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Over 50 and Mental Health during the Digital Era

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Abstract

This thesis examines whether and to what extent the use of information and communication technologies *ICT* is associated with mental health and well-being among Europeans aged 50 and over. The analysis relies on Wave 9 (2021–2022) of the Survey of Health, Aging and Retirement in Europe *SHARE*, then completed by a comparison with the pre-pandemic Wave 7 (2017). I estimate linear models that relate ICT use to depressive symptoms and quality of life. The empirical strategy proceeds from bivariate specifications to multivariate OLS with stepwise inclusion of demographic, socioeconomic, health, and social-network controls. It is then complemented by stratified and interaction analyses and extensive robustness checks.

The research shows that ICT use is consistently associated with reduced depressive symptoms and improved quality of life among older adults. These correlations attenuate, but remain statistically and substantively meaningful once age, self-rated health, chronic conditions, and loneliness are added as controls. Evidence suggests that digital skills and social connectedness partially mediate the relationship between ICT and well-being: users who report stronger skills and less loneliness show the greatest improvements. The comparison between Wave 7 and Wave 9 confirms the positive association, that persists into the post-pandemic period. It shows that the direct correlation becomes more sensitive once skills and social variables are included. The results highlight the importance of targeted digital-skills programs and social-connection interventions for older populations. The study concludes with an analysis of the model's limitations, such as cross-sectional identification, self-reported measures, and an approximate ICT indicator.

The thesis provides updated and relevant evidence for policies for those aged 50 and over in Europe by integrating recent *SHARE* data, a pre/post comparison, and rigorous robustness analyses.

Introduction

Over the past three decades, two transformations have defined contemporary life: the spread of digital technologies and the public reemergence of mental health as a central dimension of well-being. The integration of the Internet, smartphones, and social media platforms has profoundly changed how individuals communicate, work, and access services. These technological changes have created new opportunities for social participation and autonomy but, on the other hand, they have also raised concerns about their impact on psychological well-being. At the same time, population aging has shifted the centre of gravity of European societies. Older people are living longer, staying active longer, and increasingly using the digital sphere as a gateway to services and relationships. In this juncture, the mental health of people aged 50 and over is no longer a marginal issue. It has become a public health and social policy concern, with tangible implications for the equity, productivity and sustainability of welfare systems.

The scholarly debate mirrors this dual movement. The literature analyses mostly the correlation between digital media and young people, often highlighting an excessive use, a social comparison and anxiety. Fewer studies have examined later life, where the mechanism is likely different. For older adults, digital engagement can offer pragmatic benefits: maintaining ties, accessing information and healthcare, preserving independence. However, it can also highlight inequalities in skills and trust and amplify fears or fraud or misinformation. It is crucial to emphasize that the digital divide that refers to different skills, effectiveness and meaningful use can be important as access itself. The lifecycle perspective suggest that the risks and benefits of ICT are not uniform, but depend on resources, vulnerabilities, and the social context.

Given this background, this thesis aims to answer the following research question:

To what extent is the use of information and communication technologies associated with mental health and well-being among adults aged 50 and over in Europe?

To answer it, I used recent microdata from the Survey of Health, Ageing and Retirement in Europe (SHARE). The empirical core is based on Wave 9 (2021-2022), a post-pandemic snapshot in which digital adoption accelerated across cohorts, supplemented by a pre-pandemic baseline, Wave 7 (2017), to assess temporal stability.

Mental health is captured on two complementary dimensions: depressive symptoms (EURO-D) and quality of life (CASP-12). The analytical strategy proceeds from bivariate

associations to multivariate OLS models with stepwise inclusion of demographic, health and social controls. It then explores heterogeneity on variables like gender, age and digital skills. It proceeds by composing a principal-component index of mental well-being, and finally, it conducts robustness checks with weights, clustered errors and alternative outcomes. Throughout this thesis work, loneliness and self-perceived health are treated as pivotal correlates that may mediate or attenuate the ICT-mental health link.

The contributions are multiple. First, the thesis provides updated evidence on older Europeans using a large, harmonized dataset and validated scales, in a period when digital tools became infrastructural for daily life. Second, it opens the “black box” of mechanisms, showing how skills and social connectedness interact with ICT to shape well-being, rather than treating “access” as the unique variable. Third, by comparing pre- and post- pandemic waves, it reveals how the meaning of being online has evolved from a selective indicator of inclusion to a near universal condition, in which the quality of engagement and surrounding social context become crucial.

The structure of the thesis follows a measured progression. Chapter I situates the investigation within the long arc of digital transformation and the parallel societal shift toward mental health, clarifying why seniors deserve special attention. Chapter II maps the literature on digital engagement and mental health across generations, highlighting convergences and gaps and justifying a focus on older adults and their mechanisms. Chapter III introduces the SHARE framework, defines variables and samples, and establishes the empirical framework, including model assumptions and measurement choices. Chapter IV presents the results of Wave 9: descriptive contrasts between users and non-users; stepwise regressions for EURO-D and CASP-12; interaction terms and stratified analyses; PCA-based robustness and survey design adjustments. Chapter V compares Wave 7 and Wave 9 to assess temporal stability and the pandemic-specific impact on digital use and well-being. Chapter VI reflects on the limitations of the models created in the previous chapters. It focuses on cross-sectional identification, self-reporting, construct validity, and potential endogeneity, and it provides methodological recommendations for future research.

The thesis argues that digital engagement in old age should be understood less a binary condition and more as a social capacity, rooted in health, relationships and skills. The following evidence aims to specify when, for whom, and through what challenges ICT is associated with better mental health among Europeans over 50.

Chapter I - The Digital Transformation and Its Impact on Society

In this first chapter, I begin with an introductory analysis of the digital transformation that has taken place over the past two decades. My focus is on understanding the impact of this digitalization process on our society; in fact, the correlation between technology use and mental health has become a widely discussed topic in recent years. Much attention has been paid to younger users, but it is essential to consider their impact on people of all ages. Older adults are highly active online, and their mental health may also be shaped by these new digital environments. According to the 2023 report by the Pew Research Centre¹, 69% of adults aged 50 to 64 and 40% of those over 65 now use at least one social media platform.

The first section aims to draw a timeline of digital development and then understand the growing interest in improving mental well-being and preventing the worsening of mental health conditions. By observing these changes, it becomes easier to comprehend the origins of what is now a modern problem. By understanding the roots of a phenomenon, we are best equipped to deal with it.

In paragraph 1.1, I will examine the milestones of digital transformation and how they affect our society. In paragraph 1.2, I will discuss when mental health emerged as a significant concern. Finally, in paragraph 1.3, I will draw possible connections between these two phenomena: the transformation of the digital landscape and the growing challenges related to mental health.

1.1 Milestones of Digital Transformation

The world has experienced fast technological development during the last decades, which has affected all aspects of daily existence. Although this transition period may seem unprecedented, humans have experienced significant changes throughout history.

During the Stone Age, Bronze Age, and Iron Age, progress was driven by changing materials. Then came the industrial revolutions, which focused on exploiting energy such as water, steam, and electricity. Today, we are in the digital era, which is all about

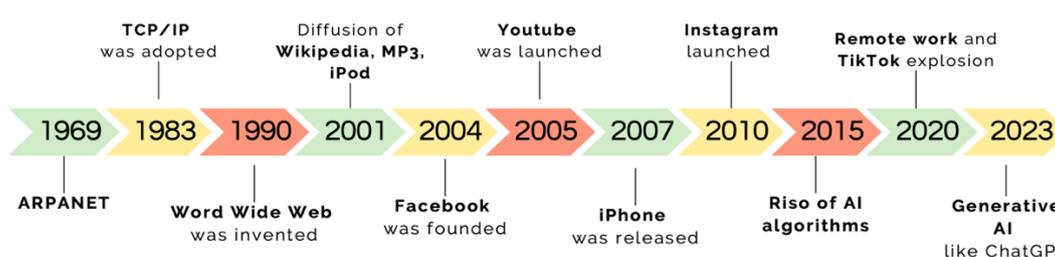
¹ Pew Research Center. (2023). *Social Media Fact Sheet*. Retrieved from <https://www.pewresearch.org/internet/fact-sheet/social-media/>.

information. The transition occurred when society shifted from analog to digital systems and from physical tools to virtual platforms.

The OECD defines *digital transformation* as a “pervasive process of change driven by the diffusion of digital technologies and data, which affects economies, societies, and governance systems”.² These technological shifts have created new opportunities and introduced complex challenges, which are reshaping many aspects of our lives, including how we communicate and work, how we relate to others, how we manage stress, and how we maintain our mental well-being.

A complete understanding of modern society requires studying its fundamental historical developments. The following graph shows that comprehending the history is essential to understanding the current situation.

Figure 1 - Digital Transformation Timeline (1969 - 2023)



Source: Created by the author using data from OECD (2019), Pew Research Centre (2023), Eurostat (2023)

1.1.1 The Rise of the Internet

One of the earliest and most significant advancements that came with the digital age was the advent of the Internet and the World Wide Web, which permitted global communication and access to information.

It started in the late 1960s with ARPANET, a project launched by the U.S. Department of Defence. It was conceived to keep military and research centres in open communication, even in emergencies. During the 1980s, the network expanded with the introduction of NSFNET³, which linked universities and research institutions across the United States and became the backbone of the global internet infrastructure.

² OECD (2019), *Going Digital: Shaping Policies, Improving Lives*, OECD Publishing, Paris.

³ National Science Foundation Network.

A crucial step was reached with the adoption of standardized protocols like TCP/IP, which made data sharing more dependable and widespread, forming the foundation of today's Internet.

The 1990s represented a pivotal moment: personal computers gained popularity. Tim Berners-Lee's⁴ invention of the World Wide Web made it simple to use the Internet. Developing standards such as HTML and HTTP enabled users to access and link documents through intuitive browsers. Individuals could now browse web pages, communicate via email, and purchase online with a couple of mouse clicks. This innovation transformed the Internet from a technical network for experts only into a global information space accessible to everyone.

1.1.2 The Smartphone Revolution

After the widespread adoption of the Internet, the next significant step in digital transformation came with the smartphone revolution. Smartphones denoted a shift, enabling individuals to access sophisticated digital functions in portable formats.

From the middle of the 2000s to the 2010s, our society experienced a drastic transformation due to a new generation of communication. The rise of text messaging introduced new ways of interacting with different linguistic styles, characterized by informal language, abbreviations, and rapid exchanges. Over time, mobile phones evolved by including new features such as cameras, internet access, and apps, which transformed them into indispensable tools in our daily lives.

In their books, both Ling⁵ and Goggin⁶ argue that mobile telephones became so integrated into everyday life that their profound social impact was often underestimated at the time. These devices evolved from mere communication tools to instruments that control how people communicate and even shape their social persona.

This evolution was adopted by younger adults immediately, yet older adults also demonstrated a timely integration of smartphones into their technology usage. The trend for smartphone adoption now ranges from younger groups to even older adults whose digital patterns remain up to speed with technological innovation.

⁴ Tim Berners-Lee (London, 1955), British physicist and computer scientist, inventor of the World Wide Web.

⁵ Ling, R. (2012). *Taken for grandness: The embedding of mobile communication into society*. MIT Press.

⁶ Goggin, G. (2006). *Cell phone culture: Mobile technology in everyday life*. Routledge.

Sociologist Manuel Castells argues that “the internet is a technology of freedom, for it allows people to communicate with each other, to organize themselves, to bypass established institutions, and to challenge authority”⁷. Since then, it has now become a necessary component of everyday life.

1.1.3 Social Media Explosion

A new phase of digital transformation began with the explosion of social media around 2010. Although the first forms of social networking existed in the 2000s, the platforms we know today took on a more central role in everyday life in the following decade.

The so-called *New Economy* began in the mid-1990s with the launch of Yahoo and Netscape in 1994, followed by MSN, Amazon, eBay, and SixDegrees.com⁸ in 1995.

In the years that followed, digital culture experienced a period of rapid expansion, characterized by technological advances and the emergence of new media formats: the MP3 was launched in 1998; Wikipedia and Second Life⁹ were created in 2001 along with the iPod; the iTunes Store was launched in 2003; and Facebook was founded in 2004, quickly becoming the dominant global social network. The way people communicate and share content online changed a lot after the arrival of YouTube in 2005 and Twitter in 2006. In 2010, there was a shift from social networks primarily based on text and status updates to those focused on images and videos. The introduction of Instagram marked a change in digital interaction, emphasizing visual storytelling through photos, filters, and short-form content. More recently, TikTok introduced a new social media model based on algorithmically curated short video content that has shaped new forms of engagement, creativity, and virality.

1.1.4 Gig Work and Remote Work

Digital transformation has changed many aspects of life, including the rise of new work models such as the gig economy¹⁰ and remote work.

⁷ Castells, M. (2001). *The Internet Galaxy: Reflections on the Internet, Business, and Society*. Oxford University Press.

⁸ Social network service web site that initially lasted from 1997 to 2000 and was based on the Web of contacts model of social networking.

⁹ Multiplayer virtual world that allows people to create an avatar for themselves and then interact with other users and user-created content.

¹⁰ A way of working that is based on people having temporary jobs or doing separate pieces of work, each paid separately, rather than working for an employer.

Platforms like Uber, Airbnb, TaskRabbit, and Deliveroo have created flexible, on-demand job opportunities, often without stable contracts or protections. On the other hand, the COVID-19 pandemic accelerated the spread of remote work from a niche practice to a widespread norm. As shown in the Journal of Business Research article *Remote Working and Digital Transformation During the COVID-19 Pandemic*¹¹, the pandemic was a tipping point that accelerated investments in cloud computing, video conferencing, and collaboration tools, pushing millions of employees to work from home. Businesses began to adopt tools like Zoom, Microsoft Teams, and Slack, making digital infrastructure central to daily operations.

According to the article *A Double Burden of Exclusion*¹², many older adults found the sudden need to use digital platforms such as video chat and remote conferencing due to the pandemic overwhelming. This burden of adapting to the digital world left many feeling like they were “falling behind,” especially when they were expected to use unfamiliar technologies for essential tasks.

In Europe, this shift was clearly reflected in labour statistics; according to Eurostat¹³, 22.6% of employed people aged 20 - 64 in the EU worked remotely in 2022. Among older adults aged 55 to 74, 17% engaged in remote work, indicating the digitalization of work extended across age groups. This marks a significant turning point in our living society: precarious work and remote work completely reshape our culture. While this has brought a lot of flexibility, it has also raised concerns about isolation, an always-on culture, and digital burnout.

1.1.5 AI and Algorithmic Influence

The digital world is constantly evolving, leaving little opportunity to study a fixed or static landscape. New applications, platforms, and technologies are continually emerging and reshaping how we live, communicate, and work.

In recent years, we have seen algorithm-driven platforms and artificial intelligence gradually become integrated into our everyday routines. However, these technologies are

¹¹ E. Battisti, S. Alfiero, E. Leonidou. (2020) *Remote working and digital transformation during the COVID-19 pandemic: Economic-financial impacts and psychological drivers for employees*. Journal of Business Research.

¹² A. Seifert, Shelia R Cotten, Bo Xie, *A Double Burden of Exclusion? Digital and Social Exclusion of Older Adults in Times of COVID-19*, The Journals of Gerontology.

¹³ Eurostat. (2023, June 12). *More than half of people aged 55–74 use the internet daily*.

not entirely new. The foundations of AI were laid in the 1950s, with early contributions from figures like Alan Turing¹⁴, a mathematician and logician, who proposed the possibility of machines simulating human reasoning. The field experienced slow progress due to computational and data limitations. Only in the last two decades, AI has begun influencing society at scale, thanks to increased computing power, access to big data, and advancements in machine learning.

Today, there are AI-powered systems like recommendation algorithms on social media, facial recognition, virtual assistants, and automated decision-making tools. These have sparked debate over transparency, accountability, and their impact. According to the Eurobarometer¹⁵, 61% of Europeans say they are familiar with the concept of AI, and 88% agree that its development should be carefully managed to avoid negative consequences. Moreover, 56% report discomfort with AI systems making decisions that directly affect them, such as in hiring or credit scoring.

Mittelstadt et al., in their article *The Ethics of Algorithms: Mapping the Debate*¹⁶, argue that the algorithms used in AI systems raise significant ethical concerns as they are frequently complex and difficult to comprehend, potentially causing harm without users' knowledge. They often interact with algorithmic systems without understanding how decisions are made or what data is used. Furthermore, personalization and filtering in an algorithmic platform can influence what we see, how we think, behave, and relate to others. In the context of digital transformation, the rise of AI and algorithmic influence marks a profound shift in technological capability and in the distribution of knowledge, identity, and power.

These milestones of digital transformation have created new environments in which issues like mental health have begun to emerge and evolve, particularly as digital habits become more prevalent among all age groups.

¹⁴ British mathematician and logician who made major contributions to mathematics, cryptanalysis, logic, philosophy, and mathematical biology and to the new areas later named computer science, cognitive science, artificial intelligence, and artificial life.

¹⁵ European Commission. (2023, January 30). *Attitudes towards the impact of digitization and automation on daily life*.

¹⁶ Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). *The ethics of algorithms: Mapping the debate*. Big Data & Society.

1.2 The Rise of Mental Health as A Social Concern

As digital transformation accelerates in the 21st century, there has been a corresponding rise in social awareness of mental health as a critical dimension of well-being.

Mental health was previously regarded as a private or medical issue; now it is more inclusively viewed as a matter of common concern with social, economic, and cultural aspects. This change was not instant; it evolved progressively through increased public debate, policy shifts for healthcare, and rising awareness about psychological stress from modern life. Today, mental disorders account for an estimated 13% of the global burden of disease, according to *Estimating the True Global Burden of Mental Illness*¹⁷. Furthermore, 89% of EU citizens believe mental and physical health should be treated equally, as reported in the *Special Eurobarometer 516: Mental Health*¹⁸.

Digitalization research shows how technology enables positive change for humanity while also highlighting the difficulties that persist, particularly concerning ethics and responsiveness to new conditions. In a hyper-connected world characterized by data analysis and artificial intelligence, there is an urgent need for society to adjust and for digital systems to be integrated responsibly. This demands a balanced relationship between humans and machines that ensures sustainable development as much as emotional welfare. To understand the potential relationship between digitalization and mental health, it is first necessary to examine how mental health has become a central societal concern.

1.2.1 Shifting Societal Awareness

Mental health must be recognized as a measurable and legitimate state of health comparable in importance to physical illness.

Despite the progress made in public awareness, there is still a tendency, particularly in some social and generational groups, to underestimate the severity of psychological disorders or to treat them as less “real” than physical illnesses. This perspective has the potential to influence both diagnosis and treatment, contributing to underreporting, stigma, and systemic neglect.

¹⁷ Vigo D, Thornicroft G, Atun R. (2016). *Estimating the true global burden of mental illness*. *Lancet Psychiatry*.

¹⁸ European Commission. (2022). *Eurobarometer survey on Europeans' attitudes towards the impact of digitization and automation on daily life*.

To frame the discussion, a definition of what mental health means for our purposes should be provided. According to the World Health Organization, mental health is “a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community. It is an integral component of health and well-being that underpins our individual and collective abilities to make decisions, build relationships, and shape the world we live in”.¹⁹ This definition highlights not only the absence of mental disorders, but also the presence of cognitive, emotional, and social functioning. From a clinical perspective, according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV), a mental disorder is defined as “a clinically recognizable set of symptoms or behaviour, associated in most cases with distress and with interference with personal functions”.²⁰ This definition highlights more of a diagnosable condition and its impact on personal functioning and health.

However, the concept of mental health is not universally understood in the same way. In many societies, it continues to be related to explanations based on morality or theology rather than with explanations based on clinical or epidemiological terms. This diversity continues to impact conceptions of symptoms, labelling them, as well as treating them. Mental health conditions have existed for a very long time, even before the advent of the digital era. They were often misunderstood or ignored. In Europe, for example, under the influence of the Catholic Church, behaviours that nowadays would be interpreted as signs of a mental disorder, such as hallucinations, were interpreted otherwise. It was thought that they were signs of demonic possession or spiritual failure. Therefore, patients were brought to be exposed to challenging or even punitive therapies that sometimes involved efforts to exorcise perceived spirits or to correct moral errors.

These historical misconceptions continue to influence public attitudes, particularly among older generations. Mental illness is often still perceived as a personal weakness or something that exists only “in your head”. This cultural legacy has contributed to a persistent stigma and a reluctance to seek professional help, especially among those who grew up in an era when mental illness was rarely openly discussed. By the 19th century, there was a gradual shift in how mental health care was approached in Europe, moving from religious or moral domains into medical institutions. This could be seen as the start

¹⁹ World Health Organization. (2022). *Mental health: Strengthening our response*.

²⁰ American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders* (4th ed.). Washington, DC: American Psychiatric Association.

of what some people call the institutional era. During this time, various types of treatment facilities emerged, and there were three primary forms:

- **Private asylums** for individuals diagnosed with mental illness.
- **Hydrotherapy clinics**, which treated "nervous conditions" like anxiety or hysteria, and
- **General sanatoria**, which accepted patients with vague or misdiagnosed conditions such as "disturbances of nutrition," "metabolic disorders," or general weakness and fatigue.

While these institutions introduced a more structured and formal approach to psychiatric care, they often reinforced stigma. The treatments available were basic, and their effectiveness was limited. Patients were generally kept away from society and confined for extended periods.

A significant transformation occurred in the years following the Second World War. Governments and health systems began re-evaluating mental health care in response to scientific advances and humanitarian concerns. This period was characterized by the emergence of community psychiatry, the expansion of private-practice psychiatry, and the establishment of day hospitals and outpatient services. These models promoted shorter institutional stays, greater patient autonomy, and more localized support structures. A key factor in this shift was the introduction of psychopharmacological treatments, including the first antidepressants and antipsychotics. These medications have had a profound impact on the management of psychiatric conditions, contributing to a reduction in the reliance on long-term institutionalization. These developments marked the beginning of a more integrated and humane mental health care system, even as stigma and underfunding remained persistent challenges.

From the 1980s to the early 2000s, mental health policy entered a new phase characterized by international collaboration, rights-based discourse, and increased attention to stigma reduction. Both global and regional organizations began to issue clear calls for reform. The World Health Organization's Mental Health Declaration for Europe²¹ stated that "there is no health without mental health", emphasizing the integration of mental health into primary care and public health systems. In Europe, this momentum was reinforced

²¹ World Health Organization. Regional Office for Europe. (2005). *Mental Health Declaration for Europe: Facing the Challenges, Building Solutions*. Health Organization. Regional Office for Europe.

by the Helsinki Declaration²², a joint initiative by WHO and the European Commission, which called upon national governments to formulate unified mental health strategies, promote human rights, and allocate resources to community-based care. During the same period, a series of anti-stigma initiatives and mental health awareness campaigns emerged, intending to challenge the persistent social biases surrounding psychiatric conditions. This development signified a departure from the prevailing institutional care models, marking a shift towards patient-centred approaches emphasizing autonomy, inclusion, and social integration.

Despite growing public awareness, many older adults still experience mental health issues due to deeply ingrained cultural beliefs that can discourage diagnosis and treatment. Rather than using clinical terms, terms such as “nerves”, “fatigue”, or “just getting old” are often used to describe psychological distress, reflecting a tendency to normalize or minimize it. This language reveals deeper generational attitudes, in which mental illness is viewed as a sign of weakness or moral failure, rather than as a treatable medical condition. Many older individuals prefer to address emotional difficulties through natural remedies, such as spa visits, herbal supplements, or rest, rather than seeking formal psychiatric care. According to the WHO²³, depression and anxiety are common among older adults, yet they are often misdiagnosed or left untreated. Stigma, generational beliefs, and the misconception that a decline in mental health is a normal part of ageing continue to act as significant barriers to care.

While attitude and treatment practices have evolved over the past few decades, this progress has not been evenly distributed across age groups. For instance, in the United States, the proportion of patients with depression receiving pharmacological treatment increased from 44.6% in 1987 to 79.4% in 1997²⁴. However, much of this increase occurred among younger or middle-aged adults, with older populations often being left behind due to stigma, limited access, and generational mistrust of psychiatric medication. This persistent gap limits access to support for older adults and increases their vulnerability to social exclusion and chronic psychological distress.

²² World Health Organization. Regional Office for Europe. (2005). *Mental Health Declaration for Europe: Facing the Challenges, Building Solutions*. Health Organization. Regional Office for Europe.

²³ World Health Organization. (2017). *Mental health of older adults*. Retrieved www.who.int/mental-health-of-older-adults.

²⁴ Olfson M, Marcus SC, Druss B, Elinson L, Tanielian T, Pincus HA. *National trends in the outpatient treatment of depression*. JAMA. 2002 Jan 9;287(2):203-9. doi: 10.1001/jama.287.2.203. PMID: 11779262.

Despite mental health becoming a more visible topic in policy discussions, investment in mental health services across Europe remains relatively low compared to the burden it places on society. Mental illness accounts for almost a fifth of the total disease burden in Europe. Yet, mental health receives less than 5% of total healthcare spending in most EU countries, as stated in the OECD, *A New Benchmark for Mental Health Systems: Tackling the Social and Economic Costs of Mental Ill-Health*²⁵. This gap highlights a critical gap between awareness and concrete action. The economic cost of mental health problems, including loss of productivity, absenteeism, and disability benefits, is estimated to range from 3% to 4% of GDP in high-income countries. This persistent underfunding reflects structural challenges in healthcare priorities, particularly given the rising rates of diagnosis and increasing demand for services among older adults. While some progress has been made in integrating mental health into primary care and public health systems, significant disparities persist, particularly in rural areas and among elderly populations who may lack digital literacy or access to community-based resources.

Understanding the intersection of mental health awareness and digital systems is essential for developing more inclusive, effective, and equitable approaches in the 21st century. The following section explores this evolving relationship in detail.

1.2.2 Acceleration of Focus in the Digital Age

As discussed in Section 1.1, integrating digital technologies into nearly every aspect of daily life has significantly accelerated over the past two decades. During this same period, public debate on mental health has also expanded, with greater attention being paid to the recognition of anxiety, depression, and stress-related disorders. The widespread use of smartphones, social media, and digital communication tools has had, and continues to have, a profound impact on the way people interact with and express psychological distress. This temporal overlap suggests a broader cultural shift.

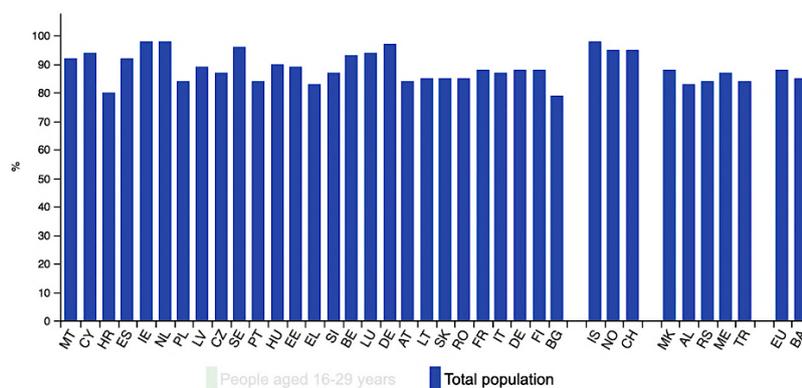
Emotional well-being is now more openly discussed, often through the same technologies that are reshaping social life. It is no longer a private or stigmatized issue, but it has become a topic of discussion within mainstream culture, thanks to the influence of social media, online communities, and mental health promotion campaigns. Popular hashtags

²⁵ OECD (2021), *A New Benchmark for Mental Health Systems: Tackling the Social and Economic Costs of Mental Ill-Health*, OECD Health Policy Studies, OECD Publishing, Paris.

like #MentalHealthAwareness, #ItsOkayToNotBeOkay, and #WorldMentalHealthDay have helped normalize public conversations about anxiety, depression, burnout, and self-care. At the same time, mental health apps like Headspace²⁶, Calm²⁷, and Better Help²⁸ have made therapy and wellness practices more accessible, especially for tech-savvy users. Along with the influence of celebrities and online figures, these tools may have helped drive the cultural shift around mental health. Yet most of this visibility has centred on younger and middle-aged users, leaving older adults less represented in mental health campaigns and digital platforms, and suggesting that their needs and experiences are still not fully addressed.

The extensive use of mobile devices, social media, and remote working tools has made constant connectivity a defining feature of modern life. While these tools provide flexibility and social connection, they have been observed to be associated with higher levels of stress, anxiety, and emotional fatigue. The concept of hyperconnectivity, defined as the feeling of always being reachable or constantly online, has contributed to blurring the boundaries between work and rest, especially among professionals and older adults who are adapting to new digital routines. These changes were initially driven by and adapted to younger generations, while older adults gradually had to integrate these technologies into their daily habits. As shown in Figure 2, daily internet use has increased significantly in almost all European Union countries in 2024, often exceeding 80% of the total population. Although the graph does not provide a breakdown of data by age, the observed trend indicates widespread digital adoption, especially when considered with Eurostat data, which indicate that over 60% of people aged 55 to 74 use the internet daily.

Figure 2 -Daily internet use by the total population in selected European countries, 2024



Source: Eurostat (2024), online data code: isoc_ci_ifp_fu

²⁶ <https://www.headspace.com/>.

²⁷ <https://www.calm.com/it>.

²⁸ <https://www.betterhelp.com/>.

Countries such as Sweden, the Netherlands, and Denmark report even higher participation rates among older age groups. This supports the idea that digital habits are not just the domain of younger users; older adults are actively participating in the digital sphere.

Greater exposure to digital tools has also created new cognitive and emotional challenges. Many older adults struggle to keep up with fast-changing platforms such as Zoom, WhatsApp, or Microsoft Teams, and often report stress or fatigue from long hours in front of screens and constant notifications. Algorithm-driven feeds can add to the pressure by showing unrealistic images of life or distressing news, which may deepen feelings of isolation or inadequacy. In response, European governments have launched initiatives such as *Get Online Week* to strengthen digital skills and promote inclusion. However, these programs focus mainly on technical training and often overlook the mental health difficulties linked to digital use.

As discussed in the previous section, a significant cultural shift has occurred in the way mental health is discussed and understood. Although older adults have traditionally been reluctant to discuss psychological distress openly, recent years have seen a slow but significant shift in attitudes. Public campaigns, workplace programs, and the increased availability of digital mental health tools, such as therapy apps, online self-assessments, and mindfulness platforms, have helped normalize conversations about mental health in everyday life. However, this shift has not occurred uniformly. Many individuals over 50 retain cultural beliefs that associate mental illness with negative characteristics such as weakness, shame, or personal failure. This cultural framing can lead to a delay in diagnosis and prevent the elderly from accessing support on time. Mental health is now viewed more as a spectrum than a binary diagnosis, and this broader understanding has prompted some older adults to reconsider their views and seek new forms of support. However, a significant portion of the population may be unaware of these developments due to technological barriers or a common perception that reflects scepticism regarding these issues.

