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Determinantes y Desafíos de la Salud Mental en Diferentes Contextos: Un Estudio Integral desde la Perspectiva de la Economía de la Salud

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PHD ECONOMICS: INSTRUMENTS OF ECONOMIC ANALYSIS

PHD THESIS

Determinants and Challenges of Mental Health in Different Contexts: A Comprehensive Study from the Perspective of Health Economics

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ABREVIATIONS

AC: Autonomous Communities

ADLs: Activities of Daily Living

AIML: Artificial Intelligence Markup Language

ATE: Average Treatment Effect

ATET: Average Treatment Efecct on the Treated

CBL: Cognitive Behavioral Therapy

CI: Condifence Intervals

DID: Differences In Differences

EDAD: Disability, Personal Autonomy, and Dependency Survey

EHIS: European Health Interview Survey

EHSS: European Health Survey in Spain

HIV: Human Immunodeficiency Virus

ICT: Information and Communication Technologies

IDIVAL: Instituto de Investigación Valdecilla

INE: National Institute of Statistics

LLMs: Large Language Models

MLE: Maximum Likelihood Estimation

NLP: Natural Language Processing Technology

OMS: Organización Mundial de la Salud

OR: Odd Ratios

PRISMA: Preferred Reporting Items for Literature REview and Meta-Analyses

SAGHS: Self-Assessed General Health Status

SHARE: Survey of Health, Aging and Retirement in Europe

SUTVA: Stable Treatment Value Assumption

WHO: World Health Organization

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Introducción

1. Objetivo y motivación general de la tesis

Durante numerosos años, el interés de tanto los científicos como público en general acerca del grado de utilización de los servicios de salud ha mantenido su posición como un asunto de gran calado. Esto es debido a la importancia de dichos hallazgos tanto para los ciudadanos, como para los responsables de la administración, tanto en el ámbito público y privado.

En la última década, se ha estado trabajando en la redefinición del paradigma relativo a la oferta de servicios de atención médica. En concreto, ahora se reconoce que el enfoque debe estar constantemente en generar beneficios para los pacientes, en lugar de, simplemente recortar gastos. Asimismo, esta apuesta por el valor debe abarcar todo el proceso de tratamiento y estar dirigido por profesionales de la salud. Así, de gran valor la transparencia en la información (Porter, 2006). En la actualidad, el panorama ha experimentado cambios continuos, como lo ilustra claramente la pandemia global del COVID-19. En 2020, la Organización Mundial de la Salud (OMS) anunció el inicio de la pandemia mundial denominada Covid-19. Desde entonces, el número de contagios de COVID-19 ha ido variando paulatinamente. Asimismo, esta misma fuente aseguró que el confinamiento agravó numerosos problemas de salud. Las muertes, los contagios, la distancia social, los propios confinamientos y, en general, todas las consecuencias del COVID-19 conducen a un empeoramiento de la salud de las personas. Estos factores son claves durante la pandemia de COVID-19, tal y como indican autores como Orea y Álvarez (2020).

En consecuencia, se ha de tener en cuenta que las personas que padecen enfermedades si ven su vida, e incluso, su día a día influenciado por dicha circunstancia. Todo ello genera malestar o sufrimiento, alterar el ritmo de vida de las personas, las relaciones familiares o con otras personas que se relacionan con su entorno, e incluso puede influir en el ámbito laboral, provocando bajas por enfermedad o incluso la renuncia definitiva a su puesto de trabajo. Por tanto, son muchos los factores que influyen a los individuos que padecen mala salud. Sin embargo, dicho interés no es solo por la pandemia. Por ejemplo, los aspectos psicológicos fueron incluidos previamente por premios Nobel de economía, como el profesor Daniel Kahneman (2002) o Richard H. Thaler (2017). Así, la salud mental y, específicamente, la economía del comportamiento, son temas considerados como muy importantes en las sociedades modernas. De tal forma que autores como Aria et al. (2020) argumentan y fundamentan que la salud mental y sus aspectos relacionados fueron un tema motor en esta década.

Por consiguiente, el motivo de interés por la salud en esta tesis viene justificado por el incremento y el alza sustancial de los problemas de salud derivados de la COVID-19. Sin embargo, la voluntad de integrar aspectos sobre la salud en la investigación dentro de la ciencia económica viene haciéndose tiempo atrás como así argumentabamos en párrafos anteriores. Además, el interés por la relación entre variables económicas y de bienestar no es nuevo a partir de la Gran Recesión del año 2008 cuando la investigación en esta área ha experimentado aumentos significativos incluso expandiéndose hacia otras áreas como la economía ambiental o ecológica (Dominko & Verbič, 2019). Además, dentro de este contexto, la salud mental se presenta como un campo de creciente interés debido a su impacto significativo en el bienestar individual y colectivo. Sin embargo, dicha cuestión ha sido históricamente subestimada en términos de recursos asignados y políticas públicas, lo que ha tenido como consecuencia una atención desigual en comparación con otros aspectos de la salud física.

Por consiguiente, la necesidad de una mayor integración de la salud mental en los estudios económicos se justifica por la carga económica que representan los trastornos mentales para los sistemas de salud y la economía en general. Dichas enfermedades mentales no solo afectan directamente a los individuos que las padecen, sino que también tienen un impacto en la productividad laboral, los costes de atención médica, su entorno y el bienestar social. Por tanto, es crucial entender cómo los recursos pueden ser asignados de manera más eficiente para abordar estos desafíos.

