT group breadth counts how many domains of digital life a respondent touched on the diary day, and ICT minutes captures total daily ICT time as an ordinal scale. Three fragmentation indicators are computed from each respondent's full activity sequence. These are the number of activity episodes, turbulence, and entropy. The outcome is life evaluation, measured with the Cantril ladder. The relationships are estimated jointly in a path model in IBM AMOS, which separates the direct association between ICT use and life evaluation from the indirect association that runs through fragmentation. The same model is estimated in six subgroups defined by gender and three age bands, and in a combined model, followed by three sensitivity tests.

The results show that ICT exposure is not a single quantity. The two ICT predictors pull in opposite directions. Group breadth predicts higher fragmentation on all three indicators in every subgroup. ICT minutes predicts lower fragmentation in every subgroup, which is best read as a measurement property of the diary. Long blocks of passive media use collapse into single episodes and make the day look more consolidated than it was. Fragmentation also splits internally. More activity episodes predict lower life evaluation, while higher turbulence and entropy predict higher life evaluation, suggesting that variety in the day can support well-being while frequent switching costs it. The direct paths from ICT use to life evaluation are mostly null, with small negative effects only for ICT minutes among young women and middle aged men. The indirect channels through fragmentation carry opposite signs for the two predictors, and total effects sit close to zero in every subgroup. The fragmentation channel is concentrated in the middle and older age groups, while the direct channel appears only in the younger half of the sample.

These findings challenge the assumption behind current screen time policy that ICT exposure is one quantity where more is worse. Reporting screen time as a single number of minutes is like

a nutrition label that only reports calories. The findings suggest that what matters is which face of ICT use and which face of fragmentation dominate, and for whom.

The study has limitations. The data cover one diary day per respondent in a single country during a pandemic year. Respondents round durations to five minute blocks, and short ICT episodes inside long passive activities disappear from the diary. Follow-up research should combine time use diaries with device level usage logs, so the device supplies the measurement and the respondent supplies the meaning.

Chapter 1

Introduction

1.1 Background

Digital connectivity has moved from the desk into the pocket. Constant network access means that work, shopping, and socializing no longer need a fixed place or a fixed time, and most adults are online and reachable for most of their waking hours. This is one of the largest behavioral shifts of the last two decades, and it raises a direct question: what does this constant digital presence do to how people feel about their lives?

A growing body of research has tried to answer this, and the balance of evidence leans negative. Heavy ICT use has been linked to poorer sleep, displacement of meaningful activities, feelings of overuse, and lower well-being, especially among younger users (Büchi et al., 2019; Khan et al., 2024; Twenge et al., 2018). At the same time, the measured effects are often small and context dependent (Orben & Przybylski, 2019), and ICT use also carries clear benefits, such as reduced loneliness among older adults (Cotten et al., 2013). The open question is therefore not whether ICT relates to well-being, but through which pathway it does so.

One candidate pathway has received little direct attention: ICT changes the structure of the day itself. Because digital connectivity allows activities to be performed in shorter pieces and switched at any moment, time becomes fragmented, and days broken into more and shorter episodes (Arranz-López & Soria-Lara, 2022; Palm et al., 2022). Fragmentation has been studied on its own and linked to cognitive load, weaker boundaries between work and private life, and stress (Mark et al., 2008; Schneider & Harknett, 2019). What is missing is the connection, whether fragmentation is the channel through which ICT use relates to well-being and to what extent.

Time use diaries offer a rare opportunity to test this question. A diary records what a person did across a full day as a sequence of episodes, which means both ICT use and the fragmentation of the day can be measured from the same record. The 2021 American Time Use Survey Well-Being Module additionally asks each respondent to evaluate their life on a linear scale, placing digital exposure, the shape of the day, and well-being side by side in the same person. This study uses that data to test whether the association between ICT use and well-being runs through the fragmentation of the day.

The contribution of this thesis is deliberately modest. The study is not a policy instrument and does not propose interventions. It offers transparent, processed evidence on how ICT use and the rhythm of the day sit together in a large representative sample, at a moment .when public debate on screen time and digital well-being is at its peak. Also, where expected patterns fail to appear, those gaps are useful too: they mark the limits of what diary data can answer and show where future research with different instruments should go next.

1.2 Problem Statement

Most people today carry a communication device that never fully switches off. Work emails arrive during dinner, social media fills the gaps between tasks, and the boundaries that once separated morning from evening, work from leisure, and home from office have become hard to define.

This changes more than what people do. It changes how the day is built. A day is not just a list of activities but a sequence of episodes, and ICT lets those episodes become shorter, more numerous, and easier to switch. The day becomes more fragmented. What is not known is whether this change in the structure of the day matters for how people feel about their lives, and how much of it ICT use actually drives.

This matters because the shift touches almost everyone. Policy advice on screen time, employer guidance on a workplace that never logs off, and public health messaging all assume some link between digital exposure and well-being, yet the mechanism behind that link is not mapped. If the structure of the day is the channel that ties ICT use to well-being, then guidance aimed only at total screen time may be aimed at the wrong place.

1.3 Research Gap

The gap this thesis addresses is direct: no study has examined ICT use, time fragmentation, and subjective well-being together in a single empirical model. As a result, it is unknown how much of the association between ICT use and well-being runs through the fragmentation of the day, and how much is direct. The mediating role of fragmentation has been suggested in theory but never quantified.

Each pairwise link is already established. First, ICT use is associated with well-being, with mostly negative but mixed findings depending on how, when, and by whom technology is used (Büchi et al., 2019; Orben & Przybylski, 2019). Second, fragmented schedules with many short episodes and frequent switches are associated with higher cognitive load, weaker boundaries, and lower well-being in some groups (Chatzitheochari & Arber, 2012; Schneider & Harknett, 2019). Third, ICT is a structural driver of fragmentation, because connectivity makes it possible to work, communicate, and consume across any time and place (Palm et al., 2022). Existing work isolates one pair at a time, examines a specific group, or uses data from a single domain. Lu (2024), for example, use national diary data to link work time fragmentation to subjective time pressure, but do not measure ICT exposure within the same model. The workplace field study of Akbar et al. (2019) ties one specific ICT channel (email) to stress in one occupational setting, but cannot speak to the structure of the full day. The three sides of the triangle have been drawn separately, but the triangle itself has never been tested.

This study closes that gap using episode level diary data from the 2021 ATUS Well-Being Module, where ICT use, the fragmentation of the day, and life evaluation are observed in the same 6,902 respondents. The aim is exploratory: to quantify the direct and the mediated path within one model and to test how they differ across age and gender groups. It is possible that strong relationships will not appear. That outcome would still be meaningful, as it would set empirical boundaries on theoretical claims that currently rest on indirect evidence.

1.4 Research Objective and Questions

The objective of this study is to examine how ICT use, time fragmentation, and subjective well being relate within the same empirical system, and to assess how these relationships vary across sociodemographic groups. To meet this objective, the following research questions guide the analysis.

1. What is the relationship between ICT use and time fragmentation of the day?
2. What is the relationship between ICT use and subjective well being?
3. What is the relationship between time fragmentation and subjective well being?
4. To what extent does ICT use affect subjective well being directly, and to what extent is this relationship mediated by time fragmentation?
5. How do sociodemographic factors (age, gender) shape these relationships across subgroups?

Questions 1 to 3 describe the pairwise associations. Question 4 is the central mediation question and the main reason a joint model is used rather than a set of separate regressions. Question 5 tests whether the pattern operates differently across groups.

1.5 Research Approach

This study takes an exploratory quantitative approach using episode level diary data from the 2021 American Time Use Survey and its Well Being Module (U.S. Bureau of Labor Statistics, 2021b, 2021c). Three constructs are built from the diary data: ICT exposure, time fragmentation, and life evaluation. Their relationships are estimated jointly in a structural equation model (SEM), which makes it possible to quantify how much of the association between ICT use and life evaluation runs directly, and how much runs through fragmentation of the day.

1.6 Thesis Outline

The rest of the thesis is organized as follows. Chapter 2 reviews the broader literature on time use research, ICT and well being, activity fragmentation, and subjective well being, and ends each section with a short bridge that states what is carried forward into the empirical work. Chapter 3 narrows this body of work into the three constructs that enter the empirical model, states the hypothesized pathways, and presents the conceptual framework and formal hypotheses. Chapter 4 describes the data, justifies the use of structural equation modelling, and specifies the model. Chapter 5 presents data preparation and variable construction. Chapter 6 reports the results. Chapter 7 closes with a discussion, limitations, and directions for further research.

Chapter 2

Literature Review

The theoretical background and the conceptual framework (Chapter 3) play different roles in this thesis. Doing empirical analysis on data is like asking a question to the chaos of information. The conceptual model builds the vocabulary for asking the question: which constructs enter and how they are defined. The literature review builds the vocabulary for understanding the answer when it is not what was expected, like surfacing alternative pathways and mechanisms. This chapter therefore does not feed variables into the model directly; it equips the reader to make sense of whatever the model returns.

This review is selective based on the narrative of the topic. The four topic areas reviewed, time use research, ICT and well-being, activity fragmentation, and subjective well-being, were chosen because together they supply the theoretical vocabulary the empirical model requires. Within each area, relevant literature was identified through keyword searches in search engines and citation chaining from foundational papers. The review does not claim to cover all published work in any of the four areas; it covers what is necessary to motivate and interpret the model.

2.1 Time Use Research

2.1.1 Time use diaries

Time use research relies primarily on the 24 hour time diary, in which respondents record their activities sequentially over the course of a full day. This design enables researchers to collect key information such as duration, frequency, timing, location, and, where available, experienced feelings during specific activities. At the same time, time use research does not end with data collection. The complexity of raw diary entries must be transformed into analytically meaningful observations through processes like coding, aggregation, and statistical analysis. Each of these stages has reductions of information. Time use measures should therefore be understood as heavily filtered representations of daily time allocation rather than direct documentation (Ås, 1978, pp. 127–132).

2.1.2 Critique of time use research

Underlying the diary method is the premise that everyday life unfolds as a continuous stream of behavior, which researchers segment into identifiable ”activities” or ”episodes” based on temporal boundaries. Activities are therefore analytical divisions of time, defined by when one behavior starts and ends. These activity segments can vary in detail: they may be broken down into smaller bits or combined into broader categories, depending on the research structure. In diary based studies, respondents typically report around 20 to 40 activities per day, capturing a filtered representation of daily life. This filtered structure is not a completely accurate representation of reality, because activities can overlap, be interrupted, or be subject to recall bias when respondents forget or miscalculate the timing of past behaviors. Most time use studies compensate for the complexities of human behavior by adding indicators such as secondary activities, interruptions, and place or context of activity. However, the result is not a perfect mirror of lived experience, but a codified reconstruction of how time is allocated across the day (Ås, 1978, pp. 125–127).

2.1.3 What this study takes from this literature

Two ideas from this literature enter the empirical model directly. First, the conception of the day as a sequence of episodes is the foundation on which the fragmentation indicators in Chapter 3 are built. Second, the understanding that diary data is a codified reconstruction, not a perfect record, shapes how the variables are interpreted: they are measures of reported time allocation, not of lived experience.

2.2 Information and Communication Technology

ICT use can be understood as everyday engagement with communication technologies and information in networks. It includes Internet based activities such as communication (email, messaging, social media), information seeking, entertainment, and maintaining social ties through internet communicators. Importantly, ICT use is a broad term, as it is multi context and multi device. It can happen from home, work, education settings, or on the go. The device used can be phones, personal computers, TVs, and many more (Graham & Dutton, 2019).

2.2.1 ICT in time use

From a time use perspective, measuring ICT use is not straightforward, as it cannot be reduced to a single metric. Instead, it reflects a combination of device based activities performed for different purposes and in different contexts across the day. This requires distinguishing between primary activities (e.g., emailing for work), simultaneous activities (e.g., scrolling while eating), and contextual domains (e.g., work versus leisure) (Graham & Dutton, 2019).

In this research, ICT use is codified by the diarists depending on whether they engage with Internet based communication technologies throughout their day. These activities are captured as episodes throughout the day and are identified through specific activity codes within the respective time use surveys. The presence of these activity codes in time use surveys has been previously validated and is described in detail in Appendix A. Survey instruments differ across countries and years, leading to variation in specific indicators, but the underlying conceptualization of ICT use based on the theory remains consistent across datasets.

2.2.2 Negative ICT associations

Intensive or unregulated ICT use has been consistently linked to adverse psychological outcomes. For adolescents, screen time and specifically social media usage negatively predicts well being, with effects getting more intensive at higher levels of exposure (Twenge et al., 2018). Earlier studies extend this pattern to broader internet use and associate it with increased loneliness and reduced social involvement, although these effects reduce with more exposure because users adapt (Kraut et al., 1998). The way of engagement additionally moderates outcomes: passive consumption of social media content predicts declines in affective well being, while active communication and engagement does not predict negative associations with well being (Burke et al., 2010). All in all, these findings suggest that harm is not uniformly distributed across ICT behaviors, but concentrated in certain sociodemographic groups with specific volumes of consumption, and also in the way the technology is being used.

2.2.3 Positive ICT associations

ICT use is also linked with well being benefits, particularly where it amplifies social connection. Among older adults, internet use is associated with lower levels of depression. This effect is attributed to its ability to limit social isolation following retirement (Cotten et al., 2013). Loneliness appears to play an important role in this link, and internet communication technology use is associated with lower levels of loneliness. These lower levels of loneliness in turn predict better subjective well being indicators and fewer symptoms of depression (Chopik, 2016). Among younger populations, positive links with ICT use are also evident. Online social network use predicts higher social capital, which is itself positively associated with life satisfaction (Ellison et al., 2007). These findings indicate that ICT can support well being when it is utilized for meaningful social engagement.

2.2.4 Perception and self regulation

The assumption that ICT use meaningfully affects well being is challenged by data driven evidence, which suggests that its effects are small and context dependent. Large-scale analyses across US and UK surveys find a consistent negative association between digital technology use and adolescent well-being; however, the effect is negligible in magnitude, explaining at most 0.4% of variance comparable to wearing glasses or eating breakfast, and substantially smaller than the effects of sleep or bullying (Orben & Przybylski, 2019). More consequential than duration of use is the subjective experience of that activity by the user. Perceived digital overuse (PDO), defined as the feeling of losing time to internet use at the expense of other activities, frames the displacement hypothesis: ICT can replace other meaningful activities. PDO is a strong negative predictor of subjective well being, independent of actual time spent online (Büchi et al., 2019). Feeling pressure to use ICTs increases PDO, while having good digital coping skills reduces it. Together, these factors explain differences in well being (Büchi et al., 2019). These results reframe the research on ICT use by adding another relevant variable: how this activity is perceived and how it is self regulated.

2.2.5 ICT and sleep disruption

In a large multi country study of adolescents (40 countries, 2017/2018), social media use and screen exposure were associated with sleep disruptions and difficulties. The study further distinguished between normal use and intense or problematic social media use, particularly around bedtime, and found that intense and problematic use was a much stronger predictor of poor sleep outcomes (Khan et al., 2024). Similar patterns appear in country specific research.

Among Italian adolescents, heavier overall device use, especially use of social platforms and platforms like YouTube, was linked to higher odds of difficulty falling asleep (Varghese et al., 2021).

A systematic review of late adolescents and young adults (16 to 25 years) concluded that digital media use, especially closer to bedtime, is consistently associated with delayed sleep onset, reduced sleep duration, and poorer sleep quality, although causal direction remains uncertain (Brautsch et al., 2023). Overall, research suggests that some of the negative associations between ICT use and well being possibly occur because ICT use disrupts sleep, and the associations are more evident when the use is close to bedtime.

2.2.6 Simultaneity and cognitive load

Beyond timing, simultaneity, how ICT is layered onto other activities, also matters. In university students, associations between ICT use and well being vary by context: use during social interactions was linked to lower social success, use during cognitive tasks to lower self control, and use during entertainment to more favorable well being (Xu et al., 2016). ICT use is therefore not inherently harmful; its associations depend on what it interrupts and on the goal of that activity.

In an attention study, all participants performed worse when multitasking, but daily multitaskers showed much smaller drops (Kobayashi et al., 2020). Reviews of ICT use and well being similarly report mostly negative but mixed results, with effects depending on user goals, the outcome measured, and individual susceptibility (Xu et al., 2022).

Theoretical work adds intensity as a key factor, varying with task overlap, perceived difficulty, and task importance. Higher intensity combinations increase cognitive load and deplete self regulatory resources, raising stress risks (Zamanzadeh, 2021). Simultaneity is therefore not a uniform predictor, harms most likely appear when ICT use undermines self regulation or fragments attention during important tasks.

2.2.7 What this study takes from this literature

ICT use enters the empirical model as a diary-derived variable that captures the best available measure of ICT exposure, constructed from the activity codes. The mixed picture of negative and positive associations motivates treating ICT exposure as a predictor with no fixed sign. These opposing effects are expected to surface in the sociodemographic models. Perception and self regulation, sleep disruption, and simultaneity are retained as context only. The ATUS 2021 Well Being Module does not contain the variables needed to test them directly (PDO scales, bedtime use, multitasking intensity), and simultaneity in particular lies beyond the scope of this thesis. These mechanisms are acknowledged as plausible alternative pathways of the analysis outcomes.

2.3 Activity Fragmentation

2.3.1 Conceptualizing activity fragmentation

Activity fragmentation is conceptualized as the spatiotemporal reorganization of activities into smaller, discontinuous components (Hubers et al., 2008). Fragmentation captures how activities are divided into multiple episodes performed at different times and, potentially, in different locations (Alexander et al., 2010). It describes the structural patterning of daily life and the degree of temporal continuity within it in a neutral way, without implying inefficiency or adverse effects on its own.

However, higher fragmentation is generally characterized as a large number of shorter activity episodes, indicating weaker temporal continuity of daily routines. Fragmentation is not reflected just in an episode count; it is also reflected in durations and distribution of activities across the day (Arranz-López & Soria-Lara, 2022).

2.3.2 Two levels of fragmentation: within activity and cross activity

Fragmentation operates at two conceptually distinct levels. The within-activity level focuses on a single activity type and asks how that activity is broken up across the day: the number of episodes, their durations, and how evenly they are spaced. Typical indicators include the mean episode size, the largest episode size, and the standard deviation of episode durations, developed primarily in the context of work fragmentation (Alexander et al., 2010, 2011; Hubers et al., 2008).

The cross-activity level steps back from any single activity and examines the structure of the day as a whole: how diverse the activities in a day are, how frequently the person switches between them, and in what order those switches occur. This perspective draws on sequence analysis tools originally designed for life-course research (Elzinga & Liefbroer, 2007; Gabadinho et al., 2010; McBride et al., 2019; Shi et al., 2022).

For example a day built around one uninterrupted work block followed by rapid cycling through cooking, childcare, and errands shows low within-activity fragmentation for work but a highly fragmented day overall.

Cross-activity fragmentation is typically captured through three complementary indicators alongside number of activities:

- **Entropy**, the evenness of time across activity types (Gabadinho et al., 2010).
- **Turbulence**, combining the diversity of ordered subsequences with the variance of episode durations (Elzinga & Liefbroer, 2007).
- **Complexity**, summarizing entropy and transition rate in a single score (Gabadinho et al., 2010; McBride et al., 2019).

2.3.3 Fragmentation and subjective time pressure

Beyond descriptive indicators, fragmentation has been theoretically linked to subjective time pressure and well being through two complementary perspectives that form a framework. (Lu, 2024).

First, the role switching hypothesis argues that frequent transitions between work and non work roles increase cognitive load and role conflict (Clark, 2000; Cornwell, 2013). Individuals increasingly juggle multiple duties throughout the day, often shifting rapidly between domains (Xue et al., 2025). While limited switching may enhance responsiveness to competing daily demands, excessive switching can lead to stress and increase perceived time pressure (Cornwell, 2013; Cornwell et al., 2019; Mark et al., 2008).

Second, the temporal regularity thesis emphasizes the importance of stable and predictable time structures for maintaining social rhythm and psychological well being (Perlow & Kelly, 2014). Fragmented schedules weaken temporal boundaries between work and private life, increasing spillover, overtime, and difficulties in psychological detachment from work (Glavin & Schieman, 2011). When temporal continuity is substantially disrupted, fragmentation may contribute to stress, cognitive fatigue, and the feeling of being rushed (Mark et al., 2008).

Fragmentation is therefore not just a structural metric of daily schedules, but a potential mechanism through which ICT use may cause heightened subjective time pressure and reduce well being.

2.3.4 Boundary management and work and nonwork integration

Beyond the structural properties of fragmented days, how individuals regulate the boundaries between work and non work shapes whether fragmentation triggers adverse effects. Boundary management theory describes these strategies as ranging from full separation, which keeps work and personal life strictly apart, to full integration, where boundaries are flexible and crossed in both directions (Kossek et al., 2012). People differ in their preferred style and in how much control they feel over their boundaries, stress arise when preference and lifestyle diverge. (Kossek et al., 2012).

ICTs complicate this conflict. Smartphones and constant connectivity make it structurally possible for work demands to spill into leisure at any moment, threatening temporal boundaries that were previously unreachable. Research on ICT enabled availability shows that the work and non work boundary is crossed in both directions and is tied to perceived pressure from supervisors, colleagues, and personal life (Palm et al., 2022). A daily diary study looked at two axes: smartphone use and work engagement. Smartphone use predicted work home interference, amplified under employer norms of constant availability. Engaged workers were the exception, detaching mentally from work after hours and showing no effect (Derks et al., 2015). The COVID 19 pandemic extended this dynamic by collapsing spatial boundaries for large portions of the workforce (Allen et al., 2021). Remote workers whose segmentation preferences were not matched by their home environment, such as dedicated office space or household size, reported the highest role conflict, reinforcing the idea that fragmentation is mediated by self perception (Allen et al., 2021). Together, these findings position activity fragmentation as partly a product of boundary management and of how work is integrated into personal life.

2.3.5 Spatial fragmentation of daily activities

Fragmentation is not only a temporal phenomenon. Activities can also be spatially dispersed, occurring across multiple locations. Spatial fragmentation is defined as the degree to which an individual's daily activity participation is spread across different locations (Ben-Elia et al., 2014). Because ICT decouples activities from fixed times and places, the spatial and temporal dimensions are closely linked: digital connectivity enables work to split across more episodes and locations, while distributed work, in turn, increases reliance on ICT. In practice, however, fragmentation remains strongly shaped by employment structure and workplace norms rather than by technology alone (Alexander et al., 2011).

At a larger scale, spatial clustering of daily fragmentation is substantial and geographically uneven, and patterns are associated with land use, household composition, and mobility behavior (Shi et al., 2022). Daily fragmentation is therefore linked to the built environment as well, which implies that even similar episode counts can reflect structurally different fragmentation patterns.

2.3.6 Work and leisure fragmentation

Fragmentation in work and leisure time has been linked to well being, but the direction and the mechanisms that allow this link to occur differ in each domain.

Work time fragmentation. Work time fragmentation refers to the number of distinct continuous work episodes within a diary day (Lu et al., 2025). Its well being consequences depend less on fragmentation itself than on its predictability. Using survey data from US service workers, Schneider and Harknett (2019) find that unstable and unpredictable schedules are associated with psychological distress, poor sleep, and unhappiness. After a 2017 Seattle law required advance schedule notice and compensation for last minute changes, workers reported better sleep and higher subjective well being than comparable workers in other cities (Schneider & Harknett, 2021).

Another example showing that fragmentation on work is multifaceted. Using UK time diary data from 2020 to 2021, Lu et al. (2025) find that both male and female workers report lower anxiety when their work schedules are more fragmented, with the effect for women suggesting that fragmentation can provide flexibility that reduces anxiety. Work time fragmentation can therefore function either as a form of adaptive flexibility, with context and gender shaping which role it plays.

Leisure fragmentation. Compared to work, fragmentation in leisure has been less directly studied, but time use research suggests that the structure of leisure matters as much as the structure of work. Using UK diary data from 2000 and 2015, Sullivan and Gershuny (2018) find no increase in time pressure despite rising ICT use and activity fragmentation. Fragmentation and feelings of being rushed show little change over time, and differences are associated with gender and occupational status. This suggests that a generalized societal acceleration is less important than the underlying structure of society. At the individual level, a meta analysis of 37 studies finds that leisure engagement is moderately associated with subjective well being. The frequency and diversity of leisure predicts well being more strongly than total time spent in leisure (Kuykendall et al., 2015). This suggests that the structure of leisure is a variable that affects its quality. Women's free time is more frequently fragmented by domestic and caregiving responsibilities, reducing its subjective quality even when total duration appears to be sufficient (Chatzitheochari & Arber, 2012).

Taken together, these findings suggest that fragmentation in leisure, much like in work, cannot be evaluated solely by counting episodes or summing time spent at leisure. In both domains, the distribution and continuity of activity episodes carry distinct implications for well being. Additionally, gender and context systematically shape the experience of fragmentation and reveal inequalities that go beyond the realm of time use.

2.3.7 What this study takes from this literature

Three ideas from the fragmentation literature enter the empirical model. First, fragmentation is multidimensional and should not be summarized with a single count. Second, this study measures fragmentation at the cross-activity level, because the research question concerns the overall structure of the day rather than how any single segment (work, leisure, care) is interrupted in isolation. The four indicators presented in Chapter 3 and constructed in Chapter 5 (number of activities, entropy, turbulence, complexity) all operate at this level. Third, the role switching hypothesis and the temporal regularity thesis motivate the expectation that higher fragmentation is associated with lower life evaluation, while the flexibility findings of Lu et al. (2025) and the leisure diversity finding of Kuykendall et al. (2015) keep open the possibility that some faces of fragmentation relate positively to well being.

2.4 Subjective Well Being

2.4.1 Affective versus cognitive well being

Subjective well being (SWB) as a construct can be broken into two distinct components. The first is affective well being, meaning the positive and negative emotions people experience in daily life. The second is cognitive well being, referring to life satisfaction as a judgment about one's life overall (Diener, 1984). Research across decades indicates that these two components are related but separable, and this is important because they correlate differently to life circumstances (Diener et al., 1999). A further distinction is drawn between registering emotions as they happen and the remembered life, meaning a reflective summary of life experiences. The memory of life often gets distorted by peak moments and sudden changes rather than the duration of events (Kahneman & Riis, 2005). This distinction has methodological weight for well being and time use research, because daily diaries capture well being in a specific way and theory shows that way well-being is lived or remembered differ.

2.4.2 Well being in time use research

Measuring well being through its connection to daily activities has proven to be a productive approach. The Day Reconstruction Method (DRM) is a structured framework that asks respondents to reconstruct their previous day as a stream of activities and to reflect on how they felt in each episode (Kahneman et al., 2004). In practice, this approach shows that experienced well being and evaluative well being often differ. An example is that commuting and work tend to produce the lowest affective ratings, while social activities produce the highest (Krueger et al., 2009). These differences appear across social groups and across multiple well being indicators, showing that people feel differently depending on the activity they are engaged in (Stone et al., 2018). Combining information on time spent in activities with the affect experienced brings a more accurate picture of a person's well being (White & Dolan, 2009). These findings show that activity metrics should be tracked alongside overall wellbeing measures to get a full picture of how someone is doing.

2.4.3 Domain based and bottom up models of well being

Overall life satisfaction can be shaped as the sum of how people feel about specific areas of their lives. Bottom up models of SWB propose that satisfaction in each domain adds up into global life satisfaction. The quality of everyday experience in specific life areas leads to overall well being (Diener, 1984). The direction of this relationship has been questioned. Domain satisfactions do predict overall life satisfaction. But global well being also shapes how people reflect on specific parts of their lives (Headey et al., 1991). This link is not static either. As life changes, so does the way each variable affects the other (Heller et al., 2007). Within leisure specifically, the DRAMMA model identifies the psychological mechanisms through which leisure enhances well being. DRAMMA stands for Detachment recovery, Autonomy, Mastery, Meaning, and Affiliation. The benefit of leisure is not free time itself but the psychological experiences it provides (Newman et al., 2014). Together these perspectives suggest that well being emerges from the balance between daily domain experiences and broader life evaluations and multiple models exist to assess it.

2.4.4 What this study takes from this literature

This study uses the Cantril ladder (a life evaluation item) from the ATUS Well-Being Module as the outcome. The ladder is a cognitive judgement and is interpreted here as evaluative well-being, not as moment-to-moment affect. The DRM and bottom-up aggregation are retained as conceptual context. This study does not attempt to test them, its focus is on how ICT exposure and daily time fragmentation relate to the evaluative judgement.

2.5 Why age and gender stand out

Two dimensions appear repeatedly across the four literatures reviewed above: age and gender and are worth exploring in this thesis. This section gathers what the reviewed evidence imply and motivates the subgroup design for the SEM models.

2.5.1 Age as a life stage

Age operates here as a marker of life stage rather than a smooth continuous control. The strongest evidence of negative ICT associations clusters in younger adults, where heavy and varied digital engagement is most prevalent (Brautsch et al., 2023; Khan et al., 2024; Orben & Przybylski, 2019; Twenge et al., 2018). Middle aged adults sit at the intersection of paid work, caregiving, and household responsibilities, where boundary management and role switching most directly translate digital connectivity into strain (Allen et al., 2021; Derks et al., 2015; Kossek et al., 2012). Older adults present the cleanest case of ICT supporting well being, primarily through communication that reduces loneliness and sustains social ties after retirement (Chopik, 2016; Cotten et al., 2013). The mechanism therefore differs qualitatively across stages, not just in magnitude.

2.5.2 Gender as a structural feature of daily life

Gender can be a structural feature of how the day is built and how it feels. Across life stages, the same activities and the same fragmentation tend to mean different things for men and women. In adolescence, girls report stronger negative effects of social media use on well being than boys, even at similar levels of exposure (Orben & Przybylski, 2019; Twenge et al., 2018). In working age adulthood, women's free time is more broken up by domestic and caregiving tasks, which lowers its quality even when the total amount matches that of men (Chatzitheochari & Arber, 2012). Differences in time pressure across two decades of UK diary data are explained by gender and job status rather than by a general societal speed up (Sullivan & Gershuny, 2018). The link between work fragmentation and anxiety also runs in different directions for men and women, and can act as useful flexibility for women (Lu et al., 2025). In older age, women are more likely to live alone and to rely on ICT for staying in touch, so the loneliness reducing role of digital communication is gendered as well (Chopik, 2016; Cotten et al., 2013). The same fragmented day therefore does not carry the same meaning across genders, and this holds at every life stage in the sample.

2.5.3 Implication for the empirical strategy

Together, these patterns motivate a subgroup design rather than a control variable adjustment. Adding age and gender as control variables would only adjust the baseline level of the outcome, while still forcing one set of paths on the whole sample. If age and gender shape which paths exist, in which direction, and with what magnitude, then a pooled model with age and gender as controls would mask the heterogeneity the literature predicts. Splitting the sample lets every path take a different value in each group, which is what the reviewed evidence calls for. Chapter 3 defines the three constructs that enter this structure, states the hypothesized pathways between them, and presents the formal hypotheses that the subgroup models will test.

2.6 Prior Empirical Work Using ATUS Data

This study is not the first to analyse ICT use, time use, fragmentation, or well-being with ATUS data. To position the present work, it helps to set out what previous ATUS studies have examined, and where this thesis departs from them.

Experienced well-being attached to specific activities has been measured with the ATUS Well-Being Module, and experienced affect varies systematically with age and income (Stone et al., 2018). The unemployed enjoy leisure less and report more sadness during specific episodes than the employed, established using the ATUS Well-Being Module as a nationally representative comparison alongside longitudinal survey data (Krueger & Mueller, 2012). In both, the outcome is the feeling attached to an individual episode, not the whole day.

ICT and time allocation have also been examined directly in ATUS. The transition into the digital age left aggregate time allocation across the 2003 to 2011 waves largely unchanged, with little evidence that internet use displaced other activities (Robinson & Lee, 2014).

The structure of the day itself has been examined with ATUS diary sequences. Women's daily time can appear more fragmented and more often interrupted by housework and childcare, patterns linked to higher stress (Kolpashnikova et al., 2021). This research is accompanying a descriptive visualisation tool rather than a tested empirical model.

Prior work on the ATUS dataset has therefore examined experienced affect by activity, ICT and time allocation, and the structure of the day, but in separate studies and never as a single chain.

2.7 From Literature to Framework

The four literatures reviewed in this chapter each hand something forward to the conceptual framework in Chapter 3. The time use literature supplies the foundation: the day as a sequence of episodes, which is the raw material from which all variables are built. The ICT literature motivates treating ICT exposure as a predictor with no fixed sign, since the evidence points both to harm and to benefit depending on context. The fragmentation literature supplies the indicators and the mechanisms. The well-being literature supplies the outcome, a single evaluative judgment of life rather than a momentary feeling. Finally, Section 2.5 establishes that age and gender shape these relationships in kind, not just in level, which motivates a subgroup design rather than control variables.

The chain from ICT use through fragmentation to well-being has been argued in theory but never estimated in one model, which is the gap this thesis fills. Chapter 3 therefore takes the pieces listed above and assembles them: it defines the three constructs that enter the empirical model, states the hypothesized pathways between them, and translates the expectations of this chapter into formal, testable hypotheses.

Chapter 3

Conceptual Framework

Chapter 2 reviewed the broader literature. This chapter narrows it into the three constructs that enter the empirical model, states the hypothesized pathways, and presents the conceptual model and formal hypotheses. Everything in this chapter maps directly onto a variable or a path in the structural equation model specified in Chapter 4.

3.1 Three Core Constructs

3.1.1 ICT exposure

ICT exposure refers to a respondent's daily engagement with internet-based activities, spanning communication, entertainment, shopping and finance, learning and work, and content and reading. It is conceived as how embedded ICT is across the different domains of the day, rather than as intensity within any single activity.