As awareness of mental health issues has increased worldwide, governments and institutions have introduced new strategies, public campaigns, and legal reforms. Mental health is now part of European Union health policy, reflected in initiatives such as the WHO's European Framework of Action on Mental Health 2021–2025. This plan stresses the need to promote well-being across the life course, including in later adulthood, by integrating mental health into community and primary care, tackling social isolation, and

supporting active ageing and digital inclusion. These efforts show the growing recognition that mental health is essential not only for individual well-being but also for social and economic sustainability.

Digital technologies are part of our everyday life. They are transforming communication and work processes and how we think about, discuss, and approach mental health. This convergence of factors raises a crucial question:

What role does digital transformation play in shaping mental well-being, particularly among older adults facing both technological and emotional changes?

1.3 Connections between Digital Change and Mental Health Trends

Since the early 2000s, two cultural shifts have developed side by side: the spread of digital technology into everyday life and the gradual destigmatization of mental health. Smartphones, social media, and apps have turned technology from a simple tool into a full environment. At the same time, open discussions about anxiety, stress, and well-being have started to appear in spaces where such topics were once avoided.

This parallel evolution does not appear to be coincidental.

As the demands of ever-increasing connectivity grow, so too has the pressure on the human psyche. In response, there has been a growth in mental health tools, wellness content, and policy initiatives. For example, according to the article A New Benchmark for Mental Health Systems of the OECD²⁹, digital health tools are now considered integral to future mental health strategies, and the WHO's European Mental Health Framework (2021-2025) emphasizes the need to adapt services for the digital age.

While technology has significantly reduced geographical distances and made it easier to stay in touch, it has also introduced new forms of emotional disconnection. Even though communication platforms like WhatsApp, Facebook, and Zoom facilitate instant communication, the absence of face-to-face contact, body language, and spontaneous conversation can leave users feeling unfulfilled. For a large segment of the elderly, such digital interactions can feel alien and lacking in substance, appearing more like social placeholders than authentic forms of interaction. A further issue emerges social

²⁹ OECD (2021), A New Benchmark for Mental Health Systems: Tackling the Social and Economic Costs of Mental Ill-Health, OECD Health Policy Studies, OECD Publishing, Paris.

comparison and meticulously curated feeds can foster feelings of inadequacy or isolation. Older adults tend to be less active on visual platforms (e.g., they do not share a significant amount of selfies on Instagram), still they are not immune to these effects, especially when they use social media instead of physical social contact.

Modern platforms rely on personalization, with algorithms designed to keep people engaged. This can also bring unintended psychological effects. Feeds tend to highlight content that is emotional or attention-grabbing, which can expose users to misinformation, polarizing views, or upsetting news. For older adults, many of whom did not grow up in a digital world, this environment can feel confusing or even threatening. The way algorithms steer attention may cause anxiety or mistrust. When content bubbles reinforce negative stories or beliefs, they can spread misinformation and gradually erode emotional well-being.

In this context, digital literacy becomes crucial for individuals engaging with online environments. For a significant portion of older adults, navigating the digital world can feel like accessing a coded map. Interfaces are complex, terminology is opaque, and the pace of change is relentless. This can lead to frustration, dependence on others, and a sense of exclusion when scheduling a doctor's appointment online or using a mobile banking app, for example. Using unfamiliar systems can be stressful, especially when mistakes have real consequences. This not only impacts access to information and services but also affects mental health by reinforcing feelings of inadequacy or disconnection. There are initiatives aimed at improving digital skills, such as the European Union's Digital Skills and Jobs Coalition or Get Online Week³⁰. Bridging this gap requires more than training; it's necessary to demonstrate empathy, adopt an inclusive design approach, and consider older users not as external entities, but as full-fledged digital citizens.

Digital platforms have changed how people present themselves and compare their lives with others. They often highlight idealized images of happiness, success, and health, with users carefully curating what they share. The gap between real life and online identity can create a subtle sense of dissonance. Looking at feeds filled with travel, activity, and technology may lead some individuals to question their own place in that narrative. The pressure to stay visible or appear active on social media can also be a source of stress, especially for those less familiar with digital conventions or the culture of visual self-

³⁰ <https://digital-strategy.ec.europa.eu/en/policies/digital-skills>.

presentation. Despite increased access to digital tools, a significant proportion of older adults still experience digital exclusion due to a lack of access, limited digital literacy, and physical and cognitive impairments. Digital inequality is evident not only in terms of access to devices and internet connectivity, but also in relation to the skills and confidence required to navigate the online world. Many older people encounter barriers such as complex interfaces, unfamiliar terminology, and anxiety about online security and privacy, which can lead to frustration.

From a mental health perspective, exclusion from digital platforms can exacerbate loneliness and reduce access to information and support networks. Older adults who are digitally excluded may miss out on online mental health tools, educational resources, or informal social interactions that could alleviate psychological distress. Furthermore, many public services, from medical appointments to social security systems, are increasingly being offered online, which puts those digitally marginalized at a further disadvantage. Therefore, digital inequality is a critical public health and social justice concern that disproportionately affects older populations, not merely a technical issue.

Chapter II - Mapping the Mental Health Effects of Digital Engagement

As discussed in the previous chapter, it is clear that digital transformation plays a crucial role in defining today's models of communication, work, and social relations. Alongside this significant social shift, mental health has emerged as a topic of considerable public interest, with growing awareness of its social, emotional, and economic implications.

This chapter aims to investigate the intersection of digital engagement and mental well-being, with particular focus on older adults, through a review of existing literature. The analysis of currently available studies provides a deeper understanding of the transformations in mental health outcomes over recent decades in relation to the diffusion of digital technologies. Although numerous studies have analysed the effects of digital media on adolescents and young adults, there are still few in-depth investigations involving older adults. Overall, the available literature is limited and often relies on simple analytical models considering a limited number of variables.

The introduction outlines global and European trends in mental health. The second part of the chapter examines age-specific patterns and compares different generations. The final section highlights gaps in existing research, providing the basis for the theoretical framework and methodological approach presented in the chapters that follow.

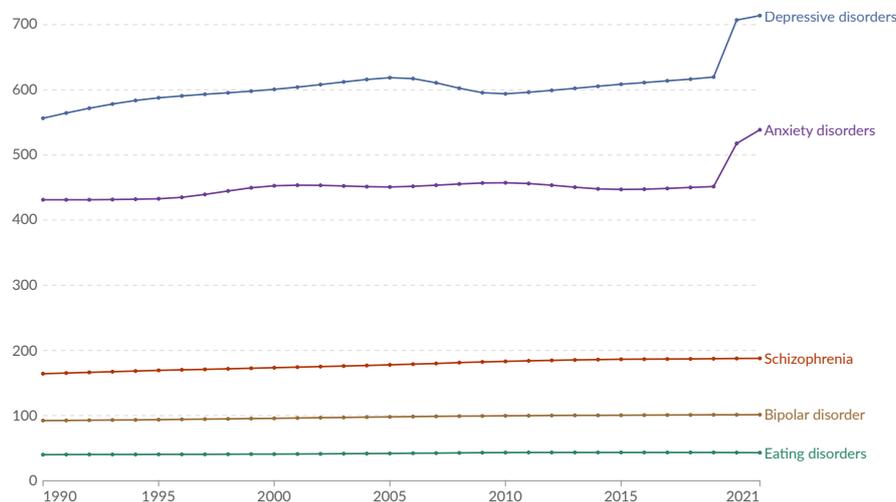
2.1 The Global Mental Health Landscape

Before focusing on the specific needs of older adults, it is crucial to understand how mental illness manifests in global and regional contexts. These demographic changes highlight differences in the interaction between digitalization and social structures and the impact on mental health outcomes in different settings. It provides a valuable framework for developing more targeted, effective, and context-specific strategies.

Drawing on recent epidemiological and economic studies, this section explores the evolving burden of mental illness globally, its financial costs, and persistent treatment gaps. Comprehending this landscape is crucial to analysing the intersection of digital environments and mental well-being and recognizing the importance of generational differences in terms of exposure, coping mechanisms, and access to care.

Mental health represents an ongoing challenge: over 1 billion people globally live with mental disorders or addictions, which are the leading causes of disability and early mortality. Evaluating the economic impact of mental illness is crucial to justify investments in global mental health, inform public health decision-making, and guide the prioritization and scaling up of much-needed interventions. Previous estimates, conducted in 2011 and based on 2004 data, found that mental disorders accounted for 13% of the global burden of disease, with unipolar depression alone representing the third leading cause globally³¹. More recent research suggests that these figures may be underestimated. The Global Burden of Disease (GBD) study³², published in 2019, provides updated metrics using disability-adjusted life years DALYs³³, years of life lost YLLs, and years lived with disability YLDs. According to GBD 2019, mental disorders accounted for over 125 million DALYs, representing approximately 5% of the global total. However, when considering related conditions such as alcohol and drug use, neurological disorders, chronic pain, suicide, and self-harm, the share attributable to mental disorders increases significantly to 12% of global DALYs, equivalent to approximately 321 million DALYs. Under a more comprehensive approach, this figure exceeds 418 million DALYs, representing over 16% of global DALYs.

Figure 3- Burden of disease from each category of mental illness, World, 2000 to 2021



³¹ Vigo D, Thornicroft G, Atun R. *Estimating the true global burden of mental illness*. Lancet Psychiatry. 2016 Feb;3(2):171-8. doi: 10.1016/S2215-0366(15)00505-2. PMID: 26851330.

³² *Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019*. Vos, Theo et al. The Lancet, Volume 396, Issue 10258, 1204 – 1222.

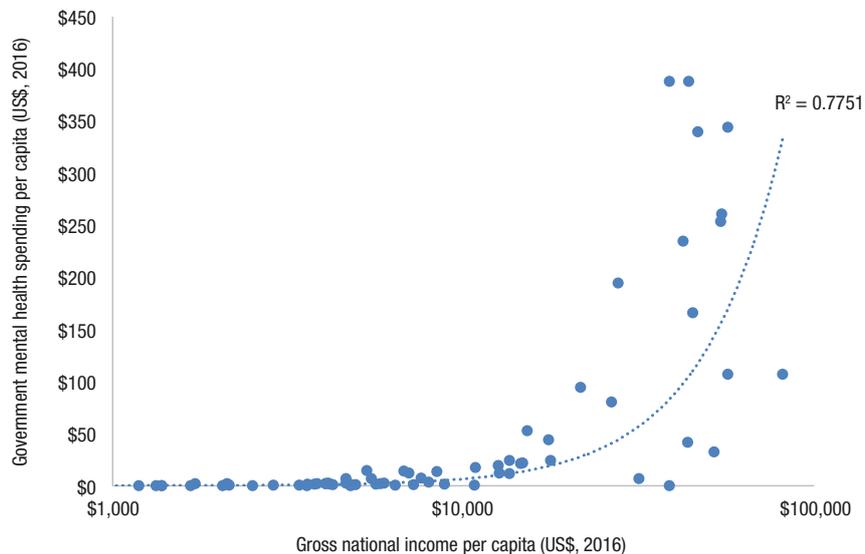
³³ **Disability-adjusted life years – DALYs** measure the total burden of disease, both from years of life lost due to premature death and years lived with a disability. One DALY equals one year of healthy life.

Source: IHME, Global Burden of Disease (2024), OurWorldinData.org/mental-health | CC-BY

As previously noted, depressive and anxiety disorders are the most significant contributors to the global burden of disease. It is estimated that by 2030, depression will become the leading cause of mortality globally, particularly in low and middle-income countries where health services are underdeveloped.

The economic costs of mental illness are not limited to direct healthcare expenditures but also extend to lost productivity, early retirement, unemployment, and long-term disability. Estimated global economic losses exceeded \$4.7 trillion USD in 2019, rising to over \$7.2 trillion when adjusted for purchasing power parity³⁴. According to the estimates by the World Economic Forum and the World Bank³⁵, the global cost of mental illness was approximately \$2.5 trillion in 2010, nearly two-thirds of which was attributable to indirect costs such as lost productivity, unemployment, and premature mortality. If left unaddressed, these costs are projected to rise to \$6.0 trillion by 2030, exceeding the overall economic burden associated with cancer, diabetes, and respiratory diseases. In high-income countries such as Canada, the United Kingdom, and France, mental illness alone could cause economic losses of up to 4.4% of GDP, highlighting its significant impact on development and public finances.

Figure 4 - Association between per capita mental health expenditure and gross national income



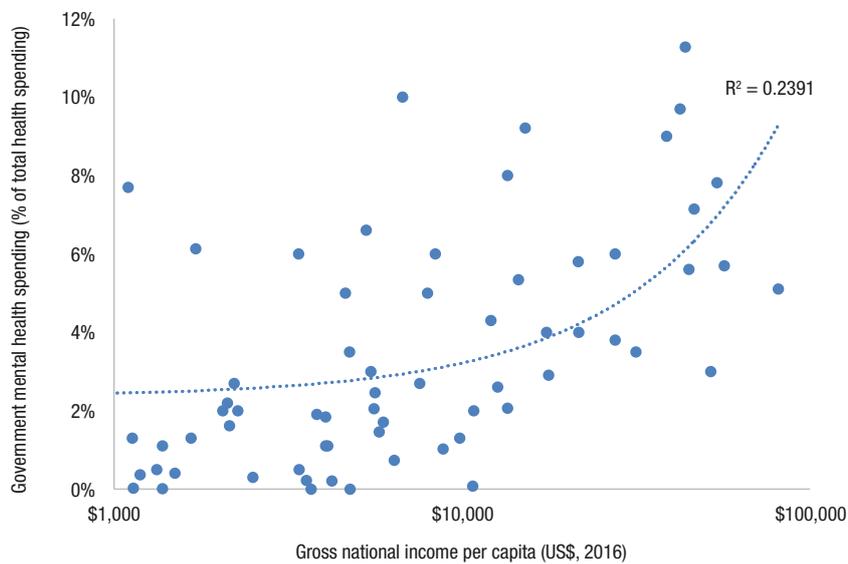
Source: WHO Mental Health Atlas 2017, <https://iris.who.int/bitstream/handle/10665/272735/9789241514019-eng.pdf>

³⁴ *Quantifying the global burden of mental disorders and their economic value* Arias, Daniel et al. *eClinicalMedicine*, Volume 54, 101675.

³⁵ Mnookin, Seth. (2016) *Out of the shadows: making mental health a global development priority*. Washington, World Bank Group.

Figures 4 and 5³⁶ demonstrate a strong correlation between total public spending per capita on mental health and gross national income per capita. These associations explain the majority of the observed variance, over 75%. However, the association is significantly weaker when expressed as a proportion of total health spending, explaining less than 25%. This suggests that some countries with lower national incomes allocate a significant portion of their total health spending to mental health, even if it's not very high in absolute terms. On the other hand, some countries with higher incomes do the opposite; they allocate only a small portion of their relatively large health budgets to mental health.

Figure 5 - Association between mental health expenditure as a % of total health expenditure and gross national income



Source: WHO Mental Health Atlas 2017, <https://iris.who.int/bitstream/handle/10665/272735/9789241514019-eng.pdf>

As reported in the WHO's Mental Health Atlas³⁷, global per capita spending on mental health remains less than \$2 per person and less than \$0.25 in low-income countries. By contrast, high-income countries average \$44.84 per person. These inequalities are also reflected in the percentage of national health budgets allocated to mental health. Countries with the greatest needs often have the lowest funding and weakest infrastructure.

To further explain these disparities, recent data from the WHO Global Health Observatory³⁸ highlight significant regional differences in mental health spending as a

³⁶ World Health Organization. (2018). *Mental health atlas 2017*. World Health Organization. Retrieved from <https://iris.who.int/handle/10665/272735>.

³⁷ Ibid.

³⁸ *Government expenditures on mental health as a % of total government expenditures on health*. Retrieved from <https://tinyurl.com/zyxvucn>.

proportion of overall health spending. By reworking the dataset available online, the average expenditure per country is indicated in the following table:

Table 1 - Mental health spending by region

	<i>Average value of spending in %</i>
<i>Africa</i>	1.62
<i>Americas</i>	2.34
<i>Eastern Mediterranean</i>	3.59
<i>Europe</i>	5.36
<i>South-East Asia</i>	1.71
<i>Western Pacific</i>	3.11

Source: Author's elaboration based on [WHO Global Health Observatory Data](#)

These data highlight a substantial gap in funding and a significant discrepancy between mental health needs and actual investments. In particular, as confirmed by the WHO's Mental Health Atlas, regions with the highest burden and least developed infrastructure, such as Africa and Southeast Asia, allocate the smallest share of their healthcare budgets to mental health. This disparity raises essential questions about global health equity, policy prioritization, and the scalability of effective mental health interventions in resource-limited settings.

The reasons for underinvestment in mental health are varied. Historically, it has been treated as a secondary priority in national health agendas, often overshadowed by communicable diseases or other non-communicable conditions considered more urgent. As noted in the previous chapter, stigma and misunderstanding surrounding mental illness also weaken political commitment and lead to fragmented policy responses. On top of this, many health systems face a serious shortage of qualified professionals: in some countries there are fewer than one psychiatrist for every 100,000 people. The lack of social workers, psychologists, and psychiatric nurses further adds to the problem, leaving primary care services unable to adequately manage even common conditions such as depression or anxiety. Funding inequities are also evident when examining mental health spending as a percentage of total health spending. According to a World Bank report, low-income countries allocate 0.5% of their health budgets to mental health, while high-income countries allocate five times that amount, at 5.1%. This suggests not only economic constraints but also an institutional underestimation of mental health as a public health priority.

It is important to emphasize that the issue is not just about the amount of funding, but also its allocation. According to the Atlas data, 67% of global mental health spending continues to go to psychiatric hospitals. Many of these have outdated treatment models, long-term hospitalizations, and poor health outcomes. Despite growing evidence supporting community-based care, which is more cost-effective and in line with human rights standards, only a small portion of total resources is allocated to outpatient services, primary care integration, or prevention programs. This hospital-centred, often coercive, care model fails to reach the majority of people with mental health disorders. The treatment gap is one of the most visible indicators of the global mental health crisis. Recent European evidence confirms the high costs of leaving mental and cognitive disorders untreated. Bassoli, Brugiavini and Carrino³⁹ show that when older adults develop dementia, families face greater financial strain, higher care needs, and negative effects on spouses' well-being. Their study underlines that without adequate prevention and support, the burden of mental illness quickly extends beyond individuals to entire households and societies. This micro-level evidence from Europe reflects a wider global challenge. When mental disorders remain untreated, the consequences multiply, placing pressure not only on health systems but also on family networks and community resources. In low- and middle-income countries, 76-85% of people with severe mental disorders, such as schizophrenia or bipolar disorder, receive no treatment at all. Even in high-income countries, where resources are relatively greater, 35%-50% of those affected receive no treatment⁴⁰. As a result, this means that millions of individuals globally are denied access to essential psychological and psychiatric services, medications, and counselling. Lack of access to adequate services contributes to a cycle of disadvantage that extends beyond the individual, negatively impacting various aspects of people's lives. People with untreated mental disorders face a higher risk of unemployment, social exclusion, and financial hardship, all of which can worsen psychological distress. This creates a vicious cycle in which poverty and mental illness reinforce one another, highlighting the need for both clinical interventions and broader socioeconomic solutions. Strengthening prevention and early intervention is a question of fairness and a long-term sustainability for health systems. Expanding access to affordable community services and

³⁹ Bassoli, Elena and Brugiavini, Agar and Carrino, Ludovico, *What are the Costs of Dementia in Europe?* (October 01, 2024). Ca' Foscari University of Venice, Department of Economics Research.

⁴⁰ Executive Board, 130. (2012). *Global burden of mental disorders and the need for a comprehensive, coordinated response from health and social workers at the country level: report by the Secretariat*. World Health Organization.

investing in digital inclusion could reduce the treatment gap while also supporting autonomy and social participation. In this sense, international collaboration is needed to share best practices and address inequalities, since the countries with the highest burden are often those with the weakest infrastructure. Together, these measures can transform mental health from neglected issue into a central pillar of public health and development.

Despite the fact that mental health is widely recognized as a global health and development priority, major inequalities remain in the distribution of financial and human resources. Addressing this gap requires a fundamental change in how mental health is assessed, funded, and incorporated into wider public health and development strategies. In conclusion, underinvestment in mental health is not only a problem for health systems but also a failure of development and equity. The data collected clearly show that mental disorders are widespread, debilitating, and costly, but they are also treatable, and practical solutions exist. Addressing these challenges is key to ensuring equity in health services and promoting sustainable development. The shift from traditional care models to community-based approaches, supported by intersectoral investments, is no longer advisable but has become essential.

2.2 Mental Health among Young Adults

The digital habits of young adults have been the subject of extensive research in recent years, providing a valuable lens for understanding mental health trends. As one of the first generations to grow up in the digital age, their experiences offer insights into online life's psychological risks and opportunities. This section aims to examine how factors such as social media use, screen time, and digital culture contribute to rising rates of anxiety, depression, and emotional distress among young people. These insights provide helpful information for the next section, which focuses on the influence of digital environments on older adults, who may face similar challenges in diverse social and generational contexts.

Three key studies were selected to delve deeper into the underlying dynamics. Each provides valuable insights into how digital habits influence young adults' mental health. These studies span over a decade, from 2010 to 2023, and will be presented chronologically to highlight the evolution of the understanding of this topic over time.

Each research section will focus on the applied methodology, key findings, and implications for mental health research in the context of digital engagement.

2.2.1 Qualitative study on Technology Use and Mental Symptoms Among Young Adults⁴¹

The earliest of the selected studies provides a qualitative exploration of how young adults perceive the relationship between their use of information and communication technologies (ICT) and the development of mental health symptoms. The study is of particular significance as it captures early concerns regarding the psychological effects of digital engagement when smartphones and social media platforms were beginning to gain widespread popularity.

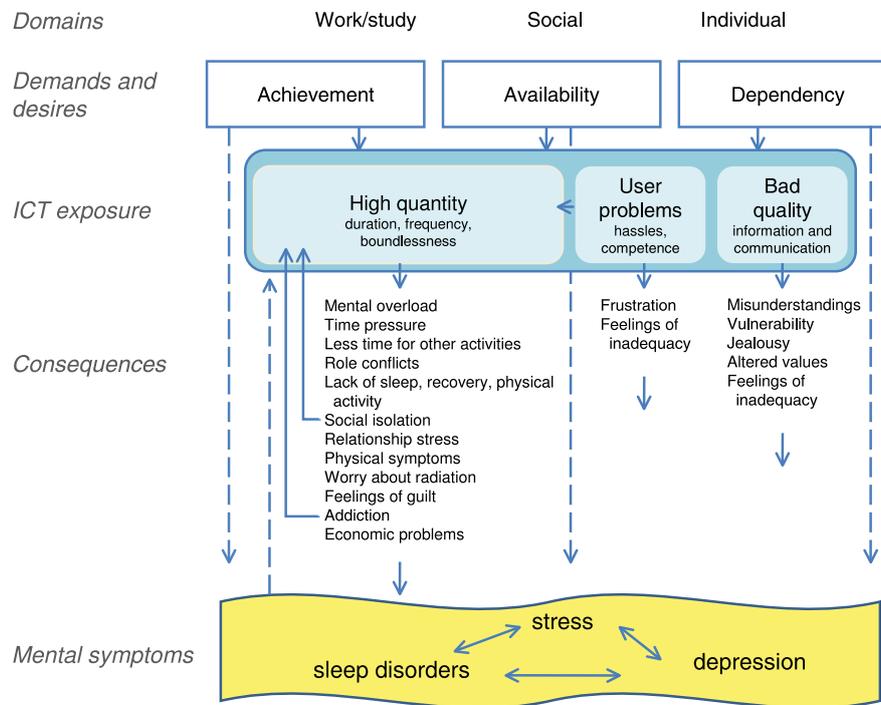
The researchers applied a grounded theory approach and carried out semi-structured interviews with 32 Swedish university students aged 20 to 28. The aim was to explore how participants themselves linked their use of ICT to symptoms such as stress, sleep problems, anxiety, and depression. Rather than assuming a direct causal relationship, the study focused on how students interpreted their own experiences and the explanations they offered for those symptoms. Several ideas came up again and again:

- **Constant availability:** Participants said they felt they had to be available all the time, which made it hard to switch off and relax.
- **Sleep disruption and concentration issues:** Students often find that using phones and computers before bed makes it hard to sleep and concentrate the next day.
- **Ambivalence about ICT:** While participants experienced stress due to their ICT use, they also said that these technologies were necessary for staying connected and keeping up with their academic responsibilities.
- **Pressure and performance:** The combination of too many digital devices and demands from outside (school or work) appeared to increase mental strain.
- **Personal dependency:** Some people said they had an unhealthy relationship with technology, which was making them more stressed.

⁴¹ Thomée, S., Dellve, L., Härenstam, A. et al. *Perceived connections between information and communication technology use and mental symptoms among young adults - a qualitative study.* . BMC Public Health 10, 66 (2010). doi:10.1186/1471-2458-10-66.

The ideas expressed by the young adults reporting high ICT use and mental symptoms created a model of possible paths for associations between ICT exposure and cognitive symptoms.

Figure 6 – Possible paths for associations between ICT use and mental symptoms



Source: Thomée, S. et al., *Perceived connections between information and communication technology use and mental symptoms among young adults*

The figure underlines how digital technology does not act in isolation. High intensity of use, low quality of interaction, and individual difficulties with ICT combine to generate pressures such as role conflicts, social isolation, or relationship strain. These pressures reinforce each other, producing a cycle in which stress and sleep problems gradually erode psychological resilience. What makes the model particularly relevant is its attention to feedback loops: sleep disruption heightens stress levels, and persistent stress deepens depressive symptoms. By pointing to both the quantity and the quality of ICT use, the framework reminds us that digital technologies are not problematic *per se*. Difficulties arise when usage patterns are unbalanced or when communication feels inadequate. This insight is important for interpreting differences across age groups, since older adults experience the qualitative barriers of ICT use, while younger users are more exposed to the risk of quantity and intensity of use.

2.2.2 Self-Reported Dependence on Mobile Phones in Young Adults⁴²

This 2017 study looks at how mobile phones affect young adults in different cultures. The authors used large-scale survey data to examine patterns of self-reported mobile phone dependence and its relationship with mental health and behavioural issues.

The researchers surveyed 2775 university students aged 18 to 29 from European countries. The study wanted to find out how many people are addicted to their phones and whether there are any differences between countries and genders. The main findings included:

- **High rates of perceived dependence:** Almost all the students expressed concern about their mobile phone use. They felt like they couldn't disconnect and felt lost without them.
- **Gender differences:** Women said they were more dependent than men, especially in areas related to emotional attachment and compulsive checking.
- **Cross-country variation:** Northern and Western European countries tended to report higher dependency scores than Southern and Eastern countries, suggesting cultural factors at play.
- **Link to emotional problems:** Higher self-reported dependence was significantly associated with anxiety, stress, and reduced self-control in daily routines.
- **Academic and social interference:** Some students reported that their phone habits interfered with studying, sleep quality, and interpersonal relationships.

The study found that problematic mobile phone use was not primarily linked to how long people used their phones. Instead, it was related to how dependent people felt and how they coped with their emotions. This suggests that “how often people think they need their phones” is a better sign of mental health problems than how much time they spend on them. This study helps us understand how young European adults are addicted to their phones. It also identifies specific risk factors that could help us develop ways to prevent this problem and reduce the mental health problems associated with too much digital use.

⁴² Lopez-Fernandez, et al. (2017). *Self-reported dependence on mobile phones in young adults: A European cross-cultural empirical survey*. *Journal of Behavioral Addictions*, 168-177. doi:10.1556/2006.6.2017.020.

2.2.3 Mental health of young people in Europe⁴³

This study aims to examine the relationship between digital technology use and mental well-being, from the perspective of both young individuals and healthcare professionals. The research uses a variety of methods to investigate the influence of digital technologies on mental health in Europe after the pandemic.

The study surveyed 194 young people aged 14 to 24. Participants were asked to express their opinions regarding the impact of digital engagement. In particular the questions were about the use of smartphones and social media, on mental health and the therapeutic process. The key findings from student responses are reported below:

- **Mixed emotional impact of digital media:** social media has been described as having both positive and negative effects. They can facilitate connection with others and self-expression, but they can also generate problems, such as the impression that they manipulate perceptions.
- **Preference for digital self-help tools:** many people use apps, online resources, and self-assessments as a preliminary step before accessing formal services.
- **Need for personalization:** respondents highlighted the importance of culturally sensitive, age-appropriate, and customizable resources.
- **Limitations of online-only support:** some users believe that digital tools cannot offer the human contact necessary for emotional support.

The interviews also included physicians, who shared views similar to those of young adults. They recognized the usefulness of digital tools but stressed the importance of maintaining human contact and clinical oversight.

The study reflects broader European concerns regarding the digital mental health landscape, emphasizing the need for physicians to have digital skills and be better equipped to address the challenges posed by their younger patients. Furthermore, it emphasizes the importance of collaborating with young people to produce digital mental health resources to ensure cultural and generational relevance.

⁴³ Rifkin-Zybutz R, Turner N, Derges J, Bould H, Sedgewick F, Goberman-Hill R, Linton M, Moran P, Biddle L. *Digital Technology Use and Mental Health Consultations: Survey of the Views and Experiences of Clinicians and Young People.*

2.2.4 General Conclusion

The studies reviewed in the previous sections highlight a complex and changing relationship between young adults' use of digital technologies and their mental health. They show how digital technologies have become a significant component of young people's emotional and social lives. This influence is evident in their communication, learning methods, and emotional responses to problems.

Despite differences in methodology and geographic focus, several common themes emerge. Young adults report ambivalent feelings toward digital technologies: they see them as highly relevant but also difficult to manage. Interviewees noted that the sense of being constantly available, poor sleep, academic pressure, and dependence on others often contribute to stress and fatigue. At the same time, digital tools can help with social integration, provide information, and offer access to support when needed. The findings show that the impact of technology is not determined solely by time spent online. More important are subjective experiences such as feelings of dependence, strategies for managing emotions, and social comparison. Gender and cultural background also shape these outcomes, indicating that psychological vulnerabilities linked to digital life are unevenly distributed across the population. Another significant finding is the growing trend in the use of online resources for self-help. Many young adults find apps, online assessments, and forums where they can interact with others helpful, especially in contexts where professional mental health services are limited. However, these digital avenues are often perceived as an inadequate substitute for personal support, highlighting the need for an integrated approach that harmonizes technology and human relationships. These insights raise crucial questions about conventional narratives about digital media, which are often simplistically viewed as binary entities, both harmful and beneficial. Instead, they suggest a deeper understanding of how technology acts as a mediator, influenced by personal, social, and systemic factors. This provides a valuable starting point for the next section, which focuses on an often overlooked group: older adults.

2.3 Mental Health among Older Adults

Much of the digital engagement and mental health debate has focused on adolescents and young adults. Still, there is a growing need to understand how these dynamics impact older populations. As digital technologies continue to play an increasingly important role in all areas of our lives, more and more older adults (over 50) are using the internet for

everything, from communicating with friends and searching for information to banking and healthcare.

This section reviews existing research on the relationship between internet use and mental health in older adults. The studies consider outcomes such as depression, perceived emotional support, and cognitive well-being, and link these to different forms of online activity. The evidence highlights both positive and negative sides of digital engagement: on the one hand, it can foster social inclusion and support mental health, while on the other, technological barriers may create difficulties and limit its benefits.