Además, el estigma asociado a las enfermedades mentales y la falta de acceso a servicios adecuados siguen constituyendo importantes barreras que impiden el manejo efectivo de estos trastornos. Esta tesis busca contribuir a la literatura existente al explorar cómo conociendo los factores asociados, se pueden desarrollar políticas adecuadas que puedan mejorar el acceso y la calidad de la atención en salud mental, y cómo estas intervenciones pueden ser diseñadas para maximizar el bienestar social y económico.

A lo largo de los capítulos que compondrán la tesis, el conocimiento acerca del estado de la salud se aproximará a partir del resultado de diferentes cuestionarios. Estos cuestionarios se han utilizado en una parte importante de la literatura que estudia el efecto de la salud sobre distintas situaciones. Sin embargo, en muchos casos no se ha consensuado claramente un criterio para denominar lo que estamos midiendo. Así, podemos encontrar los conceptos de bienestar psicológico (A. E. Clark, 2003), (buena) salud mental (Cygan-Rehm et al., 2017), bienestar mental (Farré et al., 2018) o (in)felicidad (A. E. Clark & Oswald, 1994). Así la OMS define la salud mental como "un estado de bienestar en el cual el individuo es consciente de sus propias capacidades puede afrontar las tensiones normales de la vida, puede trabajar de forma productiva y fructífera y es capaz de hacer una contribución a su comunidad". Esta definición de salud mental se aleja del modelo médico o de enfermedad, esto es, el modelo que define la salud a partir de la presencia o ausencia de un trastorno o enfermedad, y se acerca al modelo de salud mental positiva (SMP) (Jahoda, 1958), esto es, un constructo que define la salud mental a partir de la presencia/ausencia de una serie de factores como las actitudes hacia uno mismo, el grado de conocimiento que la personas tienen acerca de sus potencialidades, la autonomía, o el dominio del entorno en el que se desenvuelve la persona. Este mismo suceso ocurre con el estado de salud en general. Así los individuos consideran que pueden tener buena o mala salud, en cambio, esto puede diferir del concepto médico. La pregunta es en qué momento se consideran síntomas o afecciones anormales o normales para considerar buena o mala salud.

El uso de conceptos como salud o bienestar mental, felicidad, o satisfacción con la vida es útil en la medida en la que la particularidad de cada uno de ellos permite rastrear aspectos del estado de la salud, pero sus usos por separado implican ciertas dificultades interesantes a estudiar. En primer lugar, hoy en día conceptos como el de salud siguen muy ligados a la práctica clínica, a la presencia o ausencia de trastornos o enfermedades, a los manuales diagnósticos o a la prescripción de medicación. Por otro lado, el uso de conceptos como felicidad o satisfacción con la vida resultan insuficientes debido a la falta de objetividad empleada en su evaluación que les confiere una cierta inconsistencia temporal. Por ello, en la tesis se utilizará, en términos generales, el concepto de bienestar en salud para hacer referencia a los aspectos que esperamos encontrar entre las personas con un adecuado estado de salud dadas ciertas características.

Teniendo en cuenta el estado de la cuestión y el interés mostrado por la salud y en concreto, la salud mental, la presente tesis se estructura en torno a dos objetivos generales. El primer objetivo trata de analizar cómo los diferentes aspectos de la salud mental afectan a la utilización sanitaria por parte de las personas y la implementación de políticas públicas y el segundo objetivo, busca evaluar de qué manera pueden afectar distintos factores socioeconómicos, personales, sociodemográficos a la salud mental de los individuos.

Estos dos objetivos generales se dividen a su vez en seis objetivos específicos que se irán desarrollando y concretando a lo largo de los seis capítulos de tesis. En conclusión, la tesis girará en torno al estado de salud mental de los individuos y sus diferentes factores. Así, la presente investigación es particularmente relevante en un contexto donde la prevalencia de los trastornos mentales continúa aumentando, lo que subraya la urgencia de desarrollar estrategias económicas y sociales que respondan de manera efectiva a este desafío global.

2. Metodología y fuentes de información

Con el propósito de alcanzar los objetivos que hemos planteado, este trabajo de investigación propone centrarse en la utilización de enfoques especialmente cuantitativos. Además, se procurará la conjunción de dichos enfoques con un marco teórico adecuadamente establecido para cada uno de los apartados desarrollados en este estudio. En cuanto a las metodologías empleadas, se recurrirá a la implementación de análisis econométricos y modelos. A través de ellos, se busca simplificar la representación de relaciones estadísticas o matemáticas entre dos o más variables, resultando en estimaciones empíricas que arrojen luz sobre una variable con relación a otra, así como realizar predicciones en torno al valor futuro de las variables elegidas.