The literature reviewed in Section 2.2 shows that the relationship between ICT exposure and well-being is not fixed in sign: it can be negative through sleep disruption, displacement, or cognitive load, and positive through social connection. In this framework ICT exposure enters with no pre-committed sign, and its net direct association with life evaluation is an empirical question.

3.1.2 Time fragmentation

Time fragmentation is operationalized as the degree to which the diary day is broken into many short episodes distributed across time. Consistent with Section 2.3, fragmentation is treated as multidimensional rather than captured by a single count. Four indicators are built from each respondent's diary sequence:

- **Number of activity episodes**, a direct count of episodes.
- **Normalized Shannon entropy**, measuring how evenly the day is split across activity types.
- **Turbulence**, measuring the structural complexity of the ordered sequence together with the heterogeneity of episode durations.
- **Complexity**, combining the transition rate and normalized entropy into a single score.

These four indicators are treated as observed variables in the path model, with correlated residuals to absorb the shared variance between them. The mathematical definitions and the construction from the diary are presented in Chapter 5.

3.1.3 Life evaluation

Life evaluation is the outcome of the model. It is measured by the single Cantril ladder item in the ATUS Well Being Module, asking respondents to rate their current life on a 0 to 10 scale, where 0 is the worst possible life they can imagine and 10 is the best. Following the distinction drawn in Section 2.4, this item sits on the cognitive, evaluative side of subjective well being rather than the affective side. It is treated as a continuous observed variable.

3.2 Hypothesized Pathways

The conceptual model consists of three sets of relationships.

ICT to fragmentation. The literature reviewed in Section 2.3 argues that ICT is a structural enabler of fragmentation. Digital connectivity makes it possible to perform activities in shorter chunks, to switch roles more often, and to mix work and non work across the day. The expectation is therefore that higher ICT exposure is associated with higher fragmentation, measured across all four indicators. This is represented as a direct path from ICT exposure to each of the four fragmentation indicators.

Fragmentation to life evaluation. The role switching hypothesis and the temporal regularity thesis, reviewed in Section 2.3.3, argue that higher fragmentation is associated with increased cognitive load, role conflict, and weakened boundaries, and therefore with lower life evaluation. At the same time, the evidence is mixed: Lu et al. (2025) finds that fragmentation can reduce anxiety for some groups. The expectation is that fragmentation has a negative net association with life evaluation, but the model leaves room for heterogeneity across groups.

ICT to life evaluation, direct and mediated. The total association between ICT exposure and life evaluation is decomposed into a direct path and an indirect path. The indirect path runs through the four fragmentation indicators. The direct path captures everything else: social connection, entertainment, sleep displacement, perceived digital overuse, and any other mechanism not measured here. The mediation question (RQ4) asks how large the indirect path is relative to the direct path. This is the central reason a path model is used rather than a set of separate regressions.

3.3 Subgroups

Age and gender enter the framework as subgroups, not as controls. Section 2.5 establishes that they shape which paths exist and in which direction, not just the level of the outcomes. The paths in Figure 3.1 are therefore not assumed to be uniform across the sample, which is why age and gender define subgroups in which the model is estimated separately rather than entering as control variables in a single pooled model.

Age is split into three bands (young, middle, older) rather than entered as a continuous variable because the dominant pattern differs by life stage: heavy varied use among the young (Orben & Przybylski, 2019), boundary spillover among the middle aged (Derks et al., 2015), and loneliness reduction among older adults (Cotten et al., 2013). Gender defines subgroups because the same fragmented day carries different meaning for men and women, with leisure more often broken up by caregiving for women (Chatzitheochari & Arber, 2012) and work fragmentation linked differently to anxiety across genders (Lu et al., 2025).

Age and gender are crossed rather than treated separately, yielding six subgroups in which the same path model is estimated. This design addresses RQ5.

3.4 Conceptual Model

Figure 3.1 summarizes the framework. ICT exposure predicts fragmentation and life evaluation directly. Fragmentation predicts life evaluation. Age and gender define the subgroups in which all three constructs are estimated. The indirect path of interest, ICT to fragmentation to life evaluation, is the main object of the mediation analysis in Chapter 6.

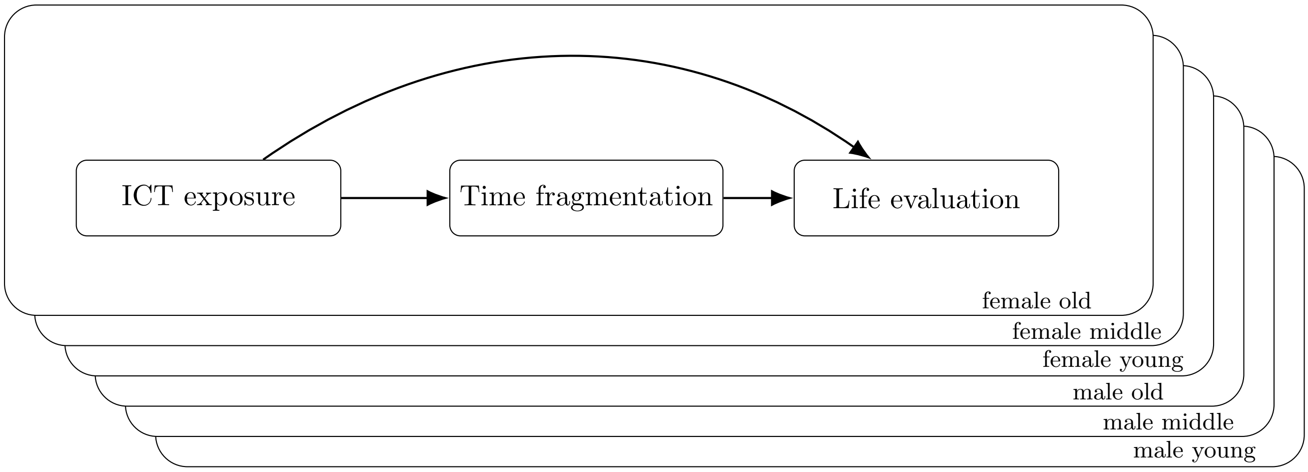


Figure 3.1: Conceptual model. Direct and mediated pathways between ICT exposure, time fragmentation, and life evaluation. The same model is estimated separately within six subgroups defined by the crossing of gender (male, female) and age group (young, middle, older).

3.5 Hypotheses

Translating the pathways above into formal hypotheses:

- **H1**: Higher ICT exposure is associated with higher time fragmentation across all indicators.
- **H2**: Higher time fragmentation is associated with lower life evaluation.
- **H3**: ICT exposure has a direct association with life evaluation.
- **H4**: Part of the association between ICT exposure and life evaluation is mediated by time fragmentation. The indirect effect is non zero and has the same sign as the combined signs of H1 and H2.
- **H5**: The magnitude of the paths in H1, H2, H3, and H4 differs across subgroups defined by gender and age.

These hypotheses are tested in Chapter 6 using the structural equation model specified in Chapter 4.

Chapter 4

Methodology

4.1 Research Design

This study is an exploratory quantitative analysis of diary-based time-use data. The analysis uses time-use diaries that record ICT use and well-being, examined at both the episode level (to construct activity fragmentation indicators) and the diary level. The goal is to develop a holistic view of an individual's ICT use, time fragmentation and subjective well-being on a given day.

4.2 Data Selection

The dataset must be based on single-day diary entries, because the research questions require the granularity that reveals the stream of behaviour within a day. The American Time Use Survey (ATUS) of 2021, together with the 2021 Well-Being Module (WBM), satisfies this requirement and is the dataset used throughout the thesis. The remainder of this section explains how the diary is built, how respondents are sampled, why the data are trustworthy, and what their limitations are.

4.2.1 How the diary is built

The ATUS diary is collected by telephone the day after the assigned diary day. The interviewer walks the respondent through a 24 hour window starting at 4:00 AM on the assigned day and ending at 3:59 AM the following morning. The respondent describes each activity in their own words, and the interviewer enters it through the Computer Assisted Telephone Interviewing (CATI) system. Start time, end time, a short description, the location, and who else was present are recorded for every episode. After the interview, trained coders assign each activity a six digit code from the ATUS lexicon, organised into 17 first tier categories with two further levels of detail (U.S. Bureau of Labor Statistics, 2025).

The diary therefore captures sequence, duration, and context for every episode in the day. This is the level of detail required to compute the fragmentation indicators presented in Chapter 5.

4.2.2 Sampling and representativeness

ATUS households are not drawn at random from the United States as a whole. They are drawn from households that have just completed their eighth and final month in the Current Population Survey (CPS), the federal labor force survey. This means that detailed demographic, employment, and household composition information has already been collected two to five months earlier and is later attached to each ATUS respondent through the ATUS-CPS file.

The sample is split in three stages (U.S. Bureau of Labor Statistics, 2025). The first stage rebalances the CPS sample of less populous states so that ATUS coverage is approximately proportional to state population. The second stage splits households on the race or ethnicity of the householder, the presence and age of children, and the number of adults, with oversampling of Hispanic and non Hispanic Black households and of households with children to improve estimates for these groups. The third stage randomly selects one household member aged 15 or older as the diary respondent. The target population is therefore the U.S. civilian population aged 15 and over.

Diary days are also distributed across the week on a fixed schedule: about 10 percent of diaries on each weekday and 25 percent on Saturday and 25 percent on Sunday, which prevents weekend behavior from being under sampled (U.S. Bureau of Labor Statistics, 2025).

4.2.3 Survey weights

The ATUS supplies a final weight, `TUFINLWGT`, and a Well-Being Module version, `WUFINLWGT`. The job of these weights is to make the sample match the country on its demographic mix, mainly age, sex, race and ethnicity, and household type, so that a reported number such as a mean or a share is representative of the population. That task is not the purpose of this thesis. This thesis does not report a population number it rather estimates structure, the size and direction of the paths linking ICT use, fragmentation, and life evaluation. For that goal the weights are not needed: when the model is correctly specified and the variables that drive the weights are handled in the model, unweighted estimation is consistent and more efficient than weighted estimation (Solon et al., 2015). The weights are built mostly from demographics, and the two demographic axes this thesis works with, gender and age, are already handled directly through the subgroup design. The rest of the demographic adjustment concerns groups the model does not target (race, ethnicity, and household income etc.).

4.2.4 The 2021 Well-Being Module

The Well-Being Module is a periodic supplement to the ATUS, fielded in 2010, 2012 to 2013, and again in 2021. The 2021 module ran from March 1 through December 31 and was sponsored by the University of Maryland and the University of Minnesota, with funding from the National Science Foundation and the National Institute of Child Health and Human Development (U.S. Bureau of Labor Statistics, 2021a). All ATUS respondents in that window were eligible. The module questions were asked at the end of the standard ATUS interview.

For each respondent, three eligible activities were randomly selected from the diary, and the respondent rated how happy, sad, tired, stressed, and in pain they felt during each, plus how meaningful the activity was and whether they were interacting with anyone. Four general health items were also asked at the respondent level, including the Cantril ladder used as the outcome in this thesis models. (U.S. Bureau of Labor Statistics, 2021a).

4.2.5 Why the data are trustworthy

The survey is carried by the Bureau of Labor Statistics and fielded by the U.S. Census Bureau under Title 13 confidentiality protections. The instrument, sampling design, weighting method, and processing pipeline are publicly documented in the ATUS User's Guide and annual data dictionaries, ensuring full reproducibility (U.S. Bureau of Labor Statistics, 2025). Collected continuously with stable methodology since 2003, the 2021 file benefits from decades of methodological refinement covering incentive testing and imputation procedures.

4.2.6 Limitations of Dataset

One day per respondent. ATUS collects exactly one diary day from each person. This is enough to characterize population averages but not enough to characterize a single individual. Day to day variation within a person is invisible. A fragmented day in the data could equally describe someone who lives a fragmented life or someone who happened to have an unusual day.

Telephone recall. Activities are reported the day after they happened, by phone, from memory. Short interruptions, simultaneous activities (such as scrolling a phone while watching television), and brief ICT episodes are systematically under reported because the respondent does not remember them or does not consider them worth reporting. The ATUS methodology mitigates this through a conversational interviewing approach, which helps respondents reconstruct the diary day in their own words. (U.S. Bureau of Labor Statistics, 2025). Even so, a precision gap remains, and is discussed in Chapter 7.

Response rate. ATUS response rates have declined over the life of the survey, consistent with the broader decline in household survey response across the United States. Designated persons who refuse are typically experiencing survey fatigue. (U.S. Bureau of Labor Statistics, 2025). The published weights correct for observable selection but cannot fix unobserved selection on the part of those who decline.

2021 specifically. The 2021 file reflects an unusual year. ATUS data collection had been paused in 2020 from mid March to mid May because of the COVID-19 pandemic and resumed under modified conditions, and the 2021 WBM was fielded only from March onward. Patterns observed in 2021 ICT use, remote work, and household time allocation likely reflect a transitional period in which pandemic conditions were still shaping daily life. Generalization to a stable post pandemic baseline should be made with care.

Table 4.1: ATUS 2021 datasets used in the analysis.

File name	Type	Lines	Columns	Description
`atusact21`	Activity	164,581	31	Episode-level diary file; each row is a single activity episode.
`atusact21wb`	Activity (WB)	20,461	15	Episode-level subset for respondents in the 2021 Well-Being Module.
`atusresp21`	Respondent	9,087	175	Respondent-level demographics and survey variables.
`atusresp21wb`	Respondent (WB)	6,902	16	Respondent-level file including subjective well-being indicators.
`atuscase21`	Case-level	6,902	19	Overview of each participant (`TUCASEID`), episodes and categories.
`atussum21`	Activity summary	9,087	400	Respondent-level totals of time spent on each activity category during the diary day.
`atuscps21`	ATUS-CPS	63,645	384	Household member information from the Current Population Survey, collected two to five months before the ATUS interview.
`atusrost21`	Roster	23,207	8	Household members and nonhousehold children of ATUS respondents, with basic information such as age and sex.

4.3 Why Structural Equation Modelling

This thesis tests a multivariate system in which daily ICT exposure is expected to relate to how fragmented a day becomes, and both are expected to relate to subjective well-being. Structural equation modelling (SEM) is appropriate because it estimates multiple relations simultaneously and allows direct and indirect (mediated) effects to be assessed within a single coherent system (Brown, 2015; MacKinnon, 2008). SEM is commonly applied in mobility and well-being research to investigate mediation mechanisms and compare groups within one framework (Gao et al., 2017; Kroesen, 2014).

Because the key predictors (ICT exposure and fragmentation) are constructed from diary entries (observed variables from self-reported information, rather than latent scales), the primary model is formulated as an observed-variable SEM (path model).In the proposed model, SEM cannot establish causality from observed data which is solely supported through theory. (Bollen, 1989).

4.4 Why SEM Rather Than Regression

Multiple linear regression is well suited to explaining a single outcome, but the system studied here involves a set of relations: ICT use is expected to predict both fragmentation and well-being, while fragmentation itself is expected to mediate part of the relation between ICT use and well-being. This requires one variable to act as both an outcome and a predictor within the same model.

Estimating this with regression would require fitting separate equations and reconstructing the indirect effect post hoc (Baron & Kenny, 1986). SEM estimates all paths simultaneously and yields direct and indirect effects with standard errors derived within the same model (MacKinnon, 2008). It also represents correlated residuals among the fragmentation indicators explicitly, which a set of separate regressions cannot do. Multi-group SEM allows the full model to be compared across the six subgroups defined by gender and age, which would otherwise require a large set of interaction terms in a regression specification.

Finally, SEM provides a better foundation for follow-up work than a set of regressions. Additional paths can be added or removed within the same specification, and any specification with positive degrees of freedom yields fit indices that allow exploratory model comparison. The graphical interface of IBM AMOS also makes the structure of the model and its estimated parameters straightforward to communicate.

4.5 SEM Specification

The empirical model is specified as a mediation-oriented path model:

$$\text{Fragmentation} \leftarrow \text{ICT use}$$

$$\text{Well-being} \leftarrow \text{ICT use} + \text{Fragmentation}$$

This structure estimates (i) the direct effect of ICT use on well-being and (ii) the indirect effect transmitted through fragmentation. Models are estimated in IBM AMOS Graphics using maximum likelihood (ML). ICT exposure and fragmentation enter as observed, diary-derived composites. The model is estimated as a multi-group SEM. The sample is divided into six subgroups by crossing gender (male, female) with age group (young, age ≤ 37; middle, age 38–59; older, age ≥ 60), and the same path model is fitted within each subgroup. The age cut points are chosen so the three bands hold roughly equal shares of the sample, keeping subgroup sizes balanced while still mapping onto reasonable life stages: early adulthood, mid-career years, and the transition into later life. A combined single-group model on the full sample is also estimated as a reference point.

4.6 Handling of Age and Gender

Following the conceptual motivation in Section 2.5 and Chapter 3, age and gender are not entered as controls. Instead, the sample is split into six subgroups defined by the crossing of gender with three age bands (Table 4.2), and the SEM is estimated separately within each subgroup. This approach has two advantages. First, it allows every path in the model to vary freely across groups rather than assuming a common structure with a mean shift. Second, it addresses RQ5 directly, which asks how the pattern differs across groups. A combined single-group model on the full sample is also estimated as a reference point. Group sizes are reported alongside each subgroup model in Chapter 6.

Table 4.2: Six analytical subgroups defined by gender and age group.

	Young (≤ 37)	**Middle** (38–59)	**Older** (≥ 60)
Female	Female, Young	Female, Middle	Female, Older
Male	Male, Young	Male, Middle	Male, Older

Chapter 5

Data Preparation and Exploration

This section describes how the analytical dataset was built from the raw ATUS 2021 files and presents the distributions of the variables used in the SEM. Variables are introduced in the order they enter the model: ICT exposure, fragmentation, and life evaluation.

5.1 Sample Trimming

As a first cleaning step, the sample is restricted to the 6,902 respondents who completed the 2021 Well-Being module, since only these respondents provide the life-evaluation outcome used in the SEM. The code filters `atusresp21`, `atusact21`, `atussum21`, `atusrost21`, and `atuscase21` on `TUCASEID` and merges the retained variables into a single respondent-level dataset, `chronos1`.

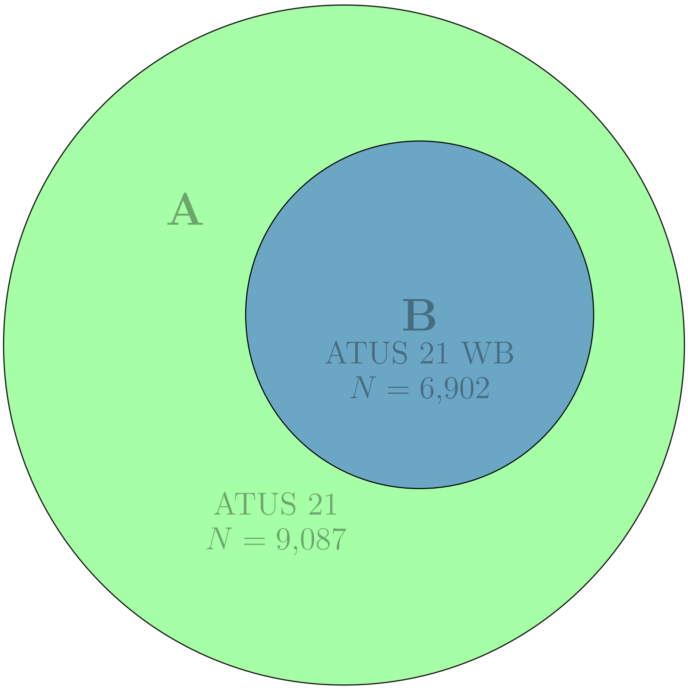


Figure 5.1: The 2021 Well-Being module respondents (N = 6,902) form a subset of the full ATUS 2021 sample ($N = 9{,}087$).

5.2 Sample Composition and Representativeness

Before turning to the variables that enter the SEM, it is useful to inspect who is in the analytical sample. Figure 5.2 reports the distribution of the analytical sample (n = 6,902) across six demographic and socioeconomic dimensions: age, sex, race and ethnicity, education, employment status, and family income. The sample skews older, with 29.5% of respondents aged 65 or above and only 7.4% aged 15 to 24, reflecting both the ATUS sampling frame and the well-known age gradient in survey response rates. Women are slightly overrepresented (54.2% vs. 45.8%), and the racial composition is dominated by non-Hispanic White respondents (67.2%), followed by Hispanic (14.3%) and non-Hispanic Black (11.9%) respondents. Education and family income show the expected spread for a U.S. adult sample, with some college and bachelor's degree holders forming the largest education groups, and the family income distribution running from a 15.1% share below $25k to a 30.8% share at $100k or above. Employment status reflects the older age profile: 38.2% of the sample is not in the labour force.

These distributions matter for the subgroup design in Chapter 6. The six subgroups defined by crossing gender with three age bands are not perfectly balanced in size but adjustments have been made in the limits of the age groups in order to accommodate for the differentiations. Beyond age and gender, education, employment, and income are not included as controls in the SEM (see Chapter 4); their distributions are reported here so that any reader can judge the population to which the results most directly apply.

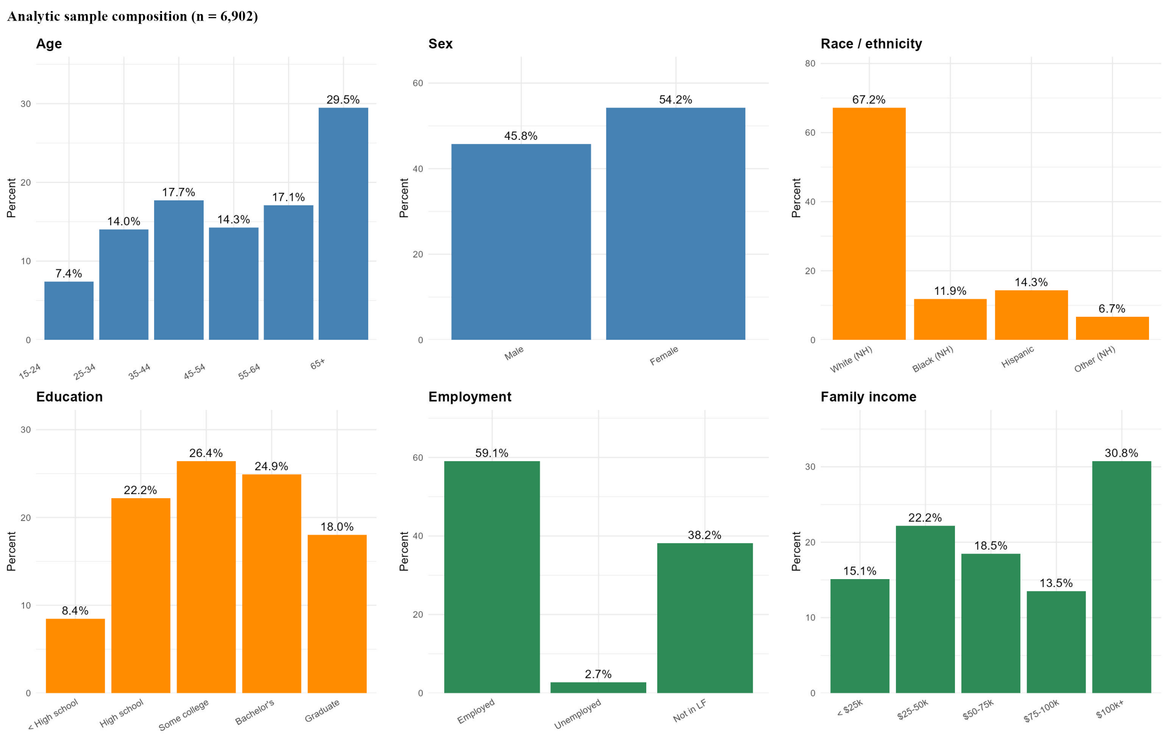


Figure 5.2: Demographic and socioeconomic composition of the analytical sample ($n = 6{,}902$): age, sex, race and ethnicity, education, employment status, and family income.

The analytical sample covers the expected age range with a slight female majority (Figure 5.3). **Age** (years, continuous) and **gender** (1 = male, 2 = female) are retained as grouping differentiators.

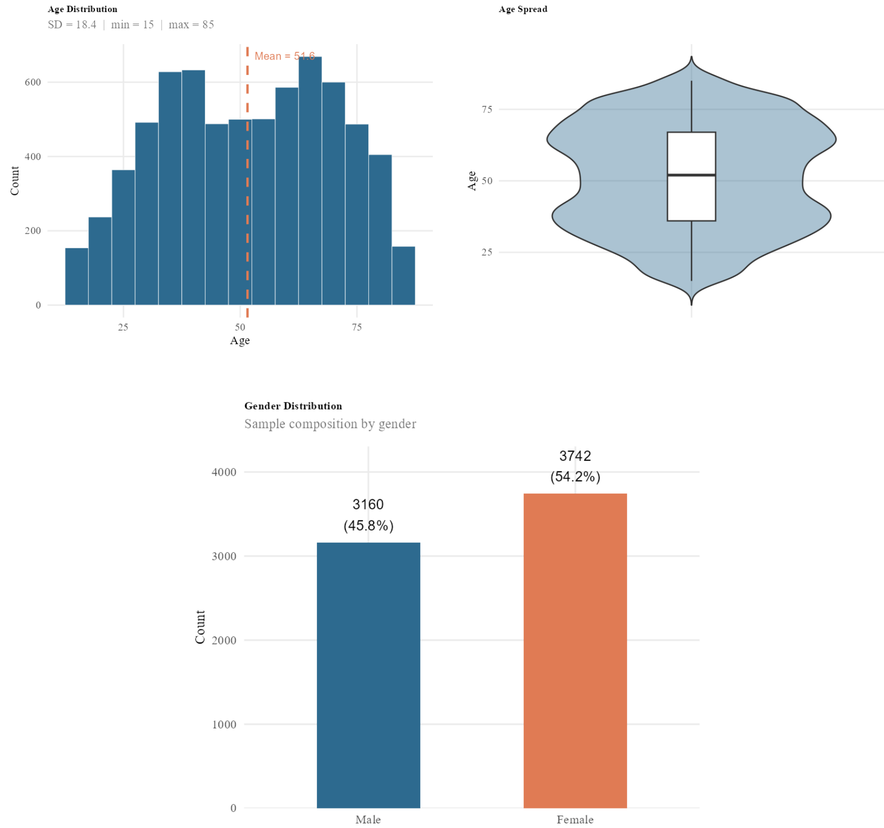


Figure 5.3: Age (top) and gender (bottom) distributions of the analytical sample (n = 6,902).

5.3 ICT Exposure

ATUS codes ICT use into 24 fine-grained activities (e-mail, streaming video, online shopping, different types of phone calls, and so on). These raw codes turn out to be unusable in the IBM AMOS as direct predictors because of zero-inflation. Therefore composite scales were made that show reality in a more SEM friendly way without altering any of the data. The path from raw codes to composite scales is described below.

5.3.1 The zero-inflation problem

On any given diary day, most respondents simply do not engage in most ICT codes. Figure 5.4 reports the share of zero observations per individual ICT code: the majority exceed the 70% threshold and several exceed 90%. An alternative specification that models each ICT activity code individually rather than as an aggregated composite is reported in Appendix A. That model is problematic precisely because of this zero inflation: codes that read zero for most respondents carry too little variation, and any two such codes share too few joint non-zero observations, so the covariances feeding the estimator are unreliable and AMOS cannot produce stable estimates.

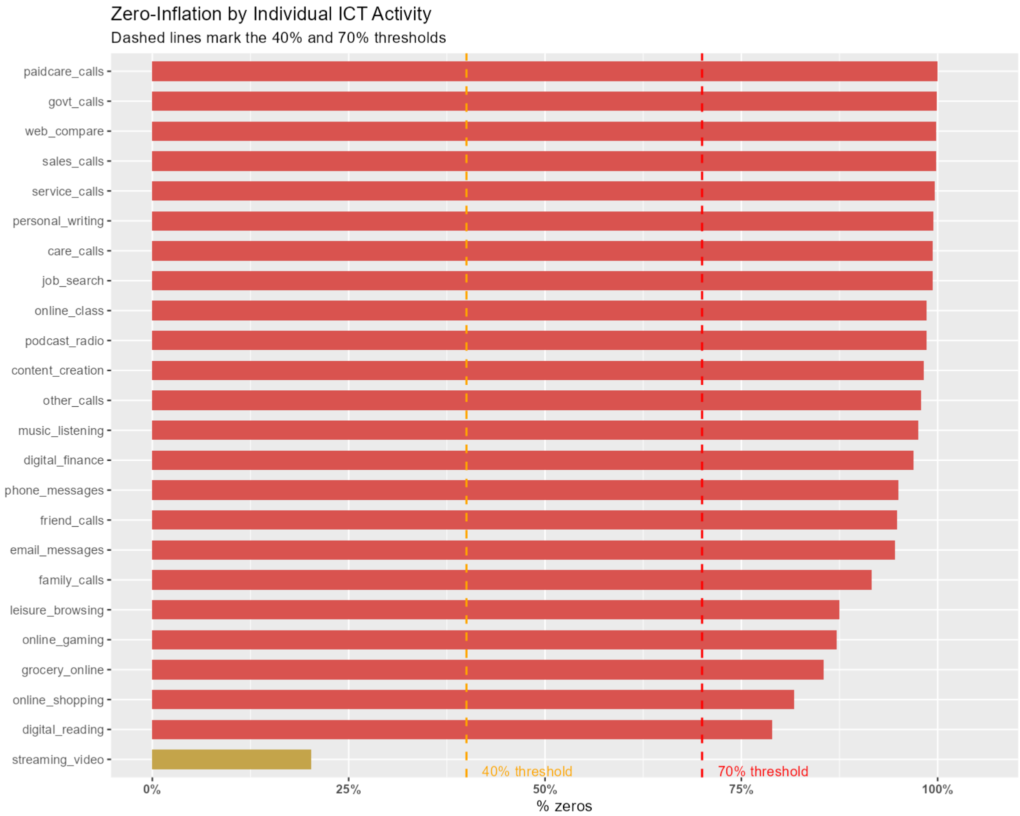


Figure 5.4: Zero-inflation rates across the 24 individual ICT activity codes. The majority of codes exceed 70% zero observations, indicating severe sparsity throughout the ICT activity spectrum.

Collapsing the 24 codes into five thematic groups (Table 5.1) eases the problem but does not fully resolve the zero inflation issue. (Figure 5.5). Treating the 24 raw codes or the 5 group-minute totals as continuous predictors is therefore not viable.

Table 5.1: Thematic grouping of the 24 ICT activity codes.

Group	**Constituent ICT activities**
Communication	`phone_messages`, `email_messages`, `family_calls`, `friend_calls`, `sales_calls`, `care_calls`, `service_calls`, `paidcare_calls`, `govt_calls`, `other_calls`
Entertainment	`streaming_video`, `podcast_radio`, `music_listening`, `online_gaming`, `leisure_browsing`
Shopping and finance	`online_shopping`, `grocery_online`, `web_compare`, `digital_finance`
Learning and work	`online_class`, `job_search`
Content and reading	`content_creation`, `digital_reading`, `personal_writing`

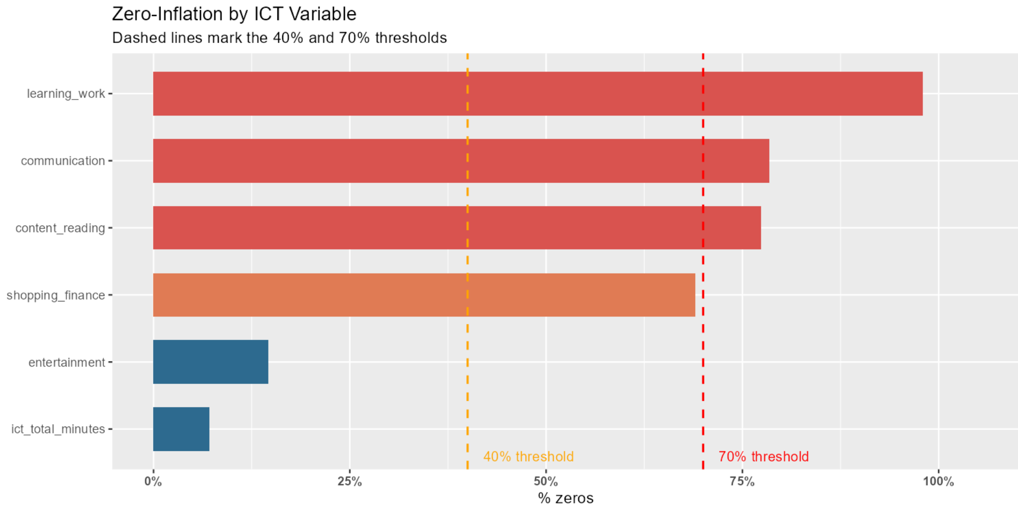


Figure 5.5: Share of zero minutes by grouped ICT variable. Aggregation reduces sparsity but does not remove it.

5.3.2 Five composite scales

To get usable predictors, five composite scales are derived from the 24 ICT codes. Each captures a distinct dimension of daily digital engagement.

- **ICT minutes** sums the time (in minutes) a respondent spent across all 24 ICT codes on the diary day. This is the raw duration measure of total daily ICT exposure.
- **ICT log minutes** applies a $\log(1 + x)$ transformation to ICT minutes to reduce the strong right skew of the raw variable while preserving the rank ordering of respondents.
- **ICT ordinal minutes** recodes total daily ICT minutes into six ordered categories. This recoding reduces skew without imposing the distributional assumptions of the raw or log transformed continuous versions.
- **ICT breadth all** counts the number of distinct ICT codes used on the diary day (range 0 to 24, recoded to 0 to 6, with values ≥ 6 collapsed into a single top category to normalise the upper tail).
- **ICT group breadth** counts how many thematic groups from Table 5.1 the respondent touched on the diary day (range 0 to 5, recoded to 0 to 4). This scale reflects how many *domains* of digital life a respondent engaged with, rather than how many specific activities.