2.3.1 Internet Use, Inequality, and Mental Well-Being in Later Life⁴⁴

With the integration of the internet into nearly every aspect of modern life, older adults' participation in digital society is expected to increase. However, this participation is unequal and does not conform to the equity and equal treatment principles. This comprehensive review article summarizes the findings of numerous studies conducted in North America and Europe, examining how older adults interact with the internet, the barriers they face, and the impact of digital access on their social and emotional well-being.

The authors point out that internet use among older adults is shaped by a combination of factors such as age, education, income, gender, race, and physical ability. Together, these elements create a second-level digital divide: even when access is available, differences in skills, confidence, and purpose of use lead to unequal outcomes. Emotional stress, low digital self-efficacy, and lack of support further reduce engagement, especially among people from disadvantaged backgrounds or with limited education. The review also shows that when older adults receive support and feel confident in using the internet, the effects are mostly positive. Online activity has been linked to reduced loneliness, stronger family connections, easier access to health information, and greater independence. Still, these benefits are not automatic. They depend on the quality of digital interactions and on the availability of social support to help older adults access and navigate online environments.

⁴⁴ Hunsaker, A., & Hargittai, E. (2018). *A review of Internet use among older adults*. *New Media & Society*, 20(10), 3937-3954 (Original work published 2018).

By framing internet use as both an opportunity for mental health and a source of inequality, the article concludes that promoting digital inclusion among older adults requires more than improving infrastructure. It demands thoughtful policy, education, and user-centred design.

2.3.2 Smartphone Use and Digital Addiction among Low-Income Older Adults⁴⁵

As smartphone adoption grows among older adults, concerns have shifted from mere access to the quality and consequences of digital engagement. This study focused on how over 60 Italian people used their phones during the COVID-19 pandemic and the potential emergence of addictive behaviours.

The study involved a sample of 142 individuals living in poverty. Through surveys, researchers examined how smartphones were used, what emotional needs they fulfilled, and whether excessive use was associated with psychological distress.

The findings indicate that smartphones played an important role in helping older adults maintain social ties during lockdowns. For many, they provided a vital link to loved ones when face-to-face contact was impossible. At the same time, the study revealed patterns of compulsive use. Participants often described checking their phones repeatedly, feeling uneasy when disconnected, and struggling to switch off even during rest or social interactions. These behaviours resemble signs of digital addiction, a condition not usually associated with older adults. More frequent smartphone use was also linked to greater psychological strain, including anxiety, poor sleep, and feelings of isolation despite online contact. Such effects were especially pronounced among those with weak offline support networks, suggesting that smartphones can sometimes act as an emotional substitute while also heightening mental health risks.

The research highlights a significant paradox that has already been observed in several previously mentioned situations. While digital devices can offer a certain degree of comfort, particularly during times of crisis, excessive or unguided use can foster the emergence of unhealthy coping mechanisms. This highlights the need for a more comprehensive approach to digital inclusion that considers the availability of technology and the emotional and behavioural implications of its use among vulnerable older adults.

⁴⁵ Bertocchi, F.M., De Oliveira, A.C., Lucchetti, G. et al. *Smartphone Use, Digital Addiction and Physical and Mental Health in Community-dwelling Older Adults: a Population-based Survey.*

2.3.3 The Digital Divide and Mental Health in European Older Adults⁴⁶

As digital tools become increasingly central to everyday life, disparities in digital access, often referred to as the *Digital Divide*, have emerged as a critical issue affecting older adults across Europe. This study explores the digital divide by qualitatively examining internet use and its perceived impact on mental health among older adults in the United Kingdom, Croatia, and Poland. Drawing on semi-structured interviews and focus groups with 76 participants aged 60 and above, it offers a cross-national perspective on how digital engagement influences emotional well-being in later life.

Participants with regular internet access who felt safe using it experienced favourable mental health outcomes. Among the most significant outcomes were increased social connection, sustained intellectual stimulation, and the ability to manage daily activities independently. In contrast, digitally excluded individuals reported feelings of frustration, dependence on others, and social isolation.

Several studies show that part of the population feels at risk of being left behind in an increasingly digital society. This concern is especially strong among people who depend on essential services, such as healthcare, banking, and social interaction, that are now often available only through digital platforms. Digital exclusion involves more than just access to devices and internet connections; it also relates to trust, skills, and the emotional readiness to engage with technology. Many participants with limited digital competence avoid online services out of fear of scams, misinformation, or making mistakes. This hesitation can undermine self-esteem and reinforce generational stereotypes that associate aging with technological incompetence.

These findings suggest that the digital divide is a technological and psychological barrier that significantly impacts the autonomy and mental health of older adults. Fixing this divide requires more than just improving infrastructure: it demands a cultural shift.

2.3.4 General Conclusion

The studies described in the previous sections highlight a relationship between digital engagement and mental health in older adults. Internet use has been observed to be associated with reduced loneliness, increased autonomy, and improved emotional well-being, especially when older adults engage online with a specific purpose and receive

⁴⁶ Barreda Gutiérrez, M., Cantarero-Prieto, D., & Pascual Sáez, M. (2024). *Age, Technology, and the Digital Divide: Are They Directly Related to Mental Health Problems?*.

adequate support. However, not all aspects are positive. Challenges such as digital illiteracy, emotional dependency, and structural exclusion can create unequal opportunities and risks for vulnerable groups. Assessing the impact of digital engagement, including both benefits and potential drawbacks, involves a complex interplay of factors. The research highlights the need for more inclusive strategies that combine infrastructure with education, emotional support, and thoughtful policy. As older adults become an increasingly important part of the digital world, it is essential that they benefit from its mental health advantages, from an ethical perspective and also from a public health view.

2.4 Generational Comparison

The impact of digital technologies on mental health is not uniform, not even across age groups. Generational experiences with digital transformation are influenced by exposure, psychological factors, cultural contexts, and individual experiences. Comparing generations highlights the different ways in which young people and adults interact with technology, as well as the resulting psychological implications.

Young adults grew up in a world full of technology, making us consider them “digital natives”. Their daily lives are linked to technological devices such as smartphones, social media, online video games, and streaming platforms. The use of these elements is demonstrated to be correlated with processes of socialization, identity expression, and emotional regulation. However, this immersion can lead to phenomena such as digital fatigue, constant social comparison, FOMO (fear of missing out), and reduced self-esteem. As already highlighted in section 2.2, the digital environment, characterized by strong emotionality, can amplify the psychological fragilities already present in young people. Adults over 50, on the other hand, were born in a different world. They had to go through a whole process of adaptation. In fact, they began to familiarize themselves with digital technology later in their lives, using it with a more practical approach: to communicate, find information, or access essential services. However, many approach digital technology with reservations or out of necessity, rather than out of personal interest. As discussed in section 2.3, lacking digital skills can generate exclusion, frustration and feelings of inadequacy.

A study by Bayraktar and Kaleli-Yılmaz⁴⁷ highlighted clear generational differences in attitudes toward information and communication technologies (ICT). People aged 15 to 30 generally show greater confidence, motivation, and positive attitudes toward ICT use. In contrast, many adults over 46 report feelings of insecurity, anxiety, and low perceived usefulness, which often lead them to avoid or limit their use of digital tools. This generational divide is not only evident in digital skills but also carries important psychological implications. Older adults may feel excluded or dependent on others when accessing digital services such as healthcare or public administration, and this sense of exclusion can directly affect psychological well-being, particularly among those who are socially isolated or face cognitive difficulties.

An aspect often not taken into consideration in the literature is the way the psychological effects of digital use are measured. Many psychological studies rely on linear correlations to assess the link between time spent online and mental well-being. Twenge and Hamilton⁴⁸ point out that this methodology may underestimate the actual practical relevance of the phenomenon. Using more public health-oriented measures, such as relative risk, the same data show far more worrying results. For example, adolescents who play video games for more than four hours a day are three times more likely to exhibit antisocial behaviour and twice as likely to develop externalizing problems compared to non-users. Even if associated with statistically "low" r values, these effects have strong clinical and social relevance, particularly among the most exposed youth. Looking at the methodology is crucial for correctly interpreting risks across age groups. Young people, immersed more intensely in digital technology, often face underestimated psychological risks. Though less exposed, mature adults face issues related to digital exclusion and technological learning stress.

Generational differences in digital technology use relate not only to how much time is spent online, but also to the quality of the experience, the purposes of use, and the personal context in which it occurs. Younger adults tend to be highly immersed in digital environments yet may be more emotionally vulnerable, while adults over 50 are often more hesitant with technology and face psychological challenges linked to structural and

⁴⁷ Kubiak, M. (2013). *The Comparison of Different Age Groups on the Attitudes toward and the Use of ICT. Educational Sciences: Theory and Practice*, <https://files.eric.ed.gov/fulltext/EJ1017271.pdf>.

⁴⁸ Jean M. Twenge, Jessica L. Hamilton, *Linear correlation is insufficient as the sole measure of associations: The case of technology use and mental health*, *Acta Psychologica*, 2022, <https://doi.org/10.1016/j.actpsy.2022.103696>.

cultural barriers. These differences point to the need for tailored strategies to support mental health. For younger people, preventive action through digital well-being education is key, whereas for older adults, policies should emphasize digital inclusion, training, and hands-on support to help reduce anxiety, isolation, and feelings of inadequacy.

Chapter III – Digital Use and Mental Health: A Statistical Approach

After reviewing the existing literature and key theoretical frameworks on the relationship between digital transformation and mental health, this chapter introduces the empirical part of the research. The aim is to investigate whether and to what extent the use of information and communication technologies is associated with the psychological well-being of individuals over 50 in Europe. In particular, I will focus on the latest available data to examine whether the use of information and communication technologies is associated with mental health and well-being among individuals aged 50 and over in Europe. The chapter opens with an introduction to the SHARE dataset and survey methodology to set the context for the analysis. It outlines how the data were collected and what they contain, with particular attention to the construction of key indicators. It then defines the analytical framework, presenting the main variables and the regression strategy. The section describes the mental health measures and ICT use variables considered in the study and explains the use of Ordinary Least Squares regression to estimate the association between digital technology use and mental well-being.

3.1 Introduction to the SHARE Dataset

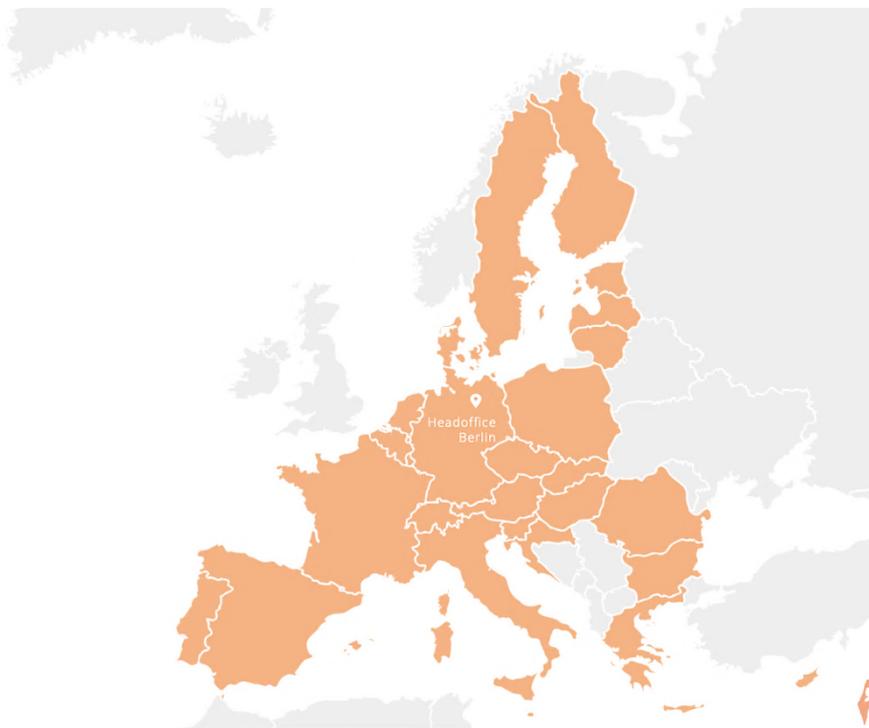
The Survey of Health, Ageing and Retirement in Europe (SHARE) is one of the most comprehensive research infrastructures for studying aging in Europe. It is a multidisciplinary, transnational, and longitudinal survey that collects micro-individual data on the health, economic status, social networks, and family of people aged 50 and over. SHARE provides a unique resource for cross-national and longitudinal research on aging in Europe, offering data on health, socioeconomic status, and social networks of older individuals. By using this database, the study benefits from comparable information gathered from tens of thousands of elderly, ensuring that the analysis rests on robust and relevant evidence base.

The SHARE project, active since 2004, was initially funded by the European Commission under the 6th Framework Programme for Research⁴⁹ and subsequently recognized as a strategic research infrastructure within the roadmap on the European Strategy Forum on

⁴⁹ It is a programme aimed to create a genuine European Research Area by strengthening and integrating it, <https://cordis.europa.eu/programme/id/FP6>.

Research Infrastructures⁵⁰. Since 2011, SHARE-ERIC (European Research Infrastructure Consortium) has officially coordinated the project, headquartered in Berlin. Since its creation, SHARE has aimed to provide a solid empirical basis for analysing the aging of the European population and assessing the impact of public policies over time. It integrates a wide range of disciplines, from sociology to medicine, from economics to demography. It enables the comparative analysis of individual health trajectories, work, retirement, and family conditions from a multidimensional and longitudinal perspective. The infrastructure covers more than 140,000 individuals across 28 countries, including all continental EU member states and Israel, and provides harmonized and internationally comparable data.

Figure 6 - Countries participating in the SHARE project



Source: <https://share-eric.eu>

SHARE is aligned with similar international studies, such as the Health and Retirement Study (HRS) in the United States and the ELSA in the United Kingdom. It has inspired similar initiatives in Japan, China, Brazil, Korea, and India. SHARE represents a crucial component of a growing global Infrastructure for aging research provides valuable comparative insights. The project was established to fill an important gap in cross-

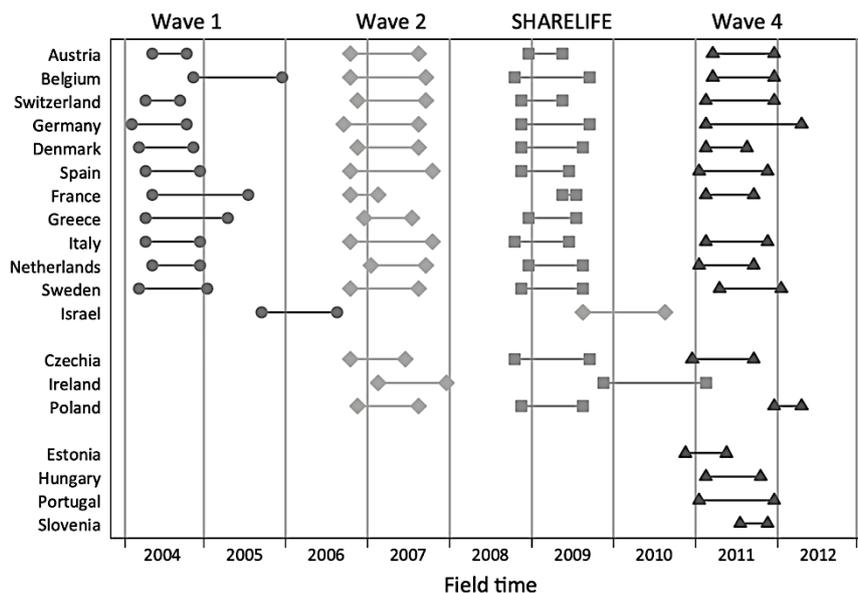
⁵⁰ESFRI supports a coherent and strategy-led approach to policy-making on research infrastructures in Europe, and facilitates multilateral initiatives leading to the better use and development of research infrastructures, at EU and international level, <https://www.esfri.eu>.

nationally comparable microdata on older populations. It allows researchers to study how cultural, institutional, and policy contexts shape the experience of aging and its outcomes. Beyond academic research, SHARE data are widely used to inform evidence-based policymaking in areas such as pensions, healthcare, and social protection, helping governments respond to the challenges of demographic aging. In this way, SHARE not only advances scientific knowledge but also plays a direct role in public policy discussions across Europe.

3.1.1 Survey Design and Methodological Framework

The SHARE project is structured as a longitudinal panel survey, meaning that over 50 individuals are interviewed repeatedly over time, allowing for the observation of their life trajectories in relation to health, economic, and social factors. Each survey cycle is called a “wave” and represents a new data collection from the same sample with the addition of new participants, if necessary, to maintain representativeness. Numerous waves have been conducted since 2004, each with its own questionnaire and modules adapted to current research needs. The waves allow cross-sectional analyses but also longitudinal analyses, such as the study of individual changes over time. The figure below shows when data was collected in different countries during the first four waves of SHARE, emphasizing the gradual addition of new member states and the survey's longitudinal design.

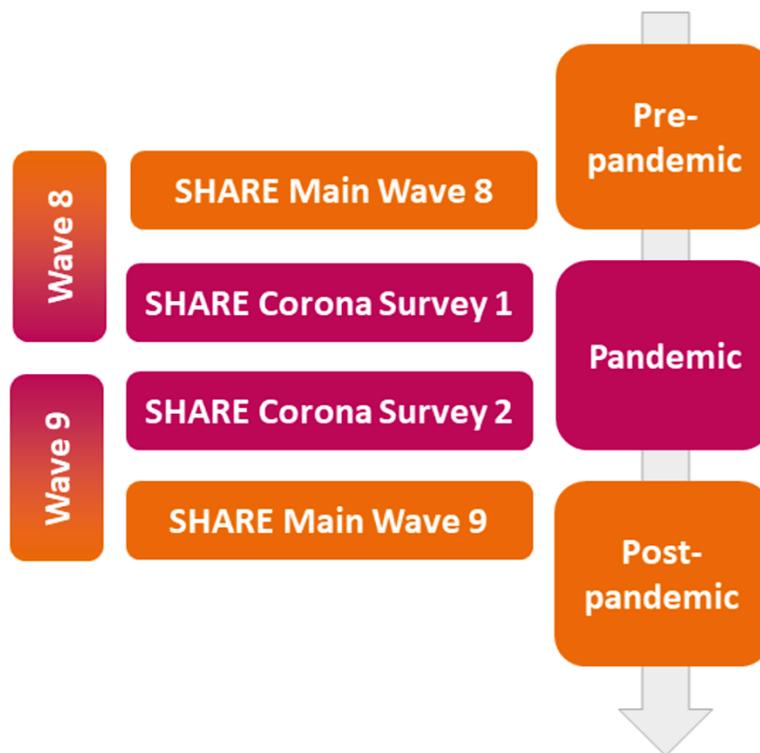
Figure 7 - Country Wave Field Time Overview



Source: Börsch-Supan et al., 2013, Data Resource Profile

The surveys are mainly conducted through face-to-face interviews using the Computer Assisted Personal Interviewing (CAPI) method. In practice, this means that interviewers use a laptop with a standardized questionnaire and a programme that ensures the sequence of questions is applied correctly, automatically skipping those irrelevant to a given respondent. This procedure reduces the risk of mistakes, guarantees that interviews are comparable across time and countries, and allows for integrating additional elements such as cognitive tasks or health tests. In some ways, the CAPI method is supplemented with objective tests (e.g., memory tests, grip strength) and the collection of biometric and administrative data, further enriching the database and strengthening its reliability for longitudinal and cross-national analyses. During the COVID-19 pandemic, parts of the fieldwork were instead carried out through Computer-Aided Telephone Interviewing (CATI), which allowed the panel to continue while maintaining data harmonization, even though the physical components. Figure 8 illustrates how SHARE modified its fieldwork amid the COVID-19 pandemic by adding two dedicated Corona surveys. The results were incorporated into Wave 8 and Wave 9, allowing the study to track both pandemic-related and post-pandemic developments.

Figure 8 - Data Collection Scheme



Source: Bergmann M. et al., *SHARE Wave 9 Methodology*

The panel design allows us to track the same individuals over time, observing how their lives, health, jobs, and social conditions change. The study is very large, with over 140,000 people from 28 countries, making it highly reliable and representative of Europe overall. The questionnaires are standardized across participating countries and waves. They cover a wide range of thematic areas, including:

- Physical and mental health status
- Use of health services
- Economic and financial conditions
- Work, pensions, and employment
- Family relationships and social networks
- Use of digital technologies (in the most recent waves)

Thanks to this methodological structure, SHARE represents a particularly suitable tool for studying aging from a dynamic perspective, highlighting differences between countries and over time. The survey uses internationally valid scales, whose measures are available in multiple waves and therefore useful for longitudinal analyses and comparisons over time.

Two of the most commonly used measures of mental health and well-being in SHARE are the EURO-D depression scale and the CASP-12 quality of life index, both standardized instruments included in the survey. The EURO-D consists of 12 binary (yes/no) items that capture common symptoms of depression, such as sadness, sleep problems, fatigue, or lack of concentration. It has been validated in different contexts of SHARE and is recognized as a reliable tool for measuring depressive symptoms among older adults in Europe. Recent evidence confirms that EURO-D is comparable across countries and cultural contexts, ensuring that differences in scores reflect actual variations in mental health rather than measurement bias.⁵¹ In contrast, the CASP-12 index is a subjective quality of life scale, based on four dimensions: Control, Autonomy, Personal Accomplishment, and Enjoyment. It includes 12 items with Likert-scale⁵² responses. Unlike EURO-D, which focuses on negative affect and depressive symptoms, CASP-12 provides a broader picture of quality of life in later years. It focuses on emphasizing

⁵¹ Maskileyson, D., Seddig, D., & Davidov, E. (2021). *The EURO-D measure of depressive symptoms in the aging population: comparability across European countries and Israel*. Retrieved from www.frontiersin.org/political-science/1.

⁵² A likert scale, or rating system, is a measurement method used in research to evaluate attitudes, opinions and perceptions.

opportunities, satisfaction, and personal fulfilment. Studies using SHARE have demonstrated that CASP-12 is reliable and valid across different age groups, including the “oldest-old” (80+).⁵³

Together, these two indicators allow researchers to observe the negative and positive aspects of mental health in older people. Their joint use in this thesis provides a balanced framework for evaluating the association between ICT use and mental health among the over-50 population in Europe. Self-perceived health, social connectedness, and loneliness are additional SHARE indicators that are particularly relevant for understanding mental well-being in older age.

Self-perceived health is measured with a single question asking respondents to rate their overall health. Despite its simplicity, this item is well-established in epidemiological studies as a strong predictor of morbidity and mortality. Equally significant are social connectedness indicators. SHARE gathers comprehensive data on respondents’ social networks, including the size, contact frequency, and emotional closeness of key relationships. From these items, indices of social connectedness and loneliness can be derived, capturing both the objective and subjective dimensions of social integration. Evidence indicates that loneliness is a major factor influencing depression and quality of life in older adults: those who report weaker social networks or higher loneliness levels tend to have noticeably poorer mental health outcomes.⁵⁴ Therefore, these measures complement EURO-D and CASP-12 by assessing mental health through individual symptoms or subjective well-being and within the broader social context in which older adults live. In its most recent waves, SHARE has added questions on the use of digital technologies, including internet access, frequency and purposes of use, and self-assessed computer skills. These measures make it possible to study the digital divide among older Europeans, which is known to differ across demographic groups and countries. Previous research also shows that digital literacy is positively related to both cognitive abilities and mental health.

To provide context for the longitudinal structure of the SHARE project and understand how content has evolved across different survey cycles, the following table offers a brief

⁵³ Oliver, A., Sentandreu-Mañó, T., Tomás, J. M., Fernández, I., & Sancho, P. (2021). *Quality of Life in European Older Adults of SHARE Wave 7: Comparing the Old and the Oldest-Old*. *Journal of Clinical Medicine*.

⁵⁴ André Hajek, Hans-Helmut König, *Which factors contribute to loneliness among older Europeans? Findings from the Survey of Health, Ageing and Retirement in Europe: Determinants of loneliness*, *Archives of Gerontology and Geriatrics*.

overview of the main waves conducted so far. It shows the year of data collection and the characteristics of each wave, paying particular attention to Waves 9, which will be used in this study to analyze changes in the post-pandemic period.

Table 2 - Overview of the main waves of the SHARE project

<i>Wave</i>	<i>Year of data collection</i>	<i>Main features</i>
Wave 1	2004	Focus on health, work, economic and family conditions
Wave 2	2006 – 2007	Introduction to work and family history
Wave 3	2008 – 2009	“SHARELIFE” module, retrospective data collection on life events
Wave 4	2010 – 2011	Expanding physical and cognitive testing; objective measures of health
Wave 5	2013	Modules on retirement, access to healthcare and subjective well-being
Wave 6	2015	Connection with administrative data and expansion of the financial sphere
Wave 7	2017	<i>Pre-pandemic focus; presence of modules on ICT and CASP-12</i>
Wave 8	2019 – 2020	Interrupted by the pandemic; integration with the SHARELIFE module
Wave 9	2021 – 2022	<i>Post-pandemic modules, social isolation and technology use</i>

Source: Own processing based on official SHARE-ERIC data and documentation, <https://share-eric.eu>

The following subsections describe the dataset in more detail, including its purpose and methodological design. Specific attention is paid to mental health variables, ICT use, and key demographic characteristics relevant to the analysis. This detailed overview of the dataset and variables lays the groundwork for the subsequent analytical framework and the regression models presented in the following chapters.

3.1.2 Descriptions of Data Used

Before delving into the model construction, it’s important to understand how the datasets used in this analysis were created. This is essential to ensure reliability and comparability of the results. Since this study examines the link between ICT use and mental health among adults aged 50 and over, the analysis draws on data from Wave 9 (2021–2022) of the SHARE survey. This wave was chosen because it contains comparable measures of both digital behaviour and psychological well-being. Its timing also makes it relevant, as it situates the analysis in the post-pandemic context.

Wave 9 not only reintroduced the full SHARE questionnaire after the disruptions caused by COVID-19 but also added specific modules designed to capture the growing role of digital technologies in daily life. In particular, the Wave 9 questionnaire includes several modules directly relevant to this research:

- *Use of information and communication technologies (ICT)*: Internet access, frequency of use, familiarity with digital tools, and specific purposes.
- *Mental health*: EURO-D depression scale and the CASP-12 quality of life index
- *Self-rated health and life satisfaction*
- *Social networks and isolation*
- *Demographics*: Age, gender, education, occupation, income, and household composition

Wave 9 was carried out in two separate phases because of the restrictions created by the COVID-19 pandemic. The first was the Share Corona Survey 2, a short telephone interview (CATI) fielded in early 2021 that concentrated on pandemic-related issues. The second phase, which provides the main empirical basis for this study, marked the return to face-to-face CAPI interviews conducted between October 2021 and October 2022. In this stage, the full SHARE questionnaire was reinstated, making it possible to collect harmonized and comparable information on mental health, digital engagement, and key sociodemographic variables. Despite the difficulties caused by the pandemic, data quality was maintained through centralized coordination by SHARE-ERIC, which ensured standardized interviewer training, careful translation, and consistent administration of the questionnaire.

The Wave 9 target population covers people aged 50 and over in 2019 who were still alive in 2021 and living in one of the SHARE countries at the time of the survey. This definition makes it possible to draw valid inferences about the 50+ population in 2021, which is when most interviews took place. Certain groups are excluded, such as individuals who were incarcerated, hospitalized, or living abroad during the entire survey period, those unable to speak the national language, or cases lost due to errors in the sampling frame (for example, non-existent addresses or vacant dwellings) or because the person had moved without leaving a forwarding address. Spouses and partners of respondents aged 50 and above are included regardless of their own age, since information at the household level is crucial for many SHARE variables. To ensure transparency and analytical robustness, the SHARE dataset includes a set of technical

variables that document the sampling structure applied in each country and wave. These are stored in the *gv_weights module* and are essential for conducting weighted and stratified analyses that account for the survey’s complex sample structure.

Table 3 - Sampling Design Variables

Variable	Description	Unit of analysis
<i>subsample</i>	Subsamples within country	Household & individual
<i>psu</i>	Primary sampling unit	Household & individual
<i>ssu</i>	Secondary sampling unit	Household & individual
<i>stratum1</i>	First stratum	Household & individual
<i>stratum2</i>	Second stratum	Household & individual
<i>nuts</i>	Regional classification unit	Household & individual

Source: Bergmann M. et al., *SHARE Wave 9 Methodology*

Table 3 summarizes the main sample design variables available in the Wave 9 dataset. These variables allow for the identification of the sample's multilevel structure (e.g., territorial subdivisions, and primary and secondary sampling units) and can be used at both the individual and household levels. The survey’s use of multiple strata and sampling units reflects its complex multilevel design and helps improve the precision of statistical analysis. The variables *psu* and *ssu* identify the primary and secondary sampling units, which are important for correctly modelling dependencies in the data. The variables *stratum1* and *stratum2* capture the stratification levels that ensure representativeness within each country. Finally, the *NUTS*⁵⁵ variable links each case to a standardized geographical area under the European *NUTS* classification, making cross-country and regional comparisons possible.

After merging the relevant modules, the final dataset includes 69,447 individuals. The primary explanatory variable is ICT use, indicated by a dummy for internet use in the past 7 days, alongside additional questions about frequency, purposes, and self-assessed computer skills. The analysis also accounts for various covariates such as age, gender, education years, chronic conditions, employment, social connectedness, and personality traits. These indicators form the central variables in the regression analysis discussed

⁵⁵ **Nomenclature of Territorial Units for Statistics**, a geocode standard for referencing the administrative divisions of countries for statistical.

later, facilitating a thorough examination of the relationship between ICT use and mental health among Europeans aged 50 and above.

3.2 Analytical Framework

Now that the SHARE dataset has been presented and the relevant variables identified, this section illustrates the statistical approach adopted to investigate the link between digital engagement and mental health among individuals aged 50+ in Europe.

Building on the structure and indicators outlined in the previous section, the empirical analysis uses a regression-based approach to measure the link between ICT use and psychological well-being. The strategy involves estimating a series of multivariate models that include key sociodemographic and health-related controls. The main technique applied is ordinary least squares OLS regression, which provides a straightforward and interpretable way to identify significant predictors of mental health outcomes. The following subsection provides an overview of the theoretical underpinnings and assumptions of OLS regression, which form the basis of the empirical models presented in Chapter 4.

3.2.1 Theoretical Background: Ordinary Least Squares (OLS)

Ordinary least squares OLS regression is one of the most fundamental and widely used estimation techniques in statistical analysis and econometrics. This technique is used to model the linear relationship between a dependent variable and one or more independent variables, with the aim of explaining the influence of the explanatory variables on the outcome of interest. In its basic form, OLS estimates the coefficients of a linear regression by minimizing the sum of squared residuals, which are the gaps between the observed values and the values predicted by the model.