Para esta tesis, se emplearán como principal fuente de información todas aquellas encuestas disponibles tanto nacionales como europeas. Entre ellas se encuentra la Encuesta Europea de Salud, Envejecimiento y Jubilación, conocida también por sus siglas en inglés como SHARE (Survey of Health, Aging and Retirement in Europe). Esta elección se fundamenta en el hecho de que es una de las bases de datos más robustas disponibles para individuos mayores de 50 años, debido a varias razones. Entre las características principales de esta encuesta, destaca su enfoque longitudinal y su enfoque multidisciplinario. Proporciona microdatos que abarcan aspectos de salud, estatus socioeconómico, y redes sociales y familiares de más de 140.000 individuos. Dicha encuesta se enfoca en analizar los impactos de políticas relacionadas con la salud, así como aspectos sociales, económicos y ambientales a lo largo de la vida de los participantes. Además, abarca un amplio rango geográfico, abarcando prácticamente todos los países europeos (27 países europeos más Israel) y se extiende a lo largo de diferentes momentos en el tiempo (diferentes años u "olas"). Para ser más específicos, esta encuesta cuenta con 8 oleadas que recopilan información desde 2002 hasta 2020, incluyendo 2 oleadas especiales dedicadas al impacto de la COVID-19. En la elaboración de los diversos capítulos, se hará uso de diferentes oleadas de la encuesta, adaptando dicha elección a los objetivos perseguidos en cada uno de los capítulos respectivos.

Además, otra encuesta utilizada para capítulos concretos de la tesis es la Encuesta de Discapacidad Autonomía Personal y Situaciones de Dependencia que aporta información detallada sobre personas con discapacidades y en situaciones de dependencia. A través de su metodología rigurosa y alcance integral, examina aspectos de salud, autonomía personal, acceso a servicios y participación social, proporcionando datos cuantitativos que permiten el análisis estadístico y la identificación de patrones. Esta encuesta no solo aborda las limitaciones funcionales, sino también la calidad de vida e influencia de factores socioeconómicos, brindando información crucial para la formulación de políticas y mejora de la atención a estos grupos en la sociedad.

Finalmente, se emplean encuestas adicionales para segmentos específicos de capítulos de la tesis como son la Encuesta Nacional de Salud, la Encuesta Nacional de

Salud o la Encuesta Europea de Salud. Ambas encuestas constituyen fuentes de información cruciales en el ámbito de la salud. De este modo, la Encuesta Nacional de Salud se enfoca en capturar datos detallados sobre la salud y los hábitos de vida de la población, proporcionando una imagen integral de las condiciones de salud a nivel nacional y permitiendo el análisis de tendencias y disparidades. Por otro lado, la Encuesta Europea de Salud, de alcance continental, recopila información en múltiples países europeos, lo que facilita la comparación entre países y la identificación de patrones de salud a nivel regional. Ambas encuestas desempeñan un papel fundamental en la toma de decisiones basadas en evidencia y formulación de políticas de salud efectivas.

Dentro de las metodologías empleadas figuran: regresiones logísticas, método de diferencias en diferencias, la técnica de emparejamiento de vecino más cercano y modelos probit.

3. Contribuciones de la Tesis

Dentro de los objetivos generales que se han especificado, a su vez existen objetivos específicos relacionados con cada uno de los capítulos desarrollados.

En consecuencia, a pesar de ser capítulos independientes en la tesis con objetivos específicos, se aspira a que todos ellos sigan una coherencia unificadora con el fin de abordar cada uno de los objetivos principales. El esquema adoptado se presenta de la siguiente forma:

- Capítulo 1: Repensar los efectos de la salud mental entre la población mayor en tiempos de COVID-19.
- Capítulo 2: Edad, tecnología y brecha digital. ¿Directamente relacionado con problemas de salud mental?
- Capítulo 3: ¿La falta de actividad en el tiempo libre es un problema en la atención mental? Un análisis de emparejamiento por propensity score matching.
- Capítulo 4: Nuestro estilo de vida como problema de salud mental.
- Capítulo 5: Bullicio urbano vs serenidad rural: análisis de las disparidades en salud mental según el entorno residencial.
- Capítulo 6: Transformando la atención sanitaria con chatbots: usos y aplicaciones. Una revisión del alcance.

El Capítulo 1 pretende como objetivo específico el determinar para los adultos mayores y para todos los países europeos cómo la salud mental se ha visto afectada por el COVID-19 y cómo la mala salud mental en la población mayor este se relaciona con las características específicas causadas por el COVID-19. En concreto, capítulo se centra en el estudio de los principales determinantes socioeconómicos que influyen en la salud mental así como en observar si el Covid-19 afecta por igual a la salud mental, examinando si existen diferencias de género entre otras cuestiones.

El Capítulo 2 consiste en examinar si existe una brecha digital entre los adultos mayores europeos y en concreto, si esto afecta a la salud mental de dichos individuos. Además, trata de examinar si la brecha digital con el paso del tiempo ha impactado en mayor medida sobre la salud mental de la población mayor europea. De este modo, con este objetivo se analiza de qué manera afectan las características sobre la salud mental de los individuos y si en concreto, las características tecnológicas (brecha digital) causan una peor salud mental en la población.

El Capítulo 3 trata de determinar y conocer la realidad que viven las personas con discapacidad en España así como su salud mental. En concreto, examina si el hecho que las personas discapacitadas realicen actividades en su tiempo libre influye en la demanda de prestación sanitaria psicológica. Este objetivo es importante para las Administraciones Públicas para poder implementar políticas eficientes en la utilización sanitaria.