The resulting distributions (Figures 5.6 and 5.7) are well behaved. Both breadth scales display informative variation across their ordinal categories without extreme piling at zero. Figure 5.6 shows the raw total ICT minutes (left) alongside the ordinal ICT minutes scale (right), which groups daily duration into six ordered categories ranging from no ICT use to more than ten hours. This ordinal recoding substantially reduces skew while preserving a clear scale of ICT engagement. Figure 5.7 presents the frequency distributions of `ict_breadthall` and `ict_minutes`.

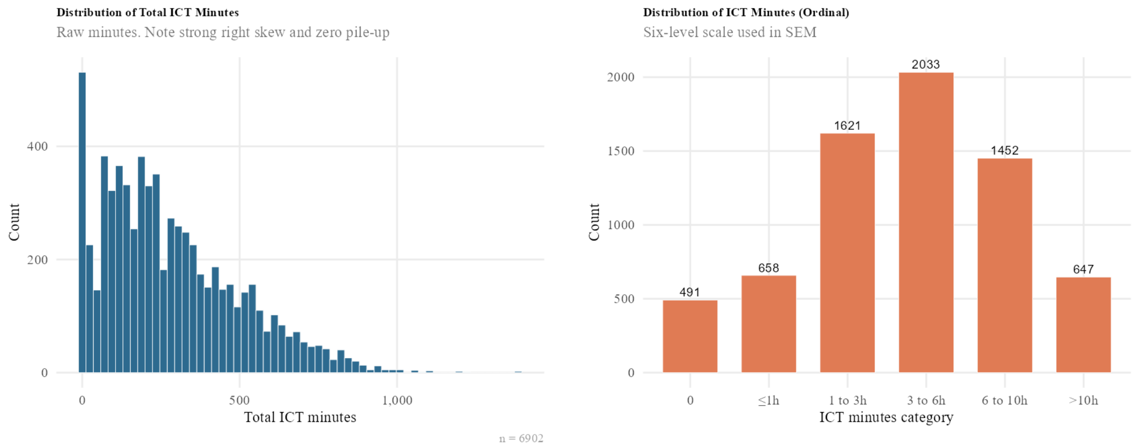


Figure 5.6: Raw total ICT minutes (left) and the six-category ordinal ICT minutes scale (right: 1 = no ICT, 2 = up to 1 h, 3 = 1–3 h, 4 = 3–6 h, 5 = 6–10 h, 6 = more than 10 h).

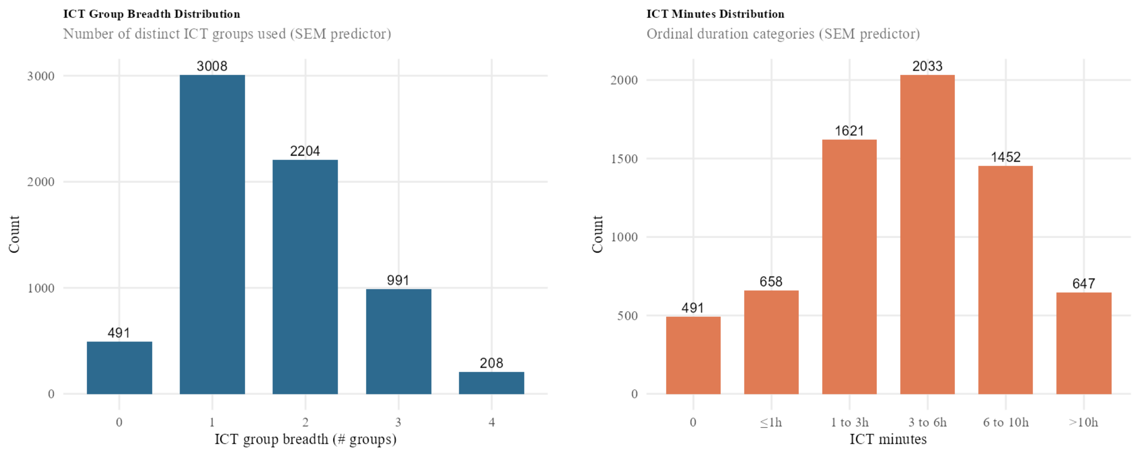


Figure 5.7: Frequency distributions of `ict_breadthall` (left, capped at 6) and `ict_group_breadth` (right, capped at 4).

5.3.3 Choice of the primary ICT scales

Of the five composite scales, two are carried into the SEM as ICT predictors: **ICT ordinal minutes** and **ICT group breadth**. Together they cover the two dimensions of digital engagement that the thesis is trying to measure: how much time is spent on ICT overall, and how broadly ICT is embedded across the different functional domains of a person's daily life.

Selected scales

ICT ordinal minutes aims to capture intensity. It expresses total daily ICT minutes as six ordered categories. This keeps respondents ordered by their level of ICT exposure while reducing the influence of extreme values and avoiding the distributional assumptions that a continuous variable brings to the SEM model.

ICT group breadth captures the functional reach of ICT use. Collapsing the 24 codes into five domains means a respondent can only score high by having ICT embedded in several different parts of daily life, not by repeating the same behaviour.

Using both scales in parallel lets the SEM separate the breadth of digital engagement from its duration, giving a more complete picture of a respondent's ICT use than either scale could provide on its own.

Dropped scales

The other three scales are dropped, but their information is preserved through the two selected scales.

ICT minutes in its raw form is too skewed and inflated by passive mono-activity users to act as a predictor. Its duration information is retained through ICT ordinal minutes.

ICT log minutes corrects for skew but still treats duration as continuous and is harder to interpret. ICT ordinal minutes carries the same intensity signal in a more usable form.

ICT breadth all double counts activities that share the same device and intention; three communication codes look broad without being so. ICT group breadth captures the same scope dimension while avoiding this overlap.

5.3.4 Correlation between the two selected ICT scales

Before moving on, the two ICT scales that will enter the SEM are inspected for redundancy. Figure 5.8 reports the pairwise Pearson and Spearman correlations between `ict_minutes_ord` and `ict_group_breadth_ord` across the analytical sample.

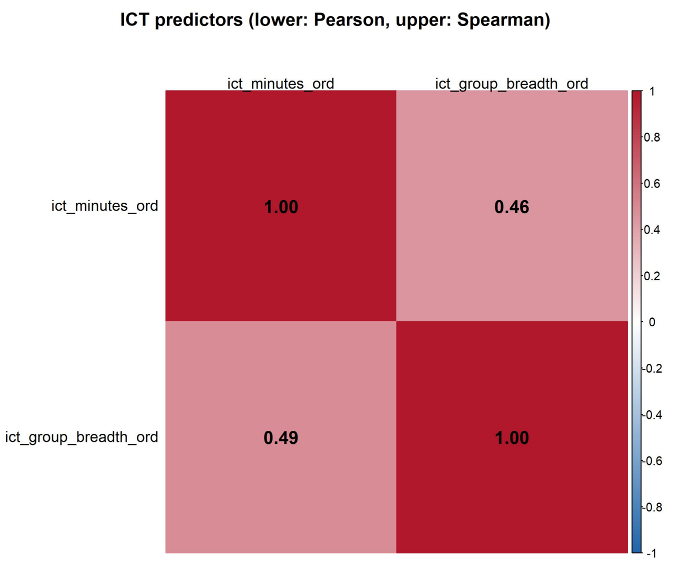


Figure 5.8: Correlation between the two ICT predictors (`ict_minutes_ord` and `ict_group_breadth_ord`). Pearson below the diagonal, Spearman above.

The two scales correlate moderately. This is the expected pattern since both measure digital engagement, but one captures duration and the other captures breadth, so they should overlap without being interchangeable. The moderate level of correlation supports retaining both predictors in the SEM.

5.4 Fragmentation

Activity fragmentation is conceptualized as the splitting of the day into multiple smaller episodes distributed across time. It is inherently multidimensional, covering at least (a) the number of fragments, (b) the distribution of fragment sizes, and (c) temporal configuration (Alexander et al., 2010). To capture these complementary aspects, four indicators are constructed at the respondent-day level from episode start/stop times and durations: **number of activities**, **Shannon entropy**, **turbulence**, and **complexity**.

Each indicator below is first defined and then illustrated on a single real respondent, to make visible how a lived day gets compressed into four numbers. All sequence-based indicators (entropy, turbulence, complexity) are computed on the diary at Tier-2 granularity (fine-grained ATUS sub-categories), which is the level used as input to the SEM. The two timeline figures below show the same day coded at Tier-1 and Tier-2, so the reader can see how coding granularity changes the appearance of the day; every numerical calculation that follows is performed at Tier-2. The Tier-1 coding scheme is listed in Appendix A.5, and the equivalent Tier-1 worked example and the full distributions of the four fragmentation indicators are reported in Appendix C.

5.4.1 An illustrative day: Respondent 22

Figure 5.9 shows the full diary day of Respondent 22 coloured by ATUS Tier-1 activity code. Figure 5.10 shows the same day at Tier-2 resolution. For visual clarity, both figures display the day in 15-minute slots; the underlying calculations are performed at one-minute granularity. At Tier-1 the day appears as a handful of broad blocks. At Tier-2 those blocks open up into 15 distinct sub-types and 26 episodes. The Tier-2 sequence is the basis for all numerical examples that follow.

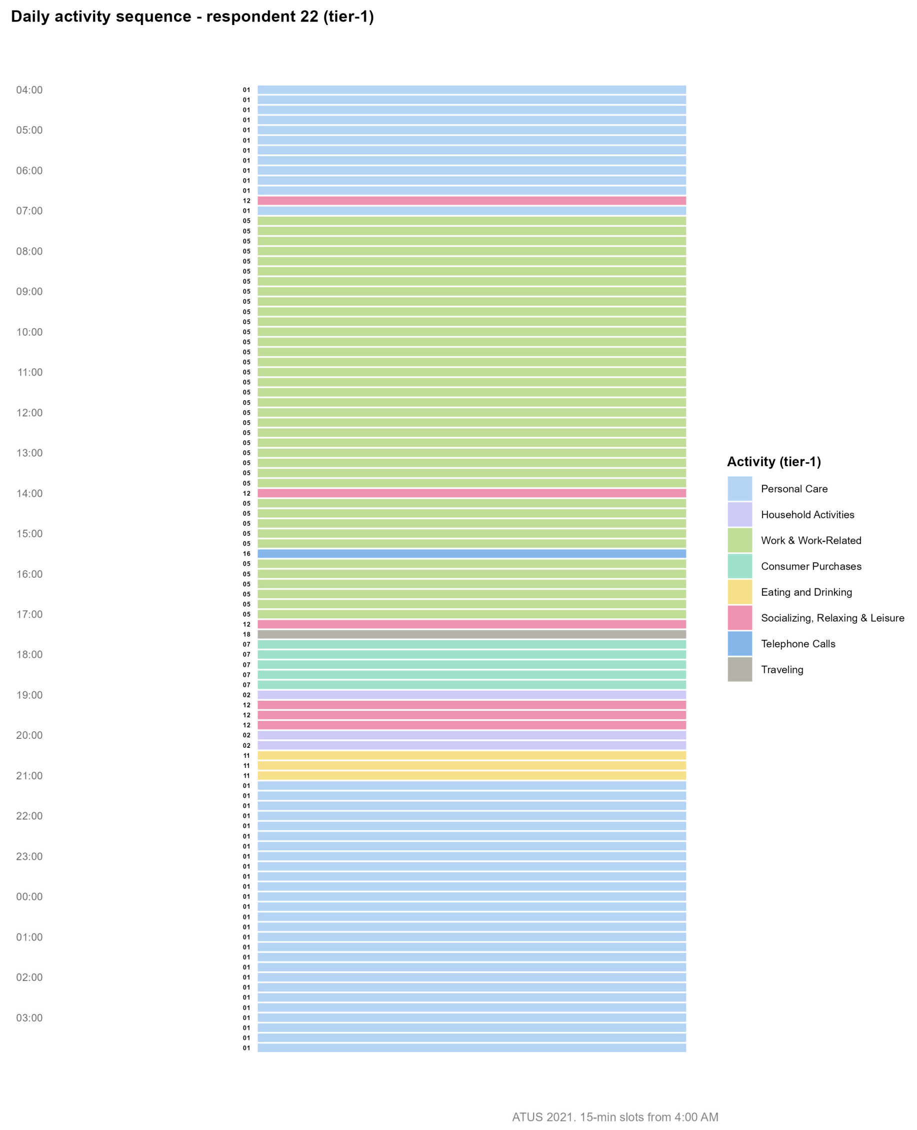


Figure 5.9: Daily activity sequence of Respondent 22 coded at Tier-1 (broad ATUS categories). Shown for comparison only; numerical calculations are performed at Tier-2.

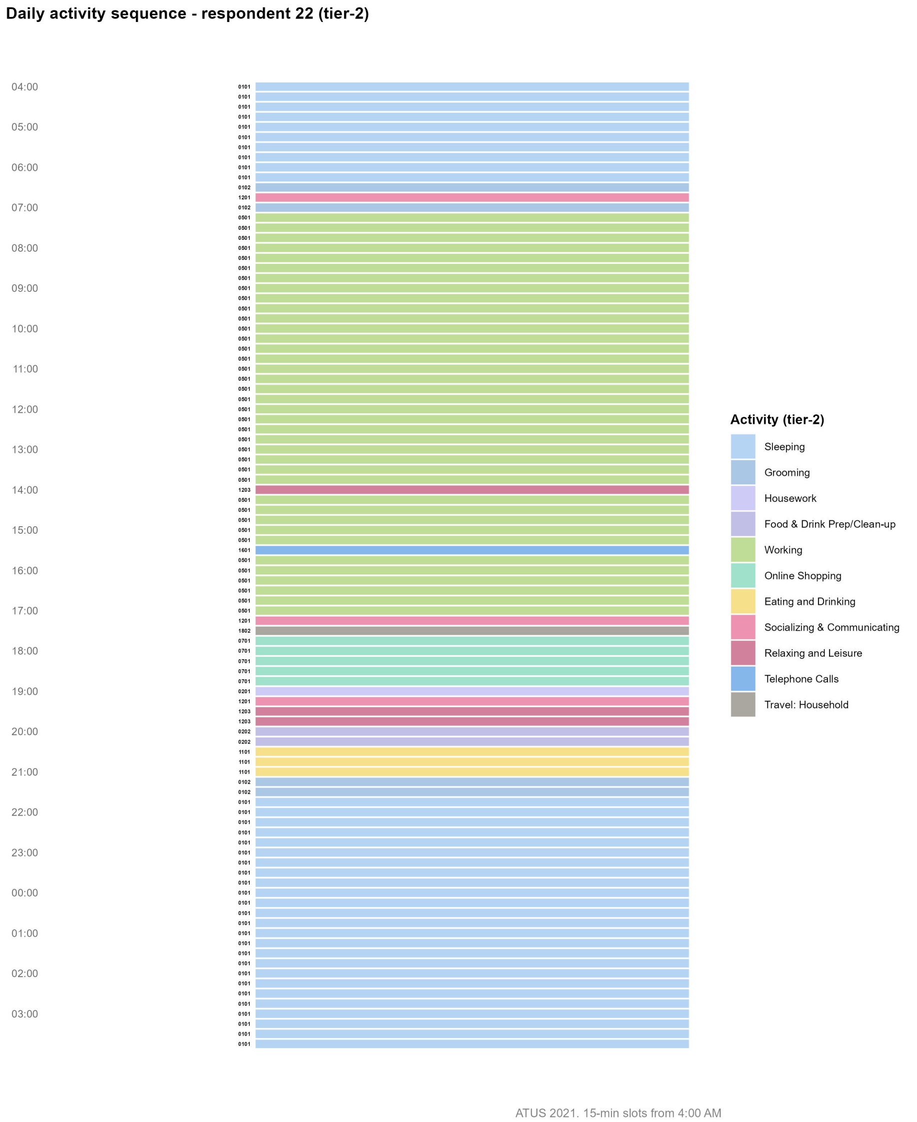


Figure 5.10: Daily activity sequence of Respondent 22 coded at Tier-2 (fine-grained ATUS sub-categories). This is the coding used to compute the fragmentation indicators.

5.4.2 Number of activities

The simplest indicator of fragmentation is the count of episodes, blocks of consecutive time spent on one activity before switching to another (Hubers et al., 2008). For Respondent 22 the Tier-2 day contains **26** episodes, with a mean episode duration of 58.89 minutes. Across the full sample, the distribution is approximately normal with mild right skew and needs no transformation (Figure 5.11). Distributions for the remaining three fragmentation indicators (entropy, turbulence, complexity) are provided in Appendix C.

Descriptive Summary

number_of_activities

N	Missing	Pct_miss	Mean	SD	Min	Median	Max	Skewness	Kurtosis	Pct_zero
6902	0	0	18.379	7.507	5	17	67	1.021	4.831	0

Figure 5.11: Distribution of `number_of_activities` across the sample.

5.4.3 Entropy

Shannon entropy measures how evenly the day is split across activity types. It is computed from the share of diary time allocated to each type:

$$H(x) = -\sum_{k \in \mathcal{K}} \pi_k \log(\pi_k), \tag{5.1}$$

where $\mathcal{K}$ is the set of activity types present in the day and π_k is the time share of type k. For cross-respondent comparison, H is normalised by dividing by its theoretical maximum $\log(K)$, yielding a value in $[0, 1]$. A person whose time is split evenly across many activity types scores high; a person dominated by one activity scores low.

For Respondent 22, sleeping absorbs 40.8% of the day, working 35.3%, grooming 4.8%, online shopping 4.7%, and socializing and communicating 3.4%, with the remaining ten Tier-2 sub-types sharing smaller slices (Figure 5.12). Substituting these shares gives raw entropy $H = 1.6043$, or $H_{\text{norm}} = 1.6043/\log(15) = 1.6043/2.7081 = 0.5924$ after dividing by the theoretical maximum across $K = 15$ distinct activity types.

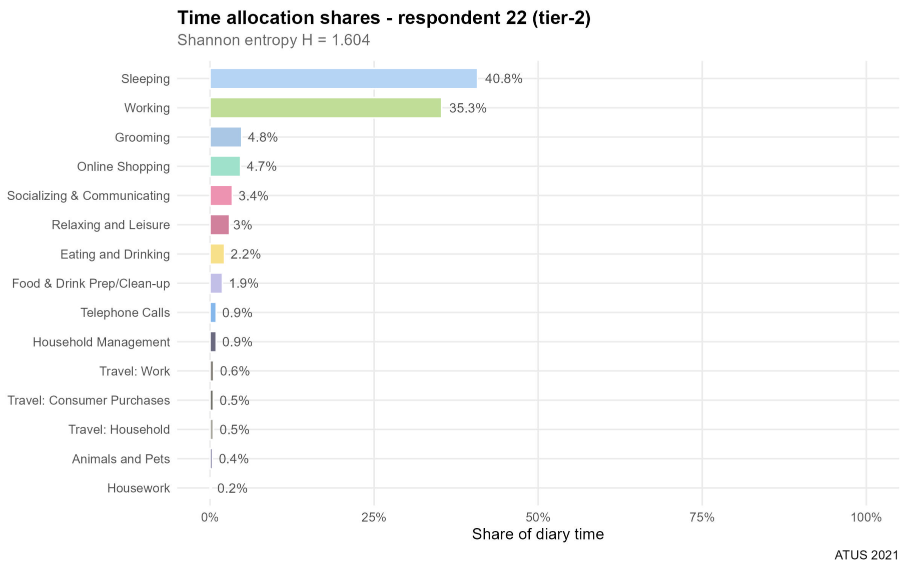


Figure 5.12: Tier-2 time allocation shares (π_k) for Respondent 22. Raw entropy $H = 1.6043$, normalised entropy $H_{\text{norm}} = 0.5924$.

5.4.4 Turbulence

Turbulence captures the structural complexity of the full activity sequence by jointly considering the diversity of ordered subsequences and the heterogeneity of episode durations (Elzinga &

Liefbroer, 2007; Gabadinho et al., 2010):

$$T(x) = \log\left(\phi(x) \cdot \frac{s^2_{t,\max}(x) + 1}{s^2_t(x) + 1}\right), \tag{5.2}$$

where $\phi(x)$ is the number of distinct subsequences of x, $s^2_t(x)$ is the variance of episode durations across the sequence, and $s^2_{t,\max}(x)$ is the theoretical maximum variance given the total sequence length. Higher values mean more intricate switching combined with greater heterogeneity in how long episodes last.

Operationally, the day is segmented into a 1,440-slot state sequence (one slot per minute) covering 4:00 AM to 3:59 AM the following day. Each slot is labelled with the Tier-2 sub-code reported at that minute. The sequence object is built with the `TraMineR` package (Gabadinho et al., 2011) in `R`, and turbulence is extracted via `seqST()`. For Respondent 22, the 26 episodes have a mean duration of 58.89 minutes and an episode-duration variance of $s^2_t = 14{,}969.95$. Combined with the diversity of ordered Tier-2 subsequences this yields $T = 15.3423$ (see Figure 5.14).

5.4.5 Complexity

Complexity combines the transition rate with normalised entropy into a single score (Gabadinho et al., 2010), and has been applied to activity-travel fragmentation by McBride et al. (2019):

$$C(x) = \sqrt{\frac{nt(x)}{l(x) - 1} \cdot \frac{H(x)}{H_{\max}}}, \tag{5.3}$$

where $nt(x)$ is the number of transitions between consecutive activity states and $l(x)$ is the sequence length. The index penalises both low diversity and infrequent switching: a monotonous day or a day with few transitions scores low, while a varied day with many switches scores high. Complexity is computed on the same 1,440-slot sequence using `seqici()` from `TraMineR`.

For Respondent 22, the Tier-2 sequence contains 24 transitions over 1,439 possible transition points (rate $= 24/1439 = 0.0167$) and normalised entropy of 0.5924, yielding $C = \sqrt{0.0167} \cdot \sqrt{0.5924} = 0.0506$. The number of transitions (24) is two fewer than the episode count (26) because two pairs of consecutive episodes share the same Tier-2 code and therefore produce no transition in the minute-level sequence. Transitions are highlighted as red diamonds in Figure 5.13.

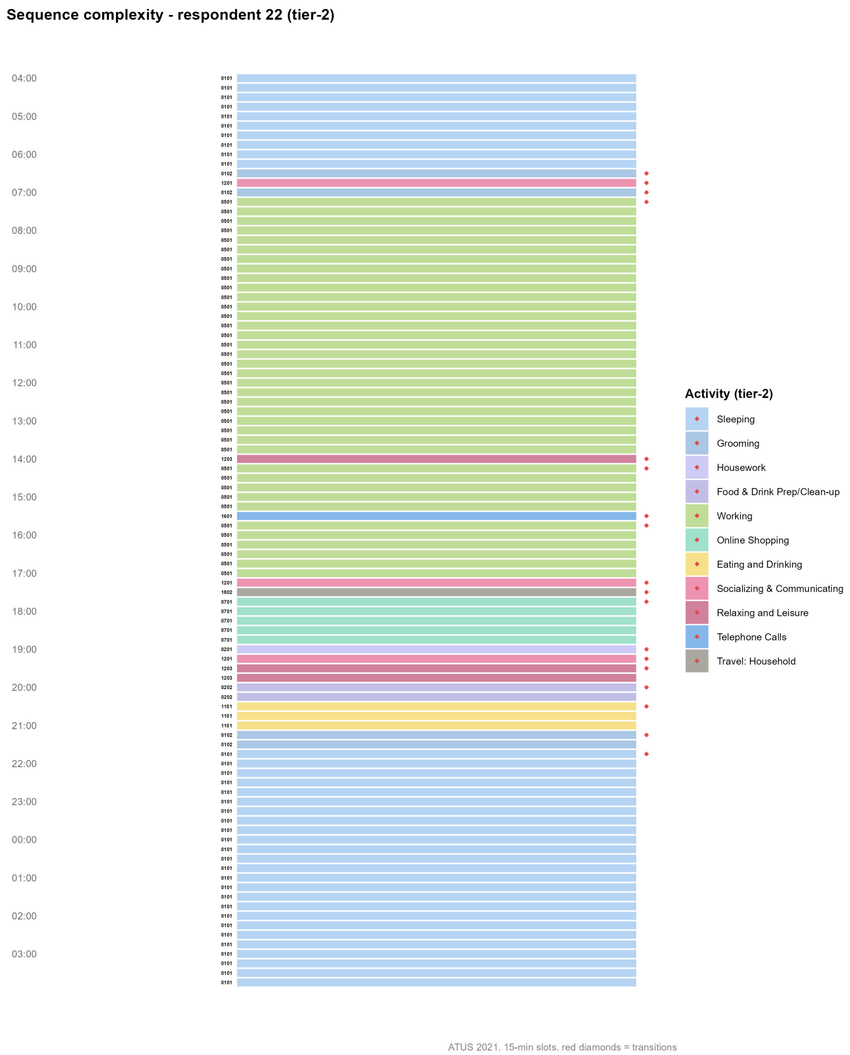


Figure 5.13: Daily Tier-2 sequence of Respondent 22 with activity transitions highlighted (red diamonds). 24 transitions over 1,439 possible transition points yield a transition rate of 0.0167.

5.4.6 Worked example: summary

The full step-by-step calculation for Respondent 22 at Tier-2 is shown in Figure 5.14, split across two panels for readability: the first panel covers the entropy and complexity calculations together with the three summary indicators, and the second panel covers the episode-by-episode turbulence calculation. The raw diary collapses into four numbers that feed the SEM: number of activities = 26, $H_{\text{norm}} = 0.5924$, $T = 15.3423$, and $C = 0.0506$. The same step-by-step calculation performed at Tier-1 granularity is reported in Appendix C for comparison.

Step-by-step calculations - respondent 22 (t2)

ATUS 2021. Tier-2 codes (TRTIER2). Part 1 of 2: entropy and complexity

Entropy H_norm	Turbulence T	Complexity C
0.5924	**15.3423**	**0.0506**
H_raw / log(K)	log(phi (s2_max+1)/(s2_t+1))	seqici()

Tier-2 (k)	Minutes	pi_k	log(pi_k)	pi_k * log(pi_k)
0101	648	0.4075	-0.8977	-0.3658
0102	77	0.0484	-3.0283	-0.1466
0201	3	0.0019	-6.2659	-0.0119
0202	30	0.0189	-3.9686	-0.075
0206	6	0.0038	-5.5728	-0.0212
0209	15	0.0094	-4.667	-0.0439
0501	561	0.3528	-1.0419	-0.3676
0701	74	0.0465	-3.0683	-0.1427
1101	35	0.022	-3.8167	-0.084
1201	54	0.034	-3.3814	-0.115
1203	47	0.0296	-3.52	-0.1042
1601	15	0.0094	-4.667	-0.0439
1802	8	0.005	-5.2983	-0.0265
1805	9	0.0057	-5.1673	-0.0295

```
H_raw  = -sum(-1.6043)  =                          1.6043
H_norm = H_raw / log(15)  =  1.6043 / 2.7081  =    0.5924
```

Component	Value	Note
Total 1-min slots	1440	full diary day
Activity transitions	24	slots where activity changes
Transition rate	0.0167	24 / 1439
Distinct activities (K)	15	unique codes observed
Normalised entropy H/log(K)	0.5924	H_norm

```
C = sqrt(0.0167) * sqrt(0.5924)  =                 0.0506
```

(a) Part 1: entropy and complexity, with summary indicators at the top.

Step-by-step calculations - respondent 22 (t2)

ATUS 2021. Tier-2 codes (TRTIER2). Part 2 of 2: turbulence

Episode	Activity	Duration (min)	Dev. from mean	Dev^2
1	0101	120	61.11	3734.57
2	0206	1	-57.89	3351.12
3	0102	40	-18.89	356.79
4	1201	19	-39.89	1591.12
5	0102	10	-48.89	2390.12
6	1805	4	-54.89	3012.79
7	0501	406	347.11	120486.12
8	1203	15	-43.89	1926.23
9	0501	75	16.11	259.57
10	1601	15	-43.89	1926.23
11	0501	80	21.11	445.68
12	1805	5	-53.89	2904.01
13	1201	15	-43.89	1926.23
14	1802	8	-50.89	2589.68
15	0209	5	-53.89	2904.01
16	0701	74	15.11	228.35
17	1807	8	-50.89	2589.68
18	0201	3	-55.89	3123.57
19	0206	2	-56.89	3236.35
20	0206	3	-55.89	3123.57
21	1201	20	-38.89	1512.35
22	1203	32	-26.89	723.01
23	0202	30	-28.89	834.57
24	1101	35	-23.89	570.68
25	0102	27	-31.89	1016.9
26	0209	10	-48.89	2390.12

```
mean = 58.89 min  |  s2_t = 14969.95  |  T =      15.3423
```

(b) Part 2: turbulence, episode-by-episode.

Figure 5.14: Step-by-step calculation of the three sequence-based fragmentation indicators for Respondent 22 at Tier-2: entropy ($H_{\text{norm}} = 0.5924$), turbulence ($T = 15.3423$), and complexity ($C = 0.0506$). These values, together with the episode count of 26, are the four fragmentation inputs to the SEM.

5.4.7 Correlation diagnostic among the four indicators

Before any SEM is specified or fitted, the four fragmentation indicators are inspected for redundancy. All four are constructed from the same daily sequence, so some overlap is expected; the question is whether any pair is so strongly correlated that the two carry effectively the same information. Figure 5.15 reports the pairwise Pearson and Spearman correlations among the four indicators across the analytical sample ($n = 6{,}902$).

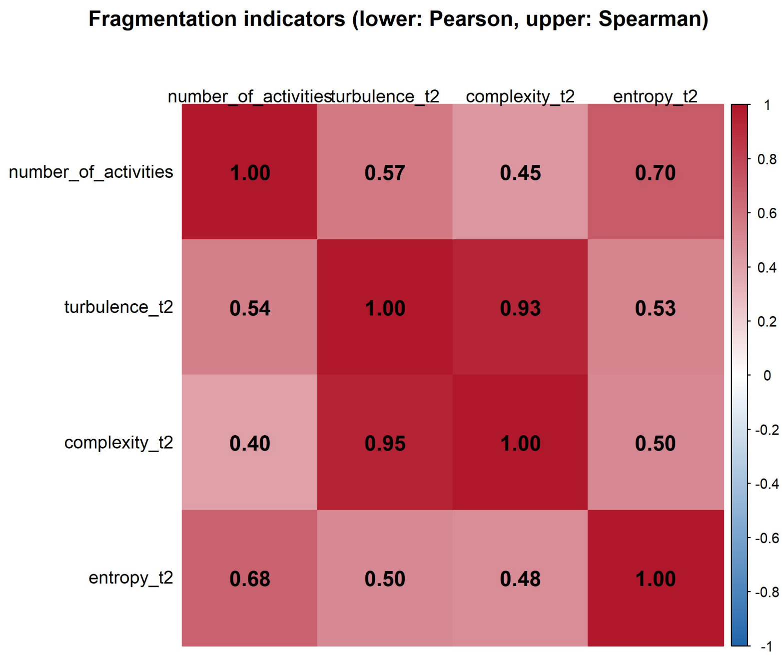


Figure 5.15: Correlations among the four fragmentation indicators across the analytical sample ($n = 6{,}902$). Pearson below the diagonal, Spearman above. Turbulence and complexity correlate far more strongly than any other pair.

Most of the six pairs sit at moderate values, which is what we would expect from indicators that all derive from the same sequence. One pair, however, stands well above the rest: turbulence and complexity sit at correlations approaching the upper bound of the scale, while every other pair (number of activities with entropy, number of activities with turbulence, number of activities with complexity, entropy with turbulence, entropy with complexity) sits at clearly lower values. This is the diagnostic that motivates the indicator selection in the next section. An indicator pair this collinear cannot both enter the SEM as separate mediators without competing for the same variance, and the question becomes which of the two should be retained.

5.5 Selection of fragmentation indicators for the SEM

The correlation diagnostic in Section 5.4.7 identified one pair, turbulence and complexity, with a correlation far above any other pair among the four indicators. This is the empirical signal that motivates a closer look at whether complexity carries information that is not already captured by the other three indicators. To answer that, the next two subsections look at what each indicator is structurally built from. The structural decomposition explains why the correlation matrix looks the way it does, and points to a clean decision rule.

5.5.1 Complexity can be dropped

Complexity (Gabadinho et al., 2010) is

$$C(x) = \sqrt{\frac{nt(x)}{l(x)-1} \cdot \frac{H(x)}{H_{\max}}}. \tag{5.4}$$

The two ingredients inside the square root are already in the SEM. The first one, $nt(x)/(l(x)-1)$, is a transition rate. The number of transitions $nt(x)$ is essentially the number of episodes, so this term is the number of activities mediator divided by a constant. The second one, $H(x)/H_{\max}$, is the same normalised entropy that enters the SEM as a separate mediator (the H_{norm} defined earlier in Section 5.4). Complexity is therefore, by construction, a function of two quantities that are already in the model. The fact that complexity also correlates very highly with turbulence (which carries additional information about subsequence diversity and episode duration variance) makes its situation worse: the information that complexity does carry is shared with another indicator that already covers more.