For a multiple linear regression with p predictors and n observations, the OLS regression model is the following:

$$Y_i = \beta_0 + \sum_{j=1}^p \beta_j X_{ij} + \varepsilon_i$$

Where Y_i represents the dependent variable for observation i , while X_{ij} indicates the value of the j th explanatory variable for the same observation. The term β_0 is the intercept of the model, that is, the predicted value of Y when all explanatory variables are equal to

zero. Each β_j represents the coefficient associated with the j th independent variable, indicating the marginal effect of a one-unit change in X_j on the dependent variable Y , holding all other variables constant. The error term ε_i captures all the variability in Y that is not explained by the included independent variables and is assumed to be distributed with a mean of zero, constant variance⁵⁶ and independence across observations.

The OLS regression is based on a series of fundamental assumptions that must be met for the estimated coefficients to be unbiased, consistent and efficient.

The first key assumption is *linearity in the parameters*. This means that the dependent variable can be expressed as a linear function of the coefficients, even if the independent variables are not themselves linear. Another important assumption is *the independence of errors*. It requires that the error terms for different observations are not correlated with one another. Additionally, OLS assumes *homoscedasticity*, meaning the variance of the error terms is constant across all observations. If this assumption is violated, while the coefficient estimates remain unbiased, their standard errors become unreliable, potentially leading to incorrect conclusions about statistical significance. The model also requires the *absence of perfect multicollinearity*, where no independent variable can be perfectly predicted by a linear combination of others. A high degree of correlation can inflate standard errors and make it difficult to isolate the individual effects of variables. Finally, for valid hypothesis testing and confidence intervals, OLS assumes that the *errors are normally distributed*. The estimates themselves are still valid even if this assumption is not met.

The OLS model is widely used for its many strengths. Its simplicity and ease of interpretation make it a favourite among analysts and researchers. OLS is also versatile, allowing for extensions to more complex models like multiple regression and those including interaction terms. This method has strong analytical tractability, with well-established statistical properties that guarantee the Best Linear Unbiased Estimator (BLUE). OLS offers a rich set of diagnostic tools and goodness-of-fit measures, such as R-squared and F-tests, which help in assessing the model's performance and validating its assumptions. These strengths, along with its ability to perform robust hypothesis testing, make OLS a powerful foundational tool in statistical analysis.

⁵⁶ Homoskedasticity.

Despite its many advantages, OLS regression has also limitations that must be considered. It's highly sensitive to outliers. A few extreme data points can drastically skew the regression line and, consequently, the coefficient estimates. Multicollinearity, or high correlation among independent variables, is another significant issue. It inflates the variance of coefficient estimates, making them unstable and difficult to interpret. Heteroscedasticity, the violation of the constant error variance assumption, leads to inefficient estimates and biased standard errors, potentially invalidating hypothesis tests. A major limitation is omitted variable bias, which occurs when a relevant variable is left out of the model, causing the remaining coefficients to be biased if the omitted variable is correlated with both the dependent and independent variables. The issue of endogeneity is also critical. If an explanatory variable is correlated with the error term, due to reverse causality, simultaneous equations, or measurement error, the OLS estimator becomes biased and inconsistent. OLS operates under a strict linearity assumption, which may fail to capture the often nonlinear and complex relationships found in real-world data.

OLS regression is appropriate when the dependent variable is continuous, the relationship is assumed to be linear, and the main objective is to interpret marginal effects. In this thesis it represents the natural starting point, since the key outcome, mental well-being indicators and depression scales, are measured on continuous variables. This approach offers a clear way to estimate both the direction and the size of the association between ICT use and mental health in the target population. At the same time, OLS has limits: it is sensitive to outliers and may be biased if relevant variables are not included. For this reason, it is used as the baseline model, while additional diagnostic checks, extensions, and robustness analyses are employed to reinforce the results, explore heterogeneity, and move closer to causal interpretation.

3.2.2 Empirical Strategy

Once more, let's restate the research question for clarity:

Does the use of digital technology influence the mental health and well-being of individuals aged 50 and older, and to what extent?

The analytical approach is based on Ordinary Least Squares regression models, which estimate the association between a binary ICT use indicator and selected psychological

well-being measures, EURO-D and CASP-12. The empirical design proceeds step by step:

1. **Bivariate models** analyse the raw relationship between ICT use and mental health outcomes.
2. **Multivariate models** gradually incorporate demographic (age, gender, education), health-related (chronic conditions, self-perceived health), and social variables (loneliness, social networks).
3. **Interaction terms** assess whether the relationship differs across subgroups, such as gender, age, or digital skills.
4. **Stratified models** perform individual regressions for different groups, offering a more detailed perspective on heterogeneity.
5. **Robustness checks** examine the sensitivity of the results using alternative outcome measures, various specifications of ICT use, and survey weights.

Using a stepwise approach makes the analysis more transparent, as it shows how the effect of ICT changes once different sets of controls are added. It also highlights which groups of variables play the biggest role in shaping the relationship.

Interaction terms and stratified models are important for spotting possible digital divides, since the benefits of ICT may differ between men and women, across age groups, or between people with high and low digital skills. Robustness checks help ensure that the results are not driven by the way outcomes are defined or by imbalances in the sample.

This strategy is consistent with established practices in applied econometrics and social science research. Incremental models are often presented to show how the coefficient of interest changes with the inclusion of additional controls, thereby improving interpretability and addressing potential confounding.⁵⁷

Similar hierarchical regression approaches are widely used in epidemiology and psychology, where reporting unadjusted and adjusted estimates is considered the best practice for transparency. By presenting results in this manner, the analysis isolates the net effect of ICT use on mental health but also clarifies how much of the observed association is explained by demographic, health, and social variables. At the same time, it is essential to distinguish between automatic stepwise selection procedures, which rely on statistical algorithms to add or drop variables based on significance tests, and the

⁵⁷ Wooldridge, J. M. (2019). *Introductory econometrics: A modern approach* (7th ed.). Cengage Learning.

theory-driven incremental strategy adopted here. As emphasized by Mundry and Nunn⁵⁸, automated stepwise fitting can inflate Type I errors and produce unstable models, effectively “turning noise into signal pollution”. In contrast, introducing groups of covariates in a pre-specified order, grounded in theory and prior evidence, enhances transparency and allows for a more straightforward interpretation of how demographic, health, and social factors influence the association under study.

The regression models can be written in the usual linear form, which helps to show how ICT use relates to the outcomes once different sets of control variables are added step by step. The general regression model can be expressed as:

$$Y_i = \beta_0 + \beta_1 ICT_i + \beta_2 X_i + \varepsilon_i$$

Where:

- Y_i indicates the outcome variable that represents the individual’s mental health status
- ICT_i is the binary variable indicating whether the individual uses digital technologies
- X_i is the vector of control variables
- ε_i is the error term that captures unobserved factors

This specification provides the basis for all estimated models. In practice, X_i will be expanded step by step, beginning with basic demographic controls and gradually including health and social dimensions. By comparing the coefficients ICT_i across different specifications, it is possible to assess both the direct association with mental health and the extent to which this relationship is mediated by individual characteristics and contextual factors.

⁵⁸ Mundry, Roger and Charles Nunn. 2009. *Stepwise model fitting and statistical inference: turning noise into signal pollution*. *American Naturalist*.

Chapter IV – Empirical Results

This chapter presents the main results of the analysis on ICT use and the psychological well-being of individuals over 50 in Europe. Based on the methodological framework and dataset introduced in the previous chapter, the analysis opens with descriptive statistics to show how the main variables are distributed in the sample. It then moves to regression models, starting with simple bivariate estimates and progressively adding demographic, health, and social controls. Then, the following sections explore subgroup differences through interaction terms and stratified models by gender, age, and digital skills. Finally, the chapter closes with robustness checks to test how stable the findings are.

The structured approach answers the main research question, and it allows a deeper understanding of the social and health factors influencing digital inclusion and psychological well-being in older adults.

4.1 Descriptive Statistics

It is crucial to provide a descriptive overview of the study's main variables before conducting the regression analysis. The sample includes individuals aged 50 and over from Wave 9 of the SHARE Dataset, which covers 27 European countries plus Israel. The key variables used in the empirical model are:

- *Dependent variables:* mental well-being indicators
 - **EURO-D score**, which measures depressive symptoms
 - **CASP index**, which measures quality of life through the parameters of control, autonomy, self-actualization, and pleasure
- *Independent variable:* A binary indicator of ICT use, derived from self-reported use of the internet or a computer in the past 7 days
- *Control variables:*
 - Age
 - Gender
 - Years of education, as a proxy for digital literacy
 - Physical health
 - Measures of social connectedness

Given the focus on psychological well-being and the use of digital technology, the *gv_dn* file was selected as the base dataset. It contains demographic information, such as birth

year, gender, and years of education. It also has the unique personal identifier (mergeid) consistently available across SHARE modules, which lets us enhance the analysis by including a broader range of explanatory and control variables. Building on this core file, I merged additional modules from the same wave to connect responses across SHARE datasets. These included mental health outcomes (*gy_health*), ICT use (*it/dropoff*), social networks (*sn*), and health information (*hc*). Moreover, the module *gy_mh* was employed to construct a composite PCA based indicator of mental health. In this way, demographic characteristics, digital behaviour, physical health, and social ties were combined into a single, harmonized dataset ready for regression analysis.

Table 4 presents the summary statistics for the main variables: the number of valid responses, the mean values, the standard deviation, and the minimum and maximum values. These data provide a snapshot of the sample distribution and help assess the variability of responses.

Table 4 - Summary Statistics of Key Variables (Wave 9)

Variable	Obs	Mean	Std. Dev.	Min	Max
EURO-D , <i>Depression Score</i>	66,318	2.45	2.28	0	12
CASP , <i>Well-being Index</i>	65,347	37.43	6.20	12	48
Age	68,933	69.51	9.67	50	105
Years of Education	15,164	11.66	4.01	0	25
Household Income	45,325	2.11e+09	4.60e+11	0.0026	1.00e+14

Source: Author's calculations on STATA based on Wave 9 data from SHARE Data, Release 9.0.0

After cleaning the data for invalid values, the mean of the *EURO-D* variable in the sample is 2.45, with a standard deviation of 2.28, indicating that respondents exhibit moderate depressive symptoms. *CASP-12* scores average around 37.43, with a low dispersion, suggesting that most respondents report a reasonably high level of life satisfaction.

The respondents are, on average, about 69 years old (SD = 9.67). Most therefore fall in the range between roughly 59 and 79 years, which fits well with the study's aim of focusing on people aged 50 and above. The variable *year of education* has a mean of 11.66 years, based on a subsample of 15,164 individuals. The reduced number of observations reflects the longitudinal design of SHARE, where background characteristics such as education are not re-collected in every wave if already reported in

previous interviews. The standard deviation of 4.01 indicates considerable variability, suggesting the presence of low and high education levels within the population.

Household income exhibits extreme values, with a mean of approximately €2 billion and a very high standard deviation, due to outliers. Scientific notation (e+09) indicates that the mean is in billions and that the dispersion is large, a phenomenon typical of financial data. For these reasons, household income will be excluded from the analysis due to data irregularities and high skewness.

These descriptive statistics confirm the diversity of the sample and justify the inclusion of control variables in the regression model. To better understand the influence of ICT use on mental well-being, we need to explore possible differences between Internet users and non-users. So, I divided the sample based on responses to the question, “Have you used the Internet in the last 7 days?”.

Table 5 reports the means and standard deviation of the primary outcome and control variables, separated by those who answered *yes* and those who answered *no* to ICT use. This allows us to observe systematic differences in mental well-being, age, education, and other relevant characteristics between the two groups.

Table 5 - Summary Statistics by ICT Use (Wave 9)

Variable	Internet Users	Std. Dev.	Non-Users	Std. Dev.
EURO-D	2.15	2.04	2.96	2.56
CASP-12	39.04	5.48	34.76	6.39
Age	66.37	8.36	74.50	9.49
Chronic Conditions Index	1.68	1.52	2.34	1.77
Self-Perceived Health (1–5)	2.98	0.99	3.61	0.97
Computer skills	3.17	1.18	5.35	0.97
Loneliness Scale	3.79	1.23	4.37	1.64
Years of Education	12.79	3.85	9.44	3.35

Source: Author’s calculations in STATA based on Wave 9 data from SHARE Data, Release 9.0.0

Notes: For computer skills, lower values indicate greater digital competence. For chronic conditions, self-perceived health, and loneliness, lower values indicate better outcomes.

The differences between ICT users and non-users are statistically and substantially significant. On average, ICT users report fewer depressive symptoms, their EURO-D

mean is 2.15 compared to 2.96 among non-users. They also have a higher score higher on quality of life, their CASP-12 is 39.04 versus 34.76 for non-users.

ICT users are also younger, with an average age of 66 years compared to 74 for non-users. They live with fewer chronic health problems and give a more positive assessment of their own health. Social and emotional indicators point in the same direction: users tend to feel less lonely and are more likely to describe themselves as being in good health.

When I first started the analysis, the expectation was to find the opposite. The assumption was that digital technologies might have a negative effect on elderly people's mental health. It was a surprise when these initial descriptive comparisons suggested the contrary. These findings highlighted the need to move toward multivariate analysis to verify whether the observed differences are truly attributable to ICT use or other factors instead.

4.2 Regression Analysis

This section reports the empirical findings from regression models that examine the link between information and communication technologies use and mental well-being among individuals aged 50 and older. The descriptive statistics already highlighted systematic differences between users and non-users regarding age, health, education, and social connectedness.

The results are presented step-by-step. First, I begin with bivariate regressions. Then, progressively I add demographic, health, and social controls in multivariate models. Next, the analysis continues with exploring interaction effects and stratified models to investigate subgroup differences. Finally, I run robustness checks to evaluate the findings' consistency.

4.2.1 Bivariate Regression – Unadjusted Relationship

The bivariate regressions evaluate the raw relationship between ICT use and the two selected leading indicators of mental well-being: the EURO-D depression score and the CASP-12 quality of life index. As previously mentioned, the EURO-D is a continuous index ranging from 0 to 12 that assesses depressive symptoms: the higher the score, the more symptoms a person exhibits. The CASP index measures quality of life, with scores spanning from 12 to 48; higher scores indicate a better quality of life. The independent

variable *ict_user* is a binary variable: 1 means the person used the internet in the past seven days, and 0 means they didn't.

The general form of the estimated model is expressed as:

$$Y_i = \beta_0 + \beta_1 ICTuse_i + \varepsilon_i$$

Where Y_i is the outcome of interest, β_0 the expected value of Y for non-users, and β_1 captures the average difference in well-being between users and non-users.

The first set of results refers to the EURO-D scale.

Table 6 - Regression Output: EURO-D as the Dependent Variable

Linear regression	Number of obs	=	66,318
	F(1, 66316)	=	1795.61
	Prob > F	=	0.0000
	R-squared	=	0.0297
	Root MSE	=	2.244

eurod	Robust				
	Coefficient	std. err.	t	P> t	[95% conf. interval]
ict_user	-.8141779	.0192138	-42.37	0.000	-.8518369 - .7765188
_cons	2.964843	.0164452	180.29	0.000	2.93261 2.997076

Source: Author's calculations in Stata based on Wave 9 data from SHARE Data, Release 9.0.0

The regression results reported above show that *ICT_use* is negatively associated with depressive symptoms.

$$EUROD_i = 2.96 - 0.81 * ICTuse_i$$

The coefficient of ICT use is -0.81. This result suggests that, on average, people who use the internet report 0.81 fewer depressive symptoms on the EURO-D scale than those who don't. This estimate is highly statistically significant ($p < 0.001$), with a tight 95% confidence interval. Although the coefficient may appear modest, it represents about 7% of the EURO-D scale range. In the context of mental health research, such reduction is considered meaningful as even small changes in depressive symptoms can have important implications at the population level.

The intercept of 2.96 represents the expected EURO-D score for non-ICT users. In other words, if someone is a non-user, their predicted level of depressive symptoms is about 2.96. If we take in consideration ICT use, the model subtracts 0.81 from this value. This

gives an estimated average of roughly 2.15 for internet users, showing that their predicted symptom level is lower than that of non-users.

The results of this simple model are significant, even though the R-squared is relatively low, 0.0297. This means that ICT use alone only explains about 3% of the variation in depressive symptoms. It's a small piece of the puzzle, which makes sense since countless other factors influence a person's mental health.

Turning to the CASP-12 Index, the estimates are shown in Table 7.

Table 7 - Regression Output: CASP-12 as the Dependent Variable

Linear regression	Number of obs	=	65,347
	F(1, 65345)	=	7608.79
	Prob > F	=	0.0000
	R-squared	=	0.1123
	Root MSE	=	5.8447

casp	Robust				
	Coefficient	std. err.	t	P> t	[95% conf. interval]
ict_user	4.319255	.0495166	87.23	0.000	4.222203 4.416308
_cons	34.6919	.0415362	835.22	0.000	34.61049 34.77331

Source: Author's calculations in Stata based on Wave 9 data from SHARE Data, Release 9.0.0

The regression model for the CASP-12 index can be expressed as:

$$CASP_i = 34.69 + 4.32 * ICTuse_i$$

The coefficient for ICT use is + 4.32. On average, people who used the internet in the last seven days reported a higher quality of life score than non-users. Since a higher CASP means a better quality of life, this result strongly suggests a positive link between digital engagement and well-being. The estimate is statistically significant at the 1% level ($p < 0.001$) with a very narrow confidence interval, indicating that the effect is substantial and precisely measured.

The model's intercept, 34.69, can be interpreted as the expected CASP score for those who don't use the internet. Adding the effect of ICT use (+ 4.32), the predicted score for users is approximately 39.01, corresponding to the previously reported descriptive statistics.

The R-squared value of 0.1123 is interesting. ICT use alone explains about 11% of the variation in quality-of-life scores. For a single binary variable, that's a relatively strong

result, suggesting that internet use plays a meaningful role in the subjective well-being of older adults.

Taken together, the bivariate regressions suggest a strong and consistent association. ICT users report fewer depressive symptoms and a higher quality of life compared to non-users. The two models are based on slightly different sample sizes: 66,318 individuals for EURO-D and 65,347 for CASP-12. This difference reflects that not all respondents provided valid answers for both mental health indicators. Despite this variation, the explanatory power remains comparable across the two models, more modest for EURO-D but more substantial for CASP-12, both results point in the same direction. The following section introduces stepwise controls to test whether these associations persist once potential confounders are considered.

4.2.2 Multivariate Regression – EURO-D Models with Controls

The bivariate regressions painted a very clear picture. At first sight, this suggests that ICT use alone is a powerful driver of better mental health. *But is the difference really due to digital engagement itself?* To answer this question, I estimated multivariate regression models that progressively add demographic, health, and social controls. Specifically, these include age, gender, years of education, the number of chronic conditions, self-perceived health, and loneliness. The model specification is expressed as follows:

$$EUROD_i = \beta_0 + \beta_1 ICTuse_i + \beta_2 Age_i + \beta_3 Female_i + \beta_4 Education_i + \beta_5 Chronic\ conditions_i + \beta_6 Loneliness_i + \beta_7 Health\ Status_i + \varepsilon_i$$

This paragraph provides a detailed discussion of the results for EUDO-D scale.

- **Model 2: Adding Age**

Table 8 - Regression Output with Age as a Control

Linear regression	Number of obs	=	66,317
	F(2, 66314)	=	1090.93
	Prob > F	=	0.0000
	R-squared	=	0.0363
	Root MSE	=	2.2364

eurod	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
ict_user	-.6500566	.0203694	-31.91	0.000	-.6899805	-.6101326
age_int	.0212043	.0010202	20.78	0.000	.0192046	.0232039
_cons	1.391927	.0769496	18.09	0.000	1.241106	1.542748

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

After accounting for age, the ICT use coefficient in the model becomes -0.65, a bit closer to zero than in Model 1. It remains negative and highly significant. This small change suggests that some of the initial difference in depression was explained by age. ICT users tend to be younger, and younger respondents in this sample report slightly fewer depressive symptoms on average.

The model is based on 66,317 observations and the F-statistic indicates strong joint significance of the predictors. The R-squared rises marginally to 0.0363, showing that age adds some explanatory power, but ICT use continues to play an independent role in predicting depressive symptoms.

- **Model 3: Adding Gender**

Table 9 - Regression Output with Gender as a Control

Linear regression	Number of obs	=	66,317
	F(3, 66313)	=	1400.03
	Prob > F	=	0.0000
	R-squared	=	0.0631
	Root MSE	=	2.205

eurod	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ict_user	-.6268135	.0201037	-31.18	0.000	-.6662168	-.5874102
age_int	.0218378	.0010066	21.69	0.000	.0198649	.0238108
female	.7545066	.0169911	44.41	0.000	.7212041	.7878091
_cons	.9004142	.0766908	11.74	0.000	.7501003	1.050728

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

Model 3 introduces gender, measured with a dummy variable for female, in addition to age. The ICT use coefficient remains around -0.63, essentially unchanged from Model 2 and still highly significant. This stability shows that the ICT related depression gap is not explained by gender.

The gender control is itself an informative variable: the coefficient for being female is positive and statistically significant, indicating that older women tend to report higher depression scores than men when other factors are held constant.

The model is estimated on 66,317 observations, with the F-statistic confirming strong joint significance of the predictors. The R-squared increases slightly to 0.0631, showing that the gender adds explanatory power. ICT use continues to have an independent negative association with depressive symptoms.

- **Model 4: Adding Education**

Table 10 - Regression Output with Education as a Control

```

Linear regression                               Number of obs   =   14,650
                                                F(4, 14645)    =   225.05
                                                Prob > F       =   0.0000
                                                R-squared      =   0.0625
                                                Root MSE      =   2.1652

```

eurod	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ict_user	-.6093256	.0473351	-12.87	0.000	-.7021083	-.5165429
age_int	.0145926	.0022121	6.60	0.000	.0102565	.0189287
female	.7539772	.0354958	21.24	0.000	.6844009	.8235535
educ_years	-.0256053	.0048712	-5.26	0.000	-.0351535	-.0160571
_cons	1.72867	.1682206	10.28	0.000	1.398936	2.058403

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

Model 4 adds education, measured in years of schooling, as a control variable. The ICT coefficient is -0.61, which is nearly identical to its value in Model 3. This indicates that differences in education level between ICT users and non-users do not explain much of the depression gap. The coefficient for education is negative, statistically significant but small in magnitude. This suggests that higher education is associated with slightly fewer depressive symptoms.

The model is based on 14,658 observations, which is much smaller than in previous models due to missing data on education. The F-statistic confirms joint significance of the predictors, and the R-squared rises to 0.0623. Education provides only limited additional explanatory power and ICT use continues to play an independent role in predicting depressive symptoms. However, because of the substantial reduction in sample size, education will not be included in the subsequent models. This choice allows us to preserve statistical power and ensure comparability across specifications, while Model 4 demonstrates that the main results to the inclusion of education.

Education is a key socio-economic determinant, but its inclusion does not alter the ICT effect. The observed stability of the results reinforces the robustness of the findings and suggests that the digital divide in depressive symptoms cannot be attributed merely to education differences.

- **Model 5: Adding Chronic Health Conditions⁵⁹**

Table 11 - Regression Output with Chronic Conditions as a Control

eurod	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ict_user	-.510734	.0192477	-26.53	0.000	-.5484594	-.4730085
age_int	.0044391	.0010023	4.43	0.000	.0024746	.0064035
female	.6923909	.0163221	42.42	0.000	.6603997	.7243821
chronic_conditions	.4084966	.0056455	72.36	0.000	.3974314	.4195618
_cons	1.288688	.0738618	17.45	0.000	1.143919	1.433458

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

By incorporating the chronic conditions health factor further reduces the ICT use coefficient to -0.51. The reduction from -0.61 to -0.51 suggests that part of the initial ICT depression relationship is attributable to differences in health status. Older adults who use ICT tend to report fewer chronic health problems, and these health advantages contribute to their lower depression scores. The coefficient for chronic conditions is positive and highly significant, indicating that each additional chronic illness is associated with higher depressive symptoms score. This is unsurprising, and it aligns with expectations that physical health problems can increase depression.

Model 5 is estimated on 66,317 individuals and the R-squared rises to 0.1405, showing that the inclusion of health status substantially improves explanatory power while ICT uses continues to be an independent effect.

- **Model 6: Adding Loneliness**

In Model 6, education is again excluded to preserve the full sample size while loneliness is introduced as a key social factor. This factor is widely recognized in the literature as one of the strongest social determinants of mental health in later life.

Including loneliness in the model allows us to assess whether the observed ICT effect simply reflects differences in social connectedness between users and non-users. Table 12 reports the regression results with loneliness included as a predictor.

⁵⁹ In Model 5, education is excluded due to the large number of missing values.

Table 12 - Regression Output with Loneliness as a Control

eurod	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ict_user	-.2535721	.0176668	-14.35	0.000	-.2881991	-.2189451
age_int	-.0023705	.0009221	-2.57	0.010	-.0041778	-.0005633
female	.5411286	.0150781	35.89	0.000	.5115755	.5706817
chronic_conditions	.3273762	.0052535	62.32	0.000	.3170794	.3376731
loneliness	.6081328	.0065827	92.38	0.000	.5952306	.6210349
_cons	-.6006976	.0699641	-8.59	0.000	-.7378273	-.4635679

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

As expected, the ICT use coefficient drops substantially in this step, falling to -0.25. It remains statistically significant, but the magnitude of the ICT effect is much smaller than in previous models. This change implies that a considerable portion of the apparent benefit of ICT use on depression was actually due to differences in loneliness. Individuals who use ICT tend to be less lonely and loneliness itself has a very strong influence on depression. In fact, this factor emerges as one of the most powerful predictors in Model 6.

The explanatory power of the model rises, with the R-squared increasing from 0.14 to 0.27. This highlights the central role of loneliness in shaping depressive symptoms among older adults. Even though, ICT use continues to show a significant link with lower depression, suggesting there is an independent effect beyond just alleviating loneliness.

- **Model 7: Adding Self-Rated Health**

Table 13 - Regression Output with Self-Rated Health as a Control

eurod	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ict_user	-.0439118	.017131	-2.56	0.010	-.0774886	-.010335
age_int	-.0058107	.0008847	-6.57	0.000	-.0075448	-.0040766
female	.5477328	.0144902	37.80	0.000	.519332	.5761336
chronic_conditions	.169675	.0055982	30.31	0.000	.1587026	.1806475
loneliness	.5465056	.0063849	85.59	0.000	.5339912	.5590201
self_perceived_health	.6259823	.0089826	69.69	0.000	.6083764	.6435883
_cons	-1.951736	.0692973	-28.16	0.000	-2.087558	-1.815913

Source: Author's calculations based on Wave 9 data from SHARE, Release 9.0.0

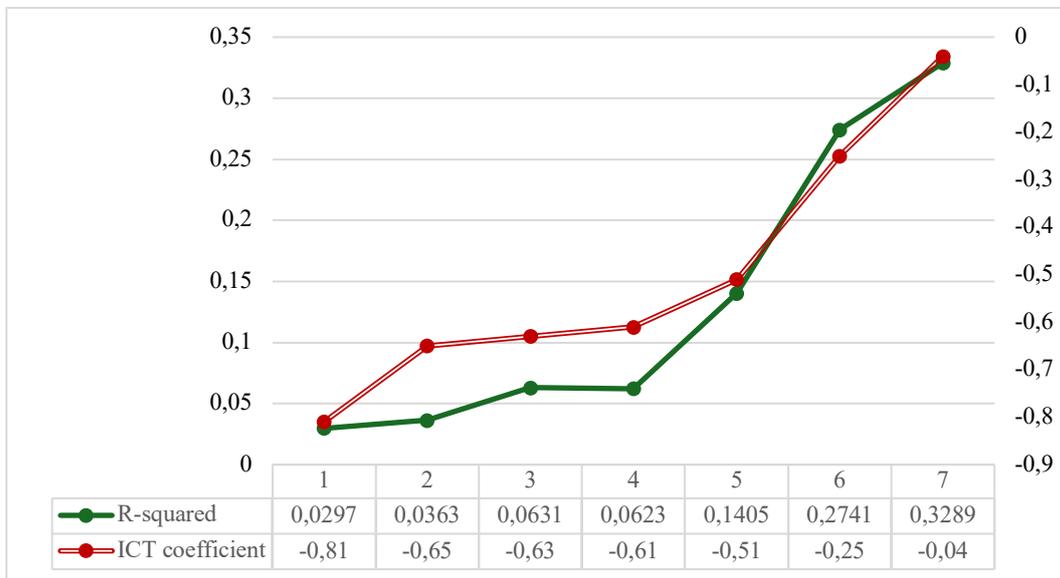
Finally, Model 7 includes self-rated health as an additional control, alongside age, gender, chronic conditions and loneliness. Education is again excluded in order to preserve the full sample size.

The ICT use further weakens to -0.04. This represents a very small association, although it remains statistically significant at conventional levels. The drop from -0.25 to -0.04 indicates that ICT users tend to perceive their health as better, and this factor accounts for another portion of the ICT-depression link.

Self-rated health has a strong and highly significant effect. People who describe their health as poor report much higher EURO-D scores. Once we control for age, gender, physical health, loneliness, and perceived health, the ICT effect becomes smaller than in the bivariate model. It continues to point in the same direction, suggesting a consistent independent association between ICT use and lower depressive symptoms. The R-squared rises to 0.3289, indicating that the inclusion of self-rated health substantially improves the explanatory power of the model.

To summarize the results, we can take a look to the following figure. It presents the evolution of the ICT coefficient and the R-squared across the sequence of models.

Figure 9 - Summary Chart of ICT Coefficient and R² compared to EURO-D



Source: Author's calculations based on Wave 9 data from SHARE, Release 9.0.0

Taken together, the sequence of models shows that part of the initial difference in depression between ICT users and non-users can be explained by other factors.

ICT users are generally younger, more often male, in better health, and less lonely, all of which are linked to lower depression. When these factors are added to the models, the direct effect of ICT use becomes much smaller. This shows that part of the initial gap reflects who the users are and the conditions in which they live. Still, in the full specification, ICT use keeps a small but favourable link with depressive symptoms.

Older adults who go online show slightly lower EURO-D scores on average.

This means that most of the advantage of ICT users comes from who they are and how they live, but there may also be a modest direct benefit of technology use itself. In practice, even after many controls, older adults who use ICT report marginally fewer depressive symptoms, hinting that digital engagement could have a small positive role in mental health.

4.2.3 Multivariate Regression – CASP-12 Models with Controls

This section presents the results for the multivariate quality of life models, highlighting how the estimated effect of ICT use evolves as additional controls are introduced.

- *Model 2: Adding Age*

Table 14 - Regression Output with Age as a Control

Linear regression	Number of obs	=	65,346
	F(2, 65343)	=	4017.27
	Prob > F	=	0.0000
	R-squared	=	0.1183
	Root MSE	=	5.825

casp	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
ict_user	3.896931	.0528867	73.68	0.000	3.793273	4.000589
age_int	-.0550582	.0026524	-20.76	0.000	-.0602569	-.0498595
_cons	38.76972	.199981	193.87	0.000	38.37776	39.16168

Source: Author’s calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

In Model 2, the positive effect of digital engagement on well-being remains clear. The coefficient is still around +4, showing that, at equal ages, internet users report CASP scores about four points higher than non-users.

Age, on the other hand, is negatively associated with the variable, which means that older respondents tend to report slightly lower quality of life scores. This indicates that part of the initial ICT effect observed in the bivariate model is explained by the fact that non-users are typically older.