El Capítulo 4 trata de profundizar en la importancia de cultivar hábitos de vida saludables tanto en el ámbito físico como emocional. Analiza cómo estos hábitos pueden influir positivamente en la salud mental y, a su vez, cómo una buena salud mental puede potenciar la adopción de conductas beneficiosas para el bienestar general, diferenciando a los individuos según la Comunidad Autónoma. Por último, estudia cómo los factores planteados impactan en la salud mental en función del tipo de trastorno mental.

El Capítulo 5 se enfoca en explorar la influencia que el lugar de residencia tiene sobre la calidad de vida y el bienestar de las personas con respecto a la salud mental. Examina cómo diferentes características del entorno como circunstancias sociales, económicas y ambientales, contribuye al bienestar psicológico, y qué aspectos de la salud mental son más susceptibles a ser influenciados por la ubicación.

El capítulo 6 aborda el impacto de la pandemia de COVID-19 en la demanda y uso de recursos sanitarios, lo que ha impulsado la búsqueda de soluciones más eficientes en un contexto de restricciones presupuestarias. En este escenario, la inteligencia artificial y la telemedicina se han consolidado como estrategias clave para optimizar la prestación de servicios y recursos en salud. Dentro de estas innovaciones, los chatbots han emergido como herramientas prometedoras en diversos campos, como la salud mental y el monitoreo de pacientes, ofreciendo conversaciones terapéuticas y facilitando intervenciones tempranas. Este capítulo presenta una revisión sistemática que explora el estado actual de los chatbots en el sector sanitario, evaluando exhaustivamente su efectividad, aplicaciones prácticas y los beneficios potenciales que pueden ofrecer en la mejora de la atención sanitaria.

El orden de los capítulos de esta tesis sigue una estructura lógica que va evolucionando desde una visión general del impacto de la COVID-19 en la salud mental de los adultos mayores, hasta la exploración de soluciones innovadoras en el ámbito sanitario. El Capítulo 1 introduce el tema al analizar cómo la pandemia afectó la salud mental de los adultos mayores en Europa, destacando los factores socioeconómicos clave. A partir de ahí, el Capítulo 2 se centra en el acceso desigual a la tecnología, investigando cómo la brecha digital afecta la salud mental de los adultos mayores y cómo este fenómeno ha evolucionado con el tiempo. El Capítulo 3 cambia de enfoque, examinando específicamente a las personas con discapacidad en España y cómo la participación en actividades recreativas influye en la demanda de servicios de salud mental. El Capítulo 4 amplía la perspectiva al abordar cómo los hábitos saludables y las características regionales impactan la salud mental, mientras que el Capítulo 5 profundiza en el impacto del lugar de residencia y las características del entorno social y económico en el bienestar psicológico. Finalmente, el Capítulo 6 cierra el ciclo al explorar cómo las innovaciones tecnológicas, como los chatbots en la salud mental, pueden optimizar los recursos sanitarios y mejorar la atención, particularmente en el contexto de la pandemia. De este modo, cada capítulo contribuye a una comprensión integral y evolutiva de los determinantes de la salud mental y las soluciones posibles.

Por otro lado, diversos resultados empíricos derivados de esta investigación han sido publicados en colaboración con otros autores, o bien han superado con éxito la primera fase del proceso de revisión en distintas revistas académicas de impacto. En particular:

- El Capítulo 1 ha sido publicado como capítulo en el libro titulado *Propuestas para la gestión de servicios sanitarios*, Editorial ARANZADI, ISBN: 978-84-1162-898-3.
- El Capítulo 2 ha sido publicado en la revista *Healthcare* 2024, 12(23), 2454; disponible en: https://doi.org/10.3390/healthcare12232454.
- El Capítulo 3 ha sido publicado en la revista *Estudios de Economía Aplicada*, ISSN 1133-3197, ISSN-e 1697-5731, Vol. 42, Nº 1, 2024, en un número especial titulado *Advances in Econometric Modeling: Theory and Applications*.
- El Capítulo 4 ha sido enviado a la revista *Indicators Research*, encontrándose actualmente en proceso de evaluación.
- El Capítulo 5 ha sido enviado a la revista *Gaceta Sanitaria*, dentro de su número especial sobre *Health Economics*, y se encuentra a la espera de la evaluación por parte de los revisores.

- El Capítulo 6 ha sido publicado en la revista *Digital Health 2025, 11*, 20552076251319174; diponible en: https://doi.org/10.1177/20552076251319174.

La participación en diversos congresos y workshops ha sido una oportunidad fundamental para la difusión de los hallazgos científicos y recopialción de ideas de esta investigación, así como para contribuir al debate académico, con un énfasis particular en el ámbito de la salud mental. A lo largo del desarrollo de esta tesis, he presentado diferentes capítulos de la misma en los siguientes congresos:

- XXXV Congreso Internacional de Economía Aplicada ASEPELT (29 de junio al 2 de julio de 2022)
- XIV Congreso de Educación Médica (15 de septiembre de 2022)
- I Jornadas de la Plataforma ISCIII de Biobancos y Biomodelos (27 y 28 de octubre de 2022)
- IV Taller de Gestión Clínica y Sanitaria - GestionAES (20 de abril de 2023)
- XXIII Reunión de Economía Mundial (25 y 26 de mayo de 2023
- X Jornadas Doctorales G-9 (31 de mayo, 1 y 2 de junio de 2023)
- Progress Reports Valdecilla (14 de junio de 2023)
- XLII Jornadas de Economía de la Salud (5 al 7 de julio de 2023)
- XXXVI Conference Asepelt (5 al 7 de julio de 2023)
- XXXI Encuentro de Economía Pública (9 y 10 de mayo de 2024)
- V Taller de Gestión Clínica y Sanitaria – GestionAES (4 de junio de 2024)
- XXVI Encuentro de Economía Aplicada (6 y 7 de junio de 2024)
- XVI Jornadas de Docencia en Economía (20 y 21 de junio 2024)
- XLIII Jornadas de Economía de la Salud (26 al 28 de junio de 2024)