5.5.2 Turbulence cannot be dropped

Turbulence (Elzinga & Liefbroer, 2007) is built differently. It combines two features that neither entropy nor the episode count can pick up. The first is how varied the order of activities is through the day. Two days can contain the same activities and the same number of transitions but cycle through them in different patterns, and turbulence sees the difference. The second is how even the episode lengths are. A day where one activity dominates and the rest are brief is anchored by that long episode and is therefore predictable, so it scores low. A day where every episode is similar in length has no such anchor and scores higher, even when both days have the same number of episodes. Turbulence therefore brings new useful information to the SEM that none of the other three indicators can supply on its own.

5.5.3 Decision

Taken together, the correlation diagnostic and the structural decomposition both point in the same direction. The pre-SEM correlation matrix flags turbulence and complexity as the only redundant pair among the four indicators. The structural decomposition explains why: complexity is, by construction, a function of two quantities that are already in the model, while turbulence carries genuinely new information.

Complexity is therefore dropped from the SEM, and three fragmentation mediators are retained: **number of activities**, **turbulence**, and **entropy**.

5.5.4 Confirmation from a preliminary SEM specification

The same decision was independently checked against a preliminary SEM specification, fitted only as a robustness check after the indicator decision had already been taken on the grounds described above. The four-mediator model returned a standardised residual covariance of 0.95 between turbulence and complexity, mirroring the pre-SEM correlation diagnostic, and the path from turbulence to life evaluation was suppressed by the collinearity ($\beta = .058$, $p = .183$). Once complexity was removed the same path strengthened to $\beta = .095$ ($p < .001$), with the other paths essentially unchanged. The full side-by-side comparison is reported in Appendix D. This SEM-based evidence confirms the decision, but is not the basis for it. The decision is based on the pre-SEM correlation diagnostic and the structural decomposition.

5.6 Diary Granularity and Respondent Rounding

The fragmentation indicators built in Section 5.4 treat the diary as if it were genuinely minute-level data. ATUS records start and stop times to the minute, but respondents themselves do not necessarily report at that resolution. Two diagnostic plots make this point. Figure 5.16 shows the distribution of the shortest episode duration per respondent. If respondents were reporting at minute-level resolution, this distribution should be concentrated at 1, 2, and 3 minutes, since almost any diary day contains at least one brief transition between activities. Instead it clusters at 5 minute multiples, with the largest peak at 5 minutes and only minor support at 1, 2, 3, or 4 minutes.

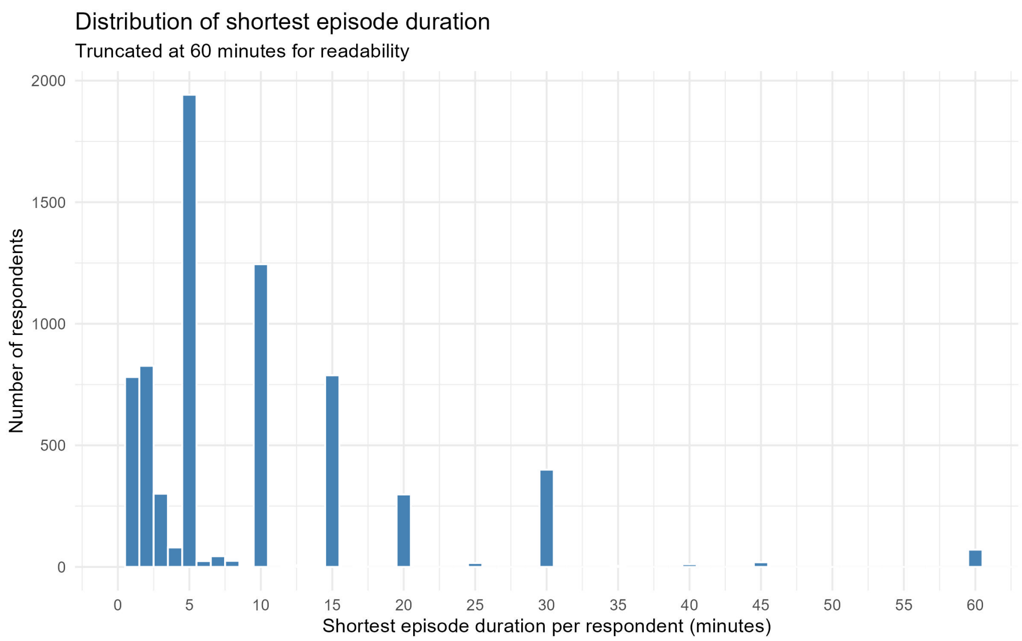


Figure 5.16: Distribution of the shortest episode duration per respondent across the analytical sample. Truncated at 60 minutes for readability.

Figure 5.17 extends the same diagnostic to the full episode-level file. Episodes whose duration is a multiple of 5 minutes are coloured in blue, others in grey. Multiples of 5 dominate so heavily that they form the entire shape of the distribution.

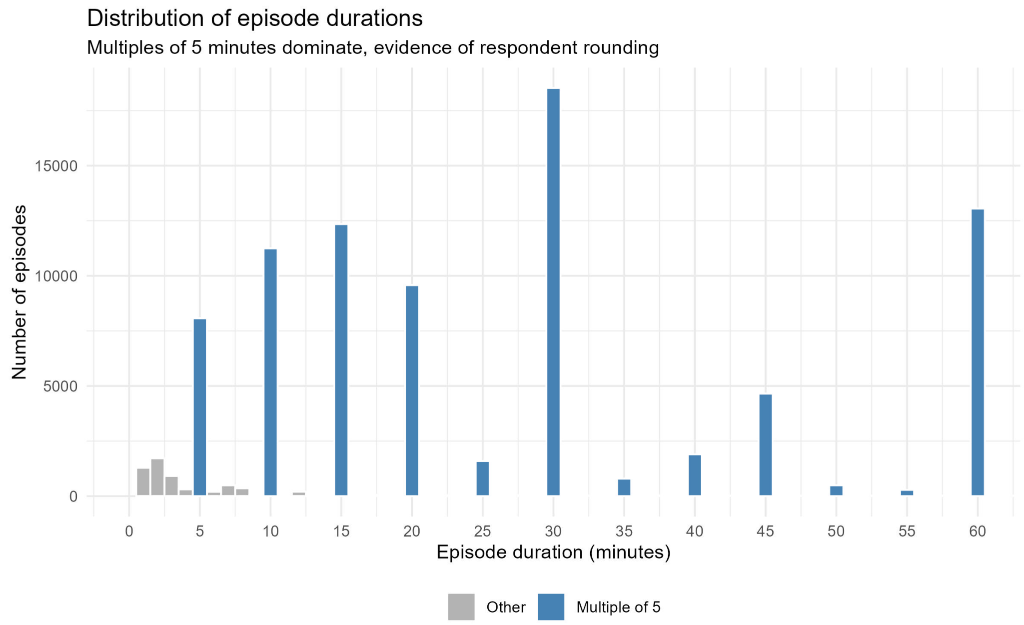


Figure 5.17: Distribution of all episode durations in the activity file. Episodes whose duration is a multiple of 5 minutes are coloured blue, others grey. Truncated at 60 minutes for readability.

The pattern is a measurement property of the diary rather than a feature of behaviour. A respondent who actually spent 7 minutes on a phone call is likely to report 5 or 10. It could be argued that the effective time resolution of ATUS is therefore closer to 5 minutes than to 1.

This observation does not invalidate the analysis. The four indicators still capture meaningful variation across respondents in how broken the day is. It does, however, raise the question of whether the headline findings are sensitive to this measurement coarseness. That sensitivity check is reported in Section 6.3, where the SEM is re-estimated on the subset of respondents who reported at least one non-multiple-of-5 episode and therefore provided finer-grained timing somewhere in the diary day.

Chapter 6

Results

6.1 Overview of the Structural Equation Model

A path model was estimated in AMOS with maximum likelihood estimation. The model has two correlated ICT predictors, ICT group breadth (ordinal, range 0 to 4) and ICT minutes (ordinal, range 1 to 6). Both feed into three fragmentation indicators (number of activities, turbulence, entropy) and into life evaluation directly. The three mediators in turn predict life evaluation. Residual covariances are specified between every pair of fragmentation error terms (e2–e3, e2–e5, e3–e5) to absorb the structural overlap between the indicators.

The decision to drop complexity from the indicator set was made on the basis of the pre-SEM correlation diagnostic and the structural decomposition presented in Sections 5.4.7 and 5.5, and is not revisited here.

The same model is estimated separately within six subgroups defined by gender (male, female) and age group (young, middle, older). A combined single-group model on the full sample is reported as a reference point. The model is just-identified ($df = 0$): the number of distinct parameters to be estimated equals the number of distinct sample moments, global fit indices carry no information, so they are not reported.

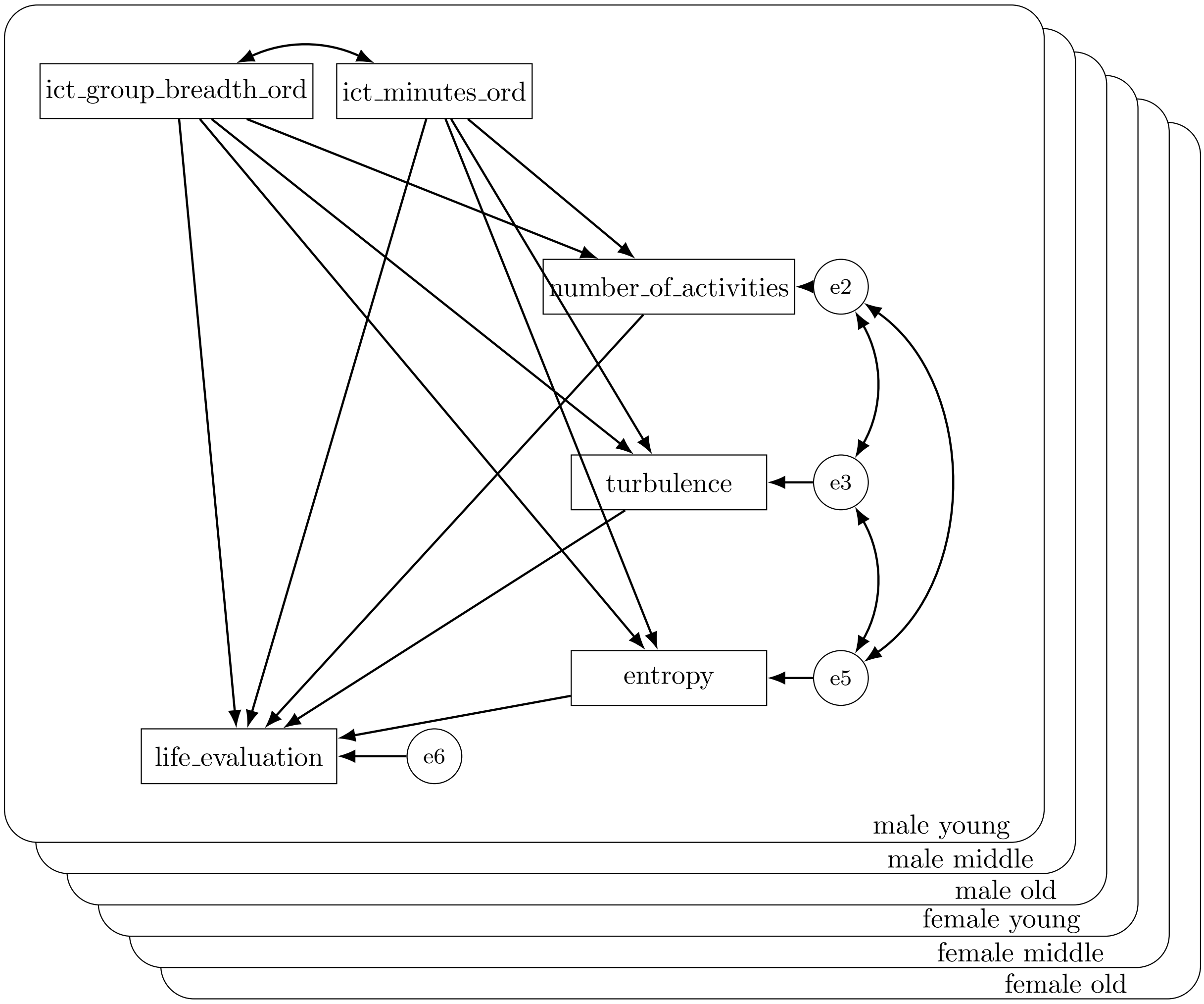


Figure 6.1: Structural model linking ICT group breadth and ICT minutes (both ordinal, correlated), three fragmentation indicators (number of activities, turbulence, entropy) with correlated residuals, and life evaluation. The same model is estimated separately within six demographic subgroups.

6.2 Subgroup Estimates

The same path model is estimated separately for six subgroups defined by gender (male, female) and age group (young, middle, older). Path diagrams for each subgroup are shown below. Full regression weight tables and effect decompositions are provided in Appendix G.

6.2.1 Combined Model

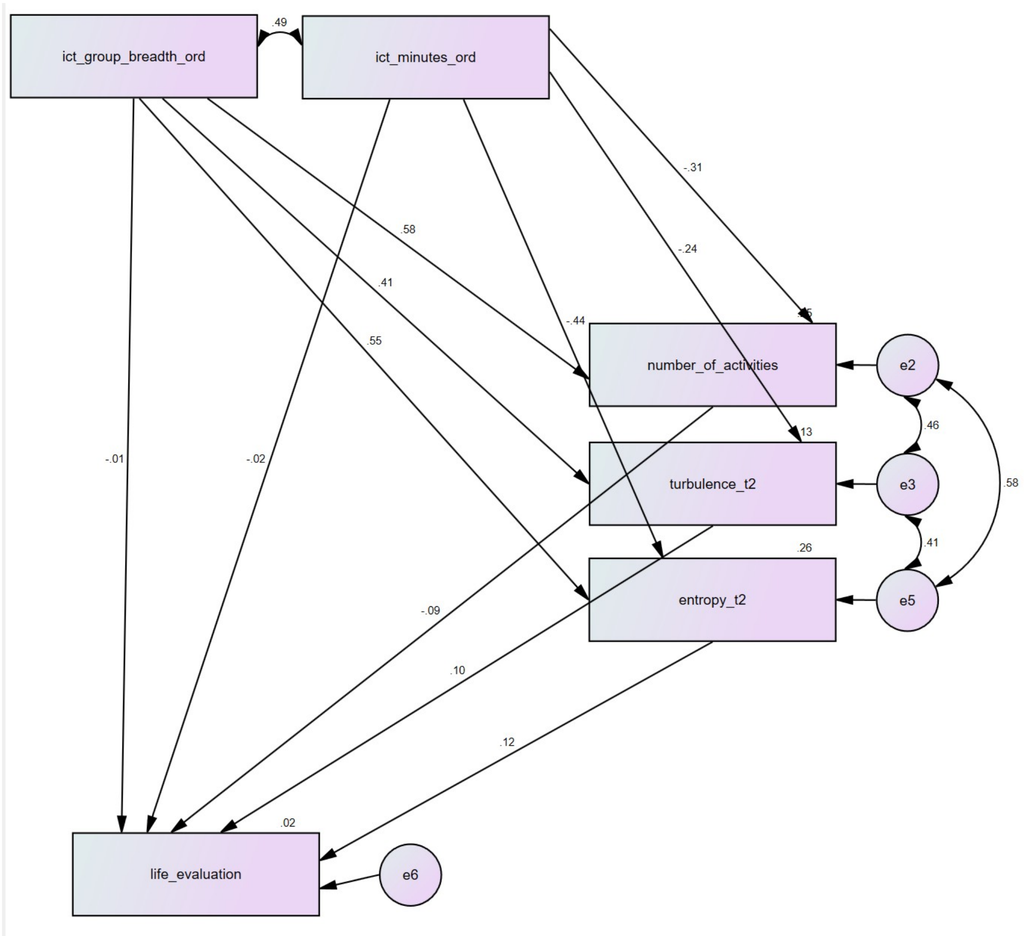
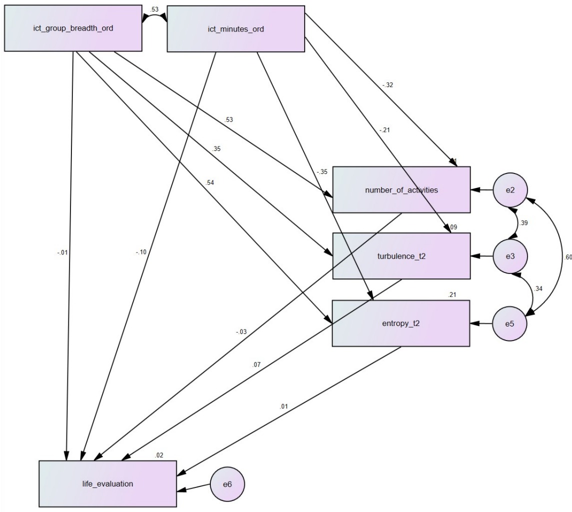
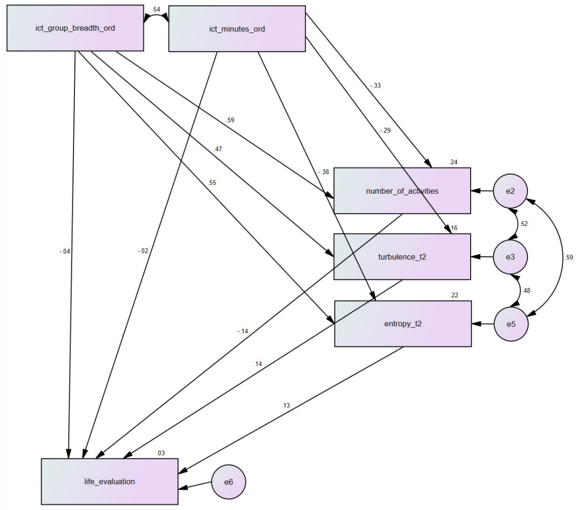


Figure 6.2: Structural path model, combined sample. Standardized regression weights shown on paths.

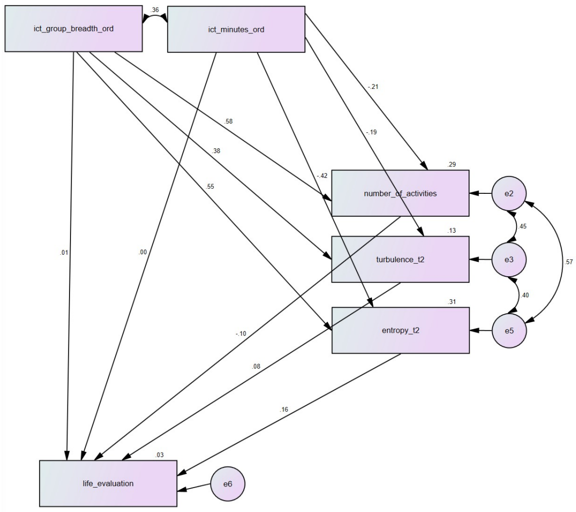
6.2.2 Female Subgroups



(a) Female, Young



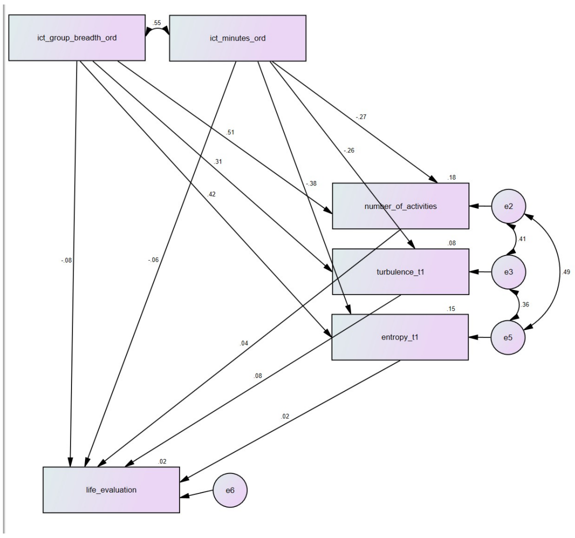
(b) Female, Middle



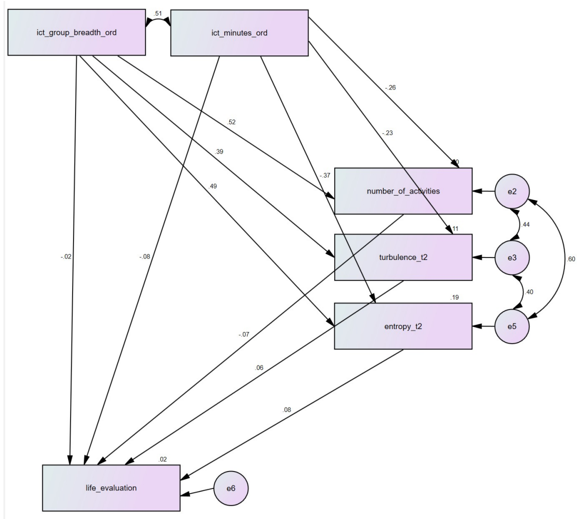
(c) Female, Older

Figure 6.3: Structural path models for female subgroups. Standardized regression weights shown on paths.

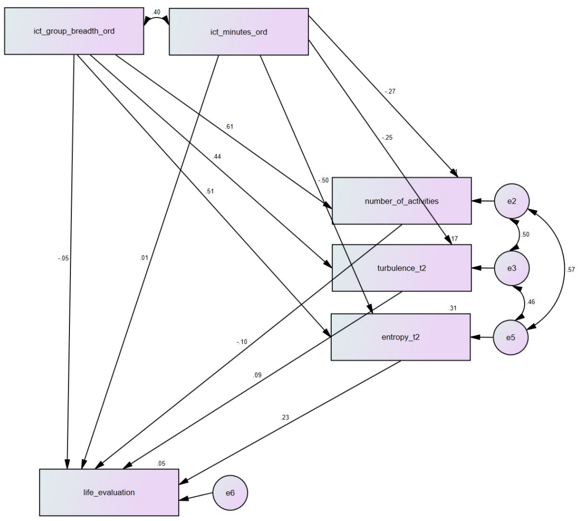
6.2.3 Male Subgroups



(a) Male, Young



(b) Male, Middle



(c) Male, Older

Figure 6.4: Structural path models for male subgroups. Standardized regression weights shown on paths.

6.2.4 Summary of Path Estimates Across Subgroups

Tables 6.1 to 6.5 summarise the standardized regression weights and effect decompositions across all six subgroups and the combined model. Significance markers throughout: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 6.1: Standardized path estimates: ICT group breadth → Fragmentation indicators. All paths shown are significant at $p < .001$.

Subgroup	**Breadth → Activities**	**Breadth → Turbulence**	**Breadth → Entropy**
Combined	.580***	.410***	.552***
Female, Young	.534***	.351***	.540***
Female, Middle	.586***	.470***	.551***
Female, Older	.578***	.381***	.548***
Male, Young	.509***	.309***	.423***
Male, Middle	.521***	.387***	.493***
Male, Older	.611***	.443***	.507***

Table 6.2: Standardized path estimates: ICT minutes (ordinal) → Fragmentation indicators. All paths shown are significant at $p < .001$ and uniformly negative.

Subgroup	**Minutes → Activities**	**Minutes → Turbulence**	**Minutes → Entropy**
Combined	−.306***	−.238***	−.440***
Female, Young	−.321***	−.212***	−.354***
Female, Middle	−.328***	−.287***	−.385***
Female, Older	−.210***	−.192***	−.424***
Male, Young	−.266***	−.263***	−.381***
Male, Middle	−.257***	−.230***	−.366***
Male, Older	−.275***	−.249***	−.503***

Table 6.3: Standardized path estimates: Fragmentation indicators → Life evaluation.

Subgroup	**Activities → Life Eval.**	**Turbulence → Life Eval.**	**Entropy → Life Eval.**
Combined	$-.091^{***}$	$.095^{***}$	$.118^{***}$
Female, Young	$-.033$	$.075^{*}$	.010
Female, Middle	$-.144^{***}$	$.136^{***}$	$.129^{**}$
Female, Older	$-.101^{**}$	$.083^{*}$	$.164^{***}$
Male, Young	.043	.076	.018
Male, Middle	$-.067$	.061	.081
Male, Older	$-.105^{*}$	$.091^{*}$	$.230^{***}$

Table 6.4: Standardized direct paths from the two ICT predictors to life evaluation.

Subgroup	**Breadth → Life Eval.**	**Minutes → Life Eval.**
Combined	$-.006$	$-.023$
Female, Young	$-.009$	$-.103^{*}$
Female, Middle	$-.044$	$-.016$
Female, Older	.005	.002
Male, Young	$-.077$	$-.064$
Male, Middle	$-.024$	$-.083^{*}$
Male, Older	$-.050$	.005

Table 6.5: Standardized direct, indirect, and total effects of the two ICT predictors on life evaluation. Indirect effects are transmitted through the three fragmentation mediators combined.

	ICT group breadth			**ICT minutes**		
Subgroup	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Combined	$-.006$	.052	.045	$-.023$	$-.047$	$-.070$
Female, Young	$-.009$	.014	.005	$-.103^{*}$	$-.009$	$-.112$
Female, Middle	$-.044$	.051	.007	$-.016$	$-.041$	$-.057$
Female, Older	.005	.063	.069	.002	$-.064$	$-.062$
Male, Young	$-.077$	.053	$-.024$	$-.064$	$-.038$	$-.102$
Male, Middle	$-.024$	.028	.004	$-.083^{*}$	$-.026$	$-.110$
Male, Older	$-.050$	.093	.043	.005	$-.110$	$-.104$

6.3 Sensitivity Analyses

Three tests check whether the combined SEM results shift under stricter measurement conditions. Two address diary granularity. The first restricts the sample to respondents who reported at least one episode whose duration is not a multiple of five minutes (non-rounders; $N = 2{,}445$). The second restricts the sample to respondents whose shortest episode is less than five minutes (under-5; $N = 1{,}989$). The third recomputes turbulence and entropy on the waking day only, with all sleep episodes (Tier-2 code 0101) removed before the indicators are calculated, following Wanigatunga et al. (2019); because this removes sleep from all diaries rather than subsetting respondents, it retains the full combined sample ($N = 6{,}902$). All three tests were estimated on the combined model. Full output for each test is provided in Appendices F, J, and I.

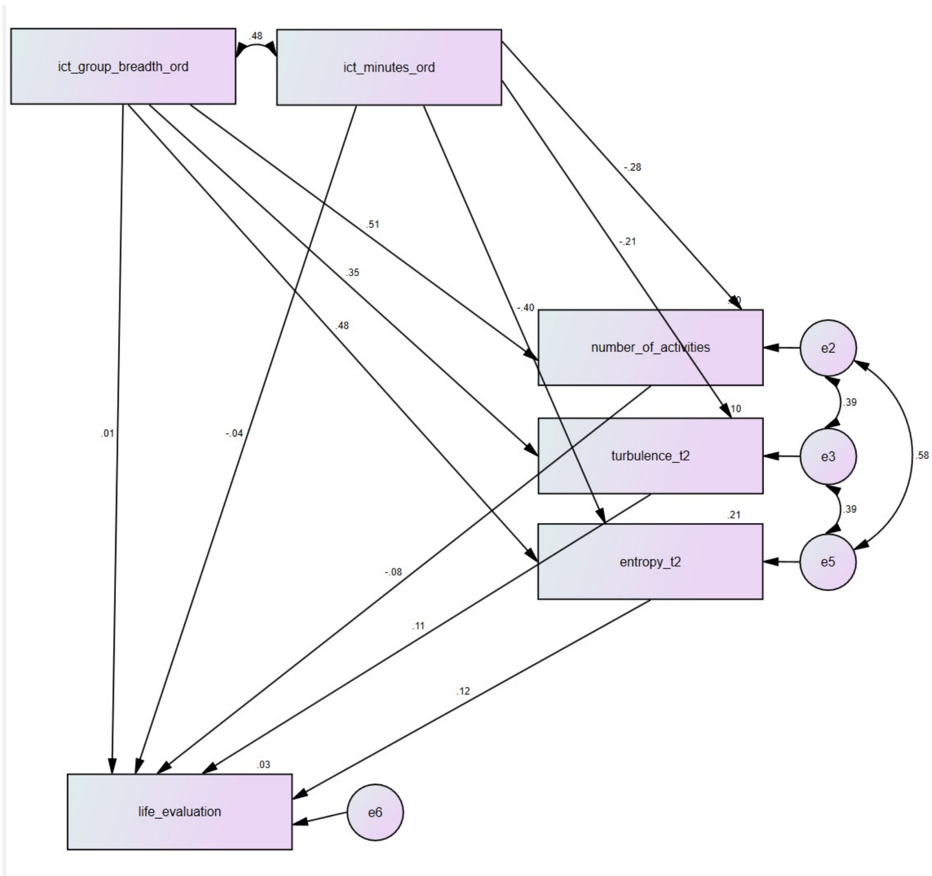


Figure 6.5: Structural path model estimated on the non-rounder subsample. Standardized regression weights shown on paths.

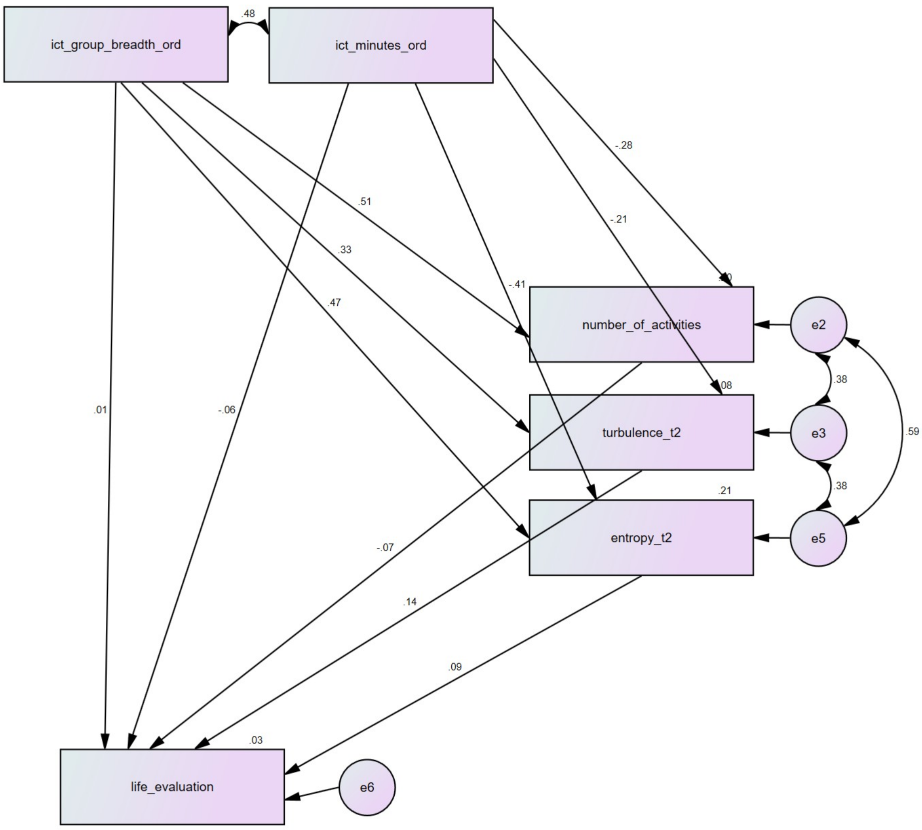


Figure 6.6: Structural path model estimated on the under-5-minute subsample. Standardized regression weights shown on paths.

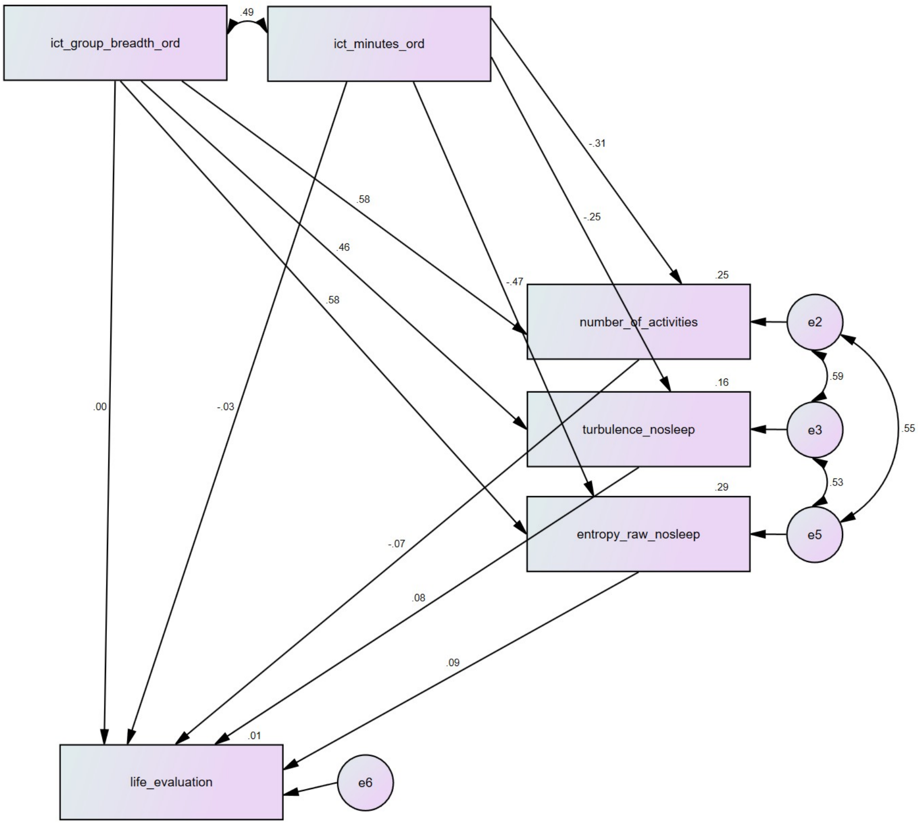


Figure 6.7: Structural path model estimated with turbulence and entropy recomputed on the waking day only. Standardized regression weights shown on paths.