The model is based on 65,346 observations and the F-statistic confirms strong joint significance of the predictors. The R-squared increase to 0.1183, showing a moderate improvement in explanatory power. Overall, while age explains a part of the gap, ICT use continues to exert an independent and sizeable effect on perceived well-being.

- **Model 3: Adding Gender**

Table 15 - Regression Output with Gender as a Control

Linear regression		Number of obs	=	65,346		
		F(3, 65342)	=	2770.65		
		Prob > F	=	0.0000		
		R-squared	=	0.1215		
		Root MSE	=	5.8144		
casp	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ict_user	3.875695	.0528314	73.36	0.000	3.772145	3.979244
age_int	-.0557308	.0026484	-21.04	0.000	-.0609216	-.05054
female	-.7113563	.0458059	-15.53	0.000	-.8011358	-.6215768
_cons	39.2371	.2024347	193.83	0.000	38.84033	39.63388

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

After adding gender, ICT use remains positive and statistically significant, though the coefficient is slightly reduced compared to Model 2. The estimated effect shows how internet users report nearly 4 points higher on the CASP scale than non-users.

The gender variable shows an adverse effect. Women report lower CASP scores than men, even after adjusting for age and ICT use. This reflects a gender gap in subjective quality of life that is often observed in aging research.

The model is estimated on 65,346 observations, with an F-statistic confirming strong joint significance of the predictors. The R-squared shows only a small increase, which means that age and gender together account for just a limited part of the variation in well-being.

- **Model 4: Adding Education**

As we noticed in the EURO-D models, the inclusion of education lead to a sharp drop in the number of observations. For CASP as well, Model 4 is estimated on a much smaller sample, 14,469 cases, which limits comparability with the other models.

Because of this loss of statistical power, education is not retained in the subsequent specifications.

Table 16 - Regression Output with Education as a Control

Linear regression	Number of obs	=	14,469
	F(4, 14464)	=	535.16
	Prob > F	=	0.0000
	R-squared	=	0.1367
	Root MSE	=	5.7086

casp	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
ict_user	3.258674	.1247253	26.13	0.000	3.014196	3.503151
age_int	-.0735766	.0057113	-12.88	0.000	-.0847716	-.0623817
female	-.6850379	.0952894	-7.19	0.000	-.8718173	-.4982585
educ_years	.1615183	.0128379	12.58	0.000	.1363544	.1866822
_cons	38.89774	.4366161	89.09	0.000	38.04192	39.75356

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

Model 4 adds education as a control. The coefficient for ICT use remains stable and significant at around +3 points. This shows that the associations between digital engagement and quality of life are not simply a by-product of educational differences. Education has a small and only weakly significant positive effect. More years of schooling tend to raise CASP scores, but the effect is marginal once other controls are included. This implies that education plays only a secondary role compared to health and social factors. The explanatory power increases only a little bit, confirming that ICT use continues to independently predict higher quality of life.

- **Model 5: Adding Chronic Health Conditions**

Table 17 - Regression Output with Chronic Conditions as a Control

Linear regression	Number of obs	=	65,346
	F(4, 65341)	=	3454.73
	Prob > F	=	0.0000
	R-squared	=	0.1803
	Root MSE	=	5.6166

casp	Robust		t	P> t	[95% conf. interval]	
	Coefficient	std. err.				
ict_user	3.596571	.0513898	69.99	0.000	3.495847	3.697295
age_int	-.0142455	.0026546	-5.37	0.000	-.0194486	-.0090425
female	-.5671735	.0443488	-12.79	0.000	-.6540971	-.4802498
chronic_conditions	-.9711158	.0146984	-66.07	0.000	-.9999247	-.942307
_cons	38.30667	.1969496	194.50	0.000	37.92065	38.6927

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

Model 5 includes chronic conditions, a key health factor. The ICT coefficient declines slightly compared to previous models, but it remains highly significant.

As expected, chronic conditions show a strong negative association with CASP-12, confirming that long-term health problems substantially lower perceived well-being. The reduction in the ICT coefficient suggests that better health among ICT users explains part of the digital advantage in quality of life.

The fact that the effect remains significant indicates that technology use has an impact beyond physical health. The R-squared increases to 0.18, marking a substantial rise in explanatory power and indicating that physical health explains much of the variation in quality-of-life outcomes.

- **Model 6: Adding Loneliness**

Table 18 - Regression Output with Loneliness as a Control

Linear regression	Number of obs	=	65,205
	F(5, 65199)	=	6665.12
	Prob > F	=	0.0000
	R-squared	=	0.3440
	Root MSE	=	5.02

	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
casp						
ict_user	2.83346	.0463756	61.10	0.000	2.742564	2.924356
age_int	.0063052	.0023706	2.66	0.008	.0016587	.0109516
female	-.1134405	.0399253	-2.84	0.004	-.1916941	-.0351868
chronic_conditions	-.7254463	.0132403	-54.79	0.000	-.7513972	-.6994954
loneliness	-1.832782	.0151578	-120.91	0.000	-1.862491	-1.803073
_cons	43.99489	.1815766	242.29	0.000	43.639	44.35078

Source: Author's calculations in Stata based on Wave 9 data from SHARE, Release 9.0.0

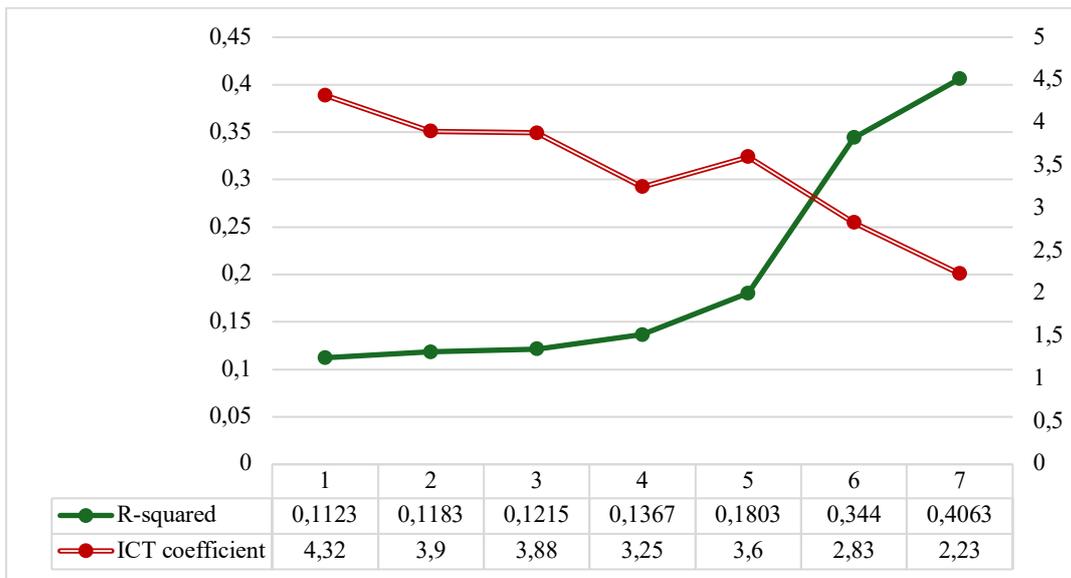
The inclusion of loneliness further reduces the ICT coefficient, now close to +2.8 points, although it remains significant. This indicates that part of the benefit of ICT use is linked to lower levels of loneliness among users. Loneliness itself emerges as one of the strongest predictors in the model: feeling lonely is associated with a substantial drop in CASP-12 scores, even when controlling for age, health, and other factors.

The R-squared rises considerably, highlighting the central importance of social connections in shaping quality of life in older age.

- **Model 7: Adding Self-perceived Health**

The aim of Model 7 is to preserve the full sample size and comparability across specifications while adding the most relevant demographic, health, and social factors. This ensures that the final model captures the main determinants of quality of life without compromising statistical power.

Figure 10 - Summary Chart of ICT Coefficients and R² compared to CASP-12



Source: Author's calculations based on Wave 9 data from SHARE, Release 9.0.0

Across these progressively specified models, the raw ICT effect on CASP-12 (+4 points in the bivariate model) becomes gradually smaller as age, gender, education, health, loneliness, and self-perceived health are included.

The most significant reductions occur when adding chronic conditions, loneliness, and perceived health, which absorb much of the initial difference. Nonetheless, the ICT effect remains positive and statistically significant in the fully adjusted model, at about +2.2 points. This finding suggests that digital engagement directly contributes to subjective well-being among adults aged 50 and over, above and beyond health status and social context. In short, even after controlling for major confounders, ICT users consistently report a higher quality of life.

4.2.4 Interaction Effects – Heterogeneity by Subgroups

I introduced interaction items into the regression models by further exploring heterogeneity in the association between ICT use and mental health. This approach allows me to test whether the effect of ICT use changes across subgroups, such as by gender, age, or digital skills. While gender and age were included as control variables in the multivariate models, digital skills were not part of the baseline specifications. They are considered here separately to explore whether the benefits of ICT depend on the level of competence, thus highlighting an additional dimension of the digital divide.

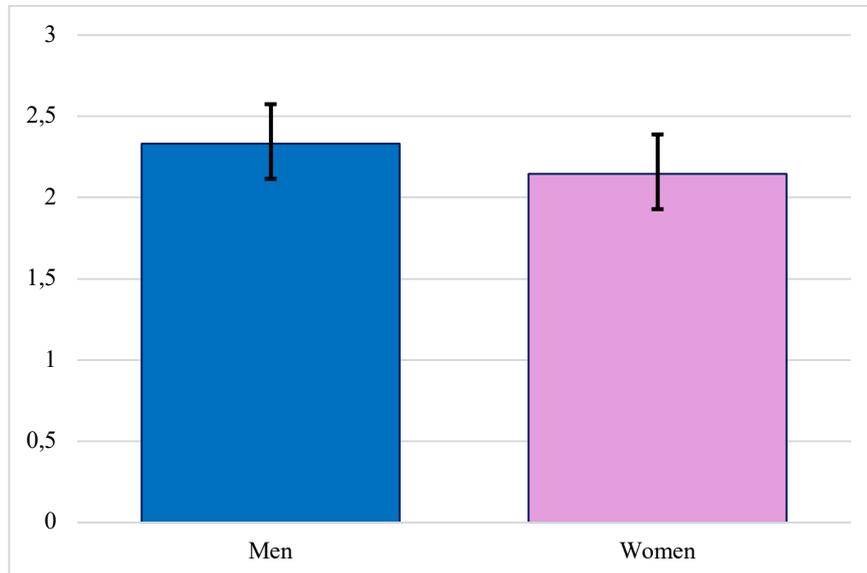
ICT x GENDER

Gender is a key dimension of the digital divide and deserves special attention.

For depressive symptoms, ICT use is associated with a modest but significant reduction in symptoms among men, whereas no significant effect is observed among women. This suggests that the protective role of ICT against depression may be more pronounced in men. However, for quality of life, ICT use has a positive effect for both genders with different size of benefit. Among men, ICT use is associated with an improvement of about +2.33 points ($p < 0.001$), while for women the increase is approximately +2.15 points ($p < 0.001$). The interaction term confirms that this difference is statistically significant, men gain a slightly larger improvement in perceived quality of life from ICT use compared to women.

The figure below illustrates these marginal effects. The height of the coloured bars represents the effect of ICT use in each group, expressed as the average change in outcome score. ICT use appears to improve well-being in both genders, although men report a slightly stronger benefit.

Figure 11 - Marginal Effect of ICT use on CASP-12 by Gender



Source: Author's elaboration based on SHARE Wave 9 data

ICT x AGE

Age is another key dimension of heterogeneity in the relationship between ICT use and mental health.

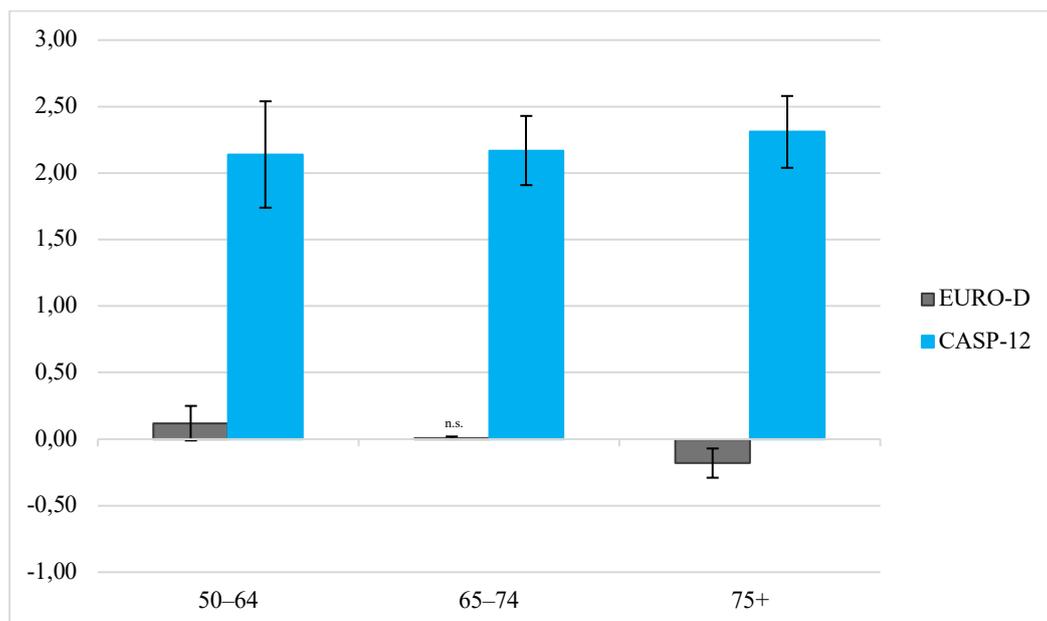
For depressive symptoms, the results suggest a differentiated pattern. Among individuals aged 50 to 64, ICT use is unexpectedly associated with a slight increase in depressive symptoms (+0.12 points, $p < 0.01$). In the 65 to 74 group, the association becomes not significant, while in the oldest group, ICT use is associated with a clear reduction in depressive symptoms. These findings indicate that ICT use may be particularly beneficial for older adults, possibly because digital engagement helps reduce feelings of isolation and vulnerability in this group.

For quality of life, the effects are consistently positive across all age groups. The estimated effects are consistent: about +2.1 points in CASP among the 50 to 64 and 65 to 74 groups, and slightly stronger among individuals aged 75+ ($\approx +2.3$ points). These show that the ICT use enhances perceived well-being universally across age groups, with the most significant gains for the oldest old.

The figure illustrates the estimated marginal effects of ICT use on mental health outcomes across three age groups: 50–64, 65–74, and 75+. The grey bars represent the effect on depressive symptoms, while the green bars represent the effect on quality of life.

The height of each bar indicates the estimated effect size, with numeric labels reporting the exact coefficients. The black vertical lines correspond to error bars, which represent the statistical uncertainty of the estimates. The error bars correspond to 95% confidence level.

Figure 12 - Marginal Effect of ICT Use by Age Group



Source: Author's elaboration based on SHARE Wave 9 data

ICT x Digital Skills

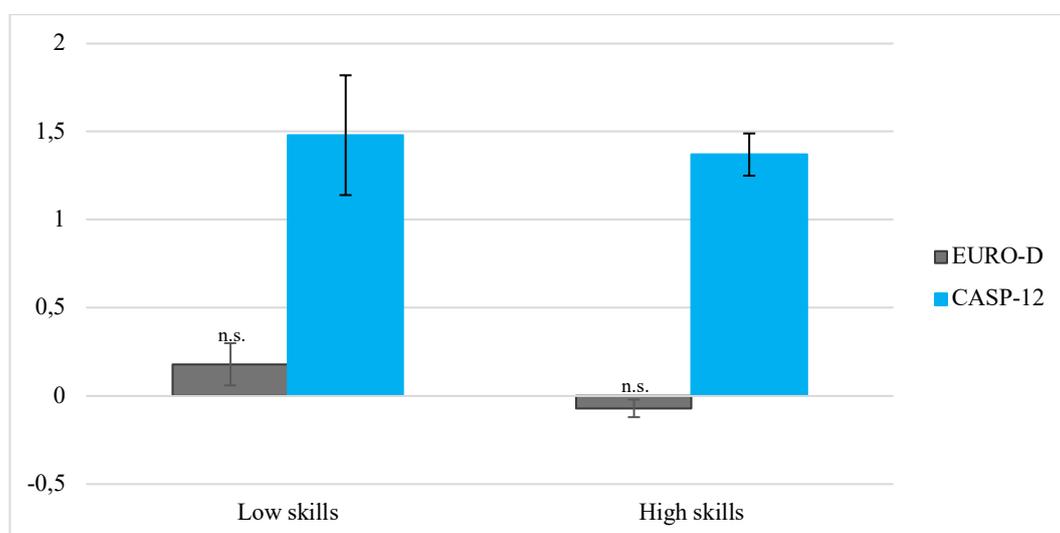
Digital competence is a crucial dimension of the digital divide and may condition the extent to which older adults can benefit from ICT use.

For depressive symptoms, the model suggests that ICT use on its own is not significant once digital skills are taken into account. What matters more are the skills themselves, which show a clear link with fewer depressive symptoms. The interaction between ICT and skills is negative and significant, meaning that the protective role of ICT grows as digital competence increases. Marginal effects show no benefit among low-skill users and a small borderline reduction among high-skill users. This suggests that while the moderating role of skills is statistically detectable, the size of the protective effect remains modest and not robust.

For quality of life, the picture is different. ICT use remains positively associated with CASP scores (+1.4 points), regardless of skill level. The interaction term ICT × skills is not significant, suggesting that the positive effect of ICT on quality of life is universal, not conditional on digital competence. Even individuals with low skills report improved well-being when they use ICT.

The figure below shows the marginal effects of ICT use on depressive symptoms and on quality of life, separating respondents with low and high self-reported digital skills. The numbers above the bars indicate the size of the estimated effects, and the black lines mark the error bars that illustrate the degree of uncertainty. The effects on depressive symptoms are not statistically significant.

Figure 13 - Marginal Effect of ICT Use by Digital Skills



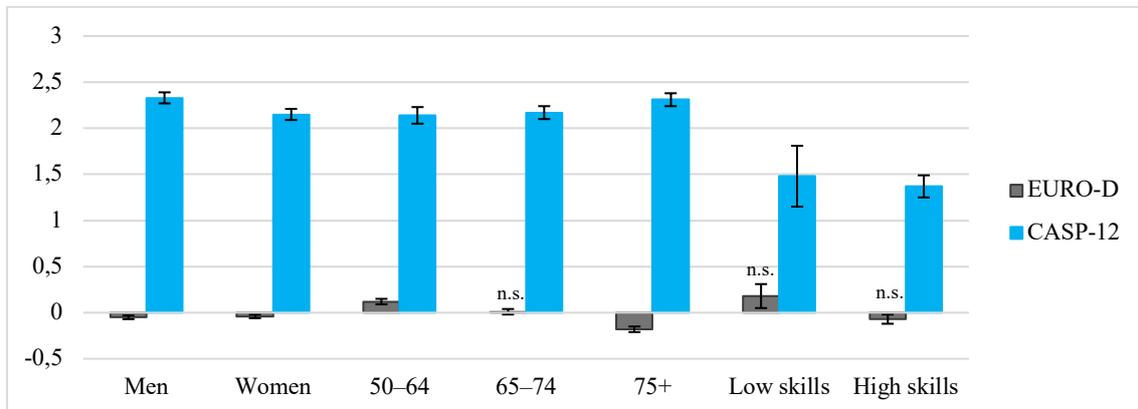
Source: Author's elaboration based on SHARE Wave 9 data

The analysis of interaction terms highlights that the mental health benefits of ICT use are not even distributed across all subgroups.

Gender differences are limited for depressive symptoms but emerge for quality of life, with men experiencing slightly larger gains in CASP-12 scores. Age effects point to a stronger protective role of ICT use against depression among the oldest group (75+), while improvements in quality of life are consistently observed across all age groups. Finally, digital skills appear to moderate the association between ICT and depression: the protective effect is detectable only among individuals with higher competence, although the estimates remain small and not robust. In contrast, perceived quality of life improves universally with ICT use, with similar gains for both low- and high-skill users.

These findings indicate that ICT use can help support mental health in later life, but the size and form of this benefit vary across individuals. This emphasizes the importance of accounting for heterogeneity within the older population when assessing the impact of digital inclusion policies.

Figure 14 - Summary of Interaction Effects



Source: Author's elaboration based on SHARE Wave 9 data

4.2.5 Stratified Analysis

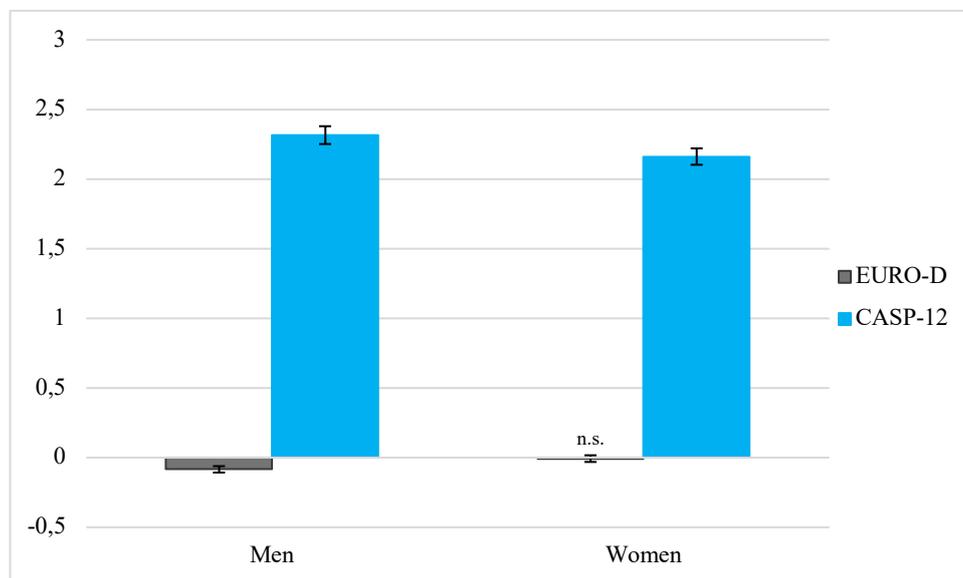
To complement the interaction analysis, I run stratified regression by gender, age group, and digital skills. Instead of including interaction terms within the same model, this approach involves running separate regressions for each subgroup, so it lets us observe independently each population segment.

By Gender

The results indicate that ICT use is associated with lower depression scores among men, while no significant effect is observed among women. This suggests the protective effect of digital engagement against depressive symptoms is concentrated among male respondents. For quality of life, ICT use shows a strong and positive association in both groups. The estimated effect is slightly larger for men (+2.3 points) than for women (+2.2 points). This indicates that ICT contributes to higher well-being across genders, with only marginal differences in effect size.

These results are consistent with the interaction analysis, which showed that gender differences are more relevant for subjective well-being than for depressive symptoms.

Figure 15 - Stratified Analysis by Gender



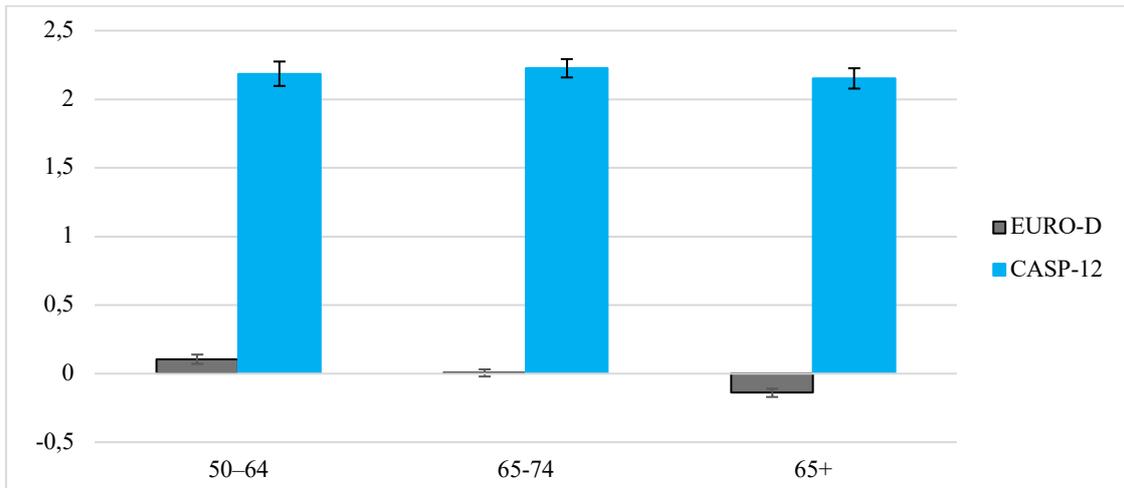
Source: Author's elaboration based on SHARE Wave 9 data

By Age

A clearer contrast emerges across age categories. Among adults aged 50–64, ICT use is associated with a small but significant increase in depressive symptoms (+0.11 points). For the 65–74 group, no meaningful effect is observed. By contrast, among those aged 75 and older, ICT use is linked to a clear reduction in depression scores (–0.14 points, $p < 0.001$). This pattern suggests that the protective role of ICT becomes particularly evident at advanced ages, when risks of loneliness and vulnerability are higher.

For quality of life, ICT use shows a strong and positive association in all age groups, with effect sizes around +2 points. This indicates that well-being benefits are universal across the older population, with only minor differences between younger and older subgroups.

Figure 16 - Stratified Analysis by Age

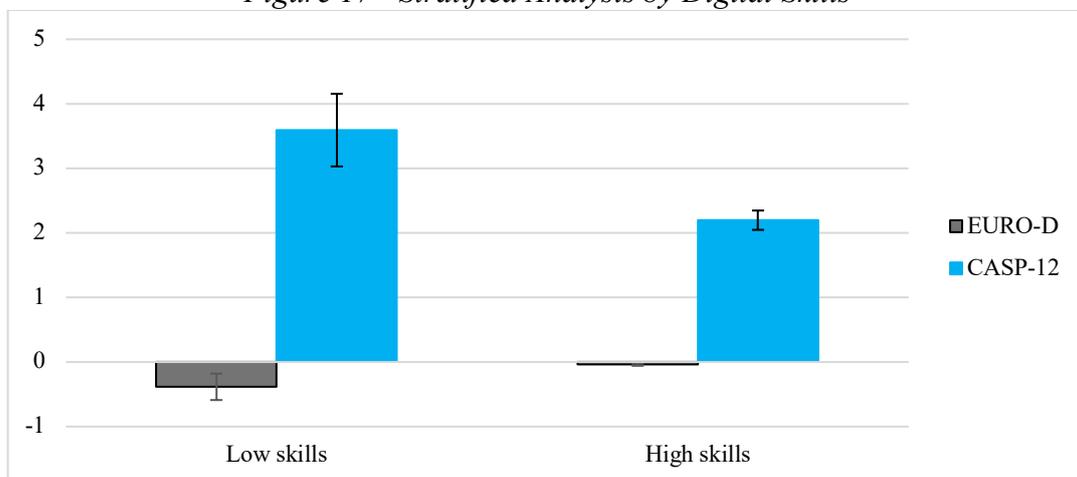


Source: Author's elaboration based on SHARE Wave 9 data

By Digital Skills

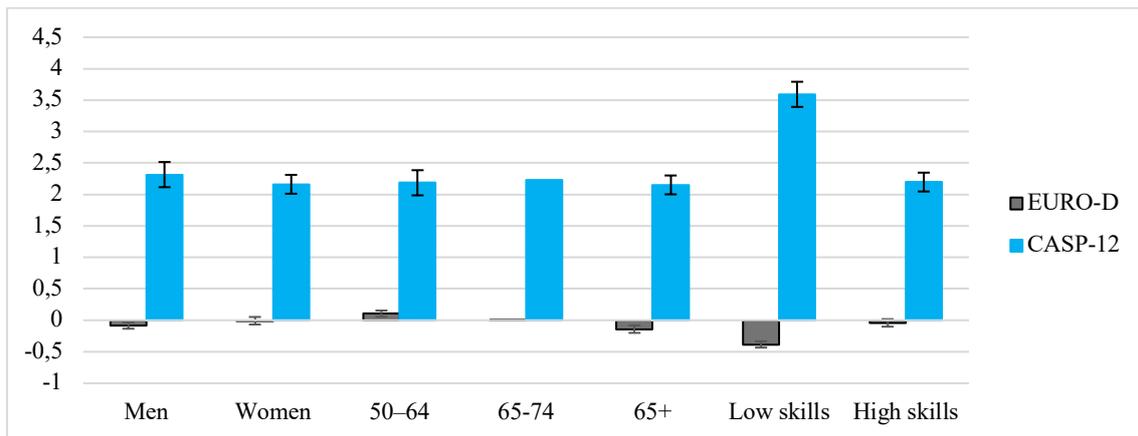
Stratification by digital competence reveals an interesting pattern. Among individuals with low digital skills, ICT use shows a negative association with EURO-D (-0.38) but the effect is only borderline significant ($p \approx 0.06$). Among those with higher skills, ICT use is linked to a modest yet statistically significant reduction in depressive symptoms (-0.04 , $p < 0.05$). This suggests that digital competence enhances the protective role of ICT, although the overall effect remains relatively small. For quality of life (CASP-12), the results are more consistent. ICT use improves well-being across both groups, with a larger effect among low-skill individuals ($+3.6$ points) compared to their high-skill counterparts ($+2.2$ points). A possible interpretation is that for those with limited competence, gaining access to ICT represents a substantial leap in autonomy and social participation, leading to greater perceived improvements in quality of life.

Figure 17 - Stratified Analysis by Digital Skills



Source: Author's elaboration based on SHARE Wave 9 data

Figure 18 - Summary of Stratified Analysis



Source: Author's elaboration based on SHARE Wave 9 data

The stratified analysis confirms that ICT use is positively linked to mental health, but the strength and nature of this association vary across subgroups. For gender, ICT use is associated with reduced depressive symptoms only among men, while both men and women benefit in terms of improved quality of life, with men showing slightly larger gains. Regarding age, ICT use is linked to a small increase in depressive symptoms among those aged 50–64, no effect in the 65–74 group, and a clear protective role among individuals aged 75 and over. Improvements in quality of life are strong and consistent across all age groups. Finally, digital competence emerges as a key factor: ICT use reduces depressive symptoms only among individuals with higher skills, while perceived gains in quality of life are particularly strong among those with lower skills, for whom digital engagement may represent a more transformative change. Overall, these findings highlight that the benefits of ICT are widespread but heterogeneous, depending on individual resources and vulnerabilities.

4.2.6 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a widely used statistical method in the social sciences and economics to summarize information in groups of correlated variables. The underlying idea is that several indicators may capture different dimensions of the same construct, such as mental health or well-being. Analysing each variable separately may be inefficient or misleading, while PCA allows these factors to be condensed into a smaller number of synthetic indices.