Finalmente, es importante resaltar la participación en diversos cursos, congresos y seminarios relacionados con esta investigación. Quisiera hacer una mención especial al Máster en Dirección y Gestión de Servicios Sanitarios y al Máster en Gestión y Planificación de Centros y Servicios de Atención a la Dependencia de la Universidad de Cantabria, ambos completados durante estos años de tesis.

Además, he asistido a otros cursos de la Universidad de Cantabria, de la Universidad Internacional Menéndez Pelayo y del Instituto de Investigación Valdecilla (IDIVAL) que han ampliado mis conocimientos en áreas clave, como la docencia y divulgación científica, el pensamiento creativo, la ética en la investigación, y las diferentes formas de colaboración entre la universidad y el sector privado, con especial incidencia en el emprendimiento.

De igual manera, cabe destacar que esta tesis se enmarca en una mención internacional debido a la estancia realizaza en el Centre for Business and Economics

Research (CeBER) of the University of Coimbra, Portugal del 1 de marzo al 3 de junio de 2024.

Además, quiero expresar mi agradecimiento por la colaboración y el apoyo del grupo de investigación en Economía de la Salud de la Universidad de Cantabria y del IDIVAL ya que sin su ayuda no habría sido posible puesto que igualmente me ha permitido participar en diversos proyectos de investigación.

Introduction

1. General Motivation and Objective of the Thesis

For many years, the interest of scientists and the general population utilize health services has remained a matter of great significance. This is due to the importance of the findings for both citizens and administrators, from the perspective of the public and private sectors. Over the past decade, efforts have been made to redefine the paradigm of delivering healthcare services. Specifically, it is now recognized that the focus must consistently be on generating benefits for patients, rather than merely cutting costs. Furthermore, this value-driven approach should encompass the entire treatment process and be guided by a healthcare professional. Hence, transparency in information is of great value (Porter, 2006).

Today, the landscape has undergone continuous changes, as clearly illustrated by the global COVID-19 pandemic. In 2020, the World Health Organization (WHO) announced the onset of the global pandemic known as COVID-19. Since then, the number of COVID-19 infections has fluctuated gradually. Additionally, the same source indicated that lockdowns exacerbated several health problems. Deaths, infections, social distancing, lockdowns, and all the consequences of COVID-19 have led to a deterioration in people's health. These factors have been critical during the COVID-19 pandemic, as noted by authors such as Orea and Álvarez (2020).

As a result, it is important to recognize that individuals with health conditions experience a profound impact on their lives, and even their daily routines. Illnesses can cause discomfort or suffering, disrupt people's lives, strain family relationships or interactions with others in their environment, and even affect work relationships, leading to sick leaves or, in some cases, permanent resignation from their jobs. Therefore, numerous factors are involved in and influence individuals who suffer from poor health. However, interest in health is not only driven by the pandemic. For example, psychological aspects were previously recognized by Nobel Prize-winning economists, such as Professor Daniel Kahneman (2002) and Richard H. Thaler (2017). Therefore, mental health, and specifically behavioral economics, are considered highly important topics in modern societies. Authors like Aria et al. (2020) have even suggested that mental health and its related aspects have been a major driving force of this decade.

Consequently, my interest in health as it relates to my studies is justified by the substantial increase in health problems resulting from COVID-19. However, the desire to integrate health aspects into economic research has been present for some time, as demonstrated in previous paragraphs. Moreover, the interest in the relationship between economic variables and well-being is not new since the Great Recession of 2008, research in this area has seen significant growth, even expanding into other fields such as environmental or ecological economics (Dominko & Verbič, 2019). Additionally, within this context, mental health has emerged as a field of growing interest due to its significant impact on individual and collective well-being. However, mental health has historically been underestimated in terms of allocated resources and public policies, resulting in unequal attention compared to other aspects of physical health.

Hence, the need for greater integration of mental health into economic studies is justified by the economic burden that mental disorders place on healthcare systems and the economy in general. Mental illnesses not only directly affect those who suffer from them but also have an impact on labor productivity, healthcare costs, their environment, and social well-being. Therefore, it is important to understand how resources can be allocated more efficiently to address these challenges.

Moreover, the stigma associated with mental illnesses and the lack of access to adequate services remain significant barriers to the effective management of these disorders. This study aims to contribute to the existing literature by exploring how understanding associated factors can help develop economic policies that improve access to mental health care and it is quality, and how these interventions can be designed to maximize social and economic well-being.