Table 6.6: Standardized path estimates across the main combined model and the three sensitivity tests.

Path	**Combined**	**Non-rounders**	**Under-5**	**No-sleep**
Breadth → Activities	$.580^{***}$	$.512^{***}$	$.509^{***}$	$.580^{***}$
Breadth → Turbulence	$.410^{***}$	$.352^{***}$	$.326^{***}$	$.462^{***}$
Breadth → Entropy	$.552^{***}$	$.479^{***}$	$.471^{***}$	$.584^{***}$
Minutes → Activities	$-.306^{***}$	$-.277^{***}$	$-.281^{***}$	$-.306^{***}$
Minutes → Turbulence	$-.238^{***}$	$-.211^{***}$	$-.209^{***}$	$-.254^{***}$
Minutes → Entropy	$-.440^{***}$	$-.402^{***}$	$-.413^{***}$	$-.472^{***}$
Activities → Life eval.	$-.091^{***}$	$-.082^{**}$	$-.071^{*}$	$-.074^{***}$
Turbulence → Life eval.	$.095^{***}$	$.113^{***}$	$.138^{***}$	$.079^{***}$
Entropy → Life eval.	$.118^{***}$	$.122^{***}$	$.091^{**}$	$.093^{***}$
Breadth → Life eval. (direct)	−.006	.006	.010	−.002
Minutes → Life eval. (direct)	−.023	−.040	$-.061^{*}$	−.029
Breadth → Life eval. (indirect)	.052	.056	.052	.048
Minutes → Life eval. (indirect)	−.047	−.050	−.047	−.041
Breadth → Life eval. (total)	.045	.062	.062	.045
Minutes → Life eval. (total)	−.070	−.091	−.108	−.070

Chapter 7

Discussion, Limitations and Further Research

7.1 Pattern of Findings

Table 7.1: Five patterns from the subgroup estimates that structure the discussion.

#	Path	Sign	Scope
1	ICT Breadth → Fragmentation	Positive	Significant in every subgroup ($p < .001$)
2	ICT Minutes → Fragmentation	Negative	Significant in every subgroup ($p < .001$); conditional on breadth, more ICT time is associated with less fragmented days
3a	Activities → Life evaluation	Negative	In every subgroup where the path is significant
3b	Turbulence, Entropy → Life evaluation	Positive	In every subgroup where the path is significant
4	ICT predictors → Life evaluation (direct)	Mostly null	Significant only for ICT minutes in Female Young and Male Middle
5	Indirect channels via fragmentation	Opposite signs	Breadth indirect positive, minutes indirect negative; total effects small in every subgroup

7.2 Discussion of Hypotheses

The model was set up to test five hypotheses. Each is now revisited against the estimated paths and against the literature reviewed in Chapter 2.

7.2.1 Hypothesis 1

H1: Higher ICT exposure is associated with higher time fragmentation across all indicators.

H1 is supported for group breadth and rejected for ICT minutes. The two indicators disagree in sign, and the disagreement is structural.

ICT group breadth predicts all three fragmentation indicators positively. Respondents who use ICT across more domains (communication, entertainment, shopping, learning, content) have days that are broken into more episodes, structured into more varied sequences, and distributed more evenly across activity types. The structural-enabler argument of Palm et al. (2022) and Arranz-López and Soria-Lara (2022) holds on this side.

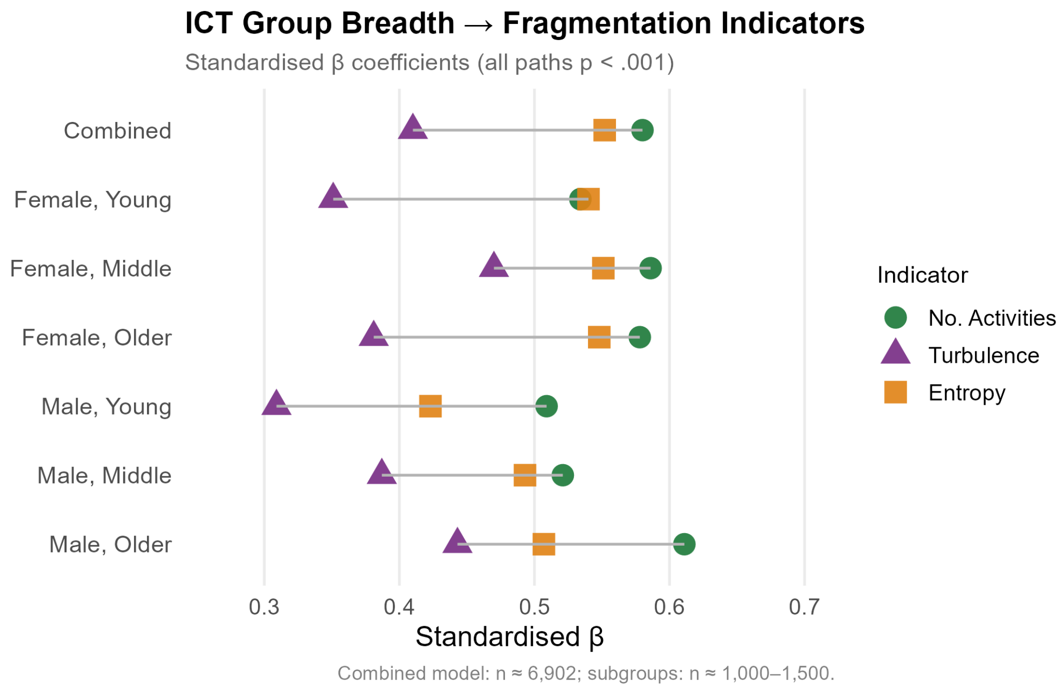


Figure 7.1: Standardised path estimates from ICT group breadth to each fragmentation indicator across all seven models. All paths are significant at $p < .001$.

ICT minutes predicts all three fragmentation indicators negatively. Holding breadth fixed, more total ICT time is associated with a less fragmented day, which is best read as a structural property of the diary rather than a behavioural finding. ATUS asks respondents to report what they were doing in each time slot, so an uninterrupted stretch of television, gaming, or browsing collapses into a single long episode, which mechanically lowers the episode count, flattens entropy, and reduces turbulence. Those long blocks are unlikely to be as continuous as the diary makes them look. Screen time is exactly the context in which simultaneous behaviour, messaging, app switching, and short interruptions is most likely to occur and not be reported.

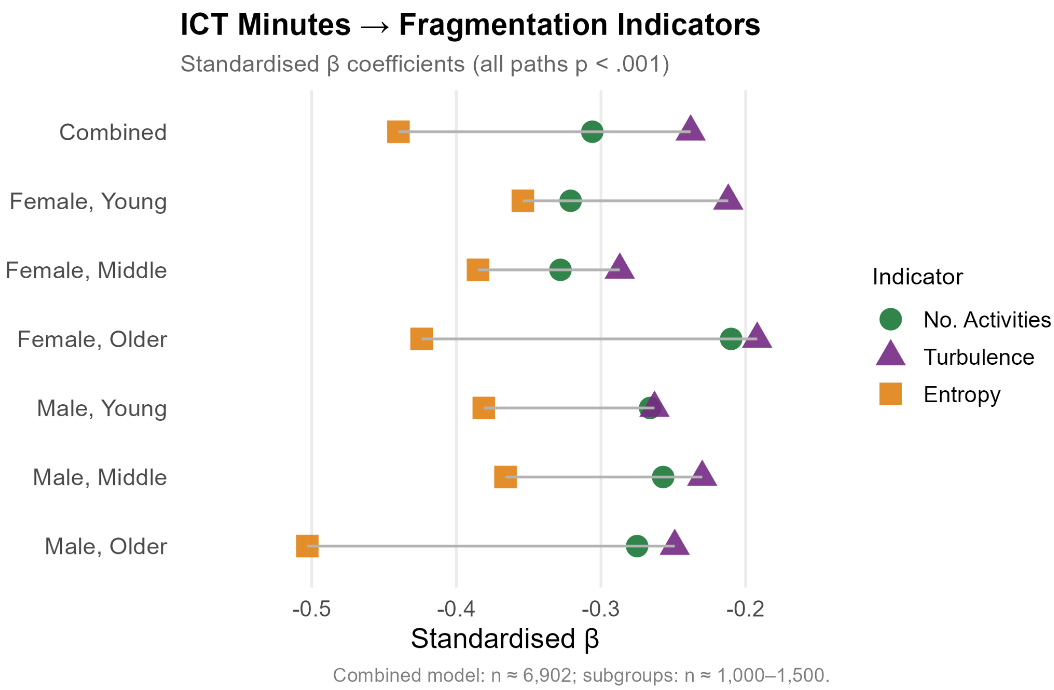


Figure 7.2: Standardised path estimates from ICT minutes to each fragmentation indicator across all seven models. All paths are negative and significant at $p < .001$.

ICT minutes was introduced as a measure of intensity and failed at that task. The variable in theory is an accurate intensity indicator but in this survey it is inflated with long blocks of passive media consumption, and the SEM picks this up as a consolidating association with the day. Group breadth remains a clean proxy for ICT exposure: it captures how widely ICT enters the respondent's day without depending on episode length. The structure of the SEM result shows that breadth fragments and minutes consolidates. This is not just a finding about two competing channels of ICT influence but a reminder that ATUS is a general time use survey covering everything a person does in a day, not an instrument designed for ICT, and within that broader frame ICT minutes from a diary-based survey is not a reliable proxy for ICT intensity.

7.2.2 Hypothesis 2

H2: Higher time fragmentation is associated with lower life evaluation.

H2 is partially supported. The three fragmentation indicators split in direction, and the split is consistent across subgroups.

Number of activities carries a negative coefficient wherever it is significant. Turbulence and entropy carry positive coefficients wherever they are significant. The split is not noise but rather an indicator that fragmentation is indeed multifaceted. The three mediators measure different aspects of fragmentation. Number of activities counts distinct episodes and is a direct measure of role switches. Turbulence captures how much the day moves between activity types. Entropy captures the evenness of time distribution across activity types.

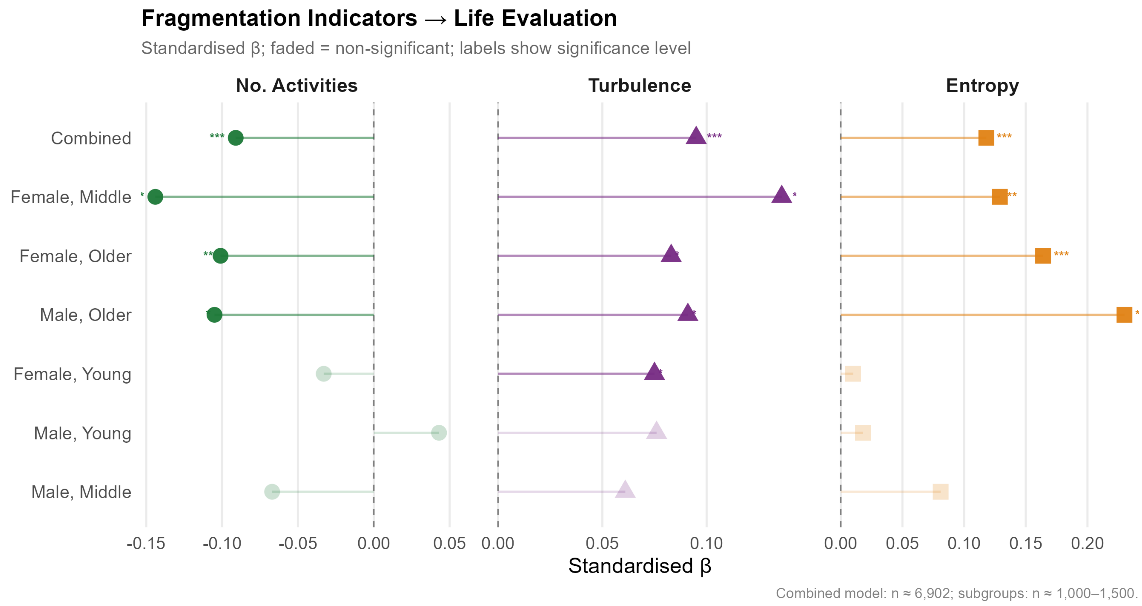


Figure 7.3: Standardised path estimates from each fragmentation indicator to life evaluation across all seven models. Faded markers are non-significant; labels denote significance level.

The negative coefficient on number of activities is consistent with the role-switching cost mechanism of Cornwell (2013) and Mark et al. (2008). More transitions mean more cognitive and emotional overhead, and that overhead registers on global life evaluation.

The temporal regularity thesis of Perlow and Kelly (2014) predicts the opposite of what turbulence and entropy deliver and is not supported. The positive coefficients instead point to a different explanation: a day that moves across activity types and distributes time evenly is a day with variety, and that structural diversity registers positively on life evaluation. This aligns with Lu et al. (2025), who report that fragmentation can reduce anxiety when it reflects flexibility rather than imposed disruption, and with Kuykendall et al. (2015), who find that the diversity of leisure predicts well being more strongly than its total duration. The distinction that matters could be between chosen and imposed fragmentation: where fragmentation is self-directed, part of the population appears to use the structure of the day as a defensive mechanism to preserve well-being.

The original H2 prediction treated fragmentation as a single construct and predicted one negative association. The model rejects that. Fragmentation is multi-dimensional, and its components pull in opposite directions on life evaluation. Grouping them would hide this structure. A latent fragmentation variable in the SEM would absorb these opposing signs into one path, and the split reported here would disappear. Whether a fragmented day feels draining or enriching likely depends on which face of fragmentation dominates and on the person experiencing it.

The pattern is concentrated in the middle and older subgroups. The younger male subgroups show none of the mediator-to-life paths reaching significance. Whether this silence is a sample-size effect or a substantive age difference is taken up under H5.

7.2.3 Hypothesis 3

H3: ICT exposure has a direct association with life evaluation. **H3 holds only on the minutes side, and only in two of the six subgroups.** Group breadth has no significant direct association with life evaluation in any subgroup. ICT minutes has a significant negative direct path for Female Young and Male Middle and is non-significant elsewhere.

Breadth and minutes capture different things. Breadth measures whether ICT is integrated across many domains of life, which reflects digital literacy and integration. Minutes measures how much time is spent on ICT once that integration is in place, which leans closer to the overuse mechanism described by Büchi et al. (2019). The negative residual association appears on minutes, not on breadth, and only in the younger half of the sample. This fits the perceived-overuse framing of digital well-being.

It is worth noting that the precursor single-predictor specification with complexity retained (Appendix E) also returns a significant negative direct path for Male Young ($-.116$, $p < .01$), alongside Female Young and Male Middle. A negative direct effect for young men sits well with theory, since open-ended passive use is most prevalent in this group and is the use most tied to perceived digital overuse (Büchi et al., 2019; Twenge et al., 2018). This should be read with a grain of salt: it comes from a different model with a single ICT predictor and a different mediator set, not from the two-predictor specification on which the main results rest.

7.2.4 Hypothesis 4

H4: Part of the association between ICT exposure and life evaluation is mediated by time fragmentation.

H4 is supported in structure. Both ICT predictors carry an indirect channel through fragmentation, but the two channels run in opposite directions.

The indirect effect is built from two links: the path from the ICT predictor to each mediator, and the path from each mediator to life evaluation. The mediator-to-life signs are fixed across the decomposition. Activities loads negatively on life evaluation in the subgroups where the path is significant, while turbulence and entropy load positively where theirs are significant. What flips the indirect sign is the first link, because breadth and minutes push the mediators in opposite directions.

For breadth, all three predictor-to-mediator paths are positive. Multiplied by the mediator-to-life signs, breadth-through-activities is negative, and breadth-through-turbulence and breadth-through-entropy are positive. The net indirect effect of breadth is positive in every subgroup.

For minutes, all three predictor-to-mediator paths are negative. The same mediator-to-life signs now produce reversed channels: minutes-through-activities is positive (two negatives), and minutes-through-turbulence and minutes-through-entropy are negative. The net indirect effect of minutes is negative in every subgroup.

Table 7.2: Sign arithmetic for the six indirect channels from ICT exposure to life evaluation.

Mediator	ICT → mediator	Mediator → life	Indirect sign
ICT group breadth			
Activities	+	−	−
Turbulence	+	+	+
Entropy	+	+	+
ICT minutes			
Activities	−	−	+
Turbulence	−	+	−
Entropy	−	+	−

A channel is treated as significant when both legs that build it, the ICT-to-mediator path and the mediator-to-life path, are significant, following the joint-significance criterion (MacKinnon et al., 2002). This replaces a bootstrap test on the indirect coefficient, which was not run across the seven models. Because every ICT-to-mediator path is significant at $p < .001$ (Tables 6.1 and 6.2), the significance of each channel is decided by its mediator-to-life leg alone.

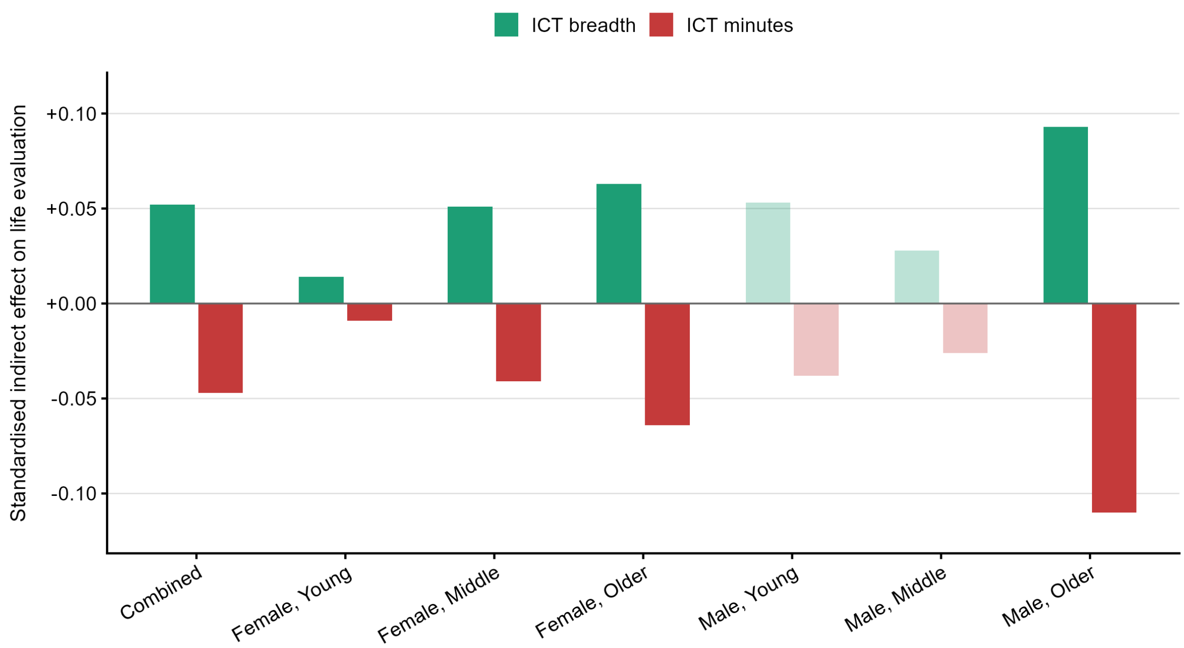


Figure 7.4: Standardised indirect effect of the two ICT predictors on life evaluation across subgroups. The indirect channel for ICT group breadth (green) is positive in every subgroup, while the indirect channel for ICT minutes (red) is negative in every subgroup. Faded bars mark channels that are not significant.

The answer to RQ4, the main reason for choosing SEM over separate regressions, is that fragmentation carries a meaningful share of the ICT-to-life-evaluation channel. The sign of that share depends on which face of ICT exposure is being decomposed and which fragmentation indicator carries it. The clean signed prediction of H4 is too coarse for this. The direction of the indirect share is not fixed: it depends on whether breadth or minutes is the predictor, and on which mediator does the carrying.

7.2.5 Hypothesis 5

H5: The magnitude of the paths in H1, H2, H3, and H4 differs across subgroups defined by gender and age.

H5 is supported. Three patterns stand out.

Age strengthens the structural channel. The breadth-to-fragmentation coefficients grow with age within each gender. A single ICT domain added to the day of an older respondent reshapes the structure of that day more than the same domain added to a younger respondent's day. This is consistent with older respondents having less rigid daily structures from work and care, so any added domain has more room to move things around. Direct paths are concentrated in the younger and middle subgroups. The two significant negative direct paths from ICT minutes to life evaluation appear in Female Young and Male Middle. Older subgroups show no significant direct path on either ICT predictor.

To see why this is happening, it is worth exploring what each age band actually does online. Figure 7.5 compares activity-level participation, with streaming video excluded because near-universal uptake in both groups compresses every other activity. The split is clear. Older respondents lead on aimed activities: communication, online shopping, digital finance, and digital reading. Each has a defined goal and ends when the goal is met. Younger respondents lead on passive activities: leisure browsing, online gaming, and online classes, which run open-ended and fill time rather than complete a task (Büchi et al., 2019).

This difference in purpose is consistent with both findings above. Older respondents use ICT to pursue connection, manage tasks, and stay mentally engaged. The communication that dominates their use maintains social ties and limits the social isolation that follows retirement, which is the cleanest documented route from ICT to well-being in later life (Chopik, 2016; Cotten et al., 2013). This may be why their direct paths are flat: for older respondents, the time is spent on purpose. For younger respondents the same minutes go to passive, open-ended use, which can displace other activities and carries the residual negative direct path on life evaluation, in line with perceived digital overuse (Büchi et al., 2019). The pattern therefore differs in kind, not just in size.

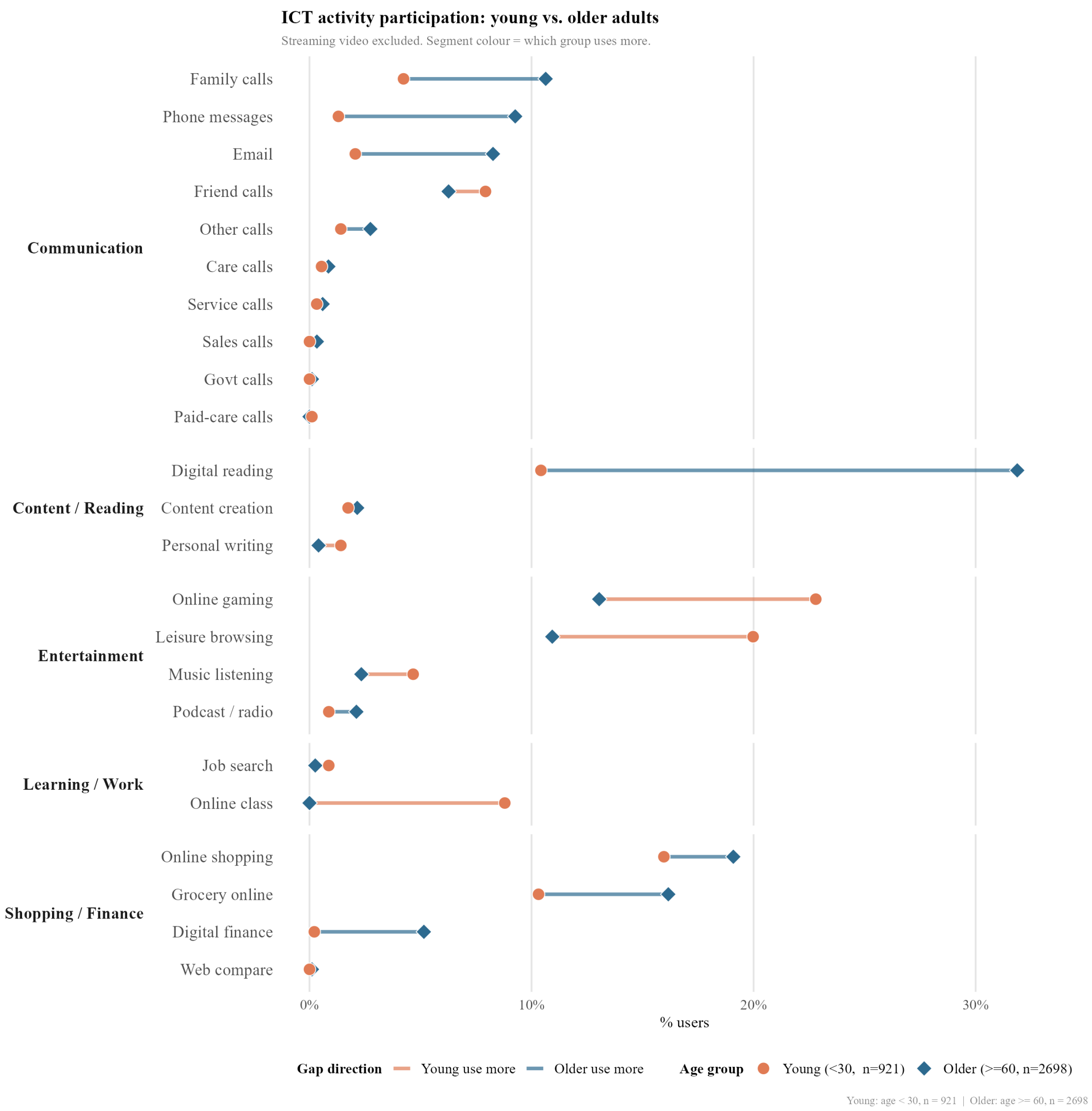


Figure 7.5: ICT activity participation for young (age < 30) and older (age ≥ 60) respondents. Streaming video is excluded for readability. Segment colour indicates which group has the higher participation rate; activities are grouped by ICT domain. Individual bar charts by age group are in Appendix A.2.

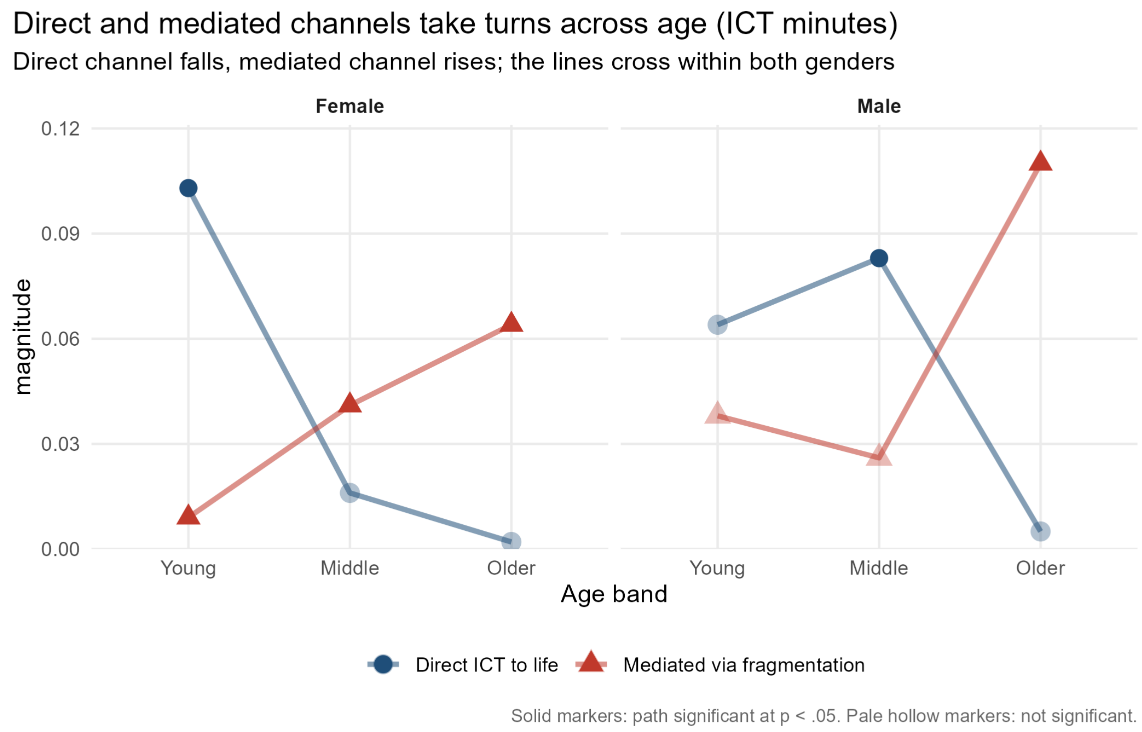
The mediator-to-life-evaluation link is concentrated in the middle and older subgroups. Table 7.3 summarises which subgroups carry significant fragmentation-to-life-evaluation paths.

Table 7.3: Significance of the three fragmentation-to-life-evaluation paths across subgroups. A filled circle (●) marks a significant path at $p < .05$.

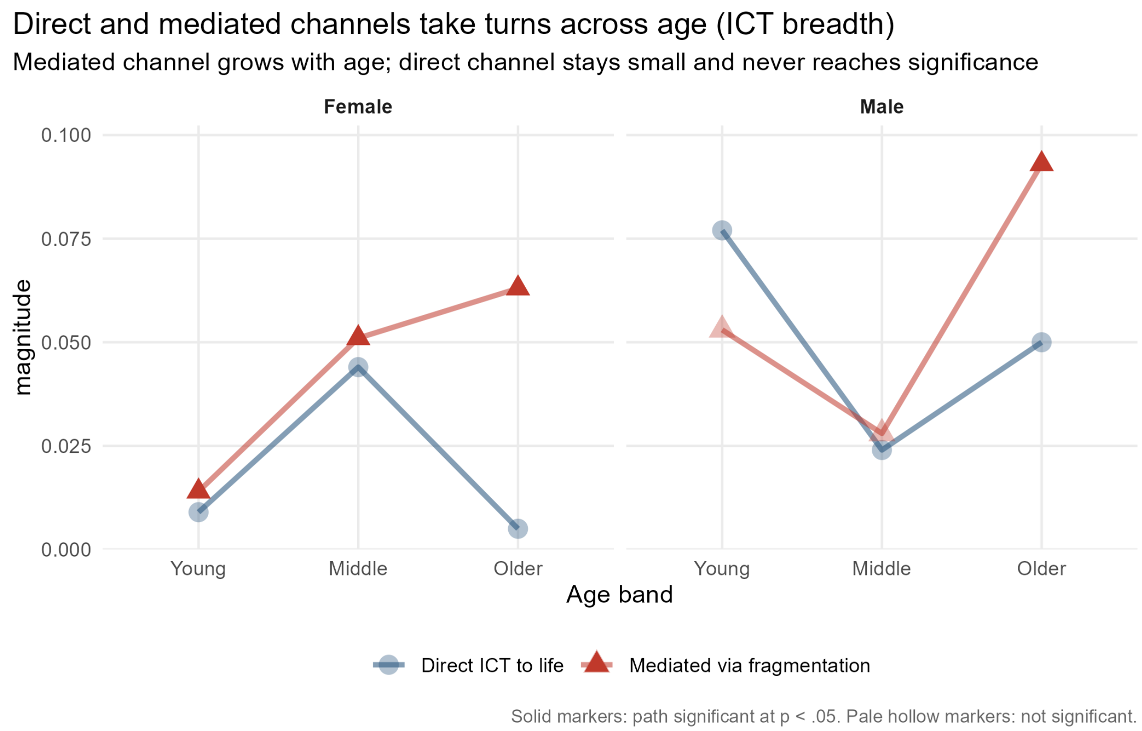
Subgroup	**Activities**	**Turbulence**	**Entropy**
Combined	●	●	●
Female, Young		●	
Female, Middle	●	●	●
Female, Older	●	●	●
Male, Young			
Male, Middle			
Male, Older	●	●	●

The pattern mirrors H3 in reverse. Where H3 found the direct ICT channel concentrated in the younger half of the sample, the mediated channel concentrates in the older half. The mediated channel runs strongest in the subgroups where the direct ICT-to-life channel is silent, and falls silent in the subgroups where the direct channel operates. Female Young is the only cell that carries both a direct path and a mediator path. The two routes to life evaluation tend to take turns across the sample rather than reinforce one another.

Figure 7.6 makes this turn-taking visible. For ICT minutes the two lines cross within both genders: the direct channel is strongest in the young, the mediated channel in the older. For ICT breadth the direct channel never reaches significance in any subgroup, while the mediated channel rises monotonically with age in the female panel and resurfaces in Male, Older.



(a) ICT minutes. The direct and mediated lines cross within both genders.



(b) ICT breadth. The mediated channel grows with age; the direct channel never reaches significance.

Figure 7.6: Direct and mediated channels of ICT on life evaluation across age. Solid markers indicate paths significant at $p < .05$; pale hollow markers indicate non-significant paths.

Gender differences are smaller. Gender differences are smaller than age differences in this model and do not produce a clean directional split. Female subgroups show stronger and more consistent mediator paths than male subgroups at comparable ages. Figure 7.7 plots the cell-wise

Female minus Male gap across the seven standardised paths feeding life evaluation. Every cell falls between −0.077 (Activities to life, Middle) and +0.075 (Turbulence to life, Middle); the rest of the surface sits close to the zero plane. The remaining variation is therefore concentrated in age and in specific mediator-to-life links rather than in gender.