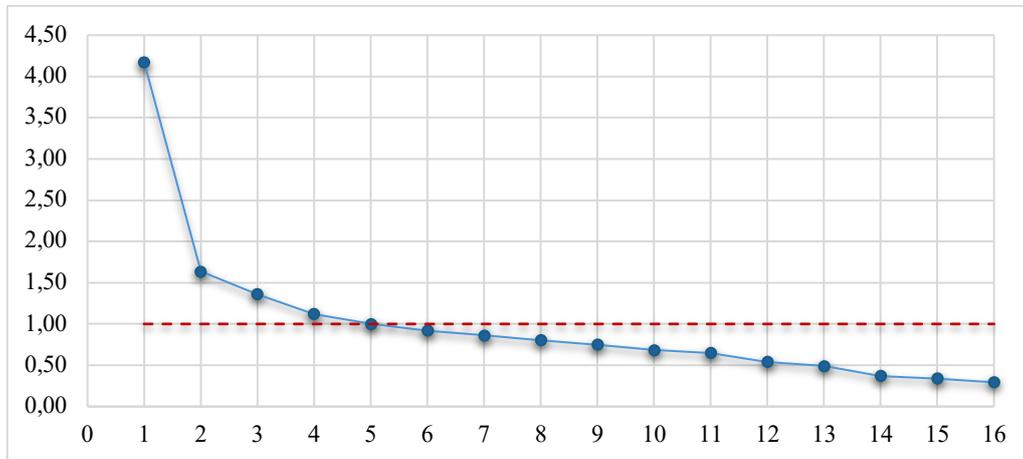
In practice, PCA takes the original variables and combines them into new ones, called principal components. Each component is a linear combination of the starting variables,

and they are ranked by how much variance they explain: the first accounts for the largest share, the second for the next, and so on. A useful feature is that the components are uncorrelated with each other, which helps to reduce overlap and multicollinearity. The coefficients, or loadings, show how much each original variable contributes to a component and guide its interpretation. For example, if depression and loneliness have high positive loadings on the first component, while measures of well-being load negatively, that component can be read as a synthetic indicator of overall mental health. This approach makes it possible to compute an individual score for each respondent in the sample, thus generating a synthetic index usable in subsequent regression models.

PCA offers two main advantages: it reduces the risk of multicollinearity when including several correlated variables in the same regression, and it provides a robustness check by verifying whether results are consistent when a composite index is used instead of single measures such as EURO-D or CASP.

As shown in Figure 19, the scree plot⁶⁰ highlights the sharp drop after the first component, confirming its dominant role in capturing variation across the mental health indicators.

Figure 19 - Scree Plot of PCA Eigenvalues



Source: Author’s elaboration based on SHARE Wave 9 data

The PCA analysis was based on a set of 16 variables capturing depressive symptoms and social isolation, as reported in Table 20. These include the EURO-D items and the three indicators of loneliness. This ensures that both psychological and social aspects of mental well-being are represented.

⁶⁰ A scree plot is a graph in principal component analysis (PCA) and factor analysis that displays the eigenvalues of each component or factor in descending order against the component number.

Table 20 - Variables included in the PCA analysis

Variable code	Short label
mh002_	Sad or depressed last month
mh003_	Hopes for the future
mh004_	Suicidal feelings or wish to be dead
mh005_	Feels guilty
mh006_	Blame for what
mh007_	Trouble sleeping
mh008_	Loss of interest in things
mh009_	Irritability
mh010_	Appetite
mh011_	Fatigue
mh012_	Concentration
mh013_	Concentration on reading
mh014_	Enjoyment
mh015_	Tearfulness
mh036_	Feels lack of companionship
mh037_	Feels isolated from others
mh038_	Feels lonely

Source: Author's elaboration based on SHARE Wave 9 data

The eigenvalues and the proportion of variance explained by the first six components are reported in Table 21. The first component has an eigenvalue of 4.17, explaining 26% of the total variance. The second, third, and fourth components add roughly 10%, 8.5%, and 7% respectively, so that the first four components together explain 52% of the variance. According to the Kaiser criterion (eigenvalues > 1)⁶¹, five elements should be retained, but the first one is clearly dominant, justifying its use as a synthetic mental health index.

Table 21 - Eigenvalues and variance explained (first six components)

Component	Eigenvalue	Proportion of Variance	Cumulative Variance
Comp1	4.1726	0.2608	0.2608

⁶¹ The Kaiser criterion is a common rule in factor analysis, it suggests keeping only the factors with an eigenvalue above one when deciding how many to retain.

Comp2	1.6369	0.1023	0.3631
Comp3	1.3605	0.0850	0.4481
Comp4	1.1225	0.0701	0.5182
Comp5	1.0009	0.0638	0.582
Comp6	0.9360	0.0585	0.6405

Source: Author's elaboration based on SHARE Wave 9 data

The first principal component was retained as a synthetic index of mental health, *mh_pca1*. This score correlates strongly and negatively with EURO-D (-0.83) and positively with CASP (+0.63), confirming that it effectively combines depressive symptoms and quality of life into a single measure. The correlation between EURO-D and CASP is negative (-0.54), consistent with theoretical expectations.

Table 22 - Correlation between *mh_pca1*, EURO-D and CASP

Variable	<i>mh_pca1</i>	EURO-D	CASP
<i>mh_pca1</i>	1.000	-0.832	0.634
EURO-D	-0.832	1.000	-0.541
CASP	0.634	-0.541	1.000

Source: Author's elaboration based on SHARE Wave 9 data

To further validate the interpretability of the PCA index, I regressed *mh_pca1* on EURO-D and CASP. Results are reported in Table 23.

Table 23 - Regression Results using PCA Index as outcome

Source	SS	df	MS	Number of obs	=	952
Model	2873.76844	2	1436.88422	F(2, 949)	=	1353.87
Residual	1007.19198	949	1.06131926	Prob > F	=	0.0000
				R-squared	=	0.7405
				Adj R-squared	=	0.7399
Total	3880.96042	951	4.08092578	Root MSE	=	1.0302

<i>mh_pca1</i>	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
eurod	-.5470742	.0155596	-35.16	0.000	-.5776093	-.5165391
casp	.0774583	.0058468	13.25	0.000	.0659841	.0889325
_cons	-.4235178	.2386272	-1.77	0.076	-.8918157	.0447801

Source: Author's elaboration based on SHARE Wave 9 data

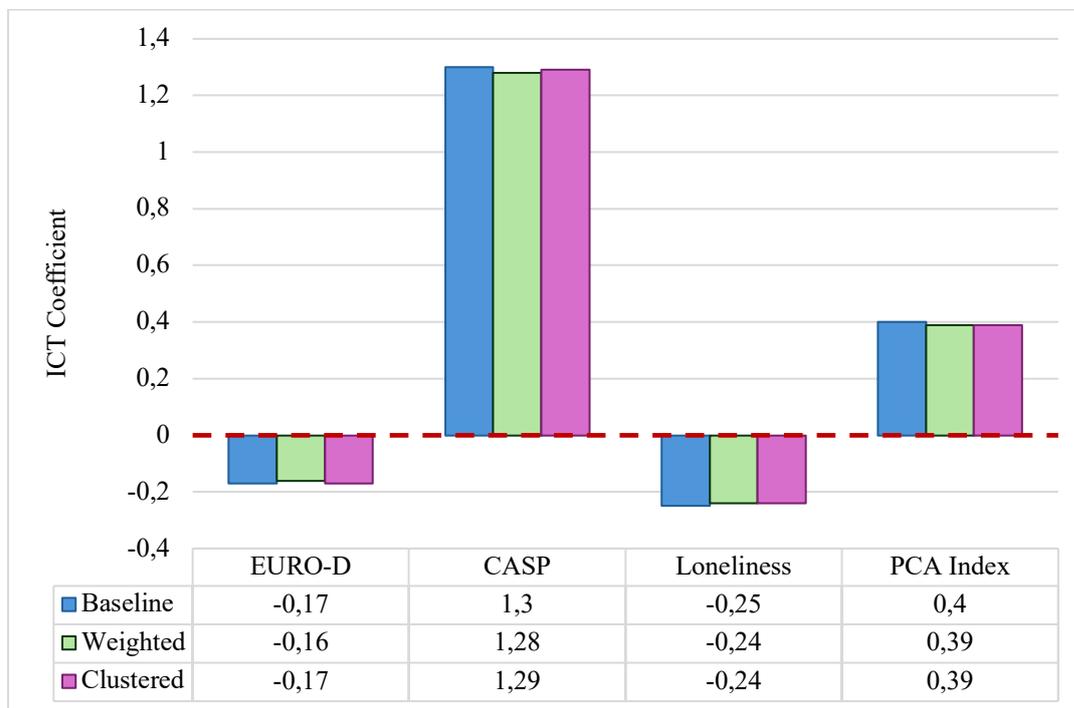
It should be noted that the PCA index could only be computed for respondents with complete answers to all depressive and loneliness items, as well as valid EURO-D and CASP scores. This requirement reduces the effective sample size compared to the main

4.2.7 Robustness Checks

Robustness check with survey weights and clustered standard errors are a common practice when dealing with complex survey data such as SHARE. The use of sampling weights corrects for unequal probabilities of selection and ensures that the estimates are representative of the target population. Clustering the standard errors adjusts for the fact that observations from the same household or country are not fully independent, which makes the confidence intervals more reliable. Used together, weighting and clustering help check whether the main results depend on sample design issues or on variability that would otherwise be underestimated.

In practice, I re-estimated the baseline models by first applying calibrated sampling weights and then introducing robust standard errors clustered at the household and country level. In these robustness checks, I also included education as a control, to verify that the effect of ICT use was not driven by differences in schooling. This specification slightly reduces the sample size, but the coefficients of ICT use remained stable when correcting for both representativeness and intra-group correlation.

Figure 20 - Effect of ICT use on Mental Health



Source: Author's elaboration based on SHARE Wave 9 data

Figure 20 summarizes the results of these robustness checks. It compares the estimated ICT coefficients across baseline, weighted, and clustered models for all mental health outcomes considered (EURO-D, CASP, loneliness, and the PCA index). The figure

shows that the coefficients remain virtually unchanged in both magnitude and sign across the different specifications. The only effect of clustering is a modest widening of the confidence intervals, as expected, but the significance of the results is preserved.

This result shows that the positive link between ICT use and mental health is not just a by-product of survey design or model choice. The fact that the coefficients stay consistent when using weights and clustered errors adds confidence in the findings.

Another robustness check I carried out was using alternative definitions of mental health outcomes. The idea is that if the association between ICT use and mental health is genuine, it should hold regardless of how psychological well-being is measured. Four different specifications were tested, as shown in the table below. First, a logistic regression model was estimated with a binary EURO-D indicator commonly used in the literature to identify clinically relevant depression. The results confirm that ICT users are significantly less likely to fall into the depressed category, with an average marginal effect of -3 percentage points. Second, a dichotomized version of the CASP index was used, distinguishing individuals with low vs high perceived quality of life. Once again, the logistics model shows a protective effect of ICT: technology users are about 12.7% less likely to report low well-being than non-users, controlling for age, gender, education, chronic conditions, loneliness, and self-perceived health. Third, loneliness was analysed directly as a dependent variable. The OLS regression indicates that ICT use is associated with significantly lower levels of loneliness (-0.29 points on the 1 to 6 scale). While the explained variance of the model remains modest, this result strengthens the hypothesis that digital engagement contributes to reducing social isolation among older adults. As a last step, I ran a robustness check using a synthetic mental health index built with principal component analysis. In this model, ICT use is positively and significantly associated (+0.40). This suggests that the benefits of digital technologies are not limited to single outcomes like depression or quality of life but also appear when mental health is measured through a broader composite index.

Table 25 - Robustness checks with alternative outcomes

Outcome	Model	ICT Coeff.	p-value	Interpretation
EURO-D	Logistic	-0.03	p<0.05	ICT users less likely to be depressed
CASP	Logistic	-0.127	p<0.01	ICT users less likely to report low well-being

Loneliness score	OLS	-0.29	p<0.01	ICT use reduces loneliness
PCA Index	OLS	+0.40	p<0.05	ICT use improves mental health

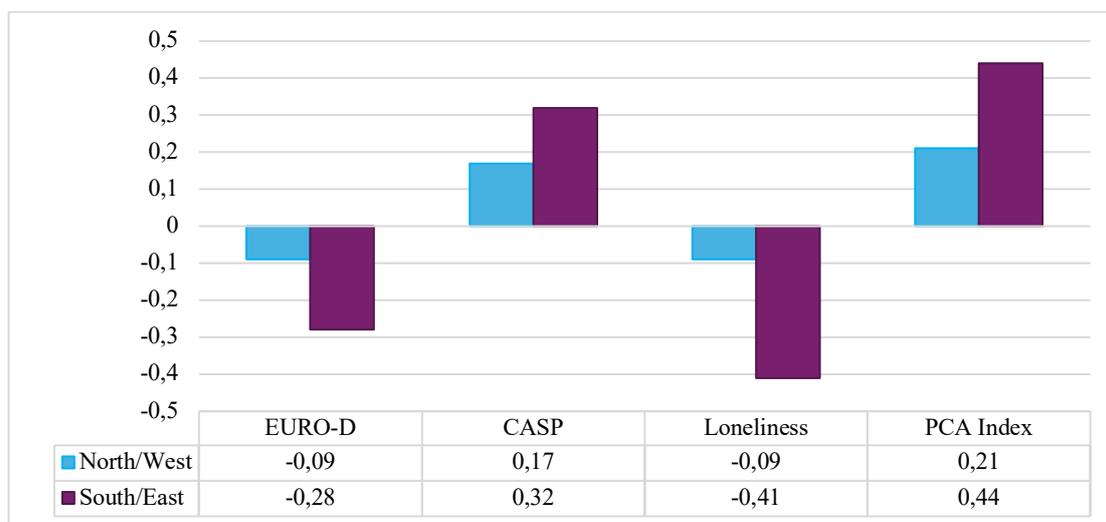
Source: Author's elaboration based on SHARE Wave 9 data

The consistency of the results across all alternative outcomes supports the robustness of the main findings: internet use among older adults is systematically linked to lower depressive symptoms, higher quality of life, reduced loneliness, and improved overall mental health.

I also looked at differences across countries. The reasoning is that the impact of ICT on mental health may change with the level of digitalization and the type of welfare system. In places where digital use is already widespread and welfare support is strong; the added value of ICT is likely smaller. In contrast, in countries with weaker infrastructures, technology can play a more important compensating role.

Figure 21 summarizes the results by macro-region. The models estimated separately for Northern/Western and Southern/Eastern Europe show apparent differences. In the North/West, the coefficients of ICT use are small and often not significant, particularly for depression and loneliness. In the South/East, instead, ICT use is significantly associated with lower depressive symptoms (-0.28), higher CASP scores (+0.32), reduced loneliness (-0.41), and higher PCA scores (+0.44). This suggests that in less digitalized or weaker welfare contexts, the beneficial impact of technology is more pronounced.

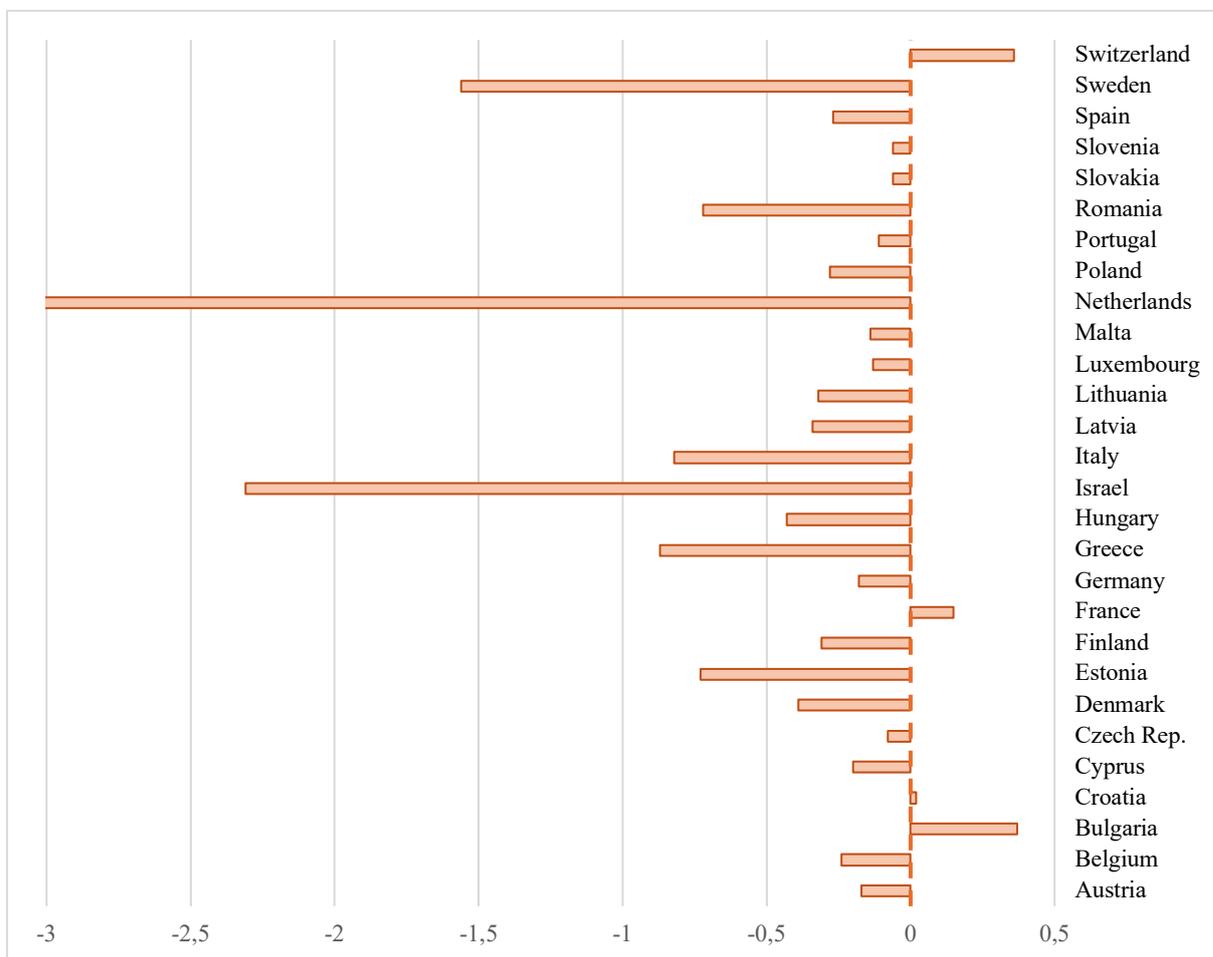
Figure 21 - ICT effect by macro-region



Source: Author's elaboration based on SHARE Wave 9 data

Figure 22 presents the coefficients estimated for each country. The pattern confirms that heterogeneity is substantial. In many Northern and Western European countries (Germany, France, Belgium, Denmark), the ICT coefficient is small and non-significant, indicating that other structural factors, such as welfare provision and social networks, play a more dominant role. Conversely, in several Southern and Eastern European countries (Bulgaria, Romania, Hungary, Greece, Italy, Poland), the effect is larger and significant, pointing to a stronger role of ICT in mitigating depressive symptoms and loneliness. Some countries with smaller samples (such as Luxembourg, Israel, or the Netherlands) show unstable or even negative coefficients; these results should be interpreted cautiously, as they likely reflect small sample sizes or local specificities.

Figure 22 - ICT effect on EURO-D by Country



Source: Author's elaboration based on SHARE Wave 9 data

Together, these analyses demonstrate that while ICT use is broadly associated with better mental health among older adults, the strength of this relationship varies across Europe. The positive effect of digital inclusion appears firmer where alternative social protections

are weaker, highlighting the importance of considering institutional and cultural contexts when evaluating the role of ICT for well-being in later life.

4.3 Analysis Conclusion

The results presented throughout this chapter provide a coherent picture of how digital engagement shapes mental health outcomes among individuals aged 50 and over in Europe. The descriptive statistics suggested that internet users differ substantially from non-users: they report fewer depressive symptoms, higher life satisfaction, better perceived health, and stronger social connections. These initial differences raised whether sociodemographic and health-related factors could explain such associations, or whether digital use contributes to improved psychological well-being.

The regression results show a clear pattern. ICT users tend to score lower on the EURO-D depression scale and higher on the CASP-12 quality of life index. The differences are not small. In the bivariate models, users report about 0.8 points fewer depressive symptoms and more than 4 points higher on CASP, substantial gaps given the scale ranges.

When controls are added step by step for age, gender, education, health status, loneliness, and self-rated health, the size of the coefficients becomes smaller but mostly remains significant. This indicates that part of the ICT effect is explained by health and social factors, but some association continues to hold, suggesting that digital use itself contributes to psychological well-being.

Heterogeneity analysis adds an important insight. Gender-stratified models indicate that ICT use is associated with lower depression scores only among men, while for women the effect is not significant. For quality of life, both men and women benefit, with slightly larger gains in CASP-12 scores among men. Age-based stratifications reveal an even clearer contrast: ICT use is linked to a small increase in depressive symptoms among the 50 to 64 group, no effect in the 65 to 74 group, and a clear protective role among those aged 75 and over. For quality of life, the association is positive across all age groups, with relatively similar effect sizes. Finally, we see the complex pattern of the role of digital skills. ICT use reduces depressive symptoms primarily among individuals with higher skills, while quality of life improvements is observed across the skills spectrum and are in fact stronger among those with limited skills. This suggests that while competence is

important for protecting against depression, even simple forms of participation can generate meaningful gains in autonomy and well-being. These findings resonate with the literature on the “second-level digital divide”, stressing that access and effective use are crucial determinants of inclusion.

The robustness of these results was tested in several ways. Constructing a composite index of psychological well-being through principal component analysis. This confirmed that EURO-D and CASP capture complementary aspects of mental health and that ICT use is associated with more favourable scores on this synthetic measure. It should be noted, however, that the PCA models rely on a much smaller subsample due to missing values. Logistic regressions with dichotomized outcomes (depression cases, low vs. high well-being) gave consistent evidence. Models with survey weights and clustered errors confirmed these findings. Notably, the association between ICT use and reduced loneliness further supports the idea that digital tools can help mitigate one of the strongest predictors of poor mental health in later life. Regional sub-samples highlight some variability, effects are more pronounced in Southern and Eastern European countries, but the overall direction remains stable across contexts.

The results suggest that using digital technologies can help protect the mental well-being of older adults. ICT use cannot remove deeper determinants such as chronic illness, gender differences, or social isolation, but it seems to add a layer of resilience. The positive impact is most visible among those who are most vulnerable: the very old, people who feel isolated, and those in poor health. These findings stand in contrast from much of the research on younger people, where ICT use is often linked to risks like anxiety or overuse. This shows that the effects of digital engagement change across the life course, depending on the challenges and resources of each age group. For this reason, digital inclusion should be seen not only as a technical issue but also as a matter of public health. From a policy perspective, the results align with European strategies on active ageing and digital inclusion, suggesting that improving access and skills for older people has implication for social participation and for public health. The findings are also in line with earlier research that describes ICT as a tool that can both integrate and exclude. Empirically, however, the evidence shows that when access is guaranteed, the overall effect for older adults is clearly beneficial. At the same time, the observational nature of the analysis does not allow for causal interpretation. Future research could build on longitudinal data or experimental settings to provide stronger evidence.

Chapter V – Temporal Comparison: Wave 7 vs Wave 9

The comparison between Wave 7 (2017) and Wave 9 (2021–2022) of the SHARE survey is particularly relevant for this research. While the core analytical framework remains the same, the two survey waves capture very different social and technological contexts. Wave 7 reflects the situation before the pandemic, when digital use among older adults was still relatively limited and more clearly shaped by socio-demographic differences. Wave 9, instead, captures the post-pandemic years, a period in which COVID-19 sped up digital adoption across generations and brought out not only the benefits but also the risks tied to greater reliance on technology.

By examining results from both waves, we can observe whether the association between ICT use, and mental well-being has remained stable or evolved. One might expect a stronger effect of ICT use in earlier waves, when access to technology was a distinguishing factor between included and excluded groups. On the other hand, the post-pandemic context may have accentuated the importance of digital skills, social connectivity through technology and the capacity to incorporate ICT into daily life.

From a methodological perspective, the temporal comparison also enables us to assess the robustness of the empirical strategy. If similar associations emerge in both waves, the results will be considered more robust and less dependent on period-specific circumstances. Conversely, if differences emerge, they could reveal the impact of broader structural and contextual transformations, such as digitalization trends, pandemic disruptions and changes in the socio-demographic profile of ICT users, on the relationship between technology and mental health.

5.1 The Role of COVID-19 in Our Lives

The COVID-19 pandemic was an unprecedented shock that reshaped social, economic, and personal life, and it deeply affected how people interact with digital technologies.

For older adults, it marked a turning point. Many activities that had always taken place face to face, such as medical visits, dealing with public offices, keeping in touch with family, or even leisure, were suddenly moved online. This shift meant that older people, often less familiar with digital tools, had to start using them if they wanted to stay connected both socially and economically.

From the perspective of this research, the pandemic context is crucial for two reasons. First, it accelerated the spread of remote interactions, highlighting both the benefits and risks of digital engagement. For some, online platforms provided essential opportunities for connection and continuity, mitigating social isolation during lockdowns. For others, however, the rapid digitalization intensified feelings of exclusion and stress, especially among those lacking adequate skills or confidence with technology. Second, the COVID-19 crisis amplified pre-existing inequalities, creating what Seifert, Cotten, and Xie⁶² describe as a “double burden of exclusion”. Older adults who were already socially isolated often found themselves digitally excluded as well, reinforcing their vulnerability to mental health risks. At the same time, studies also highlighted that when older adults successfully engaged with digital platforms, they were able to sustain social connections, preserve autonomy, and reduce feelings of loneliness.

The pandemic acted both as a push and as a test for digital inclusion. It sped up the spread of ICT use but at the same time revealed the emotional, cognitive, and infrastructural obstacles that many older adults still face. For research on mental health, this makes Wave 9 of SHARE especially useful. It captures outcomes after COVID-19 and can be compared with the pre-pandemic situation recorded in Wave 7. Looking at the two waves together helps to separate the broader role of digital use in supporting well-being from the specific effects of the pandemic.

5.2 Results of Wave 7

In 2017, SHARE carried out the Wave 7 main data collection across 28 countries. Full EU coverage was achieved by adding eight new countries to the panel: Finland, Lithuania, Latvia, Slovakia, Romania, Bulgaria, Malta, and Cyprus. Fieldwork was organized on a largely synchronous schedule across nations with standardized quality controls on training, back-checks, and response/retention targets. These operational features ensured high cross-national comparability of the evidence used in this chapter.

In Wave 7, the survey used two different instruments. Participants who had not taken part in Wave 3 were given a SHARELIFE life-history interview, which collected information on family, housing, work, health, and healthcare across the life course. Those who had already completed SHARELIFE earlier received the standard panel questionnaire instead.

⁶² Seifert A, Cotten SR, Xie B. *A Double Burden of Exclusion? Digital and Social Exclusion of Older Adults in Times of COVID-19*. *J Gerontol B Psychol Sci Soc Sci*. 2021.

To keep continuity on key outcomes, the SHARELIFE group also answered a shorter version of the core survey.

Within this framework, I replicate for Wave 7 the same empirical strategy used in Chapter IV for Wave 9. The analysis focuses on the association between ICT use and two mental-health outcomes for the 50+ population: EURO-D and CASP-12.

Wave 7 provides a pre-pandemic baseline. At this time, digital penetration among older adults in Europe was lower and more uneven than in later years, reflecting persistent socio-demographic divides in ICT use. This context is crucial for interpreting the results, as ICT adoption may have carried stronger correlations with health and social characteristics compared to post-pandemic data in Wave 9.

5.2.1 Bivariate results

To begin the comparison, I first look at descriptive statistics from Wave 7. The aim is to check whether ICT users and non-users already showed systematic differences before the pandemic.

The results point to clear gaps. On average, users had lower EURO-D scores (1.78 vs. 2.78), meaning fewer depressive symptoms, and higher CASP-12 scores (39.8 vs. 37.2), suggesting a better quality of life. They also tended to be a bit younger and, although the difference is smaller than in Wave 9, somewhat more educated.

Table 26 - Summary statistics by ICT use, Wave 7

Variable	Users Obs	Users Mean	Non-Users Obs	Non-Users Mean
EURO-D	1,236	1.78	1,716	2.78
CASP-12	1,220	39.81	21,918	37.23
Age	1,248	69.28	23,246	69.08
Years of Education	53	11.79	4,868	11.39

Source: Author's elaboration based on SHARE Wave 9 data

To further investigate the gaps shown in the table above, I estimate a series of regression models, starting with a simple bivariate specification.

The bivariate regression confirms that ICT use is significantly associated with fewer depressive symptoms. The coefficient of ICT use is -0.85 ($p < 0.001$), indicating that users score almost one point lower on the EURO-D scale compared to non-users. Given that the scale ranges from 0 to 12, this effect size is meaningful.

The model is based on a relatively small sample of 2,952 observations, as not all respondents completed the EURO-D questionnaire in Wave 7. Despite this smaller sample, the association is still significant, suggesting a robust relationship between ICT use and lower levels of depressive symptoms.

Table 27 - variate regression, EURO-D as the dependent variable

Source	SS	df	MS	Number of obs	=	2,952
Model	726.011463	1	726.011463	F(1, 2950)	=	159.86
Residual	13397.6467	2,950	4.54157516	Prob > F	=	0.0000
				R-squared	=	0.0514
				Adj R-squared	=	0.0511
Total	14123.6582	2,951	4.78605835	Root MSE	=	2.1311

eurod	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	-1.005222	.0795048	-12.64	0.000	-1.161113	-.8493315
_cons	2.780303	.0514452	54.04	0.000	2.679431	2.881175

Source: Author's elaboration in Stata based on SHARE Wave 9 data

The bivariate model with CASP-12 as the dependent variable also shows a strong and significant effect of ICT use. The coefficient is +2.59 ($p < 0.001$), which means that ICT users report on average a CASP-12 score over two and a half points higher than non-users. Considering that CASP-12 ranges from 12 to 48, this represents a substantial improvement in perceived quality of life.

This regression relies on a larger sample of 23,138 cases, as the CASP-12 was asked to more respondents in Wave 7. The bigger sample increases the reliability of the estimates and confirms that the effect is consistent.

Table 28 - Bivariate regression, CASP-12 as dependent variable

Source	SS	df	MS	Number of obs	=	23,138
Model	7632.77769	1	7632.77769	F(1, 23136)	=	199.38
Residual	885722.968	23,136	38.2833233	Prob > F	=	0.0000
				R-squared	=	0.0085
				Adj R-squared	=	0.0085
Total	893355.746	23,137	38.6115635	Root MSE	=	6.1874

casp	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	2.569945	.1820067	14.12	0.000	2.2132	2.92669
_cons	37.23825	.0417931	891.01	0.000	37.15633	37.32017

Source: Author's elaboration in Stata based on SHARE Wave 9 data

In sum, the bivariate results from Wave 7 provide clear evidence that ICT use was already positively associated with mental health outcomes before the COVID-19 pandemic. While the sample size differs considerably between EURO-D and CASP due to the survey design, the consistency of the findings across both measures reinforces the reliability of the association. These results suggest that digital inclusion was already a relevant protective factor for psychological well-being in 2017, establishing a baseline against which the post-pandemic dynamics of Wave 9 can later be compared.