Throughout the chapters of this thesis, health status will be approached through the results of various questionnaires. That it have been widely used in the literature to study the effect of health on different situations. However, in many cases, there has not been a unified criterion for naming what we are measuring. Thus, concepts such as psychological well-being (A. E. Clark, 2003), (good) mental health (Cygan-Rehm et al., 2017), mental well-being (Farré et al., 2018), or (un)happiness (A. E. Clark & Oswald, 1994) can be found. The WHO defines mental health as “a state of well-being in which an individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community.” This definition of mental health departs from the medical or disease model, which defines health based on the presence or absence of a disorder or illness, and moves closer to the positive mental health model (SMP) (Jahoda, 1958), which defines mental health based on the presence or absence of a series of factors such as attitudes toward oneself, the degree of self-awareness of one’s potential, autonomy, or mastery of the environment in which the person operates. The same situation applies to general health status. Individuals may consider themselves to have good or poor health, yet this may differ from the medical concept. The question is at what point symptoms or conditions are considered abnormal or normal to determine good or poor health.

The use of concepts such as mental health or well-being, happiness, or life satisfaction is useful in that the particularity of each allows us to track aspects of health status, but their separate use implies certain difficulties worth studying. Firstly, concepts like health are still closely tied to clinical practice, the presence or absence of disorders or illnesses, diagnostic manuals, or the prescription of medication. On the other hand, the use of concepts such as happiness or life satisfaction is insufficient due to the lack of objectivity in their evaluation, which gives them a certain temporal inconsistency. Therefore, in the following pages of the thesis, the concept of health well-being will generally be used to refer to the aspects we expect to find among people with an adequate health status given certain characteristics.

Considering the state of the art and the interest shown in health, and specifically mental health, this thesis is structured around two general objectives. The first objective is to analyze how different aspects of mental health affect people's use of healthcare and the search for public policies, and the second objective is to evaluate how various socioeconomic, personal, and sociodemographic factors affect individuals' mental health.

These two general objectives are further refined into six specific objectives that will be developed and detailed throughout the six chapters of the thesis. In conclusion, the thesis will revolve around the mental health of individuals and its different factors, where the research is particularly relevant in a context where the prevalence of mental disorders continues to rise, highlighting the urgency of developing economic and social strategies to effectively address this global challenge.

2. Methodology and Sources of Information

To achieve the outlined objectives, this research work proposes to focus on quantitative approaches. Additionally, efforts will be made to combine these quantitative approaches with a well-established theoretical framework tailored to each section of this study. Regarding the methodologies employed, the research will rely on the implementation of econometric analyses based on models. It aims to simplify the representation of statistical or mathematical relationships between two or more variables, resulting in empirical estimates that shed light on one variable concerning another, as well as enabling predictions about the future value of the chosen variables.

For this thesis, national and European surveys will serve as the primary sources of information. Among them is the Survey of Health, Aging, and Retirement in Europe (SHARE). This choice is based on the fact that SHARE is one of the most robust databases available for individuals over 50 years old, for several reasons. Notable characteristics of this survey include longitudinal approach and multidisciplinary focus. It provides microdata covering health, socioeconomic status, and social and family networks for over 140,000 individuals. The survey focuses on analyzing the impacts of policies related to health, social, economic, and environmental aspects throughout the participants' lives. Furthermore, it covers a wide geographic range, encompassing nearly all European countries (27 European countries plus Israel) and extends over different periods (different years or "waves"). More specifically, this survey includes 8 waves collecting information from 2002 to 2020, including 2 special waves dedicated to the impact of COVID-19. In several chapters, different waves of the survey will be used, adapting the choice according to the objectives pursued in each respective chapter.

Additionally, other surveys used for specific chapters include the Survey on Disability, Personal Autonomy, and Dependency Situations, which provides detailed information on people with disabilities and in situations of dependency. Through its rigorous methodology and comprehensive scope, it examines aspects of health, personal autonomy, access to services, and social participation, providing quantitative data that allow statistical analysis and the identification of patterns. This survey not only addresses functional limitations but also quality of life and the influence of socioeconomic factors, providing basic information for policy formulation and improving care for these groups in society.

Finally, additional surveys are used for chapters, such as the National Health Survey and the European Health Survey. Both represent crucial sources of information in the health field. The National Health Survey focuses on capturing detailed data on the health and lifestyle habits of the population in a specific country, providing a comprehensive picture of health conditions at the national level and allowing the analysis of trends and disparities. On the other hand, the European Health Survey collects information in multiple European countries, facilitating comparisons between nations and identifying health patterns at the regional level. Both surveys play a fundamental role in evidence-based decision-making and the formulation of effective health policies.

The methodologies employed in this research include logistic regressions, the difference-in-differences method, the nearest neighbor matching technique, and probit models.

3. Thesis Contributions

Within the specified general objectives, there are specific ones related to all the chapters developed. Despite being independent chapters with their own specific objectives, the aim is for all of them to follow a unifying coherence to address the main objectives. The structure adopted is as follows:

- Chapter 1: Rethinking the effects of mental health among older Europeans in COVID-19 times.

- Chapter 2: Age, technology, and the digital divide: Directly related to mental health issues?.
- Chapter 3: Is a lack of leisure time activity a problem in psychological healthcare? A propensity score matching analysis.
- Chapter 4: Our lifestyle as a mental health problem.
- Chapter 5: Urban bustle vs. rural serenity: Analysis of mental health disparities by residential environment.
- Chapter 6: Transforming Healthcare with Chatbots: Uses and Applications. A scoping review.