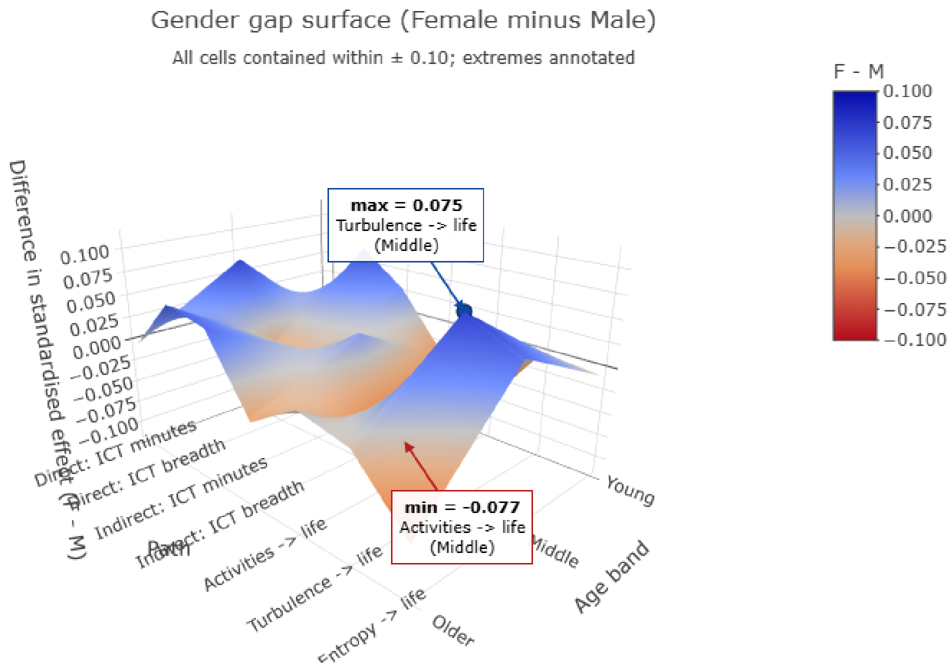


Figure 7.7: Gender gap surface. All cells fall between −0.077 and +0.075; the two extremes are annotated.

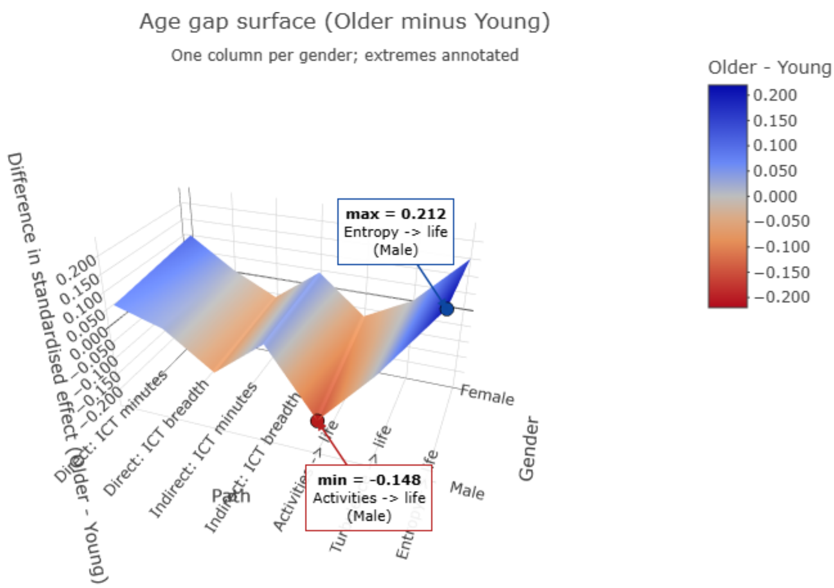


Figure 7.8: Age gap surface (Older minus Young), one column per gender. Cells fall between −0.148 and +0.212, both extremes occurring in the male panel; the two extremes are annotated.

7.3 Sensitivity Analyses

Three robustness tests were reported in Section 6.3. Each addresses a different threat to the main results.

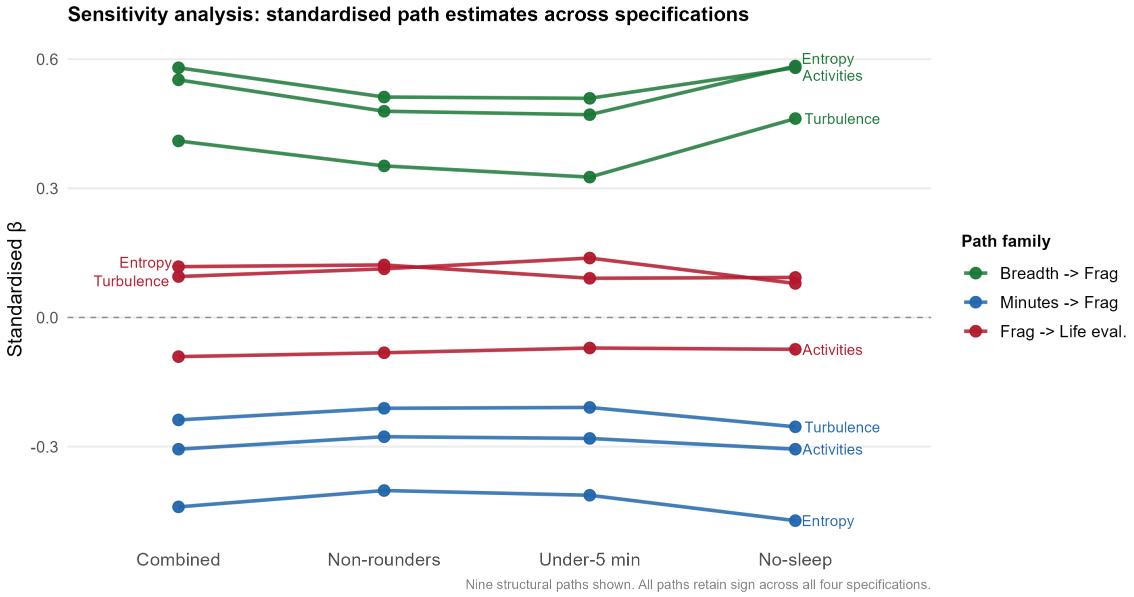


Figure 7.9: Standardised path estimates across the four model specifications. Near-horizontal lines indicate robustness of direction and magnitude across tests.

Non-rounder test. The non-rounder test asks whether the main findings are a product of respondents reporting durations only in five-minute blocks. The results survive. Breadth still fragments, minutes still consolidates, and the mediator paths split by indicator in the same way. Magnitudes shift slightly outward in both directions, but the direction of every path is preserved.

Under-5 test. The under-5 test applies the same logic more strictly. A respondent passes the filter only if the diary actually reached a sub-five-minute resolution somewhere in the day. The structural pattern holds again. One change is worth noting. The direct path from ICT minutes to life evaluation reaches significance in this subsample, where it did not in the main combined model. A plausible reading is that the full sample is inflated by long passive blocks that absorb shorter simultaneous ICT use, while the under-5 subsample isolates respondents whose diaries capture the brief micro-episodes of ICT use. Among that subsample, the displacement effect of time on device is easier to see. The main results are preserved and the under-5 test sharpens them rather than reversing them.

No-sleep test. The no-sleep test recomputes turbulence and entropy after sleep episodes are removed from the diary. Sleep takes roughly a third of the day for nearly every respondent. Removing it shifts both halves of the mediation chain in opposite directions. Predictor-to-mediator paths strengthen: with the sleep block gone, the indicators track ICT use more directly because the diary contains less unrelated structure. Mediator-to-life paths weaken: the main-model versions of these indicators are partly loaded with information about sleep duration and timing, both of which have their own link to life evaluation.

Path	Combined	No-sleep
Breadth → Turbulence	.410	.462
Breadth → Entropy	.552	.584
Turbulence → Life	.095	.079
Entropy → Life	.118	.093
Breadth → Life (total)	.045	.045
Minutes → Life (total)	−.070	−.070

Table 7.4: Selected standardised path coefficients, combined model versus no-sleep specification.

None of the three tests changes the pattern reported in Section 7.1. The broader limitation that is addressed about whether diary day can accurately track ICT and time fragmentation is not fully addressed by these tests and is taken up in the Further Research section.

7.4 Limitations

7.4.1 Single country, single year

The data cover one country in one year. ATUS 2021 is the most recent year for which the Well-Being Module exists, but it is also a year of ongoing pandemic effects, with remote work patterns and household time allocations still unsettled. Screen and ICT exposure rose markedly during the pandemic across all age groups (Trott et al., 2022), so the levels recorded in 2021 likely reflect an elevated, transitional state rather than a stable baseline. The patterns observed here may therefore carry that imprint. Using this dataset was a deliberate trade-off: it was the most recent ATUS release that combined the required variables, episode-level granularity, and public accessibility needed to address the research question. Generalisation to other countries or to later years should be made with care.

7.4.2 Just-identified model

With $df = 0$, the model is just-identified. All observed covariances are reproduced exactly and global fit indices carry no information. The estimates are only meaningful if the specified structure is correct based on the theory examined. Because the model has no spare degrees of freedom, it cannot be tested against the data or compared with rival structures. The direction of the paths is imposed by theory, not recovered from the data. A model with positive degrees of freedom would allow alternative structures to be fitted and compared, and some of those alternatives are plausible here. ICT use is assumed to drive fragmentation, but the reverse is defensible, meaning fragmentation causing ICT use.

7.4.3 Two ICT predictors with opposite signs

The model retains both ICT group breadth and ICT minutes. In the raw data the two are positively correlated: respondents who touch more ICT domains also spend more total minutes on ICT. In the model, the coefficients have opposite signs because each one is estimated holding the other fixed. Breadth then captures scope at a given level of minutes, and minutes captures duration at a given level of scope. Read together they are interpretable. Read in isolation either one is misleading.

7.4.4 Omitted covariates and mechanism variables

Several covariates that the literature identifies as relevant are not in the model. Education affects both ICT exposure and life evaluation. Employment status, household composition, and parental status are also absent. Perceived digital overuse, bedtime use, and multitasking intensity, the mechanism variables flagged in Chapter 2, are not available in ATUS 2021 or are difficult to define from diary entries alone.

7.4.5 Diary granularity and respondent rounding

A second granularity limitation, separate from the single-primary-activity issue, is the five-minute rounding pattern documented in Section 5.6. The effective temporal resolution of the dataset is closer to five minutes than to one, and any switching behaviour finer than that is invisible to the fragmentation indicators. The sensitivity tests in Section 6.3 rule out the narrow concern that rounding alone might be generating the pattern. However, the data are shaped in an artificial way and there is no answer to the cause of the rounding.

7.4.6 Umbrella episodes

ATUS records activities at minute-level resolution, but respondents report one primary activity per time slot. Long passive blocks act as umbrellas. A two-hour television session is one episode of watching TV, even if the phone was checked four times during it. A ninety-minute gaming session is one episode, even if messages were exchanged throughout. Short ICT use inside those blocks disappears into the dominant label. The diary captures the umbrella and loses the activity underneath it.

7.5 Further Research

7.5.1 Implications

Policy

Several governments have legislated on digital exposure ahead of clear empirical evidence on what the relevant variable actually is. Australia passed a social media ban for users under sixteen in 2024 (Parliament of Australia, 2024b). France has restricted phones in schools since 2018 (République française, 2018). Several US states have introduced age verification for social platforms. The shared assumption behind these measures is that the variable to regulate is time or access.

The findings here do not debunk the legislation. They challenge the assumptions behind them. Current policy treats ICT exposure as a monochromatic quantity: more is worse, the relationship is linear. The model rejects that picture. The picture that this model points to is that ICT use is multifaceted and not monochromatic.

Research that measures the effect of screen time on adolescent well-being finds that the effect is small and the size of the effect shifts depending on how the researcher sets up the analysis (Odgers & Jensen, 2020; Orben & Przybylski, 2019). Legislation built on assumptions and not on empirical evidence can backfire and produce the opposite of its intended effect.

The results here amplify that legislative warning. The structural channel that connects ICT use to life evaluation through fragmentation is weakest in the young subgroups: the mediator-to-life-evaluation paths that are significant cluster in the middle and older bands, while Male Young and Male Middle show none reaching $p < .05$. The direct effects, which sit outside that structure, are negative but very small and mostly non-significant. The only significant negative direct path from ICT minutes appears for Female Young ($-.103$) and Male Middle ($-.083$); breadth has no significant direct effect on life evaluation in any subgroup. In short, the young half of the sample shows a very unstable effect.

Limiting people's access to ICT for a population group horizontally is a direct and clear intervention on a tool that is now central to expression, participation in society, and digital literacy. The data, viewed through the angle of this thesis, point away from across-the-board restriction and toward intervention that is more precise, more detailed, and better informed: targeted at which face of ICT use is involved, and for whom. This circles back to the research aim: a deeper and more complete understanding of the technology at our fingertips, so that public opinion and the democratic and legislative response rest on accurate evidence and do not unintentionally harm the society they mean to protect.

Employers

The shift after the pandemic has pushed work into the same devices and time slots as private life. Right-to-disconnect laws in France (2017) and Australia (2024) respond to this, but they regulate hours, not structure (Parliament of Australia, 2024a; République française, 2016). The model here suggests that an evening of fragmented work, where short tasks switch in and out of family and leisure, is a different load than a longer but unbroken work block. The lever for employers is therefore the shape of work time, not only its total amount.

Design

Digital well-being tools on iOS and Android currently report screen time as a single number of minutes per app (Lukoff et al., 2018). This is the calorie count of digital exposure. It is useful but incomplete. A nutrition label that reports only calories tells you nothing about whether the food was protein, fat, or sugar, and the health implications for those three are different. A similar logic applies here. A user who is informed about their multi-facet ICT use, may make better decisions and have a better life evaluation.

This thesis split ICT exposure into two faces, group breadth and minutes, and showed that even these two carry indirect effects of opposite sign. Two faces are enough to break the single-number view, but they are far from the full picture. Other faces exist and are measurable. Content separates a news feed from a video call from a banking app. Intention separates use that serves a goal the user set from use that is passive or habitual. Timing separates daytime use from late-night use that competes with sleep. Activeness separates producing and communicating from scrolling and watching. Each face adds a dimension the calorie count hides, and each can move well-being in a different direction. The data needed for this is already collected by the operating systems of the devices used.

7.5.2 A better way to do this research

The Obstacle

Stepping back from the specific modelling choices, the hardest limitation of this study is not in the model but where the question is asked. A broad diary-based survey is being asked to answer a specific question about how moment-to-moment digital exposure reshapes the structure of a day. The two operate at different resolutions. Time use diaries record what a person remembers doing in coarse blocks, while ICT use is a near-continuous stream of small interactions that the person is often not aware of.

ICT use has become such an automatic part of daily life that it starts to resemble breathing. People forget how many times they picked up a phone, glanced at a notification, or switched tabs, because the device has become a normal extension of living rather than a discrete activity worth reporting. A diary entry that says "communication for twenty minutes" compresses something that may have been thirty interleaved micro episodes spread across the day. The measurement instrument and the behaviour are no longer at the same scale.

This mismatch is a plausible explanation for the contradictory signs of breadth and minutes. Breadth survives the coarse-grained diary because crossing into a new domain (a call, an online purchase, a streaming session) is the kind of event respondents do remember.

A Metaphor

René Magritte's *The Treachery of Images* is a useful metaphor here. The painting of a pipe with the caption "this is not a pipe" makes the point that the representation of an object is not the object. The confusion felt by a viewer of the painting reveals how easily the boundary between a real object and its representation collapses in the mind. The same illusion applies here: the diary is the representation, the lived day is the reality, and the paradox that Magritte stages on canvas reemerges once it becomes clear that the metrics of this thesis are not the lived experience they stand in for. That gap between representation and behaviour is precisely where the signal gets blurred in the mind of the survey participant. The diary is a pipe painted on canvas, not the pipe itself, and the viewer cannot tell the difference.

An Idea

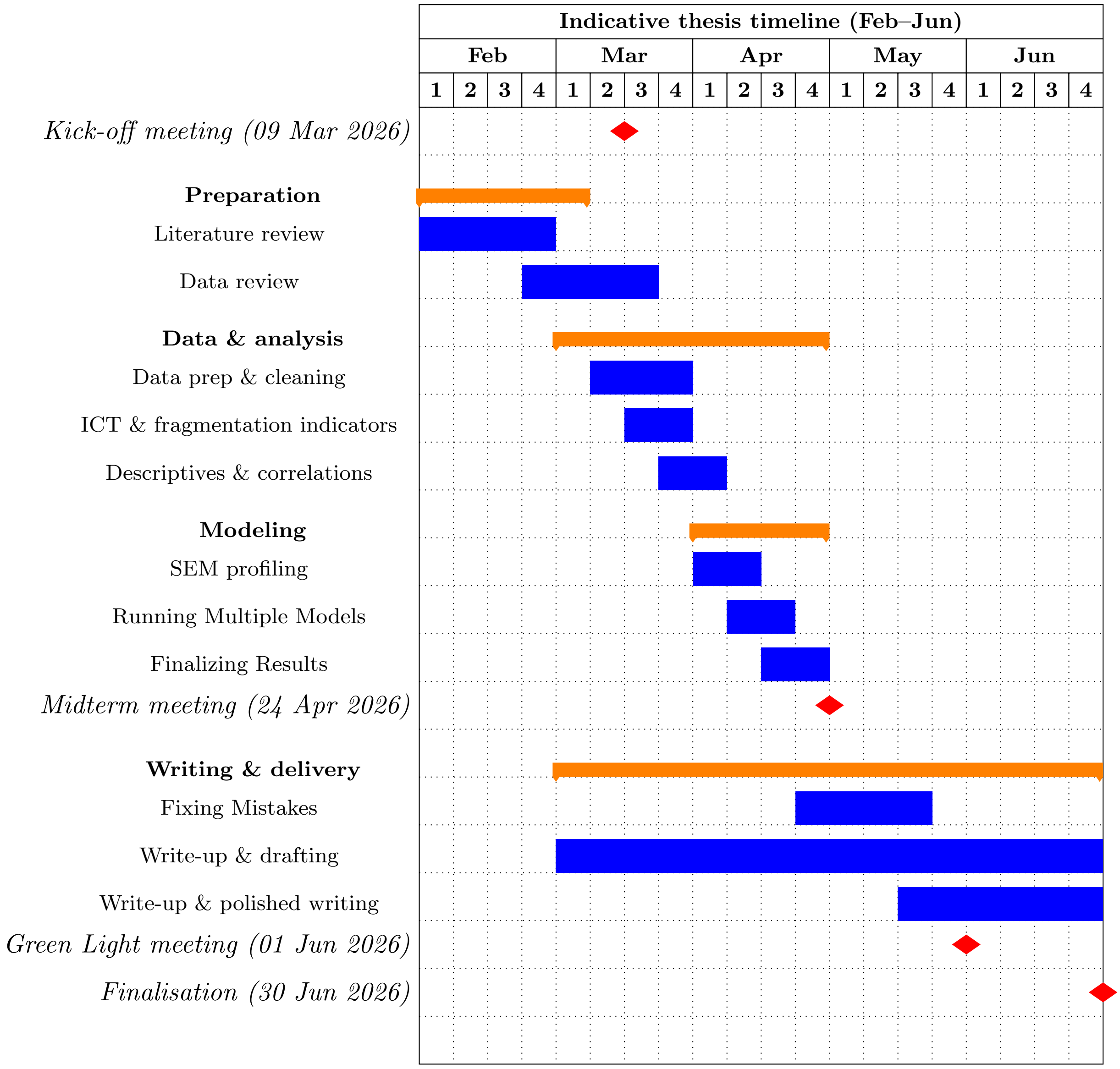
A better way to answer the question this thesis set out to answer would be to close that gap by letting the devices report on themselves, within a controlled and ethically supervised study. Most ICT today runs on connected hardware (phones, laptops, wearables, smart TVs) that already logs usage continuously. A study designed for legislators or public health researchers would combine a time use diary for the context of the day (what the person was doing, where, with whom) with device level telemetry for the ICT exposure (what was used, for how long, how often, at what time). The diary provides meaning. The device provides measurement. Each compensates for what the other cannot see.

This kind of design would remove the recall burden on the respondent, capture the fine-grained switching behaviour that is theoretically central to fragmentation, and allow timing effects (bedtime use, work hours use) to be tested directly rather than inferred. It would also separate wanted from unwanted use, interruptions received from interruptions initiated, and passive from active engagement. These are distinctions the ICT well-being literature has been asking for but diary data cannot deliver.

The design is not hypothetical. The TimeUse+ study at ETH Zurich has already run a version of it at scale (Winkler et al., 2026). Participants used a smartphone application over a four week period that passively tracked their movement via GPS, and they then annotated each recorded episode with activity, social context, and expenditure information (Winkler & Axhausen, 2024). This is the similar research design proposed here: the device supplies the objective record, and the respondent supplies the meaning. TimeUse+ demonstrates that the method is ethically feasible and that respondents are willing to engage with it.

Chapter 8

Timeline



Chapter 9

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Acronyms

Acronym	Definition
AMOS	Analysis of Moment Structures (SEM software)
APA	American Psychological Association (citation style)
ATUS	American Time Use Survey
CATI	Computer-Assisted Telephone Interviewing
COVID-19	Coronavirus Disease 2019
CPS	Current Population Survey
DRAMMA	Detachment, Recovery, Autonomy, Mastery, Meaning, Affiliation
DRM	Day Reconstruction Method
GPS	Global Positioning System
ICT	Information and Communication Technologies
ML	Maximum Likelihood
MTUS	Multinational Time Use Study
NICHD	National Institute of Child Health and Human Development
NSF	National Science Foundation
PDO	Perceived Digital Overuse
RQ	Research Question
SEM	Structural Equation Modeling
SWB	Subjective Well-Being
TUCASEID	ATUS respondent identifier (case ID used to link files)
WBM	Well-Being Module (ATUS)

Appendix A

Supportive tables

A.1 Summary of Key Descriptives

Table A.1 collects central tendency, spread, skewness, kurtosis, and zero-share statistics for every variable entering the SEM.

Descriptive Statistics — Key Variables											
Variable	**N**	**Missing**	**Pct_miss**	**Mean**	**SD**	**Min**	**Median**	**Max**	**Skewness**	**Kurtosis**	**Pct_zero**
ict_minutes_ord	6902	0	0	3.759	1.336	1	4	6	-0.275	2.507	0.0
ict_group_breadth	6902	0	0	1.626	0.919	0	1	4	0.490	2.860	7.1
ict_total_minutes	6902	0	0	281.664	215.866	0	240	1385	0.854	3.357	7.1
ict_breadthall	6902	0	0	1.972	1.278	0	2	6	0.874	3.627	7.1
communication	6902	0	0	12.351	37.381	0	0	541	5.287	44.266	78.4
entertainment	6902	0	0	219.218	200.293	0	175	1385	1.219	4.437	14.6
shopping_finance	6902	0	0	20.735	46.491	0	0	720	4.052	31.486	69.0
learning_work	6902	0	0	4.675	37.917	0	0	630	9.383	98.208	98.0
content_reading	6902	0	0	24.683	68.344	0	0	1200	5.146	46.304	77.4
number_of_activities	6902	0	0	18.379	7.507	5	17	67	1.021	4.831	0.0
life_evaluation	6902	0	0	7.314	1.937	0	8	10	-0.680	3.446	0.3

Figure A.1: Descriptive statistics for all variables used in the SEM.

A.2 ICT Activity Participation by Age Group

Figures A.2 and A.3 show the individual activity-level participation rates for the older (≥ 60) and young (< 30) subsamples respectively. Streaming video is excluded from both charts because near-universal uptake ($> 85\%$ in the older group and $> 70\%$ in the young group) compresses every other activity to the left of the axis and makes within-chart comparisons unreadable. The combined lollipop comparison is shown in the main text as Figure 7.5.

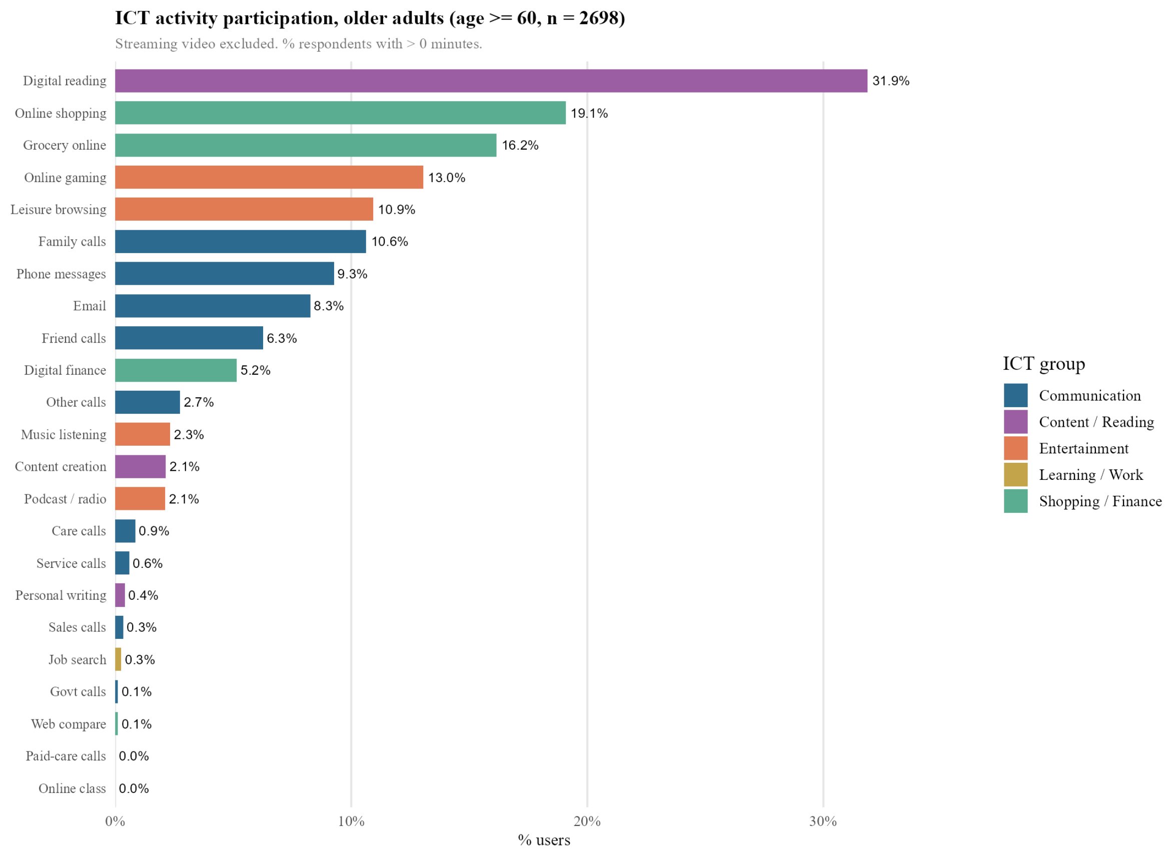


Figure A.2: ICT activity participation rates for older adults (age ≥ 60, $n = 2{,}698$). Bars show the percentage of respondents with more than zero minutes in each activity on the diary day. Streaming video excluded. Activities are sorted by participation rate. Colour indicates ICT group.

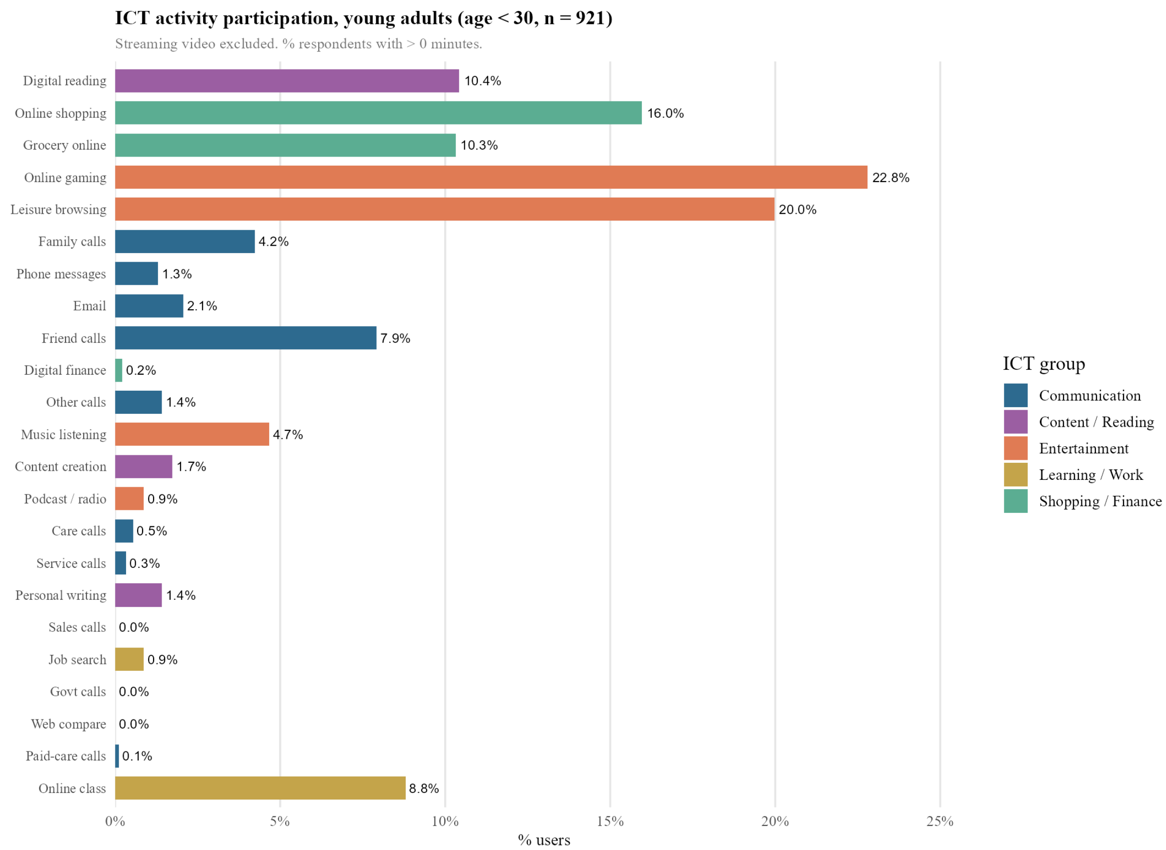


Figure A.3: ICT activity participation rates for young adults (age < 30, $n = 921$). Bars show the percentage of respondents with more than zero minutes in each activity on the diary day. Streaming video excluded. Activities are sorted on the same order as Figure A.2 for comparability. Colour indicates ICT group.

The contrast between the two charts makes the aimed vs. passive split visible at the individual activity level. Digital reading dominates among older adults (31.9%) and is modest among young adults (10.4%). Online gaming and leisure browsing rank first and second among young adults (22.8% and 20.0% respectively) but sit in the middle of the older adults distribution. Communication activities (family calls, phone messages, email) are substantially higher in the older group. Learning and work activities (online class, job search) are present only in the young group at meaningful rates.

A.3 SEM with Individual ICT Codes

Figure A.4 shows the SEM specification estimated on the male, middle age group using individual ICT codes, illustrating the instability of the model under this approach. For comparison, Figure A.5 shows the equivalent specification for the same subgroup using grouped ICT codes.

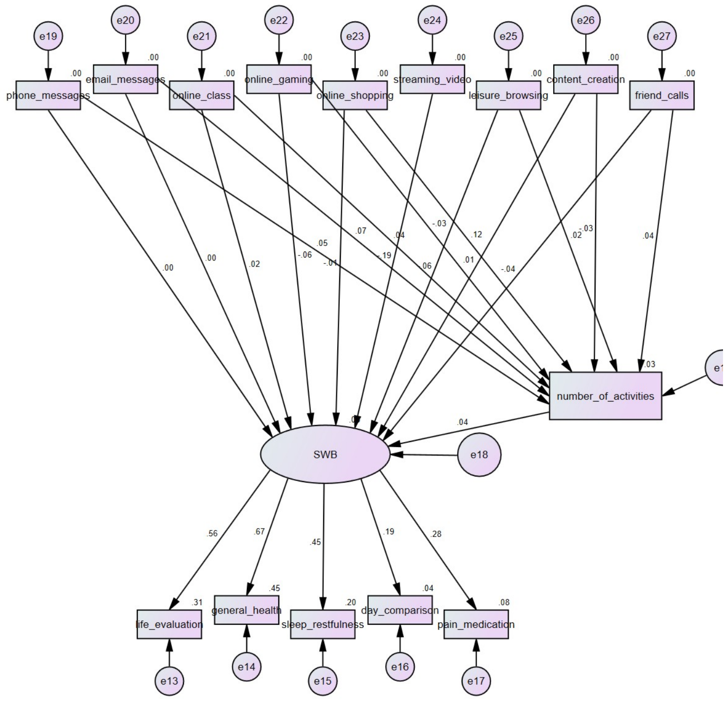


Figure A.4: Individual ICT codes model – male, middle age group.

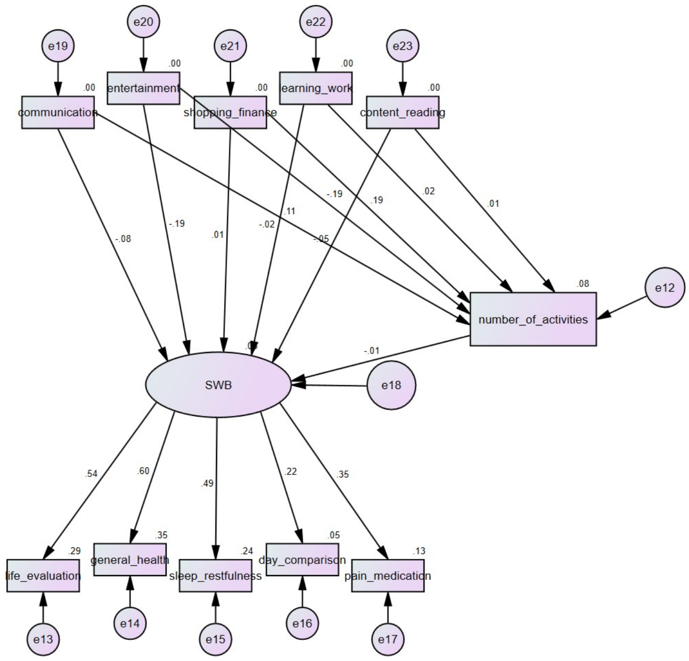


Figure A.5: Grouped ICT codes model – male, middle age group.