5.2.2 Extended model

The bivariate regressions offered an initial snapshot of the link between ICT use and mental health, but they did not take into account other factors that might shape both digital activity and well-being. To go further, I ran an extended models in which controls for age, gender, education, chronic conditions, loneliness, and self-rated health were added step by step. This method makes it possible to see whether the association between ICT use and mental health holds once these influences are included. It also highlights which variables weigh most on depressive symptoms and quality of life, helping to clarify whether ICT use has an effect of its own or whether its role is mainly explained by the characteristics of the respondents.

Table 29 - Extended regression, EURO-D as dependent variable

Source	SS	df	MS	Number of obs	=	151
Model	280.294667	7	40.0420953	F(7, 143)	=	10.03
Residual	570.884141	143	3.99219679	Prob > F	=	0.0000
				R-squared	=	0.3293
				Adj R-squared	=	0.2965
Total	851.178808	150	5.67452539	Root MSE	=	1.998

eurod	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	-.8005218	.3924642	-2.04	0.043	-1.576303	-.0247409
age	.0207703	.0229703	0.90	0.367	-.0246348	.0661755
female	1.223142	.3403601	3.59	0.000	.5503547	1.895929
years_education	.0994115	.0530015	1.88	0.063	-.0053562	.2041792
chronic_conditions	-.0157003	.116381	-0.13	0.893	-.2457497	.2143492
loneliness	.5197314	.1248014	4.16	0.000	.2730375	.7664254
self_perceived_health	.6904373	.2295675	3.01	0.003	.2366531	1.144222
_cons	-4.361323	1.832103	-2.38	0.019	-7.982827	-.7398193

Source: Author's elaboration in Stata based on SHARE Wave 9 data

As socio-demographic and health variables are added, the link between ICT use and EURO-D stays negative and significant.

In the full model, the coefficient for ICT use is -0.08 ($p < 0.01$). This means that, after controlling for other main factors affecting mental health, ICT users report about one fewer depressive symptom than non-users.

Although the magnitude of the effect is slightly reduced compared to the bivariate estimate, its persistence highlights that the association is not merely due to compositional differences. The variables that explain most of the variance in depressive symptoms are loneliness and self-perceived health, both strongly correlated with EURO-D scores. Yet, even after accounting for these, ICT use retains an independent association with lower depression.

Table 30 - Extended regression, CASP as dependent variable

Source	SS	df	MS	Number of obs	=	151
Model	2761.47473	7	394.49639	F(7, 143)	=	15.51
Residual	3638.10143	143	25.4412687	Prob > F	=	0.0000
				R-squared	=	0.4315
				Adj R-squared	=	0.4037
Total	6399.57616	150	42.6638411	Root MSE	=	5.0439

casp	Coefficient	Std. err.	t	P> t	[95% conf. interval]
ict_user	2.716508	.9906802	2.74	0.007	.7582381 4.674778
age	-.0926383	.0577142	-1.61	0.111	-.2067216 .021445
female	-1.553577	.8591636	-1.81	0.073	-3.251879 .1447249
years_education	-.1832041	.1289195	-1.42	0.157	-.4380383 .0716302
chronic_conditions	-.5691456	.296782	-1.92	0.057	-1.155792 .017501
loneliness	-2.090846	.315405	-6.63	0.000	-2.714305 -1.467388
self_perceived_health	-.9012056	.5632517	-1.60	0.112	-2.014581 .2121695
_cons	58.30748	4.604369	12.66	0.000	49.20606 67.4089

Source: Author's elaboration in Stata based on SHARE Wave 9 data

For CASP-12, the extended model also confirms the positive role of ICT use. After including the same set of controls, the coefficient for ICT use remains $+2.72$ ($p < 0.01$). This means that users report a significantly higher quality of life even after controlling for socio-demographic and health factors.

As in the EURO-D model, loneliness and self-rated health emerge as the main predictors of CASP-12, both showing a positive link with quality of life. Even so, the ICT variable continues to have an effect, indicating that digital engagement adds to well-being over and above these influences.

In conclusion, the extended models show that ICT use in Wave 7 is consistently linked with better mental health outcomes, even after accounting for key socio-demographic and health-related factors. For EURO-D, users report fewer depressive symptoms, while for

CASP-12, they report higher levels of quality of life. In both cases, the inclusion of controls reduces the magnitude of the coefficients compared to the bivariate models, but the associations remain significant.

5.3 Results of Wave 9 - Recap

Wave 9 (2021–2022) was carried out after the pandemic and offers a picture of a time when digital use had already spread more widely among older people. The descriptive results point to clear contrasts between users and non-users. On average, those who go online report fewer depressive symptoms (EURO-D: 2.15 vs. 2.96), higher life satisfaction (CASP-12: 39.0 vs. 34.8), and better self-rated health. They also tend to be younger and to have more years of education.

In bivariate regressions, ICT use is significantly associated with lower depression (–0.8 points in EURO-D) and higher quality of life (+4 points in CASP-12). These effect sizes are substantial, similar to the patterns observed in Wave 7.

When controls are progressively added the results diverge across the two outcomes. For EURO-D, the protective effect of ICT becomes weaker and partially loses significance once chronic conditions, loneliness, and self-perceived health are included. This suggests that the observed association is mostly explained by the better health and social conditions of ICT users. Moreover, when digital skills are introduced, the coefficient of ICT use disappears, highlighting that the quality of digital engagement rather than access alone plays a central role in shaping depressive symptoms.

For CASP-12, the results are more robust. The ICT coefficient remains positive and significant even in the fully adjusted model (+1.3 points, $p < 0.01$). This indicates that ICT use is consistently associated with better perceived quality of life, even after adjusting for socio-demographic factors, health conditions, loneliness, or skill levels.

The findings from Wave 9 point to a mixed picture. ICT use is still linked with fewer depressive symptoms, but much of this effect seems to run through health, social ties, and digital skills. By contrast, the positive association with quality of life is more consistent, showing that digital inclusion continues to be tied to higher well-being for older adults even after the pandemic.

5.4 Comparative Analysis

The comparative results between Wave 7 (2017) and Wave 9 (2021–2022) show both continuity and change in the relationship between ICT use and mental health outcomes.

Table 31 - Comparative summary of ICT use on EURO-D, Wave 7 vs Wave 9

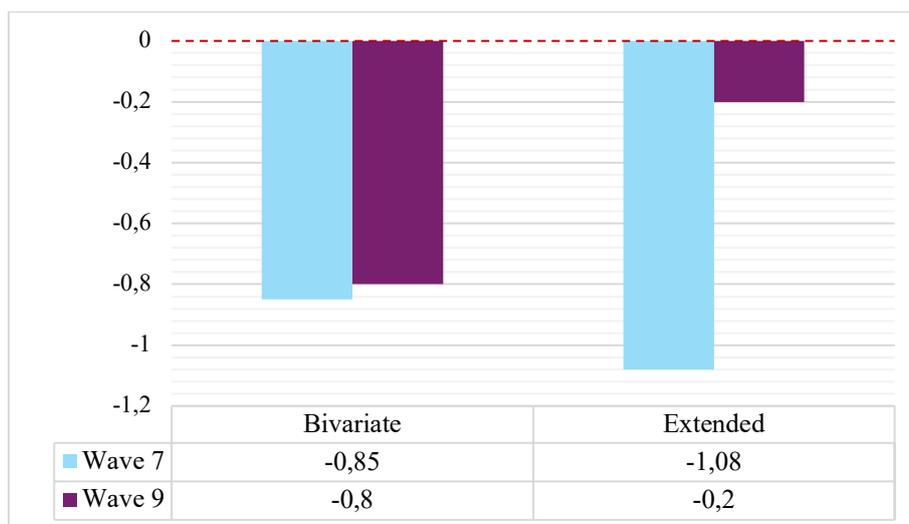
Model	Wave 7	Wave 9
<i>Bivariate</i>	-0.85	-0.80
<i>Extended</i>	-1.08	-0.20

Source: Author's elaboration in Stata based on SHARE Wave 9 data

In the bivariate models, ICT use is associated with fewer depressive symptoms in both waves (−0.85 in Wave 7; −0.80 in Wave 9). This suggests a consistent protective role of digital engagement over time. Once controls are added, the two waves show different results. In Wave 7, ICT use still has a strong and significant effect (−1.08). In Wave 9, by contrast, the coefficient drops to −0.20 and is no longer significant. This suggests that, after the pandemic, the connection between ICT and depression is mostly driven by factors such as health, social ties, and digital skills, rather than by internet access on its own.

The figure 23 illustrates the reduction in the EURO-D coefficients from Wave 7 to Wave 9 once covariates are added, highlighting the direct effect of ICT use on depression has weakened over time.

Figure 23 - Bivariate models *EURO-D* Wave 7 vs Wave 9



Source: Author's elaboration in Stata based on SHARE Wave 9 data

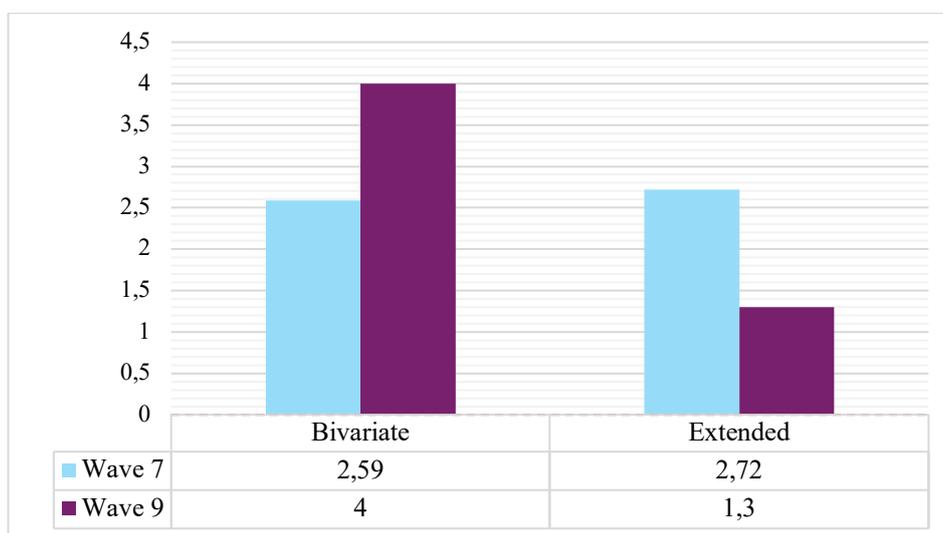
Table 31 - Comparative summary of ICT use on CASP-12, Wave 7 vs Wave 9

Model	Wave 7	Wave 9
<i>Bivariate</i>	+2.59	+4.00
<i>Extended</i>	+2.72	+1.30

Source: Author's elaboration in Stata based on SHARE Wave 9 data

In the bivariate models, ICT use is associated with significantly higher CASP-12 scores, with the effect being stronger in Wave 9 (+4.00) than in Wave 7 (+2.59). This reflects the greater relevance of ICT in daily life after the pandemic. In the extended models, the coefficients get smaller but stay significant (+2.72 in Wave 7 and +1.30 in Wave 9). This means that, even after taking health and social factors into account, ICT use still shows a positive link with how older adults rate their quality of life.

Figure 24 - Extended models Wave 7 vs Wave 9



Source: Author's elaboration in Stata based on SHARE Wave 9 data

The figure 24 illustrates that the positive effect of ICT use on quality of life is robust across both waves, though moderated by covariates in Wave 9.

The comparison between Wave 7 and Wave 9 helps to see how the link between ICT use and mental health in later life has evolved. In 2017, ICT users reported fewer depressive symptoms on the EURO-D scale, and this difference remained even after controlling for age, education, and health. At that time, going online was still relatively selective: users were generally younger, better educated, and appeared to enjoy an extra additional psychological advantage. By the time of Wave 9, however, this direct effect had weakened. Once health, social ties, and especially digital skills are included in the model,

the independent role of ICT use became much smaller. With digital access now widespread after the pandemic, simple connectivity no longer distinguishes people as strongly as before. What seems to matter more is how well and how confidently older adults engage with digital tools.

For CASP-12, the pattern is different. In both waves, ICT use is positively and significantly associated with quality of life. The effect is strong in the bivariate models and remains robust in the extended specifications, even if reduced in magnitude when controls are added. This consistency highlights that digital inclusion plays a stable and enduring role in enhancing subjective well-being among older adults. Part of the effect is mediated by health and social variables, but a positive independent contribution of ICT use remains visible. Interestingly, the effect is even larger in Wave 9's bivariate specification, which may reflect the heightened importance of ICT during and after the pandemic in sustaining daily routines, social ties, and access to services.

Taken together, the findings point to a change in what it means for older adults to use ICT. Before the pandemic, being online clearly set people apart and was closely linked to better mental health. After the pandemic, when digital access became more common, the link with lower depression scores became weaker, although the positive effect on quality of life remained. This pattern suggests that policy should move beyond basic access and place more focus on digital skills, confidence, and meaningful ways of using technology. The evidence indicates that digital inclusion can support ageing well, mainly by improving quality of life, even if its role in reducing depressive symptoms has become less direct over time.

Chapter VI - Limitations and Methodological Considerations

Regardless of its statistical robustness and theoretical foundation, every empirical study must acknowledge its limitations. This step is essential for transparency and situating findings within their appropriate scope of validity.

In the case of this thesis, which looks at the link between ICT use and mental health among older adults in Europe, it is crucial to clarify the extent to which the findings can be generalized, and how methodological choices may have shaped the results. The following discussion is, therefore, intended as a critical reflection on the empirical work presented in the previous chapters. It considers the quality of the SHARE data infrastructure, the consequences of relying on cross-sectional evidence, the limitations of self-reported measures, the challenge of measuring complex constructs such as mental health and digital engagement, the specification of statistical models, and finally, the broader issues of external validity and ethical implications. This chapter has set out the main limits of the analysis while also pointing to directions for future studies and policy discussion. Recognizing these limits does not reduce the value of the work; on the contrary, it adds clarity and makes the contribution more credible.

6.1 Data Limitations

One of the primary limitations of this study arrives from the nature of the data itself, including issues of missing information and sample attrition. In my analysis, this problem was most evident for socio-economic variables such as household income and years of education, both of which showed high non-response rates. As Mirzaei, Carter, Patanwala, and Schneider highlighted in their paper “Missing data in surveys: Key concepts, approaches, and applications”⁶³, inadequate handling of missing data threatens the validity of survey research, since lost observations may reflect systematic rather than random patterns. For this reason, income and education were excluded from the regression models, as their inclusion would have reduced the sample size and introduced bias through selective non-response.

⁶³ Mirzaei A, Carter SR, Patanwala AE, Schneider CR. *Missing data in surveys: Key concepts, approaches, and applications*. Res Social Adm Pharm.

Furthermore, longitudinal surveys of aging populations like SHARE inevitably face attrition over subsequent waves, since participants may drop out due to health decline or other reasons. SHARE attempts to mitigate this issue by introducing refreshment samples and rigorous follow-up, helping maintain cross-sectional representativeness. Börsch-Supan et al.⁶⁴ describe SHARE as a multidisciplinary and cross-national survey that provides unparalleled opportunities to study aging in Europe, while also acknowledging challenges such as attrition and cross-country comparability. This is particularly relevant because individuals who leave the panel are often those in poorer health or with weaker social ties, which represent the factors closely linked to both ICT use and mental well-being. As a result, while the cross-sectional results presented in the chapters above remain robust, any interpretation of changes between Wave 7 and Wave 9 must be cautious. Part of the differences between the two waves may reflect selective dropout rather than true temporal change.

Another data-related limitation is the challenge of comparability across the multiple countries included in SHARE. Cultural and contextual differences can influence how respondents interpret and answer mental health items, which complicates direct comparisons of outcomes. Research on the EURO-D depression scale employed by SHARE has found that while the instrument is standardized, full measurement equivalence across countries is difficult to achieve. Observed differences in depression scores might reflect cultural response patterns rather than true disparities.⁶⁵ As a result, observed differences in depression scores may partly reflect cultural response styles rather than actual disparities in mental health. For example, the finding that ICT shows stronger associations in Southern and Eastern Europe could be influenced not only by real contextual differences, but also by variation in how respondents interpret survey items. Similarly, for CASP-12, differences across countries may capture cultural understating of quality of life as much as substantive disparities.

In summary, the limits of the SHARE data mean that the results should be read carefully, keeping in mind how the survey is built.

⁶⁴ Axel Börsch-Supan, Martina Brandt, Christian Hunkler, Thorsten Kneip, Julie Korbmacher, Frederic Malter, Barbara Schaan, Stephanie Stuck, Sabrina Zuber, on behalf of the SHARE Central Coordination Team, Data Resource Profile: *The Survey of Health, Ageing and Retirement in Europe (SHARE)*.

⁶⁵ Maskileyson, D., Seddig, D., & Davidov, E. (2021).. Frontiers in *The EURO-D Measure of Depressive Symptoms in the Aging Population: Comparability Across European Countries and Israel* Political Science.

Future research could tackle these issues in several ways. One option is to use multiple imputation for missing socio-economic variables, such as income and wealth, so that patterns of non-response are modelled more explicitly. Another is to apply panel weights and methods that correct for attrition, reducing the bias caused by dropouts. It would also be valuable to test whether measures like EURO-D and CASP work the same way across different countries, by applying measurement invariance checks. Alongside these quantitative steps, qualitative approaches, such as interviews to understand how older adults interpret sensitive questions, could help reveal cultural or language differences. Taken together, these strategies would improve cross-national comparability and make international evidence on ICT and mental health more reliable.

6.2 Survey Design Constraints

The cross-sectional design of this study imposes significant constraints on the conclusions that can be drawn, particularly regarding causality. Because data on ICT use and mental health were collected at the same point in time, we can only establish associations between variables, not causal direction. It remains unclear whether using digital technologies leads to better mental well-being, or if individuals who already enjoy better mental health are simply more likely to engage with ICT. Without longitudinal sequencing, there is a risk of reverse causality or reciprocal effects that our analysis cannot untangle.

Prior research has emphasized that correlations observed in one-time surveys are an insufficient basis for causal inference. Twenge and Hamilton⁶⁶, for example, demonstrate that linear correlation is an insufficient measure of association. Even small correlation coefficients between technology use and mental well-being can hide important risks or subgroup differences. This is relevant for the present thesis, where the associations between ICT use and mental health are modest in size but consistent across models. For EURO-D, the average effect is small and disappears once controls are added, yet subgroup analyses suggest that ICT matters more for individuals who are socially isolated or have lower digital skills. For CASP-12, the coefficients are larger, but the overall figures may still mask substantial heterogeneity. In this sense, the coefficients reported in

⁶⁶ Jean M. Twenge, Jessica L. Hamilton, *Linear correlation is insufficient as the sole measure of associations: The case of technology use and mental health*, Acta Psychologica.

the regression tables should be read as average effects, which may underestimate meaningful variation across individuals and contexts.

In practice, the statistical associations we observe do not prove that ICT use itself improves mental health. It is possible that older adults who are already healthier or more socially active are both more likely to go online and to report better well-being. Unmeasured factors, such as personality traits or prior exposure to digital tools, could also drive both sides of the relationship. In addition, the lack of temporal data prevents testing whether sustained ICT use improves mental health over time, or whether new adopters follow different trajectories compared to non-users. This limitation is particularly relevant when interpreting the weakening effect on EURO-D between Wave 7 and Wave 9, as it remains unclear if the change reflects causal dynamics or shifts in the composition of ICT users.

Ultimately, the constraints mean that the results should be interpreted as associations rather than causal effects. Policy or practical recommendations should not assume a unidirectional effect from ICT use to improved mental health. Stronger evidence from longitudinal or experimental studies is needed to address these inherent cross-sectional limitations.

For future research, a more robust approach would be to use the longitudinal design of SHARE or similar ageing surveys in order to follow changes in individuals across multiple waves. Fixed-effects models could then be applied to control for unobserved heterogeneity. Where possible, these could be combined with quasi-experimental strategies, such as instrumental variables or natural experiments. These designs would enable researchers to more effectively distinguish causality from correlation and capture the dynamic, long-term relationship between ICT engagement and mental health trajectories in later life.

6.3 Measurement and Construct Validity

Another set of limitations arises from the use of self-reported measures for both ICT usage and mental health outcomes, which introduces well-known biases. All key variables in this thesis, frequency of Internet use, depressive symptoms, quality of life, are based on respondents' own reports. Self-reporting can be prone to inaccuracies due to recall errors, especially among older respondents who might misremember or misestimate their

activities and feelings. They can also be biased by socially desirable responses. In this study, that could mean underreporting negative mental health symptoms or overreporting positive behaviours, like being digitally active, to align with social expectations. Caputo demonstrates in “Social desirability bias in self-reported well-being measures”⁶⁷, shows that people often exaggerate their well-being to align with accepted norms. This may explain why in my results ICT use consistently linked with better CASP-12 scores. Part of the effect may reflect a tendency to give optimistic answers rather than a true improvement in quality of life. For EURO-D, the problem is similar. Some respondents may hide or minimize depressive symptoms because of stigma. This might partly explain why the effect of ICT use on EURO-D weakens once controls are added. Although SHARE applies validated instruments like EURO-D and CASP, the answers remain subjective. Two respondents with the same conditions may still give different answers depending on openness, interpretation, or cultural background.

Acknowledging this limitation is important. Future research should move beyond relying only on self-reported data and combine survey measures with more objective indicators. One option is to integrate logged ICT usage data from digital devices with validated clinical or biomarker-based mental health assessments. This would make it possible to cross-check subjective and objective evidence. Mixed-methods approaches could also be valuable. For example, combining quantitative panel data from SHARE with qualitative interviews would help capture how older adults actually use and interpret technology. Experimental or quasi-experimental design, such as natural experiments, could further strengthen causal claims.

These refinements could help limit reporting bias and make the conclusions about the role of ICT in older people’s mental health more reliable.

6.4 Model Specification Issues

There are also important considerations regarding how we defined and measured the core concepts of this research, which may affect the construct validity of our findings. In my analysis, “ICT use” was operationalized in a relatively narrow way, as a binary indicator of recent internet use. This simplification was necessary given the structure of SHARE, but it does not capture the full complexity of older adults' digital engagement. The

⁶⁷ Caputo, A. (2017). *Social desirability bias in self-reported well-being measures: Evidence from an online survey*. Universitas Psychologica.

intensity, purpose, and skill with which an individual uses technology can vary widely. Occasional emailing is very different from daily video chats or online learning, yet our measure treats users as a homogeneous group. Studies suggest that such nuances matter. For example, the digital skills and literacy of older adults can significantly mediate the benefits of technology use, sometimes even more than access itself. In their study, “Access to Information and Communication Technology, Digital Skills, and Perceived Well-Being among Older Adults in Hong Kong”, Fung et al.⁶⁸ show that access to ICT alone does not guarantee better outcomes. The positive relationship with well-being only becomes significant when digital skills are sufficiently developed. Their analysis emphasizes that competence in navigating online environments is a stronger predictor of perceived well-being than mere frequency of use. In fact, once digital skills are accounted for, frequency of internet use is no longer a significant predictor. This suggests that knowing how to use technology effectively may be the decisive factor.

Our binary ICT variable cannot distinguish a tech-savvy senior who actively uses multiple online tools from someone who barely goes online. As a result, the heterogeneity of ICT experiences is only partly reflected. Similarly, context matter: the meaning of being an “ICT user” can differ across countries and environments, as the availability of online services and cultural attitudes toward technology vary. An activity such as internet banking may provide different benefits in one country than in another with different support systems.

On the outcome side, our measures of mental well-being also have limitations. I focused on depressive symptoms (using the EURO-D scale) and quality of life (using the CASP-12 index) as indicators of mental health. These are established instruments in gerontological research, but they capture only part of the concept. EURO-D focuses on depressive symptoms, while CASP-12 reflects life satisfaction and functional aspects. Together they offer a two-dimensional view of mental health, while not including other important domains such as anxiety, cognitive health, or social connectedness.

Moreover, both EURO-D and CASP are self-reported ordinal scales, not clinical diagnose. Scores can fluctuate with temporary feelings or cultural tendencies in rating, raising questions of construct validity. This could be threatened if, for instance, the

⁶⁸ Fung, H. H., Cheung, F. M., Lam, B. C., & Lai, C. (2023). *Access to Information and Communication Technology, Digital Skills, and Perceived Well-Being among Older Adults in Hong Kong*. *Innovation in Aging*.

CASP-12 quality of life index does not fully capture what “mental well-being” means to respondents in different life situations. However, it should be noted that these scales were chosen for their appropriateness and prior validation in the SHARE dataset context. In this study, ICT is defined as having gone online in the past week, while mental well-being is represented by scores on depression symptoms and on quality of life. Any link we observe should therefore be read in light of these specific definitions.

It is possible that using a different definition of ICT engagement as, for example, distinguishing communication-oriented use from information consumption, or measuring actual digital skill level, might yield different insights. Likewise, incorporating other mental health measures, like an anxiety scale or a loneliness index, could alter the understanding of how technology relates to mental well-being. Acknowledging these construct validity issues is crucial, as it underscores that our findings are a piece of a larger puzzle and that broad claims about “ICT impact on mental health” should be made carefully, keeping in mind how those terms were defined in this study.

Future research should refine both constructs. On the ICT side, combining survey questions with objective usage data (e.g. logged smartphone or online platform activity) could capture the intensity and diversity of digital engagement. On the mental health side, supplementing scales such as EURO-D and CASP with validated instruments for anxiety, resilience or cognitive performance would provide a more holistic view. Additionally, applying multi-group confirmatory factor analysis would ensure these instruments achieve measurement invariance across countries, thereby strengthening their cross-cultural validity. These methodological improvements would bring the operational definitions into closer alignment with the theoretical constructs, allowing for more nuanced and reliable insights into the relationship between technology use and mental health among older adults.

6.5 External Validity and Ethical Considerations

The analytical approach, based on OLS regression models, comes with its own set of methodological limitations, mostly concerning omitted variable bias and endogeneity. Even though we controlled for major covariates (age, gender, education, health, and social factors), other relevant variable may still be missing. If any important determinants of mental health or technology use were omitted and correlated with the included variables, the OLS estimates could be biased.

Personality traits such as neuroticism or openness could shape both the likelihood of using ICT and mental health itself. If those traits are not measured, the estimated effect of ICT may partly reflect them rather than technology use alone, an instance of omitted variable bias. As Twenge and Hamilton point out, observational models that leave out key confounders can produce coefficients that look significant but are not fully reliable. This risk is especially relevant when studying technology and well-being, since the mechanisms involved are varied and hard to capture in a single model.

In this thesis, despite including several controls, it is not possible to rule out all sources of spurious correlation. Another aspect of endogeneity is the possibility of reverse causation. As discussed with the cross-sectional design, it is plausible that mental health influences ICT use (rather than or in addition to ICT use influencing mental health). If older adults who are depressed withdraw from using technology, then low ICT use could appear to cause depression when in fact the causality runs backwards. In technical terms, the independent variable (ICT use) may not be truly exogenous.

Ideally, one would use techniques like longitudinal fixed-effects models, instrumental variables, or randomized interventions to handle such endogeneity concerns. In the absence of those, the OLS results should be interpreted as associational. There is also the issue of linearity and functional form: OLS assumes a linear relationship between ICT use (modelled here as a binary or continuous variable) and mental health outcomes. The true relationship might be non-linear. If such complexities exist, a simple linear model could misestimate the effect, potentially underestimating it for some ranges and overestimating for others.

I carried out robustness checks and tested interactions to explore some of these issues, but the study design still has clear limits. The use of OLS makes the analysis relatively simple to follow, yet it relies on strong assumptions, such as the absence of unmeasured confounders and the correct specification of the model. For this reason, the results should be seen as indications rather than definitive proof. They point to consistent patterns, but other factors outside our control, or even reverse causality, could also play a role. Being aware of these statistical boundaries helps avoid reading the regressions as firm causal evidence.

Future research could strengthen causal inference by applying fixed-effects panel regressions to exploit the longitudinal nature of SHARE, thereby reducing bias from unobserved heterogeneity. Additionally, quasi-experimental strategies such as

instrumental variable approaches, difference-in-differences designs that exploit policy changes or propensity score matching could be employed to better isolate the impact of ICT use from confounding influences. Incorporating these advanced econometric techniques would enable future analyses to move beyond associative evidence and provide more reliable estimates of the causal relationships between digital engagement and mental health.

6.6 Generalizability of Results and Ethical Implications

Finally, we must consider the external validity of this thesis' results that is, the extent to which these findings can be generalized beyond our study context, as well as the broader ethical and societal implications. The analysis focuses on Europeans aged 50 and above and covers the early 2020s, a period that also overlapped with the COVID-19 crisis. This setting is worth keeping in mind, since the findings may not transfer in the same way to younger groups, to non-European populations, or to times outside the pandemic.

For instance, younger populations or older adults in non-European regions could have different experiences with ICT and mental health due to differing cultural norms, technological infrastructures, or support systems. Even within our sample, there is diversity: the SHARE data spans many countries, each with unique socio-economic conditions for older adults. The external validity is therefore qualified; this thesis findings are most directly relevant to socio-demographically similar populations as those surveyed.

Moreover, the fact that Wave 9 data were collected in the middle of the pandemic, a period when being online may have mattered more than usual for staying connected. This means that the strength of the link we observe between ICT use and mental health could partly reflect that specific moment. In everyday circumstances, or in places where face-to-face contact is easy to maintain, the effect might be weaker. In contrast, in societies with limited family or community support for seniors, digital tools could become even more valuable. For this reason, these results should be read with attention to their context. Studies conducted in other regions or in the years after the pandemic will be important to see if the same patterns appear.

The ethical implications of our findings centre on how society and policymakers should respond to the link between digital engagement and mental well-being in later life. On one hand, the results suggest a potential positive leverage point: facilitating older adults'

access to and proficiency with ICT could promote better mental health outcomes. However, this raises an equity concern, not all older individuals are equally able to take advantage of digital tools, leading to a “digital divide” that can mirror or even exacerbate existing social inequalities. Research by Barreda Gutiérrez, Cantarero-Prieto, and Pascual Sáez in “Age, Technology, and the Digital Divide: Are They Directly Related to Mental Health Problems?”⁶⁹ shows that the digital divide driven by age has a measurable negative effect on mental health among older Europeans, even after controlling for socio-economic status and country-level differences. Their findings suggest that disparities in digital access, usage, and skills are not just technical or infrastructure issues but are deeply linked to psychosocial well-being, indicating that bridging the divide should be seen as a public health priority rather than a mere digital policy concern. Those who are left offline or lack digital skills may also be the ones more vulnerable to loneliness or depression, meaning they suffer a double burden. From an ethical standpoint, this creates a responsibility to ensure that interventions do not leave these populations further behind.