Chapter 1 has the specific objective of determining how mental health has been affected by COVID-19 for older adults across all European countries and how poor mental health among older adults is related to specific characteristics caused by COVID-19. More specifically, this chapter focuses on studying the main socioeconomic drivers that influence mental health and observing whether COVID-19 affects mental health equally, examining whether there are gender differences, among other factors.

Chapter 2 involves examining whether there is a digital divide among older European adults and, specifically, whether this affects the mental health of individuals. Additionally, it is interesting to examine whether the digital divide over time has had a greater impact on the mental health of older adults. This objective examines how different characteristics affect individuals' mental health and whether, in particular, technological ones (the digital divide) lead to poorer mental health in the population.

Chapter 3 aims to determine and understand the reality faced by people with disabilities in Spain concerning psychological healthcare. Specifically, it examines whether people with disabilities who engage in leisure activities influence the demand for psychological healthcare. This objective is important for public administrations to establish correct policies and be more efficient in the use of psychological healthcare services.

Chapter 4 aims to analyze how these habits can positively influence mental health and, in turn, how good mental health can promote the adoption of behaviors beneficial to overall well-being, differentiating individuals according to their autonomous community. Finally, it examines how the studied factors impact mental health depending on mental disorder.

Chapter 5 focuses on exploring the influence that the place of residence has on the quality of life and well-being of individuals with respect to mental health. It examines how different characteristics of the environment, such as social, economic, and environmental particularities, contribute to psychological well-being and which aspects of mental health are most susceptible to being influenced by location.

Chapter 6 addresses the impact of the COVID-19 pandemic on the demand and use of healthcare resources, which has driven the search for more efficient solutions within a context of budgetary constraints. In this scenario, artificial intelligence and telemedicine have emerged as key strategies to optimize the delivery of healthcare services and resources. Among these innovations, chatbots have emerged as promising tools in various fields, such as mental health and patient monitoring, offering therapeutic conversations and facilitating early interventions. This chapter presents a systematic review that explores the current state of chatbots in the healthcare sector, thoroughly evaluating their effectiveness, practical applications, and the potential benefits they can offer in improving healthcare delivery.

The order of the chapters in this thesis follows a logical structure that evolves from an overview of the impact of COVID-19 on the mental health of older adults to the exploration of innovative solutions in the healthcare sector. Chapter 1 introduces the topic by analyzing how the pandemic affected the mental health of older adults in Europe, highlighting key socioeconomic factors. From there, Chapter 2 focuses on unequal access to technology, investigating how the digital divide affects the mental health of older adults and how this phenomenon has evolved over time. Chapter 3 shifts the focus to examine individuals with disabilities in Spain, specifically how participation in recreational activities influences the demand for mental health services. Chapter 4 broadens the perspective by addressing how healthy habits and regional characteristics impact mental health, while Chapter 5 delves into the impact of place of residence and the characteristics of the social and economic environment on psychological well-being. Finally, Chapter 6 closes the cycle by exploring how technological innovations, such as chatbots in mental health, can optimize healthcare resources and improve care, particularly in the context of the pandemic. In this way, each chapter contributes to an integrated and evolving understanding of the determinants of mental health and possible solutions.

On the other hand, several empirical results derived from this research have been published in collaboration with other authors, or have successfully passed the first stage of the review process in different academic journals. More specifically:

- Chapter 1 has been published as a chapter in the book titled *Propuestas para la gestión de servicios sanitarios,* Editorial ARANZADI, ISBN: 978-84-1162-898-3.
- Chapter 2 has been published in the journal *Healthcare* 2024, 12(23), 2454; available at: https://doi.org/10.3390/healthcare12232454.

- Chapter 3 has been published in the journal *Estudios de Economía Aplicada*, ISSN 1133-3197, ISSN-e 1697-5731, Vol. 42, No. 1, 2024, in a special issue titled *Advances in Econometric Modeling: Theory and Applications*.
- Chapter 4 has been submitted to the journal *Indicators Research*, and is currently under evaluation.
- Chapter 5 has been submitted to the journal *Gaceta Sanitaria*, within its special issue on *Health Economics*, and is awaiting reviewer evaluation.
- Chapter 6 has been published in the journal *Digital Health 2025*, *11*, 20552076251319174; available at: https://doi.org/10.1177/20552076251319174.

Participation in various conferences and workshops has been a key opportunity to disseminate the findings and ideas of this research, as well as to contribute to academic debate, with a particular emphasis on mental health. Throughout the development of this thesis, I have had the privilege of presenting different chapters at the following conferences:

- XXXV International Conference on Applied Economics ASEPELT (June 29 to July 2, 2022)
- XIV Medical Education Congress (September 15, 2022)
- I ISCIII Biobanks and Biomodels Platform Conference (October 27-28, 2022)
- IV Workshop on Clinical and Healthcare Management - GestionAES (April 20, 2023)
- XXIII World Economy Meeting (May 25-26, 2023)
- X G-9 Doctoral Conference (May 31, June 1-2, 2023)
- Progress Reports Valdecilla (June 14, 2023)
- XLII Health Economics Conference (July 5-7, 2023)
- XXXVI ASEPELT Conference (July 5-7, 2023)
- XXXI Public Economics Meeting (May 9-10, 2024)
- V Workshop on Clinical and Healthcare Management - GestionAES (June 4, 2024)
- XXVI Applied Economics Meeting (June 6-7, 2024)
- XVI Teaching Conference in Economics (June 20-21, 2024)
- XLIII Health Economics Conference (June 26-28, 2024)

Finally, it is important to highlight my participation in various courses, conferences, and seminars related to this research. I would like to make special mention of the Master's in Healthcare Services Management and the Master's in Management and Planning of Centers and Services for Dependent Care at the University of Cantabria, which I completed during these thesis years.