A.4 Survey availability table

Table A.1: Survey-Level Availability of ICT and Well-being (feeling rushed)

Survey (Country – Year)	**Well-being**	**ICT**
Argentina 2021	✓	
Armenia 2008		✓
Austria 1992		✓
Bulgaria 2001	✓	✓
Canada 1992	✓	
Canada 2005	✓	
Canada 2010	✓	✓
Finland 2009		✓
France 1985	✓	✓
France 1998	✓	
France 2009		✓
Hungary 1999		✓
Hungary 2009		✓
Italy 2002	✓	
Italy 2008	✓	✓
Netherlands 1985		✓
Netherlands 1990		✓
Netherlands 1995		✓
Netherlands 2000	✓	✓
South Africa 2000		✓
South Africa 2010		✓
South Korea 1999	✓	
South Korea 2004	✓	
South Korea 2009	✓	✓
Spain 2002	✓	✓
United Kingdom 1983		✓
United Kingdom 1987	✓	✓
United Kingdom 2000	✓	✓
United Kingdom 2005		✓
United States 1975	✓	
United States 1985	✓	✓
United States 1993		✓
United States 1995	✓	✓
United States 1998	✓	✓
United States 2003–2009, 2011, 2014-2020, 2022–2024		✓
United States 2010, 2012, 2013, 2021	✓	✓

A.5 TUTIERCODE Activity Classification

Table A.2 lists the Tier 1 activity codes used to label each one-minute slot in the state sequence. Every minute of the 24-hour diary is assigned exactly one of these codes. Table A.3 lists the corresponding Tier 2 sub-categories used as the input granularity for the SEM fragmentation indicators.

Table A.2: TUTIER1CODE activity categories.

Code	Activity
00	Void / not recorded
01	Personal care (incl. sleep)
02	Household activities
03	Caring for/helping HH members
04	Caring for/helping non-HH members
05	Work & work-related activities
06	Education
07	Consumer purchases
08	Professional & personal care services
09	Household services
10	Government services & civic obligations
11	Eating and drinking
12	Socialising, relaxing & leisure
13	Sports, exercise & recreation
14	Religious & spiritual activities
15	Volunteer activities
16	Telephone calls
18	Travelling
50	Unable to code

Table A.3: TUTIER2CODE activity sub-categories. Tier 1 group headers are shown in bold; Tier 2 codes are listed beneath each header. n.e.c. = not elsewhere classified.

Code	Activity	Code	Activity
01 Personal Care		**10 Government Services & Civic Obligations**	
0101	Sleeping	1001	Using government services
0102	Grooming	1002	Civic obligations & participation
0103	Health-related self care	1003	Waiting assoc. w/ govt services/civic oblig.
0104	Personal activities	1004	Security procedures rel. to govt services
0105	Personal care emergencies	1099	Government services, n.e.c.
0199	Personal care, n.e.c.	**11 Eating and Drinking**	
02 Household Activities		1101	Eating and drinking
0201	Housework	1102	Waiting assoc. w/ eating & drinking
0202	Food & drink prep, presentation, clean-up	1199	Eating and drinking, n.e.c.
0203	Interior maintenance, repair, decoration	**12 Socializing, Relaxing, Leisure**	
0204	Exterior maintenance, repair, decoration	1201	Socializing and communicating
0205	Lawn, garden, and houseplants	1202	Attending or hosting social events
0206	Animals and pets	1203	Relaxing and leisure
0207	Vehicles	1204	Arts and entertainment (non-sport)
0208	Appliances, tools, toys	1205	Waiting assoc. w/ socializing/leisure
0209	Household management	1299	Socializing, relaxing, leisure, n.e.c.

Continued on next page

Table A.3 continued from previous page

Code	Activity	Code	Activity
0299	Household activities, n.e.c.	**13 Sports, Exercise, Recreation**	
03 Caring For & Helping HH Members		1301	Participating in sports/exercise/rec.
0301	Caring for & helping HH children	1302	Attending sporting/rec. events
0302	Activities rel. to HH children's education	1303	Waiting assoc. w/ sports/exercise/rec.
0303	Activities rel. to HH children's health	1304	Security procedures rel. to sports/rec.
0304	Caring for HH adults	1399	Sports, exercise & rec., n.e.c.
0305	Helping HH adults	**14 Religious & Spiritual Activities**	
0399	Caring for/helping HH members, n.e.c.	1401	Religious/spiritual practices
04 Caring For & Helping NonHH Members		1499	Religious/spiritual activities, n.e.c.
0401	Caring for & helping NonHH children	**15 Volunteer Activities**	
0402	Activities rel. to NonHH children's educ.	1501	Administrative & support activities
0403	Activities rel. to NonHH children's health	1502	Social service & care (non-medical)
0404	Caring for NonHH adults	1503	Indoor/outdoor maintenance, build., clean-up
0405	Helping NonHH adults	1504	Performance & cultural activities
0499	Caring/helping NonHH members, n.e.c.	1505	Attending meetings, conferences, training
05 Work & Work-Related Activities		1506	Public health & safety activities
0501	Working	1507	Waiting assoc. w/ volunteer activities
0502	Work-related activities	1508	Security procedures rel. to volunteering
0503	Other income-generating activities	1599	Volunteer activities, n.e.c.
0504	Job search and interviewing	**16 Telephone Calls**	
0599	Work and work-related activities, n.e.c.	1601	Telephone calls (to or from)
06 Education		1602	Waiting assoc. w/ telephone calls
0601	Taking class	1699	Telephone calls, n.e.c.
0602	Extracurricular school activities (non-sport)	**18 Traveling**	
0603	Research/homework	1801	Travel rel. to personal care
0604	Registration/administrative activities	1802	Travel rel. to household activities
0699	Education, n.e.c.	1803	Travel rel. to caring/helping HH members
07 Consumer Purchases		1804	Travel rel. to caring/helping NonHH members
0701	Shopping (store, telephone, internet)	1805	Travel rel. to work
0702	Researching purchases	1806	Travel rel. to education
0703	Security procedures rel. to consumer purchases	1807	Travel rel. to consumer purchases
0799	Consumer purchases, n.e.c.	1808	Travel rel. to prof./personal care services
08 Professional & Personal Care Services		1809	Travel rel. to household services
0801	Childcare services	1810	Travel rel. to govt services/civic oblig.
0802	Financial services and banking	1811	Travel rel. to eating and drinking
0803	Legal services	1812	Travel rel. to socializing/leisure
0804	Medical and care services	1813	Travel rel. to sports, exercise, rec.
0805	Personal care services	1814	Travel rel. to religious/spiritual activities
0806	Real estate	1815	Travel rel. to volunteer activities
0807	Veterinary services (excl. grooming)	1816	Travel rel. to telephone calls
0808	Security procedures rel. to prof./personal services	1818	Security procedures rel. to traveling
0899	Professional and personal services, n.e.c.	1899	Traveling, n.e.c.
09 Household Services		**50 Data Codes**	
0901	Household services (not done by self)	5001	Unable to code
0902	Home maintenance/repair (not done by self)	5099	Data codes, n.e.c.

Continued on next page

Table A.3 continued from previous page

Code	Activity	Code	Activity
0903	Pet services (not done by self, not vet)		
0904	Lawn & garden services (not done by self)		
0905	Vehicle maintenance & repair services (not self)		
0999	Household services, n.e.c.		

Appendix B

ATUS Interview Methodology and Quality Controls

This appendix expands on the brief discussion of telephone recall in Section 4.2. It documents how the ATUS interview is run, how missing recall is handled, and which cases are removed before the file is published. All content is drawn from the ATUS User's Guide (U.S. Bureau of Labor Statistics, 2025).

B.1 CATI safeguards

All interviews use Computer-Assisted Telephone Interviewing (CATI). The system carries earlier responses forward into later questions, checks that all items have been answered, flags inconsistencies during the call, and applies skip patterns so respondents only see relevant questions. Pop-up prompts tell the interviewer when to probe for more detail. After the interview the data are already stored, so no manual data entry is required. All activities are given a six-digit code automatically and cannot be edited by coders.

B.2 Handling memory lapses

The diary is collected through conversational interviewing rather than scripted questions. This lets the interviewer guide the respondent through gaps in recall, probe for detail without leading, and redirect when the respondent strays. Each activity is recorded word for word on a new line. Interviewers emphasise the word *yesterday* throughout the call to keep the respondent anchored to the diary day rather than a typical day.

If the respondent cannot recall part of the day, the activity is assigned a data code rather than guessed. Total minutes per diary marked with these codes are tracked as a quality indicator.

B.3 Coding controls

The same staff conduct interviews and coding, but coders are never assigned their own cases. Every case is coded twice by different staff. If any activity code differs between the two, the case goes to an adjudicator who assigns the final codes and records an error against the coder, the verifier, or both. Coders are expected to keep their monthly error rate below ten percent. Those who exceed it are removed from interviewing and coding and must pass a re-qualification cycle to return.

B.4 Cases dropped during processing

Published response rates are post-processing rates. A case is reclassified from complete to nonresponse if it contains fewer than five activities, if refusals or *don't remember* responses cover three or more hours of the diary day, or both. This reclassification lowers the final annual response rate by one to three percentage points. Two indicators are tracked quarterly: the average number of episodes per diary (around nineteen historically), and the average minutes per diary marked with insufficient-detail or missing-travel codes. Interviewers with high rates on either indicator are retrained, and those with high error rates are removed from ATUS interviewing until they pass a re-qualification test. Item nonresponse is tracked annually and is below two percent for most variables.

B.5 Implication for the present analysis

CATI checks, two-coder verification, and the removal of low-quality cases mean that the diaries used here come from a sample that has already been filtered for the most common sources of error. The recall bias and the gap discussed in Chapter 7, the under-reporting of brief and simultaneous ICT episodes, remains, but it sits on top of a dataset where interviewer error, coder error, and gross recall failure are actively managed.

Appendix C

Tier-1 Worked Example and Fragmentation Histograms

This appendix complements the Tier-2 worked example presented in Chapter 5, Section 5.4. Two sets of supporting material are provided. First, the same step-by-step calculation of the three sequence-based fragmentation indicators is reproduced for Respondent 22 at Tier-1 granularity, so the reader can compare how coding resolution changes the numerical outputs. Second, the full distributions of the four fragmentation indicators (number of activities, entropy, turbulence, complexity) across the analytical sample are reported, complementing Figure 5.11 in the main text which shows only the number-of-activities distribution.

C.1 Tier-1 Worked Example: Respondent 22

The Tier-1 versions of the timeline, entropy decomposition, transition map, and full step-by-step calculation for Respondent 22 are shown below. At Tier-1 the day is collapsed into broad ATUS categories rather than fine-grained sub-codes, so the same lived day yields fewer distinct activity types and fewer transitions. The numerical outputs of the indicators differ accordingly, but the procedure is identical to the Tier-2 case. At Tier-1 the day contains $K = 8$ distinct activity types (versus $K = 15$ at Tier-2) and 21 transitions (versus 24 at Tier-2), yielding $H_{\text{norm}} = 0.65$, $T = 11.8695$, and $C = 0.0466$.

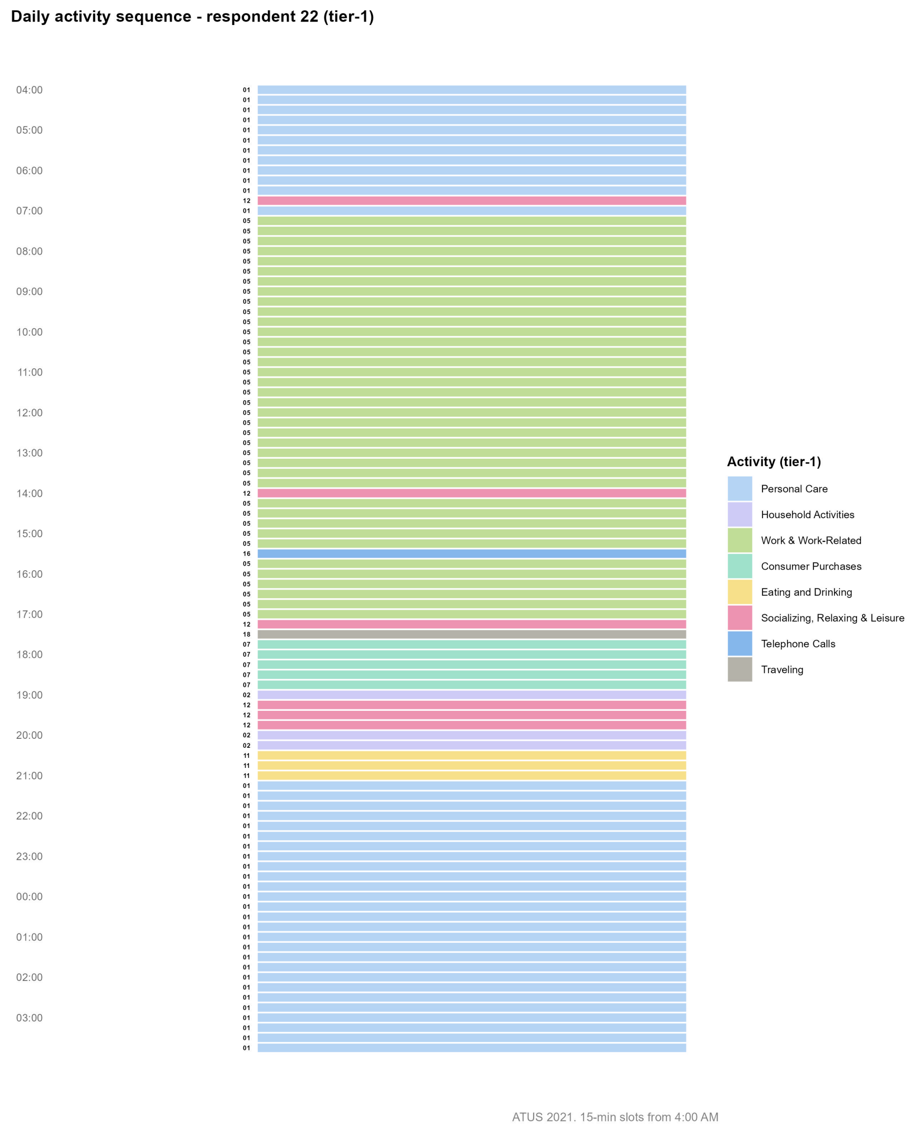


Figure C.1: Daily activity sequence of Respondent 22 coded at Tier-1 (broad ATUS categories).

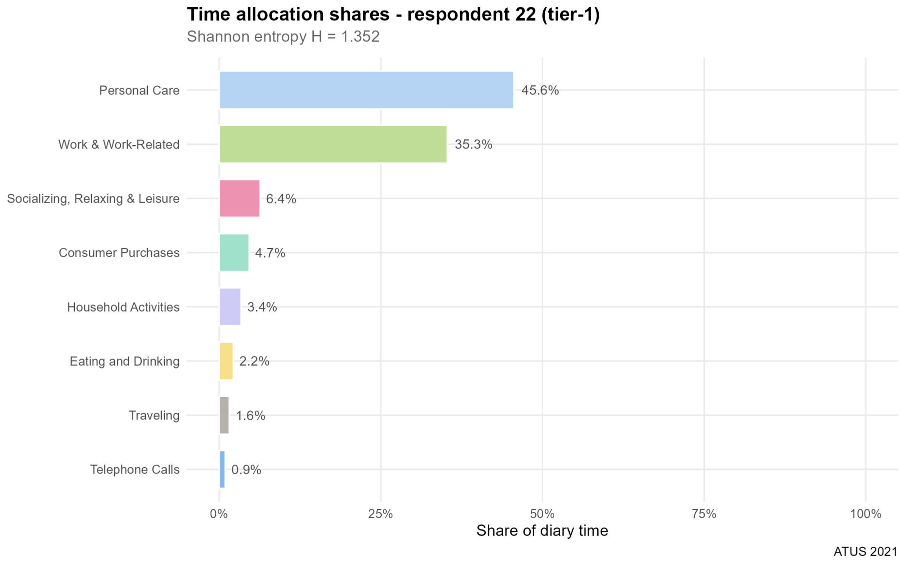


Figure C.2: Tier-1 time allocation shares (π_k) for Respondent 22. Entropy is computed from the share of diary time allocated to each Tier-1 category. Raw entropy $H = 1.3516$, normalised entropy $H_{\text{norm}} = 0.65$.

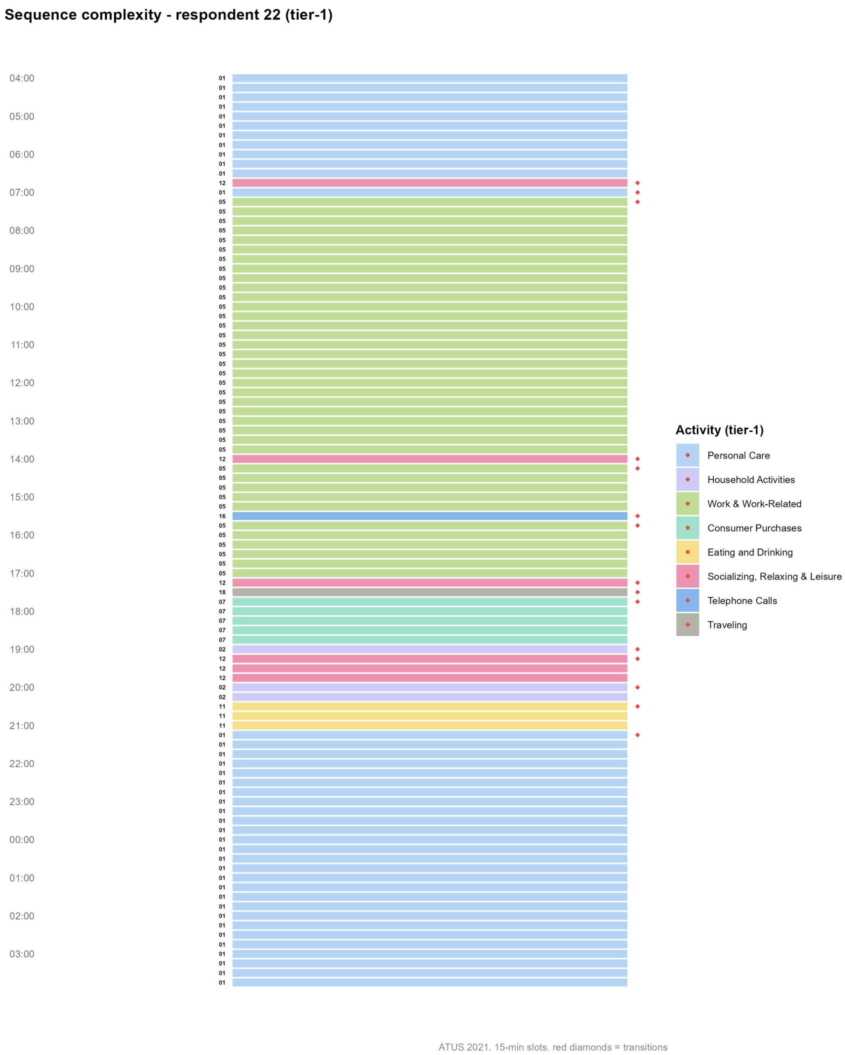


Figure C.3: Daily Tier-1 sequence of Respondent 22 with activity transitions highlighted. 21 transitions over 1,439 possible transition points yield a transition rate of 0.0146.

Step-by-step calculations - respondent 22 (t1)

ATUS 2021. Tier-1 codesPart 1 of 2: entropy and complexity

Entropy H_norm	Turbulence T	Complexity C
0.65	11.8695	0.0466
H_raw / log(K)	log(phi (s2_max+1)/(s2_t+1))	seqici()

Tier-1 (k)	Minutes	pi_k	log(pi_k)	pi_k * log(pi_k)
01	725	0.456	-0.7853	-0.3581
02	54	0.034	-3.3814	-0.115
05	561	0.3528	-1.0419	-0.3676
07	74	0.0465	-3.0683	-0.1427
11	35	0.022	-3.8167	-0.084
12	101	0.0635	-2.7567	-0.1751
16	15	0.0094	-4.667	-0.0439

H_raw = -sum(-1.3516) = 1.3516

H_norm = H_raw / log(8) = 1.3516 / 2.0794 = 0.65

Component	Value	Note
Total 1-min slots	1440	full diary day
Activity transitions	21	slots where activity changes
Transition rate	0.0146	21 / 1439
Distinct activities (K)	8	unique codes observed
Normalised entropy H/log(K)	0.65	H_norm

C = sqrt(0.0146) * sqrt(0.65) = 0.0466

(a) Part 1: entropy and complexity, with summary indicators at the top.

Step-by-step calculations - respondent 22 (t1)

ATUS 2021. Tier-1 codesPart 2 of 2: turbulence

Episode	Activity	Duration (min)	Dev. from mean	Dev^2
1	01	120	61.11	3734.57
2	02	1	-57.89	3351.12
3	01	40	-18.89	356.79
4	12	19	-39.89	1591.12
5	01	10	-48.89	2390.12
6	18	4	-54.89	3012.79
7	05	406	347.11	120486.12
8	12	15	-43.89	1926.23
9	05	75	16.11	259.57
10	16	15	-43.89	1926.23
11	05	80	21.11	445.68
12	18	5	-53.89	2904.01
13	12	15	-43.89	1926.23
14	18	8	-50.89	2589.68
15	02	5	-53.89	2904.01
16	07	74	15.11	228.35
17	18	8	-50.89	2589.68
18	02	3	-55.89	3123.57
19	02	2	-56.89	3236.35
20	02	3	-55.89	3123.57
21	12	20	-38.89	1512.35
22	12	32	-26.89	723.01
23	02	30	-28.89	834.57
24	11	35	-23.89	570.68
25	01	27	-31.89	1016.9
26	02	10	-48.89	2390.12

mean = 58.89 min | s2_t = 14969.95 | T = 11.8695

(b) Part 2: turbulence, episode-by-episode.

Figure C.4: Step-by-step calculation of the three sequence-based fragmentation indicators for Respondent 22 at Tier-1: entropy ($H_{\text{norm}} = 0.65$), turbulence ($T = 11.8695$), and complexity ($C = 0.0466$). Together with the episode count of 26, these are the Tier-1 analogues of the four fragmentation inputs to the SEM, computed at coarser coding resolution for comparison.

C.2 Distributions of the Fragmentation Indicators

Figure C.5 compares the marginal distributions of the fragmentation indicators at Tier-1 and Tier-2 granularity across the analytical sample ($n = 6{,}902$). Tier-2 is the level used as input to the SEM. The two tiers produce broadly similar shapes: entropy and complexity are unimodal and bounded by construction on $[0, 1]$, while turbulence has a longer right tail at both tiers. Tier-2 distributions shift slightly upward in entropy and turbulence, consistent with the finer activity coding capturing more distinct episodes per day.

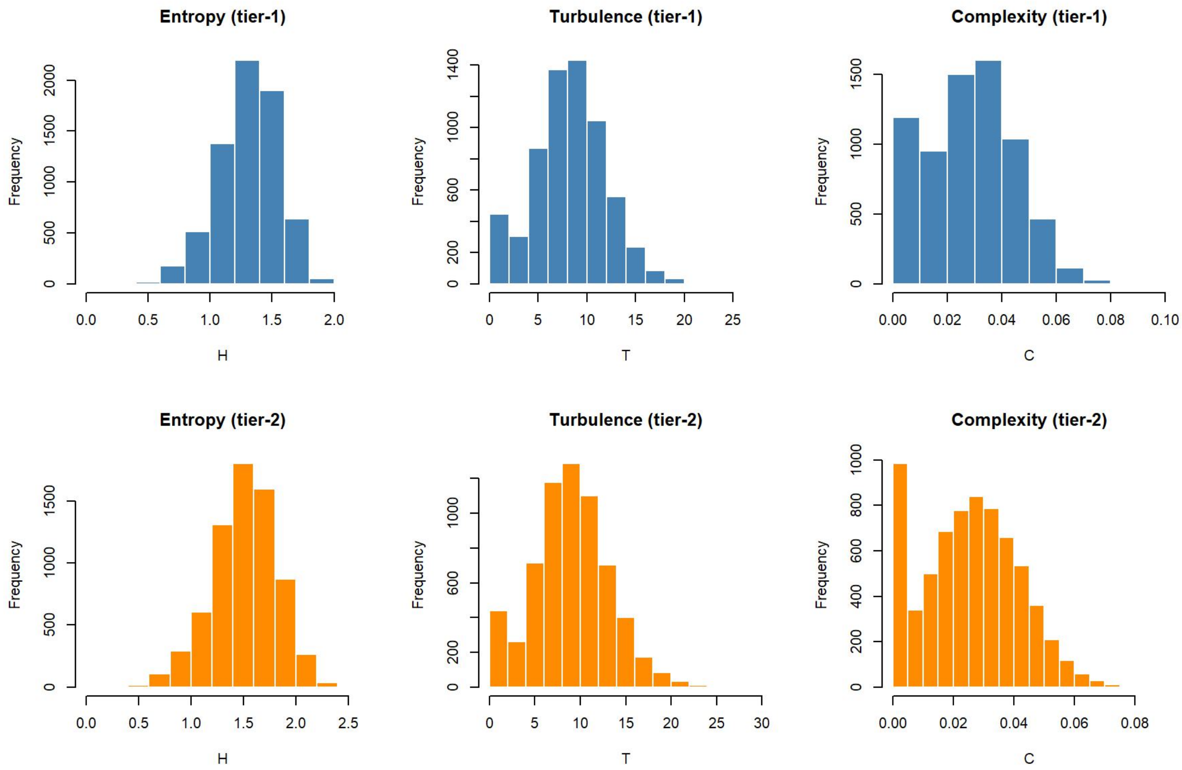


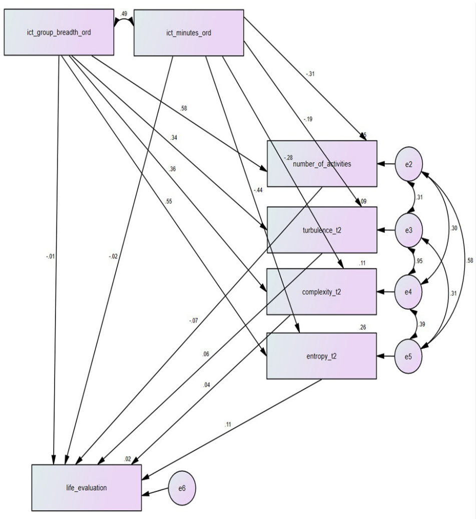
Figure C.5: Distributions of the fragmentation indicators across the analytical sample ($n = 6{,}902$) at Tier-1 (top row) and Tier-2 (bottom row) granularity: normalised entropy, turbulence, and complexity.

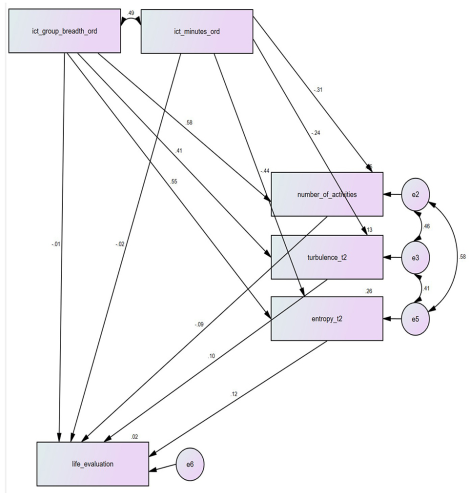
Appendix D

Comparison of SEM models with and without complexity

Figure D.1 compares two specifications of the structural model. The left panel includes all four fragmentation mediators (number of activities, turbulence, complexity, and entropy). The right panel drops complexity and retains the other three.

In the four mediator specification, the paths from turbulence to life evaluation ($p = .183$) and from complexity to life evaluation ($p = .376$) are both non significant. Once complexity is removed, the path from turbulence to life evaluation becomes significant at $p < .001$, alongside the already significant paths from entropy and number of activities.





Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.734	.098	48.493	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.650	.065	25.513	***	par_3
complexity_t2	<---	ict_group_breadth_ord	.006	.000	27.584	***	par_4
entropy_t2	<---	ict_group_breadth_ord	.184	.004	46.264	***	par_5
number_of_activities	<---	ict_minutes_ord	-1.720	.067	-25.605	***	par_14
turbulence_t2	<---	ict_minutes_ord	-.631	.045	-14.171	***	par_15
complexity_t2	<---	ict_minutes_ord	-.003	.000	-21.127	***	par_19
entropy_t2	<---	ict_minutes_ord	-.101	.003	-36.897	***	par_20
life_evaluation	<---	ict_group_breadth_ord	-.018	.034	-.531	.595	par_1
life_evaluation	<---	entropy_t2	.720	.117	6.149	***	par_6
life_evaluation	<---	turbulence_t2	.025	.019	1.332	.183	par_7
life_evaluation	<---	number_of_activities	-.019	.005	-4.206	***	par_8
life_evaluation	<---	complexity_t2	4.791	5.409	.886	.376	par_12
life_evaluation	<---	ict_minutes_ord	-.030	.022	-1.367	.172	par_21

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.580
turbulence_t2	<---	ict_group_breadth_ord	.339
complexity_t2	<---	ict_group_breadth_ord	.361
entropy_t2	<---	ict_group_breadth_ord	.552
number_of_activities	<---	ict_minutes_ord	-.306
turbulence_t2	<---	ict_minutes_ord	-.188
complexity_t2	<---	ict_minutes_ord	-.276
entropy_t2	<---	ict_minutes_ord	-.440
life_evaluation	<---	ict_group_breadth_ord	-.009
life_evaluation	<---	entropy_t2	.114
life_evaluation	<---	turbulence_t2	.058
life_evaluation	<---	number_of_activities	-.074
life_evaluation	<---	complexity_t2	.040
life_evaluation	<---	ict_minutes_ord	-.021

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2	complexity_t2
number_of_activities	-1.720	4.734	.000	.000	.000	.000
turbulence_t2	-.631	1.650	.000	.000	.000	.000
entropy_t2	-.101	.184	.000	.000	.000	.000
complexity_t2	-.003	.006	.000	.000	.000	.000
life_evaluation	-.102	.096	-.019	.025	.720	4.791

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2	complexity_t2
number_of_activities	-.306	.580	.000	.000	.000	.000
turbulence_t2	-.188	.339	.000	.000	.000	.000
entropy_t2	-.440	.552	.000	.000	.000	.000
complexity_t2	-.276	.361	.000	.000	.000	.000
life_evaluation	-.070	.045	-.074	.058	.114	.040

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2	complexity_t2
number_of_activities	-1.720	4.734	.000	.000	.000	.000
turbulence_t2	-.631	1.650	.000	.000	.000	.000
entropy_t2	-.101	.184	.000	.000	.000	.000
complexity_t2	-.003	.006	.000	.000	.000	.000
life_evaluation	-.030	-.018	-.019	.025	.720	4.791

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2	complexity_t2
number_of_activities	-.306	.580	.000	.000	.000	.000
turbulence_t2	-.188	.339	.000	.000	.000	.000
entropy_t2	-.440	.552	.000	.000	.000	.000
complexity_t2	-.276	.361	.000	.000	.000	.000
life_evaluation	-.021	-.009	-.074	.058	.114	.040

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2	complexity_t2
number_of_activities	.000	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000	.000
complexity_t2	.000	.000	.000	.000	.000	.000
life_evaluation	-.072	.114	.000	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2	complexity_t2
number_of_activities	.000	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000	.000
complexity_t2	.000	.000	.000	.000	.000	.000
life_evaluation	-.049	.054	.000	.000	.000	.000

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.734	.098	48.493	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.875	.061	30.835	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.184	.004	46.264	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.720	.067	-25.605	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.749	.042	-17.902	***	par_11
entropy_t2	<---	ict_minutes_ord	-.101	.003	-36.897	***	par_13
life_evaluation	<---	ict_group_breadth_ord	-.013	.034	-.388	.698	par_1
life_evaluation	<---	entropy_t2	.749	.110	6.805	***	par_5
life_evaluation	<---	turbulence_t2	.044	.007	6.268	***	par_6
life_evaluation	<---	number_of_activities	-.023	.005	-5.094	***	par_7
life_evaluation	<---	ict_minutes_ord	-.034	.022	-1.551	.121	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.580
turbulence_t2	<---	ict_group_breadth_ord	.410
entropy_t2	<---	ict_group_breadth_ord	.552
number_of_activities	<---	ict_minutes_ord	-.306
turbulence_t2	<---	ict_minutes_ord	-.238
entropy_t2	<---	ict_minutes_ord	-.440
life_evaluation	<---	ict_group_breadth_ord	-.006
life_evaluation	<---	entropy_t2	.118
life_evaluation	<---	turbulence_t2	.095
life_evaluation	<---	number_of_activities	-.091
life_evaluation	<---	ict_minutes_ord	-.023

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.720	4.734	.000	.000	.000
turbulence_t2	-.749	1.875	.000	.000	.000
entropy_t2	-.101	.184	.000	.000	.000
life_evaluation	-.102	.096	-.023	.044	.749

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.306	.580	.000	.000	.000
turbulence_t2	-.238	.410	.000	.000	.000
entropy_t2	-.440	.552	.000	.000	.000
life_evaluation	-.070	.045	-.091	.095	.118

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.720	4.734	.000	.000	.000
turbulence_t2	-.749	1.875	.000	.000	.000
entropy_t2	-.101	.184	.000	.000	.000
life_evaluation	-.034	-.013	-.023	.044	.749

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.306	.580	.000	.000	.000
turbulence_t2	-.238	.410	.000	.000	.000
entropy_t2	-.440	.552	.000	.000	.000
life_evaluation	-.023	-.006	-.091	.095	.118

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.068	.109	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.047	.052	.000	.000	.000

Figure D.1: Structural model with all four fragmentation mediators (left) versus the reduced model with complexity removed (right). Red boxes highlight the path coefficients to life evaluation. In the four mediator model, the paths from turbulence and complexity are both non significant; once complexity is dropped, turbulence reaches significance.