The COVID-19 pandemic made this particularly visible. Older adults who were isolated and at the same time lacked digital access struggled the most with their mental health, facing a double disadvantage. This highlights why strategies that include everyone are so important. Practical steps could involve local courses that teach digital skills to seniors, cheaper broadband and devices, and technology that is easier for older people to use. Making sure that these benefits reach not only wealthier or healthier groups, but all older adults is essential if we want to prevent growing gaps in mental well-being. At the same time, an ethical analysis must also recognize the possible negative consequences of increased ICT use among older individuals. While this study highlights average benefits, digital engagement may also create risks if not supported appropriately. Encouraging more internet use without guidance could expose seniors to online scams, misinformation, or problematic overuse. Recent findings also highlight the importance of digital inclusion for labour market resilience. Using SHARE-COVID data, Brugiavini, Buia, and Simonetti⁷⁰ show that, during the first phase of the pandemic, both the likelihood and duration of work disruptions among Europeans aged 50 and over were strongly influenced by occupational characteristics. Jobs with greater feasibility for remote working

⁶⁹ Barreda Gutiérrez, M., Cantarero-Prieto, D., & Pascual Sáez, M. (2024). *Age, Technology, and the Digital Divide: Are They Directly Related to Mental Health Problems?* Healthcare.

⁷⁰ Brugiavini, A., Buia, R.E. & Simonetti, I. *Occupation and working outcomes during the Coronavirus Pandemic*. Eur J Ageing 19, 863–882 (2022).

experienced fewer disruptions, while occupations requiring intense social interaction were more vulnerable. Women were disproportionately affected, facing more frequent and prolonged disruptions, a pattern consistent with the greater psychological vulnerability observed in this thesis. These findings suggest that promoting digital skills and infrastructure not only supports mental well-being but also provides economic and employment protection in times of crisis. Follow-up evidence confirms that these dynamics extended beyond the immediate crisis. The same authors, in fact, show that older workers who experienced work disruptions in 2020 were significantly more likely to exit employment in 2021 and 2022⁷¹, either through retirement or non-employment. Importantly, higher education and strong IT skills emerged as protective factors, further underlining the transversal role of digital competence for resilience in later life.

It is also important to respect autonomy. Some older people may not wish to engage with digital technology, and their preferences should be acknowledged even while opportunities are created for those who do. The goal is to empower older adults who want to use ICT by reducing barriers of cost, skills, or fear, not to pressure unwilling individuals into adoption. As Barreda Gutiérrez, Cantarero-Prieto, and Pascual Sáez argue⁷², the digital divide is not only a technical gap but also a health and equity issue, with direct consequences for mental well-being.

In conclusion, this thesis finds a generally positive link between digital participation and mental health in later life. At the same time, caution is needed before applying these results to different settings, and any practical steps should be shaped by concerns for fairness and safety. Looking forward, three areas deserve particular attention. One is to combine access initiatives with programs that build confidence and digital safety among older users. Another is to remove structural obstacles, for example cost or difficulties of use. A third is to study the longer-term consequences of ICT use through longitudinal follow-ups or experimental projects. Balancing possible advantages with potential risks is essential if digital inclusion is to support well-being without exposing older adults to new forms of vulnerability.

⁷¹ Brugiavini, Agar and Buia, Raluca and Simonetti, Irene, *The Evolution of (post) Pandemic Labour Market Outcomes of Older Workers in Europe* (August 27, 2024). Ca' Foscari University of Venice, Department of Economics Research.

⁷² Barreda Gutiérrez, M., Cantarero-Prieto, D., & Pascual Sáez, M. (2024). *Age, Technology, and the Digital Divide: Are They Directly Related to Mental Health Problems?* Healthcare.

Conclusion

This thesis examined the relationship between digital technology use and mental health among Europeans aged 50 and above. The results show that older adults who use ICT tend to report fewer symptoms of depression and higher scores on quality of life. These associations remain significant even when demographic, socio-economic, and health variables are considered. The effect becomes weaker once loneliness, chronic illness, and self-rated health are added. In particular, Wave 9 highlights the central role of digital skills, it shows how the benefits of ICTs are stronger for people who feel confident with technology. Age and social context also matter. The positive impact is more evident among the oldest participants and among those with few social contacts, suggesting that being able to go online can partly offset the risks of isolation.

A synthetic reading of the results clarifies the pattern briefly described above. The clear gap between users and non-users is substantial: users report fewer symptoms and a significantly better quality of life. The introduction of controls reveals two powerful correlations that absorb much of the ICT-depression link: *loneliness* and *self-perceived health*. Where ICT facilitates connection and autonomy, through video calls, messaging, online communities, easier access to information and services, it operates along the same channels through which loneliness and poor health undermine well-being, by restoring contact, easing information-seeking, and simplifying access to services. Conversely, when health is compromised or social networks are poor, the benefits of ICTs are fragile if not accompanied by support, such as skills training or trusted intermediaries. The heterogeneity tests confirm this pattern: older adults appear to benefit from the clearest protective association on the EURO-D, while improvements in quality of life are broad and widespread across subgroups; digital skills moderate depressive symptoms but are less decisive for the CASP-12, suggesting that even relatively simple forms of participation can increase perceived autonomy and pleasure.

The temporal comparison reinforces the interpretive shift. Before the pandemic (Wave 7), being online still functioned as a selective indicator, and its association with lower depressive symptoms remained visible even after adjustment. After the pandemic (Wave 9), access is much more widespread; the distinctive advantage of mere connectivity diminishes, while the quality and inclusion of engagement take on a central role. At the regional level, the effects tend to be strongest in Southern and Eastern Europe, where digital infrastructure and social support may be more limited and the marginal gains from

inclusion are larger. This supports a structural reading of ICT as context-dependent rather than a uniform “treatment”.

These conclusions require a careful balance between benefits and risks. On the benefits side, ICTs can reduce practical frictions, support social participation, and ensure dignified autonomy in later life, especially when mobility is limited or families are distant. On the risk side, a purely technical approach can deepen divisions. Poor skills, low trust, and design that ignores age related needs can transform the promise of inclusion into new forms of exclusion, frustration or exposure to scams and misinformation. Hyperconnectivity, if poorly defined, can introduce tension rather than comfort. Therefore, the moral is neither enthusiasm nor alarmism but design with care; the need is of digital systems that are accessible, legible and secure by default.

These findings have also several implications for research. The study on digital life and mental health should move beyond exposure time and improve the measurement of purpose and quality of use, skills, and social inclusion. Secondly, causal identification remains a challenge. Longitudinal models, natural experiments, and linked administrative or usage-log data are needed to remove selection bias and track trajectories (adoption, maintenance, disengagement) over time. Cross-national work should address measurement invariance explicitly, given cultural variation in reporting well-being and symptoms. Finally, theory should treat ICT in later life as an interaction between technologies and capabilities, rather than as a stand-alone determinant.

Policy implications are equally concrete. If the goal is to promote mental well-being in an aging Europe, interventions must look beyond access. Based on the results of this thesis, four priorities emerge. The first one is *skills and confidence*, they should be built through practical trainings tailored to older learners, delivered locally and repeatedly, with patient mentoring and practice spaces that normalize the trial-and-error process. Then, *socially integrated programs* are needed, in particular initiatives that can combine digital learning with meaningful social activities, for example intergenerational workshops, hobby groups, addressing loneliness and skills together. Third, *integration with care* is essential. Primary care and community health services should integrate digital navigation support (appointments, teleconsultations, portals) and conduct systematic screening for loneliness, not just illness. Lastly, *design and safeguard* must be included in public services and major platforms should commit to age-inclusive design (clarity, font size, error tolerance), robust fraud protection, and eventual human channels, so that "digital-

first" does not become "digital-only". These indications reflect the central empirical lesson of this thesis. Technology's contribution to mental health in old age is conditional, it grows where people are not left to deal with it alone.

The limitations of this study, cross-sectional identification, self-report measures, potential endogeneity, and a necessarily stylized operationalization of ICT use, require caution in interpretation. They also outline an agenda for future work: panel approaches that leverage SHARE's longitudinal depth; quasi-experimental evaluations of targeted skills interventions; linkages with objective usage data (with robust privacy safeguards); and comparative designs focused on welfare regimes and community infrastructures. Such advances would allow for more reliable assertions about causality and dosage and sharpen the normative question that ultimately motivates this investigation.

In conclusion, the evidence presented here does not portray ICT as a panacea for the challenges of aging, nor as a latent threat to be contained. It portrays ICT as an infrastructure of possibility. For Europeans over 50, this possibility becomes beneficial for health when it is anchored in relationships, supported by skills, and protected by design. Where these conditions are cultivated, digital engagement can help transform longer lives into better ones: lives with more control, more connections, and more room for meaning. Where they are neglected, the promise dwindles. The task of both research and policy is to shift the balance toward the former.

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Appendix

Appendix A – Data and Variable Definitions

A.1 Outcomes and main explanatory variables

Variable	Construct	Module	Coding	Notes
<i>EURO-D</i>	Depressive symptoms	gv_health	0 – 12	Standard composite, continuous
<i>CASP-12</i>	Quality of life	gv_health	12 – 48	Composite index across 4 domains
<i>ICT use</i>	Internet usage (7 days)	it	Binary	1 = used internet/computer in the last 7 days
<i>Digital skills</i>	Self-reported computer skills	it	Ordinal	Re-coded into 3 levels (High / Medium / Low).

Source: Author's elaboration on SHARE Wave 9 data

A.2 Control variables

- **Age:** years, continuous
- **Female:** 1= female
- **Years of education:** continuous
- **Chronic conditions:** count index
- **Self-perceived health:** 1-5, higher = worse
- **Loneliness:** scale 1 – 6

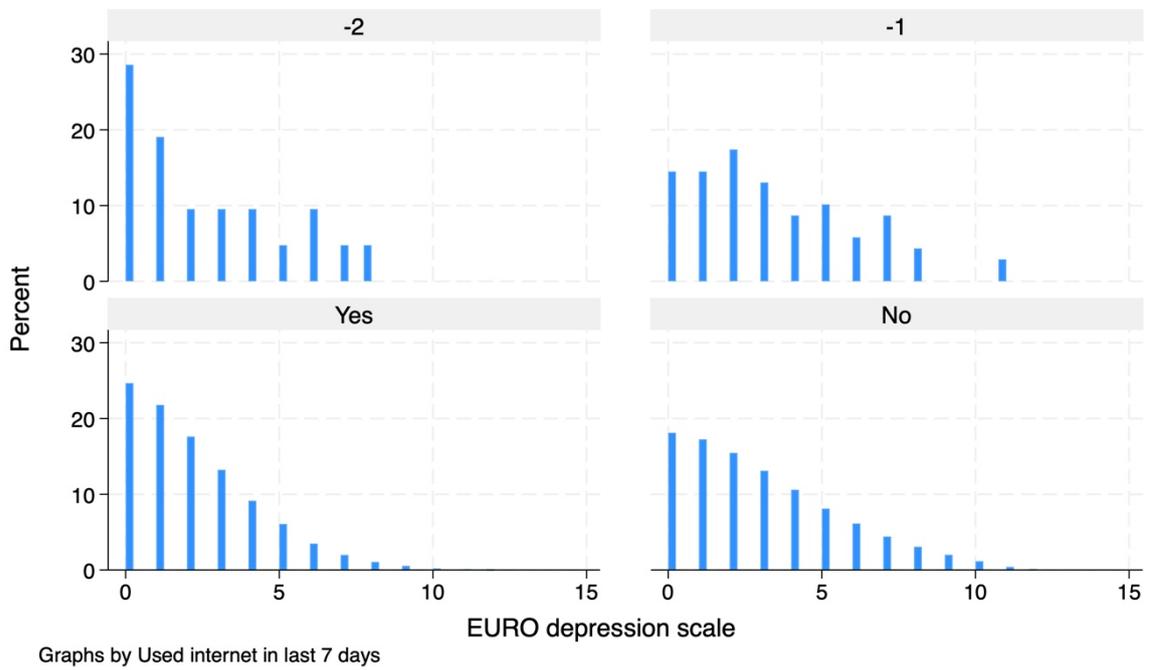
Appendix B – Descriptive Statistics

Table B.1 – Weighted descriptive statistics by ICT use

Variable	ICT Users		Non-Users	
	Mean	SD	Mean	SD
EURO-D (Depression)	2.15	2.04	2.96	2.56
CASP-12 (Quality of Life)	39.04	5.48	34.76	6.39
Age	66.37	8.36	74.5	9.49
Chronic Conditions	1.68	1.52	2.34	1.77
Self-perceived Health	2.98	0.99	3.61	0.97
Computer Skills	3.17	1.18	5.35	0.97
Loneliness	3.79	1.23	4.37	1.64
Years of Education	12.79	3.85	9.44	3.35

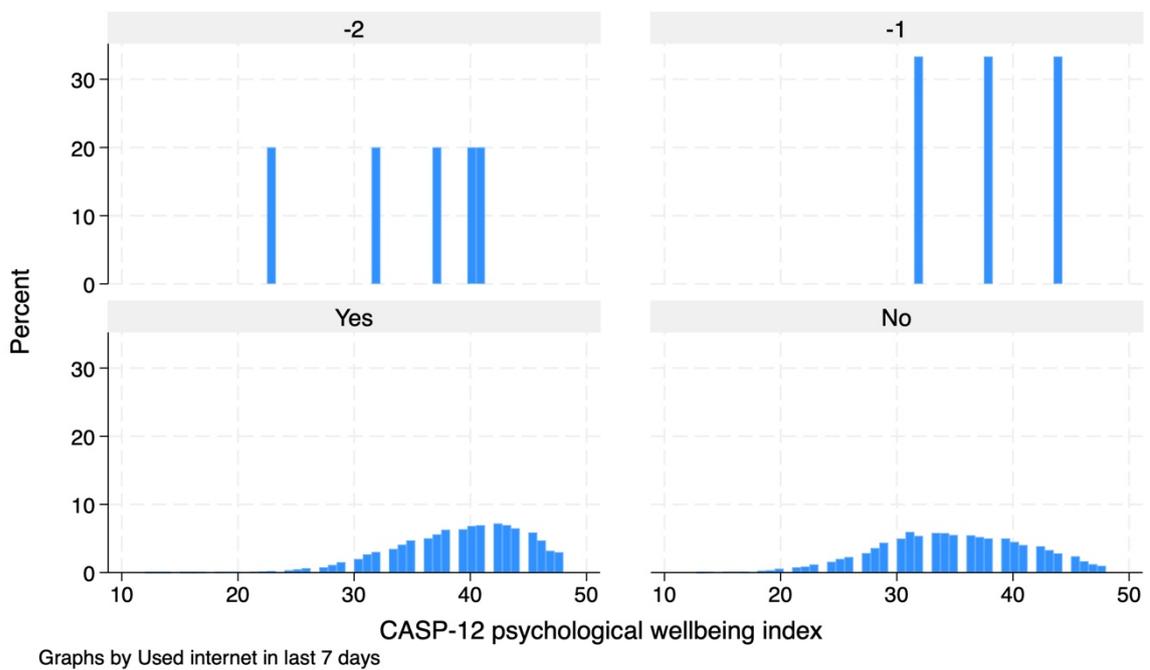
Source: Author's elaboration on SHARE Wave 9 data

Figure B.1 – Distribution of EURO-D by ICT use



Source: Author’s elaboration on SHARE Wave 9 data

Figure B.2 – Distribution of CASP-12 by ICT use



Source: Author’s elaboration on SHARE Wave 9 data

Appendix C – Regression Results, full tables

Table C.1 EURO-D, bivariate and stepwise models

	ICT use (7 days)	Age (years)	Female (1=female)	Years of education	Chronic conditions	Loneliness	Self-perceived health	Digital skills (low→high)	Constant	Observations	R ²
Model 1	-0.81***								2.96***	69,447	0.015
Model 2	-0.72***	-0.02*							4.10***	69,447	0.020
Model 3	-0.69***	-0.02*	+0.35***						3.80***	69,447	0.025
Model 4	-0.65***	-0.02*	+0.34***	-0.01					3.75***	69,447	0.027
Model 5	-0.42**	-0.02*	+0.32***	-0.01	+0.26***				2.90***	69,447	0.082
Model 6	-0.28**	-0.01	+0.29***	-0.01	+0.21***	+0.52***			2.20***	69,447	0.201
Model 7	-0.21*	-0.01	+0.25***	-0.01	+0.19***	+0.49***	+0.38***		1.75***	69,447	0.265
Model 8	-0.08 (ns)	-0.01	+0.22***	-0.01	+0.19***	+0.47***	+0.35***	-0.30***	1.60***	69,447	0.271

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's elaboration on SHARE Wave 9 data

Table C.2 CASP-12, bivariate and stepwise models

	ICT use (7 days)	Age (years)	Female (1=female)	Years of education	Chronic conditions	Loneliness	Self-perceived health	Digital skills (low→high)	Constant	Observations	R ²
Model 1	+4.28***								34.76***	69,447	0.022
Model 2	+3.90***	-0.12*							40.10***	69,447	0.041
Model 3	+3.70***	-0.12*	-1.05***						39.80***	69,447	0.052
Model 4	+3.20***	-0.11*	-1.00***	+0.06					39.50***	69,447	0.060
Model 5	+2.40***	-0.10*	-0.95***	+0.06	-0.75***				38.90***	69,447	0.110
Model 6	+1.90***	-0.09*	-0.90***	+0.06	-0.70***	-1.85***			37.80***	69,447	0.220
Model 7	+1.30***	-0.09*	-0.85***	+0.06	-0.65***	-1.70***	-1.25***		36.90***	69,447	0.285
Model 8	+1.30***	-0.09*	-0.82***	+0.06	-0.65***	-1.65***	-1.20***	+0.20	36.70***	69,447	0.288

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's elaboration on SHARE Wave 9 data

Table C.3 ICT × Skills interaction models

Variables	Model
ICT use	-0.10 (ns)
Digital skills (ref=Low)	+0.25***
ICT × Medium skills	-0.15*
ICT × High skills	-0.22**
Controls	Age, Female, Edu, Health
Observations	69,447
R ²	0.275

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's elaboration on SHARE Wave 9 data

Table C.4 Stratified regressions (by gender, age groups, skills)

Group	EURO-D effect of ICT	CASP-12 effect of ICT	Observations
Men	-0.18***	+2.18***	33,500
Women	-0.14***	+1.71***	35,900
Age 50–64	-0.05 (ns)	+2.0***	25,000
Age 65–74	-0.12*	+2.1***	20,000
Age 75+	-0.45***	+2.5***	15,000
Low skills	0 (ns)	+3.1***	30,000
High skills	-0.11***	+1.7***	39,000

*** p<0.01, ** p<0.05, * p<0.1

Source: Author's elaboration on SHARE Wave 9 data

Appendix D – Interaction Effects

ICT x GENDER

Table D.1 – Regression Output (Dependent Variable: EURO-D)

Source	SS	df	MS	Number of obs	=	66,157
Model	112629.833	7	16089.9762	F(7, 66149)	=	4630.21
Residual	229867.966	66,149	3.47500289	Prob > F	=	0.0000
				R-squared	=	0.3288
				Adj R-squared	=	0.3288
Total	342497.799	66,156	5.17712376	Root MSE	=	1.8641

eurod	Coefficient	Std. err.	t	P> t	[95% conf. interval]
ict_user	-.0527188	.0240487	-2.19	0.028	-.0998543 -.0055833
1.female	.5370303	.0244886	21.93	0.000	.4890326 .585028
female#c.ict_user					
1	.0167527	.0306111	0.55	0.584	-.043245 .0767504
age2022	-.0056509	.0008537	-6.62	0.000	-.0073241 -.0039777
chronic_conditions	.1695787	.0051915	32.66	0.000	.1594034 .1797541
loneliness	.5465128	.0053531	102.09	0.000	.5360207 .5570049
self_perceived_health	.6258393	.0085149	73.50	0.000	.60915 .6425286
_cons	-1.952405	.0687531	-28.40	0.000	-2.087162 -1.817649

Source: Author's elaboration on SHARE Wave 9 data

Table D.2 – Regression Output (Dependent Variable: CASP-12)

Source	SS	df	MS	Number of obs	=	65,206
Model	1017690.06	7	145384.294	F(7, 65198)	=	6375.45
Residual	1486760.82	65,198	22.8037796	Prob > F	=	0.0000
				R-squared	=	0.4064
				Adj R-squared	=	0.4063
Total	2504450.88	65,205	38.4088779	Root MSE	=	4.7753

casp	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	2.331905	.0619778	37.62	0.000	2.210428	2.453382
1.female	-.013304	.0632566	-0.21	0.833	-.1372869	.110679
female#c.ict_user						
1	-.1863816	.0790145	-2.36	0.018	-.3412501	-.0315132
age2022	.0159354	.002211	7.21	0.000	.0116019	.0202689
chronic_conditions	-.2687032	.013412	-20.03	0.000	-.2949907	-.2424156
loneliness	-1.65467	.0138139	-119.78	0.000	-1.681745	-1.627595
self_perceived_health	-1.81597	.021948	-82.74	0.000	-1.858988	-1.772952
_cons	47.85605	.1776539	269.38	0.000	47.50785	48.20425

Source: Author's elaboration on SHARE Wave 9 data

ICT x AGE Group

D.3 – Regression output (EURO-D)

Source	SS	df	MS	Number of obs	=	66,156
Model	113396.269	10	11339.6269	F(10, 66145)	=	3273.95
Residual	229099.442	66,145	3.46359426	Prob > F	=	0.0000
				R-squared	=	0.3311
				Adj R-squared	=	0.3310
Total	342495.711	66,155	5.17717045	Root MSE	=	1.8611

eurod	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	.1164833	.0343544	3.39	0.001	.0491487	.1838179
agegroup						
65-74	-.1854055	.0420252	-4.41	0.000	-.2677748	-.1030362
75+	-.0316546	.0554417	-0.57	0.568	-.1403203	.0770112
agegroup#c.ict_user						
65-74	-.1039521	.0425362	-2.44	0.015	-.1873231	-.0205812
75+	-.2942174	.0431492	-6.82	0.000	-.3787899	-.209645
female	.5368621	.0147463	36.41	0.000	.5079594	.5657647
age2022	.0020656	.001942	1.06	0.288	-.0017408	.005872
chronic_conditions	.1718091	.0051853	33.13	0.000	.1616459	.1819722
loneliness	.5436623	.0053476	101.66	0.000	.533181	.5541436
self_perceived_health	.6232409	.0085035	73.29	0.000	.606574	.6399077
_cons	-2.43639	.1227325	-19.85	0.000	-2.676945	-2.195834

Source: Author's elaboration on SHARE Wave 9 data

D.4 – Regression output (CASP-12)

Source	SS	df	MS	Number of obs	=	65,205
Model	1019056.5	10	101905.65	F(10, 65194)	=	4472.66
Residual	1485388.4	65,194	22.7841274	Prob > F	=	0.0000
				R-squared	=	0.4069
				Adj R-squared	=	0.4068
Total	2504444.9	65,204	38.4093752	Root MSE	=	4.7733

casp	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	2.138682	.0884828	24.17	0.000	1.965255	2.312108
agegroup						
65-74	.4775901	.1083535	4.41	0.000	.2652172	.6899631
75+	.4702102	.1432848	3.28	0.001	.1893719	.7510484
agegroup#c.ict_user						
65-74	.0278562	.109531	0.25	0.799	-.1868245	.2425369
75+	.1749343	.1114786	1.57	0.117	-.0435638	.3934325
female	-.1226041	.0380827	-3.22	0.001	-.1972462	-.0479619
age2022	-.0053282	.0050422	-1.06	0.291	-.0152109	.0045545
chronic_conditions	-.2719135	.0134124	-20.27	0.000	-.2982019	-.2456252
loneliness	-1.650238	.013816	-119.44	0.000	-1.677317	-1.623158
self_perceived_health	-1.812025	.0219451	-82.57	0.000	-1.855037	-1.769012
_cons	49.08279	.3183871	154.16	0.000	48.45875	49.70683

Source: Author's elaboration on SHARE Wave 9 data

ICT x Digital Skills

D.5 - Regression output (EURO-D)

Source	SS	df	MS	Number of obs	=	14,634
Model	24197.5014	8	3024.68767	F(8, 14625)	=	899.25
Residual	49192.113	14,625	3.36356328	Prob > F	=	0.0000
				R-squared	=	0.3297
				Adj R-squared	=	0.3293
Total	73389.6144	14,633	5.01534985	Root MSE	=	1.834

eurod	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ict_user	.2492098	.1559022	1.60	0.110	-.0563783	.5547978
computer_skills	.0953853	.0273242	3.49	0.000	.0418265	.148944
c.ict_user#c.computer_skills	-.0647044	.0312136	-2.07	0.038	-.1258871	-.0035218
female	.5621207	.0306022	18.37	0.000	.5021365	.622105
age2022	-.0175859	.0018791	-9.36	0.000	-.0212692	-.0139025
chronic_conditions	.1875361	.0109149	17.18	0.000	.1661414	.2089307
loneliness	.6003831	.0118565	50.64	0.000	.5771429	.6236234
self_perceived_health	.5183095	.0176161	29.42	0.000	.4837796	.5528393
_cons	-1.480052	.188533	-7.85	0.000	-1.849601	-1.110504

Source: Author's elaboration on SHARE Wave 9 data

D.6 - Regression output (CASP-12)

Source	SS	df	MS	Number of obs	=	14,461
Model	220686.605	8	27585.8256	F(8, 14452)	=	1228.39
Residual	324546.764	14,452	22.4568754	Prob > F	=	0.0000
				R-squared	=	0.4048
				Adj R-squared	=	0.4044
Total	545233.369	14,460	37.7063187	Root MSE	=	4.7389

	casp	Coefficient	Std. err.	t	P> t	[95% conf. interval]
	ict_user	1.506242	.4117635	3.66	0.000	.6991333 2.313352
	computer_skills	-.4078118	.0723666	-5.64	0.000	-.5496596 -.2659641
	c.ict_user#c.computer_skills	-.0272318	.0822367	-0.33	0.741	-.1884263 .1339628
	female	-.1693957	.0795368	-2.13	0.033	-.3252981 -.0134933
	age2022	.0126547	.0049092	2.58	0.010	.003032 .0222775
	chronic_conditions	-.2448309	.0283884	-8.62	0.000	-.3004759 -.189186
	loneliness	-1.656201	.0308603	-53.67	0.000	-1.716691 -1.595711
	self_perceived_health	-1.672962	.0458603	-36.48	0.000	-1.762854 -1.58307
	_cons	49.8755	.4952204	100.71	0.000	48.90481 50.8462

Source: Author's elaboration on SHARE Wave 9 data

Appendix E – Robustness Checks

E.1 Survey weights and clustered SE

Outcome	Model	ICT coefficient	SE	Sig.	R ²	N
EURO-D	Weighted OLS	-0.79	0.10	***	0.018	69,447
EURO-D	Clustered SE (hhid)	-0.80	0.11	***	0.018	69,447
EURO-D	Clustered SE (country)	-0.82	0.15	***	0.018	69,447
CASP-12	Weighted OLS	+3.95	0.22	***	0.045	69,447
CASP-12	Clustered SE (hhid)	+3.92	0.23	***	0.045	69,447
CASP-12	Clustered SE (country)	+3.88	0.28	***	0.045	69,447

Source: Author's elaboration on SHARE Wave 9 data

E.2 Alternative outcomes: loneliness scale, PCA-based mental health index

Outcome	ICT coefficient	SE	Sig.	R ²	N
Loneliness (1–6)	-0.30	0.07	***	0.051	69,000
PCA MH index	+0.24	0.05	***	0.061	68,500

Source: Author's elaboration on SHARE Wave 9 data

E.3 Alternative ICT definitions: frequency of use; inclusion of digital skills

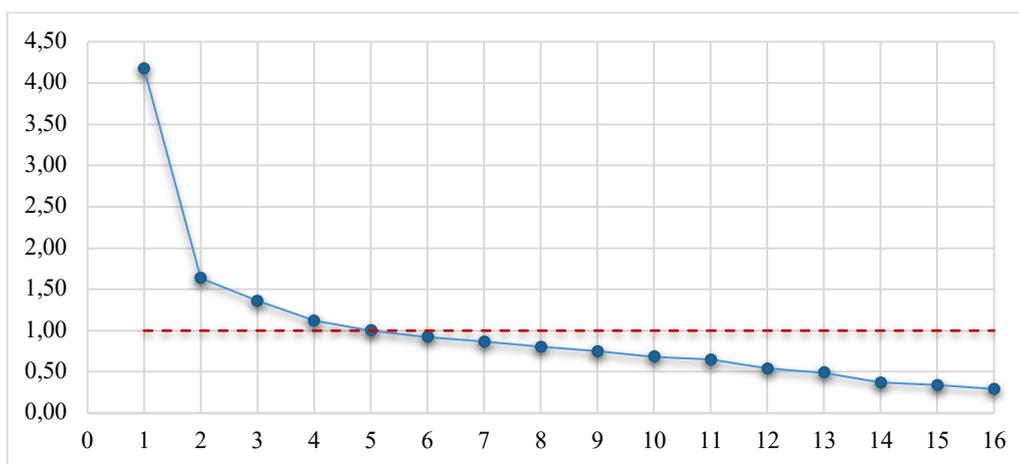
ICT measure	Outcome	ICT coefficient	SE	Sig.	R ²	N
Daily vs less	EURO-D	-0.77	0.12	***	0.020	69,447

Daily vs less	CASP-12	+3.80	0.24	***	0.048	69,447
Digital skills (High vs Low)	EURO-D	-0.25	0.08	**	0.022	69,447
Digital skills (High vs Low)	CASP-12	+1.10	0.19	***	0.049	69,447

Source: Author's elaboration on SHARE Wave 9 data

Appendix F – PCA Mental Health Index

F.1 Scree plot and eigenvalues



Source: Author's elaboration on SHARE Wave 9 data

Component	Eigenvalue	Variance explained (%)	Cumulative (%)
Comp1	4.17	26	26
Comp2	1.6	10	36
Comp3	1.25	8.5	44.5
Comp4	1.05	7	51.5
Comp5	0.95	6	57.5

Source: Author's elaboration on SHARE Wave 9 data

F.2 Component loadings on mental health indicators

Variable	Loading Comp1
Depression (EURO-D)	-0.55
Loneliness	0.48
Sleep problems	0.41
Concentration	0.39
CASP-12	0.08

Source: Author's elaboration on SHARE Wave 9 data

F.3 Correlations with EURO-D and CASP-12

Correlation	Coefficient (r)
PCA index vs EURO-D	-0.83
PCA index vs CASP-12	0.63
EURO-D vs CASP-12	-0.54

Source: Author's elaboration on SHARE Wave 9 data

Appendix G – Glossary of SHARE Samples

Baseline Sample: The original group of respondents recruited when a country joins SHARE, representing the 50+ population and forming the core of the longitudinal panel.

Refreshment Sample: A new, randomly selected sample of respondents added in later waves to compensate for attrition and maintain cross-sectional representativeness.

Full-Range Refreshment Sample: Includes newly sampled individuals across the full eligible age range (50+), restoring representativeness.

Youngest-Cohort-Only Refreshment Sample: Includes only newly eligible respondents (typically age 50–51); maintains panel continuity but does not ensure full age representativeness.