Appendix E

Full Subgroup Results with Complexity Retained

This appendix reports the full subgroup path estimates from the precursor specification in which complexity was retained alongside the other three fragmentation indicators, before the decision in Section 5.5 to drop it. This model uses a single combined ICT predictor rather than the two-predictor (ICT group breadth and ICT minutes) specification reported in Chapter 6. These tables are provided as numerical backup to the qualitative comparison in Appendix D and are not the basis for any result reported in the main text.

Table E.1: Standardized path estimates: ICT → Fragmentation indicators (complexity retained). All paths significant at $p < .001$ unless otherwise noted. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Subgroup	**ICT → Activities**	**ICT → Entropy**	**ICT → Turbulence**	**ICT → Complexity**
Combined	.429***	.304***	.232***	.224***
Female, Young	.363***	.332***	.195***	.217***
Female, Middle	.409***	.329***	.239***	.227***
Female, Older	.503***	.389***	.248***	.257***
Male, Young	.364***	.215***	.114***	.106***
Male, Middle	.390***	.306***	.219***	.220***
Male, Older	.501***	.313***	.267***	.252***

Table E.2: Standardized path estimates: Fragmentation indicators → Life evaluation (complexity retained). $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Subgroup	**Activities → Life Eval.**	**Entropy → Life Eval.**	**Turbulence → Life Eval.**	**Complexity → Life Eval.**
Combined	−.040*	.094***	.026	.070
Female, Young	−.006	.043	−.010	.095
Female, Middle	−.084*	.135***	.198*	−.095
Female, Older	−.062	.148***	.017	.067
Male, Young	.066	.009	−.066	.162
Male, Middle	−.041	.084*	−.039	.119
Male, Older	−.021	.162***	−.079	.161

Table E.3: Standardized direct, indirect, and total effects of ICT on life evaluation across subgroups (complexity retained). Indirect effects are transmitted through the four fragmentation mediators combined. P-values for indirect effects are not available as bootstrap was not performed. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Subgroup	**Direct Effect ICT → Life Eval.**	**Indirect Effect ICT → Frag. → Life Eval.**	**Total Effect**
Combined	−.022	.033	.011
Female, Young	−.086*	.031	−.055
Female, Middle	−.060	.036	−.024
Female, Older	−.001	.047	.046
Male, Young	−.116**	.036	−.080
Male, Middle	−.078*	.027	−.051
Male, Older	−.059	.060	.001

Appendix F

Non-rounder Subsample SEM Output

This appendix contains the AMOS output for the sensitivity analysis reported in Section 6.3: the combined SEM re-estimated on the subsample of respondents who reported at least one non-multiple-of-5 episode during the diary day.

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.340	.175	24.853	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.681	.109	15.470	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.153	.007	23.344	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.751	.130	-13.438	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.752	.081	-9.277	***	par_11
entropy_t2	<---	ict_minutes_ord	-.096	.005	-19.585	***	par_13
life_evaluation	<---	ict_group_breadth_ord	.011	.053	.212	.832	par_1
life_evaluation	<---	entropy_t2	.778	.180	4.324	***	par_5
life_evaluation	<---	turbulence_t2	.048	.011	4.591	***	par_6
life_evaluation	<---	number_of_activities	-.020	.007	-2.915	.004	par_7
life_evaluation	<---	ict_minutes_ord	-.062	.037	-1.652	.098	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.512
turbulence_t2	<---	ict_group_breadth_ord	.352
entropy_t2	<---	ict_group_breadth_ord	.479
number_of_activities	<---	ict_minutes_ord	-.277
turbulence_t2	<---	ict_minutes_ord	-.211
entropy_t2	<---	ict_minutes_ord	-.402
life_evaluation	<---	ict_group_breadth_ord	.006
life_evaluation	<---	entropy_t2	.122
life_evaluation	<---	turbulence_t2	.113
life_evaluation	<---	number_of_activities	-.082
life_evaluation	<---	ict_minutes_ord	-.040

Figure F.1: Unstandardized and standardized regression weights for the non-rounder subsample model.

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.751	4.340	.000	.000	.000
turbulence_t2	-.752	1.681	.000	.000	.000
entropy_t2	-.096	.153	.000	.000	.000
life_evaluation	-.138	.126	-.020	.048	.778

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.277	.512	.000	.000	.000
turbulence_t2	-.211	.352	.000	.000	.000
entropy_t2	-.402	.479	.000	.000	.000
life_evaluation	-.091	.062	-.082	.113	.122

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.751	4.340	.000	.000	.000
turbulence_t2	-.752	1.681	.000	.000	.000
entropy_t2	-.096	.153	.000	.000	.000
life_evaluation	-.062	.011	-.020	.048	.778

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.277	.512	.000	.000	.000
turbulence_t2	-.211	.352	.000	.000	.000
entropy_t2	-.402	.479	.000	.000	.000
life_evaluation	-.040	.006	-.082	.113	.122

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.076	.115	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.050	.056	.000	.000	.000

Figure F.2: Total, direct, and indirect effects (unstandardized and standardized) for the non-rounder subsample model.

Appendix G

SEM Screenshots: Regression Weights and Effect Decompositions

This appendix contains the full AMOS output for all subgroup models and the combined model: standardized regression weight tables, and standardized direct/indirect/total effect tables. Bootstrap validation was not performed. The analysis properties screenshot (Figure G.1) is shared across all models.

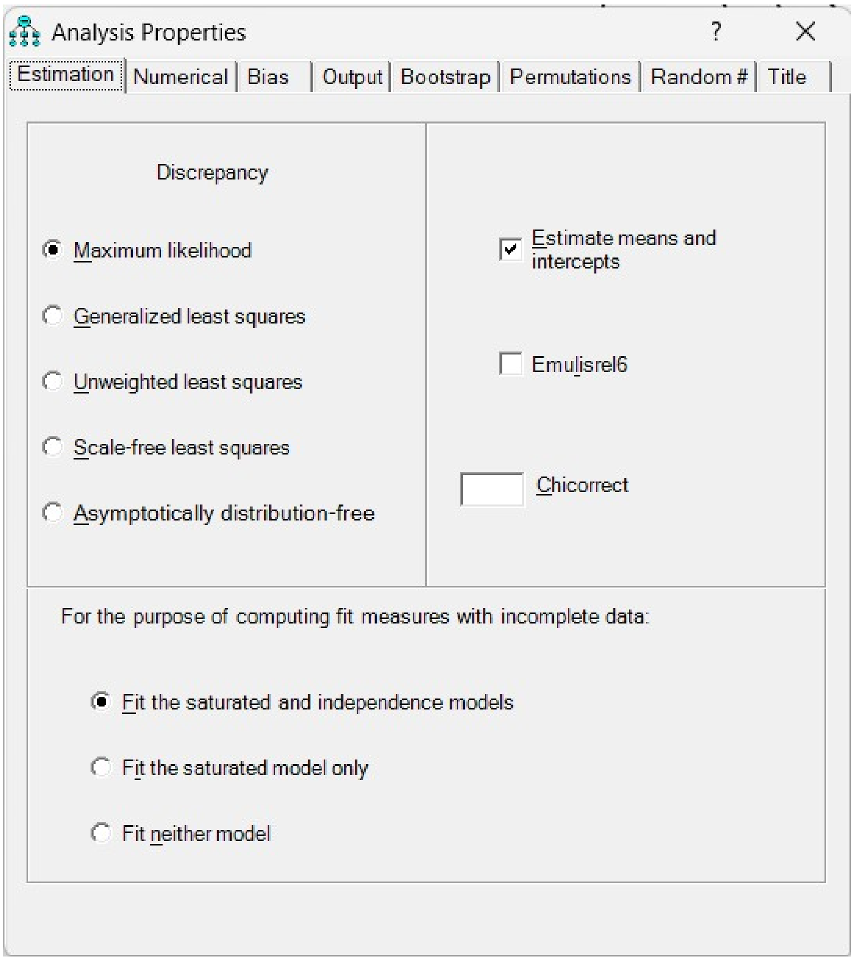


Figure G.1: AMOS analysis properties used for all subgroup models.

G.1 Combined Model

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.734	.098	48.493	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.875	.061	30.835	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.184	.004	46.264	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.720	.067	-25.605	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.749	.042	-17.902	***	par_11
entropy_t2	<---	ict_minutes_ord	-.101	.003	-36.897	***	par_13
life_evaluation	<---	ict_group_breadth_ord	-.013	.034	-.388	.698	par_1
life_evaluation	<---	entropy_t2	.749	.110	6.805	***	par_5
life_evaluation	<---	turbulence_t2	.044	.007	6.268	***	par_6
life_evaluation	<---	number_of_activities	-.023	.005	-5.094	***	par_7
life_evaluation	<---	ict_minutes_ord	-.034	.022	-1.551	.121	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.580
turbulence_t2	<---	ict_group_breadth_ord	.410
entropy_t2	<---	ict_group_breadth_ord	.552
number_of_activities	<---	ict_minutes_ord	-.306
turbulence_t2	<---	ict_minutes_ord	-.238
entropy_t2	<---	ict_minutes_ord	-.440
life_evaluation	<---	ict_group_breadth_ord	-.006
life_evaluation	<---	entropy_t2	.118
life_evaluation	<---	turbulence_t2	.095
life_evaluation	<---	number_of_activities	-.091
life_evaluation	<---	ict_minutes_ord	-.023

Figure G.2: Standardized regression weights – combined model.

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.720	4.734	.000	.000	.000
turbulence_t2	-.749	1.875	.000	.000	.000
entropy_t2	-.101	.184	.000	.000	.000
life_evaluation	-.102	.096	-.023	.044	.749

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.306	.580	.000	.000	.000
turbulence_t2	-.238	.410	.000	.000	.000
entropy_t2	-.440	.552	.000	.000	.000
life_evaluation	-.070	.045	-.091	.095	.118

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.720	4.734	.000	.000	.000
turbulence_t2	-.749	1.875	.000	.000	.000
entropy_t2	-.101	.184	.000	.000	.000
life_evaluation	-.034	-.013	-.023	.044	.749

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.306	.580	.000	.000	.000
turbulence_t2	-.238	.410	.000	.000	.000
entropy_t2	-.440	.552	.000	.000	.000
life_evaluation	-.023	-.006	-.091	.095	.118

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.068	.109	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.047	.052	.000	.000	.000

Figure G.3: Standardized direct, indirect, and total effects – combined model.

G.2 Female – Young

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	5.151	.327	15.768	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.684	.180	9.345	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.180	.011	16.023	***	par_4
number_of_activities	<---	ict_minutes_ord	-2.115	.223	-9.485	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.695	.123	-5.645	***	par_11
entropy_t2	<---	ict_minutes_ord	-.081	.008	-10.520	***	par_13
life_evaluation	<---	ict_group_breadth_ord	-.020	.091	-.218	.827	par_1
life_evaluation	<---	entropy_t2	.064	.284	.226	.821	par_5
life_evaluation	<---	turbulence_t2	.033	.017	1.957	.050	par_6
life_evaluation	<---	number_of_activities	-.007	.010	-.711	.477	par_7
life_evaluation	<---	ict_minutes_ord	-.147	.057	-2.577	.010	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.534
turbulence_t2	<---	ict_group_breadth_ord	.351
entropy_t2	<---	ict_group_breadth_ord	.540
number_of_activities	<---	ict_minutes_ord	-.321
turbulence_t2	<---	ict_minutes_ord	-.212
entropy_t2	<---	ict_minutes_ord	-.354
life_evaluation	<---	ict_group_breadth_ord	-.009
life_evaluation	<---	entropy_t2	.010
life_evaluation	<---	turbulence_t2	.075
life_evaluation	<---	number_of_activities	-.033
life_evaluation	<---	ict_minutes_ord	-.103

(a) Regression weights

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-2.115	5.151	.000	.000	.000
turbulence_t2	-.695	1.684	.000	.000	.000
entropy_t2	-.081	.180	.000	.000	.000
life_evaluation	-.160	.010	-.007	.033	.064

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.321	.534	.000	.000	.000
turbulence_t2	-.212	.351	.000	.000	.000
entropy_t2	-.354	.540	.000	.000	.000
life_evaluation	-.112	.005	-.033	.075	.010

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-2.115	5.151	.000	.000	.000
turbulence_t2	-.695	1.684	.000	.000	.000
entropy_t2	-.081	.180	.000	.000	.000
life_evaluation	-.147	-.020	-.007	.033	.064

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.321	.534	.000	.000	.000
turbulence_t2	-.212	.351	.000	.000	.000
entropy_t2	-.354	.540	.000	.000	.000
life_evaluation	-.103	-.009	-.033	.075	.010

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.013	.030	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.009	.014	.000	.000	.000

(b) Direct, indirect, and total effects

Figure G.4: AMOS output – Female, Young subgroup.

G.3 Female – Middle

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	5.182	.260	19.916	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	2.108	.143	14.782	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.179	.010	18.490	***	par_4
turbulence_t2	<---	ict_minutes_ord	-.939	.104	-9.037	***	par_10
entropy_t2	<---	ict_minutes_ord	-.091	.007	-12.910	***	par_12
number_of_activities	<---	ict_minutes_ord	-2.113	.190	-11.148	***	par_14
life_evaluation	<---	ict_group_breadth_ord	-.090	.081	-1.109	.268	par_1
life_evaluation	<---	entropy_t2	.823	.260	3.166	.002	par_5
life_evaluation	<---	turbulence_t2	.063	.018	3.556	***	par_6
life_evaluation	<---	number_of_activities	-.034	.010	-3.380	***	par_7
life_evaluation	<---	ict_minutes_ord	-.023	.054	-.433	.665	par_13

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.586
turbulence_t2	<---	ict_group_breadth_ord	.470
entropy_t2	<---	ict_group_breadth_ord	.551
turbulence_t2	<---	ict_minutes_ord	-.287
entropy_t2	<---	ict_minutes_ord	-.385
number_of_activities	<---	ict_minutes_ord	-.328
life_evaluation	<---	ict_group_breadth_ord	-.044
life_evaluation	<---	entropy_t2	.129
life_evaluation	<---	turbulence_t2	.136
life_evaluation	<---	number_of_activities	-.144
life_evaluation	<---	ict_minutes_ord	-.016

(a) Regression weights

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-2.113	5.182	.000	.000	.000
turbulence_t2	-.939	2.108	.000	.000	.000
entropy_t2	-.091	.179	.000	.000	.000
life_evaluation	-.086	.014	-.034	.063	.823

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.328	.586	.000	.000	.000
turbulence_t2	-.287	.470	.000	.000	.000
entropy_t2	-.385	.551	.000	.000	.000
life_evaluation	-.057	.007	-.144	.136	.129

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-2.113	5.182	.000	.000	.000
turbulence_t2	-.939	2.108	.000	.000	.000
entropy_t2	-.091	.179	.000	.000	.000
life_evaluation	-.023	-.090	-.034	.063	.823

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.328	.586	.000	.000	.000
turbulence_t2	-.287	.470	.000	.000	.000
entropy_t2	-.385	.551	.000	.000	.000
life_evaluation	-.016	-.044	-.144	.136	.129

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.062	.105	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.041	.051	.000	.000	.000

(b) Direct, indirect, and total effects

Figure G.5: AMOS output – Female, Middle subgroup.

G.4 Female – Older

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.510	.180	25.114	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.741	.120	14.480	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.178	.007	24.207	***	par_4
entropy_t2	<---	ict_minutes_ord	-.116	.006	-18.750	***	par_11
number_of_activities	<---	ict_minutes_ord	-1.380	.151	-9.140	***	par_13
turbulence_t2	<---	ict_minutes_ord	-.739	.101	-7.308	***	par_15
life_evaluation	<---	ict_group_breadth_ord	.011	.068	.162	.871	par_1
life_evaluation	<---	entropy_t2	1.038	.239	4.350	***	par_5
life_evaluation	<---	turbulence_t2	.037	.014	2.571	.010	par_6
life_evaluation	<---	number_of_activities	-.026	.010	-2.629	.009	par_7
life_evaluation	<---	ict_minutes_ord	.004	.052	.074	.941	par_12

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.578
turbulence_t2	<---	ict_group_breadth_ord	.381
entropy_t2	<---	ict_group_breadth_ord	.548
entropy_t2	<---	ict_minutes_ord	-.424
number_of_activities	<---	ict_minutes_ord	-.210
turbulence_t2	<---	ict_minutes_ord	-.192
life_evaluation	<---	ict_group_breadth_ord	.005
life_evaluation	<---	entropy_t2	.164
life_evaluation	<---	turbulence_t2	.083
life_evaluation	<---	number_of_activities	-.101
life_evaluation	<---	ict_minutes_ord	.002

(a) Regression weights

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.380	4.510	.000	.000	.000
turbulence_t2	-.739	1.741	.000	.000	.000
entropy_t2	-.116	.178	.000	.000	.000
life_evaluation	-.107	.141	-.026	.037	1.038

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.210	.578	.000	.000	.000
turbulence_t2	-.192	.381	.000	.000	.000
entropy_t2	-.424	.548	.000	.000	.000
life_evaluation	-.062	.069	-.101	.083	.164

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.380	4.510	.000	.000	.000
turbulence_t2	-.739	1.741	.000	.000	.000
entropy_t2	-.116	.178	.000	.000	.000
life_evaluation	.004	.011	-.026	.037	1.038

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.210	.578	.000	.000	.000
turbulence_t2	-.192	.381	.000	.000	.000
entropy_t2	-.424	.548	.000	.000	.000
life_evaluation	.002	.005	-.101	.083	.164

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.111	.130	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.064	.063	.000	.000	.000

(b) Direct, indirect, and total effects

Figure G.6: AMOS output – Female, Older subgroup.

G.5 Male – Young

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.260	.300	14.180	***	par_2
turbulence_t1	<---	ict_group_breadth_ord	1.421	.181	7.853	***	par_3
entropy_t1	<---	ict_group_breadth_ord	.125	.011	11.544	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.267	.171	-7.406	***	par_10
turbulence_t1	<---	ict_minutes_ord	-.688	.103	-6.678	***	par_11
entropy_t1	<---	ict_minutes_ord	-.064	.006	-10.387	***	par_14
life_evaluation	<---	ict_group_breadth_ord	-.181	.104	-1.742	.082	par_1
life_evaluation	<---	entropy_t1	.143	.334	.428	.668	par_5
life_evaluation	<---	number_of_activities	.012	.012	.978	.328	par_6
life_evaluation	<---	ict_minutes_ord	-.087	.056	-1.538	.124	par_9
life_evaluation	<---	turbulence_t1	.039	.020	1.901	.057	par_13

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.509
turbulence_t1	<---	ict_group_breadth_ord	.309
entropy_t1	<---	ict_group_breadth_ord	.423
number_of_activities	<---	ict_minutes_ord	-.266
turbulence_t1	<---	ict_minutes_ord	-.263
entropy_t1	<---	ict_minutes_ord	-.381
life_evaluation	<---	ict_group_breadth_ord	-.077
life_evaluation	<---	entropy_t1	.018
life_evaluation	<---	number_of_activities	.043
life_evaluation	<---	ict_minutes_ord	-.064
life_evaluation	<---	turbulence_t1	.076

(a) Regression weights

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t1	entropy_t1
number_of_activities	-1.267	4.260	.000	.000	.000
turbulence_t1	-.688	1.421	.000	.000	.000
entropy_t1	-.064	.125	.000	.000	.000
life_evaluation	-.138	-.057	.012	.039	.143

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t1	entropy_t1
number_of_activities	-.266	.509	.000	.000	.000
turbulence_t1	-.263	.309	.000	.000	.000
entropy_t1	-.381	.423	.000	.000	.000
life_evaluation	-.102	-.024	.043	.076	.018

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t1	entropy_t1
number_of_activities	-1.267	4.260	.000	.000	.000
turbulence_t1	-.688	1.421	.000	.000	.000
entropy_t1	-.064	.125	.000	.000	.000
life_evaluation	-.087	-.181	.012	.039	.143

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t1	entropy_t1
number_of_activities	-.266	.509	.000	.000	.000
turbulence_t1	-.263	.309	.000	.000	.000
entropy_t1	-.381	.423	.000	.000	.000
life_evaluation	-.064	-.077	.043	.076	.018

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t1	entropy_t1
number_of_activities	.000	.000	.000	.000	.000
turbulence_t1	.000	.000	.000	.000	.000
entropy_t1	.000	.000	.000	.000	.000
life_evaluation	-.051	.125	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t1	entropy_t1
number_of_activities	.000	.000	.000	.000	.000
turbulence_t1	.000	.000	.000	.000	.000
entropy_t1	.000	.000	.000	.000	.000
life_evaluation	-.038	.053	.000	.000	.000

(b) Direct, indirect, and total effects

Figure G.7: AMOS output – Male, Young subgroup.

G.6 Male – Middle

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.194	.253	16.592	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.983	.174	11.386	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.183	.012	15.614	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.263	.154	-8.177	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.720	.106	-6.765	***	par_11
entropy_t2	<---	ict_minutes_ord	-.083	.007	-11.601	***	par_13
life_evaluation	<---	ict_group_breadth_ord	-.056	.094	-.597	.550	par_1
life_evaluation	<---	entropy_t2	.513	.270	1.902	.057	par_5
life_evaluation	<---	turbulence_t2	.028	.017	1.630	.103	par_6
life_evaluation	<---	number_of_activities	-.020	.013	-1.542	.123	par_7
life_evaluation	<---	ict_minutes_ord	-.120	.053	-2.254	.024	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.521
turbulence_t2	<---	ict_group_breadth_ord	.387
entropy_t2	<---	ict_group_breadth_ord	.493
number_of_activities	<---	ict_minutes_ord	-.257
turbulence_t2	<---	ict_minutes_ord	-.230
entropy_t2	<---	ict_minutes_ord	-.366
life_evaluation	<---	ict_group_breadth_ord	-.024
life_evaluation	<---	entropy_t2	.081
life_evaluation	<---	turbulence_t2	.061
life_evaluation	<---	number_of_activities	-.067
life_evaluation	<---	ict_minutes_ord	-.083

(a) Regression weights

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.263	4.194	.000	.000	.000
turbulence_t2	-.720	1.983	.000	.000	.000
entropy_t2	-.083	.183	.000	.000	.000
life_evaluation	-.157	.011	-.020	.028	.513

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.257	.521	.000	.000	.000
turbulence_t2	-.230	.387	.000	.000	.000
entropy_t2	-.366	.493	.000	.000	.000
life_evaluation	-.110	.004	-.067	.061	.081

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.263	4.194	.000	.000	.000
turbulence_t2	-.720	1.983	.000	.000	.000
entropy_t2	-.083	.183	.000	.000	.000
life_evaluation	-.120	-.056	-.020	.028	.513

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.257	.521	.000	.000	.000
turbulence_t2	-.230	.387	.000	.000	.000
entropy_t2	-.366	.493	.000	.000	.000
life_evaluation	-.083	-.024	-.067	.061	.081

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.038	.066	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.026	.028	.000	.000	.000

(b) Direct, indirect, and total effects

Figure G.8: AMOS output – Male, Middle subgroup.

G.7 Male – Older

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.552	.197	23.065	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	2.017	.136	14.804	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.180	.009	19.020	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.417	.137	-10.372	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.784	.094	-8.312	***	par_11
entropy_t2	<---	ict_minutes_ord	-.123	.007	-18.846	***	par_13
life_evaluation	<---	ict_group_breadth_ord	-.113	.087	-1.308	.191	par_1
life_evaluation	<---	entropy_t2	1.466	.277	5.296	***	par_5
life_evaluation	<---	turbulence_t2	.045	.019	2.343	.019	par_6
life_evaluation	<---	number_of_activities	-.032	.014	-2.333	.020	par_7
life_evaluation	<---	ict_minutes_ord	.008	.056	.145	.885	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.611
turbulence_t2	<---	ict_group_breadth_ord	.443
entropy_t2	<---	ict_group_breadth_ord	.507
number_of_activities	<---	ict_minutes_ord	-.275
turbulence_t2	<---	ict_minutes_ord	-.249
entropy_t2	<---	ict_minutes_ord	-.503
life_evaluation	<---	ict_group_breadth_ord	-.050
life_evaluation	<---	entropy_t2	.230
life_evaluation	<---	turbulence_t2	.091
life_evaluation	<---	number_of_activities	-.105
life_evaluation	<---	ict_minutes_ord	.005

(a) Regression weights

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.417	4.552	.000	.000	.000
turbulence_t2	-.784	2.017	.000	.000	.000
entropy_t2	-.123	.180	.000	.000	.000
life_evaluation	-.163	.097	-.032	.045	1.466

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.275	.611	.000	.000	.000
turbulence_t2	-.249	.443	.000	.000	.000
entropy_t2	-.503	.507	.000	.000	.000
life_evaluation	-.104	.043	-.105	.091	.230

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.417	4.552	.000	.000	.000
turbulence_t2	-.784	2.017	.000	.000	.000
entropy_t2	-.123	.180	.000	.000	.000
life_evaluation	.008	-.113	-.032	.045	1.466

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.275	.611	.000	.000	.000
turbulence_t2	-.249	.443	.000	.000	.000
entropy_t2	-.503	.507	.000	.000	.000
life_evaluation	.005	-.050	-.105	.091	.230

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.171	.210	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.110	.093	.000	.000	.000

(b) Direct, indirect, and total effects

Figure G.9: AMOS output – Male, Older subgroup.

Appendix H

AI tool usage and disclosure

AI-based language models (ChatGPT, Claude and Grammarly) were used as support tools during the preparation of this thesis.

Specifically, AI tools were used to:

- support the structuring of the LaTeX document, including section organization, tables, figures, appendices and cross references.
- assist with sanity checks related to the literature review
- help format references according to APA style and draft BibTeX entries;
- identify typographical errors, spelling, and grammatical issues;

Appendix I

No-sleep Specification SEM Output

This appendix contains the AMOS output for the sensitivity analysis reported in Section 6.3: the combined SEM re-estimated with turbulence and entropy recomputed on the waking day only (sleep episodes removed before indicator calculation).

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.734	.098	48.493	***	par_2
turbulence_nosleep	<---	ict_group_breadth_ord	1.920	.053	36.423	***	par_3
entropy_raw_nosleep	<---	ict_group_breadth_ord	.300	.006	50.150	***	par_4
entropy_raw_nosleep	<---	ict_minutes_ord	-.167	.004	-40.547	***	par_9
turbulence_nosleep	<---	ict_minutes_ord	-.728	.036	-20.080	***	par_12
number_of_activities	<---	ict_minutes_ord	-1.720	.067	-25.605	***	par_13
life_evaluation	<---	ict_group_breadth_ord	-.005	.035	-.134	.893	par_1
life_evaluation	<---	entropy_raw_nosleep	.381	.073	5.212	***	par_5
life_evaluation	<---	ict_minutes_ord	-.042	.022	-1.898	.058	par_10
life_evaluation	<---	turbulence_nosleep	.040	.009	4.605	***	par_14
life_evaluation	<---	number_of_activities	-.019	.005	-4.036	***	par_15

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.580
turbulence_nosleep	<---	ict_group_breadth_ord	.462
entropy_raw_nosleep	<---	ict_group_breadth_ord	.584
entropy_raw_nosleep	<---	ict_minutes_ord	-.472
turbulence_nosleep	<---	ict_minutes_ord	-.254
number_of_activities	<---	ict_minutes_ord	-.306
life_evaluation	<---	ict_group_breadth_ord	-.002
life_evaluation	<---	entropy_raw_nosleep	.093
life_evaluation	<---	ict_minutes_ord	-.029
life_evaluation	<---	turbulence_nosleep	.079
life_evaluation	<---	number_of_activities	-.074

Figure I.1: Unstandardized and standardized regression weights for the no-sleep specification.

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_nosleep	entropy_raw_nosleep
number_of_activities	-1.720	4.734	.000	.000	.000
turbulence_nosleep	-.728	1.920	.000	.000	.000
entropy_raw_nosleep	-.167	.300	.000	.000	.000
life_evaluation	-.102	.096	-.019	.040	.381

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_nosleep	entropy_raw_nosleep
number_of_activities	-.306	.580	.000	.000	.000
turbulence_nosleep	-.254	.462	.000	.000	.000
entropy_raw_nosleep	-.472	.584	.000	.000	.000
life_evaluation	-.070	.045	-.074	.079	.093

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_nosleep	entropy_raw_nosleep
number_of_activities	-1.720	4.734	.000	.000	.000
turbulence_nosleep	-.728	1.920	.000	.000	.000
entropy_raw_nosleep	-.167	.300	.000	.000	.000
life_evaluation	-.042	-.005	-.019	.040	.381

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_nosleep	entropy_raw_nosleep
number_of_activities	-.306	.580	.000	.000	.000
turbulence_nosleep	-.254	.462	.000	.000	.000
entropy_raw_nosleep	-.472	.584	.000	.000	.000
life_evaluation	-.029	-.002	-.074	.079	.093

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_nosleep	entropy_raw_nosleep
number_of_activities	.000	.000	.000	.000	.000
turbulence_nosleep	.000	.000	.000	.000	.000
entropy_raw_nosleep	.000	.000	.000	.000	.000
life_evaluation	-.060	.101	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_nosleep	entropy_raw_nosleep
number_of_activities	.000	.000	.000	.000	.000
turbulence_nosleep	.000	.000	.000	.000	.000
entropy_raw_nosleep	.000	.000	.000	.000	.000
life_evaluation	-.041	.048	.000	.000	.000

Figure I.2: Total, direct, and indirect effects (unstandardized and standardized) for the no-sleep specification.

Appendix J

Under-5-Minute Subsample SEM Output

This appendix contains the AMOS output for the sensitivity analysis reported in Section 6.3: the combined SEM re-estimated on the subsample of respondents whose shortest reported episode is less than 5 minutes.

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
number_of_activities	<---	ict_group_breadth_ord	4.386	.197	22.253	***	par_2
turbulence_t2	<---	ict_group_breadth_ord	1.579	.123	12.796	***	par_3
entropy_t2	<---	ict_group_breadth_ord	.151	.007	20.645	***	par_4
number_of_activities	<---	ict_minutes_ord	-1.812	.148	-12.279	***	par_10
turbulence_t2	<---	ict_minutes_ord	-.756	.092	-8.191	***	par_11
entropy_t2	<---	ict_minutes_ord	-.099	.005	-18.129	***	par_13
life_evaluation	<---	ict_group_breadth_ord	.021	.059	.349	.727	par_1
life_evaluation	<---	entropy_t2	.585	.201	2.909	.004	par_5
life_evaluation	<---	turbulence_t2	.059	.011	5.149	***	par_6
life_evaluation	<---	number_of_activities	-.017	.007	-2.255	.024	par_7
life_evaluation	<---	ict_minutes_ord	-.095	.042	-2.258	.024	par_14

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
number_of_activities	<---	ict_group_breadth_ord	.509
turbulence_t2	<---	ict_group_breadth_ord	.326
entropy_t2	<---	ict_group_breadth_ord	.471
number_of_activities	<---	ict_minutes_ord	-.281
turbulence_t2	<---	ict_minutes_ord	-.209
entropy_t2	<---	ict_minutes_ord	-.413
life_evaluation	<---	ict_group_breadth_ord	.010
life_evaluation	<---	entropy_t2	.091
life_evaluation	<---	turbulence_t2	.138
life_evaluation	<---	number_of_activities	-.071
life_evaluation	<---	ict_minutes_ord	-.061

Figure J.1: Unstandardized and standardized regression weights for the under-5-minute subsample model.

Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.812	4.386	.000	.000	.000
turbulence_t2	-.756	1.579	.000	.000	.000
entropy_t2	-.099	.151	.000	.000	.000
life_evaluation	-.167	.128	-.017	.059	.585

Standardized Total Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.281	.509	.000	.000	.000
turbulence_t2	-.209	.326	.000	.000	.000
entropy_t2	-.413	.471	.000	.000	.000
life_evaluation	-.108	.062	-.071	.138	.091

Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-1.812	4.386	.000	.000	.000
turbulence_t2	-.756	1.579	.000	.000	.000
entropy_t2	-.099	.151	.000	.000	.000
life_evaluation	-.095	.021	-.017	.059	.585

Standardized Direct Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	-.281	.509	.000	.000	.000
turbulence_t2	-.209	.326	.000	.000	.000
entropy_t2	-.413	.471	.000	.000	.000
life_evaluation	-.061	.010	-.071	.138	.091

Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.072	.107	.000	.000	.000

Standardized Indirect Effects (Group number 1 - Default model)

	ict_minutes_ord	ict_group_breadth_ord	number_of_activities	turbulence_t2	entropy_t2
number_of_activities	.000	.000	.000	.000	.000
turbulence_t2	.000	.000	.000	.000	.000
entropy_t2	.000	.000	.000	.000	.000
life_evaluation	-.047	.052	.000	.000	.000

Figure J.2: Total, direct, and indirect effects (unstandardized and standardized) for the under-5-minute subsample model.