Additionally, I have attended other courses at the University of Cantabria, the Menéndez Pelayo International University, and the Valdecilla Research Institute (IDIVAL), which have expanded my knowledge in key areas such as teaching and

scientific dissemination, creative thinking, research ethics, and the various forms of collaboration between the university and the private sector or entrepreneurship.

On the other hand, it is worth noting that this thesis is framed within an international mention due to the stay at the Centre for Business and Economics Research (CeBER) of the University of Coimbra, Portugal, from March 1st to June 3rd, 2024.

I would also like to express my gratitude for the collaboration and support of the Health Economics Research Group at the University of Cantabria and IDIVAL, as this work would not have been possible without their assistance, and for allowing me to participate in various research projects.

Chapter 1. Rethinking the effects of Mental Health among Older Europeans in times of COVID-19

1.1 Introduction

In 2020, the World Health Organization (WHO) officially declared the outbreak of COVID-19 a global pandemic. Since then, the incidence of COVID-19 infections has varied over time, with successive waves of contagion and corresponding responses. Beyond its physical health implications, the WHO also highlighted that the lockdown measures introduced to curb the spread of the virus significantly exacerbated existing mental health problems. In this context, several scholars, including Serrano-Alarcón et al. (2022), have observed a deterioration in mental health associated with the pandemic, although it remains uncertain whether this decline is directly attributable to containment policies. Nonetheless, an expanding body of research, including work by Muldrew et al. (2022), Zhou and Kann (2021), among others, provides mounting evidence of the profound psychological effects of both the pandemic itself and the associated social restrictions.

The cumulative toll of deaths, infections, prolonged social distancing, and lockdowns, along with the broader consequences of the pandemic, has contributed to a widespread decline in individuals' psychological well-being. These stressors played a pivotal role during the COVID-19 crisis, as noted by Orea and Álvarez (2020). Moreover, public health guidelines often urged people to avoid close contact with older adults and vulnerable populations, which further compounded issues such as loneliness and social isolation.

Mental illness, in any context, can profoundly disrupt individuals’ daily functioning. Psychological distress may manifest in emotional suffering, breakdowns in daily routines, strained family dynamics, and difficulties in social interactions. These effects can also extend to professional life, contributing to increased absenteeism or, in more severe cases, prompting individuals to permanently exit the workforce.

Importantly, concern for mental health is not a phenomenon that emerged solely in response to the pandemic. Psychological factors have long been recognized as central to understanding human behavior, as evidenced by the work of Nobel Prize-winning economists such as Daniel Kahneman (2002) and Richard H. Thaler (2017). Consequently, mental health and the broader field of behavioral economics have gained prominence as critical areas of inquiry in contemporary societies. Indeed, authors like Aria et al. (2020) have identified mental health and its related dynamics as a defining research theme of the current decade.

Against this backdrop, the aim of this study is to explore how the COVID-19 pandemic has affected the mental health of older adults across European countries. Specifically, it seeks to investigate how deteriorations in mental health relate to various pandemic-related experiences and to identify the main sociodemographics factors that influence psychological well-being. Additionally, the study examines whether the mental health impact of COVID-19 differs by gender. The analysis draws on data from two specialized datasets—COVID Waves SCS1 and SCS2—covering the period from June-September 2020 and June- August 2021.

Finally, this chapter is structured as follows. First, a literature review presents the main negative determinants of mental health identified in recent research. This is followed by a detailed description of the data sources used in the analysis, along with the key variables considered. Next, the methodology section outlines the analytical approach employed to assess the relationship between mental health outcomes and their potential drivers. The chapter then presents the empirical results, highlighting significant patterns and differences across population groups. Finally, the discussion interprets the findings in light of the existing literature, and the chapter concludes with a summary of the main insights and implications.

1.2 Negative determinants of mental health: a review

A substantial and growing body of literature has examined the mental health consequences of the COVID-19 pandemic. Studies such as those by Vindegaard & Benros (2020), Xiong et al. (2020), and Gaggero et al. (2022) have documented increased rates of anxiety, depression, and psychological distress across diverse population groups. While many of the factors influencing mental health predated the pandemic, the crisis significantly intensified their impact. Moreover, the pandemic also gave rise to new stressors and risk factors contributing to psychological distress.

To comprehensively understand the pandemic's impact on mental health, it is essential to consider both individual characteristics and broader socioeconomic conditions. Research that explores the influence of specific variables, both during and prior to the COVID-19 outbreak, offers valuable insight into how these determinants have evolved over time. In particular, findings from the last two years indicate that multiple factors have exerted a detrimental effect on individuals' mental well-being.

One notable factor shaping mental health outcomes is the mode of consultation for mental health care. Following the pandemic, new digital formats for therapy and psychological support gained prominence. According to Phillips et al. (2022), there is evidence that both mental health professionals and patients prefer a hybrid model that combines digital and face-to-face elements, rather than relying solely on online platforms.

Their findings suggest that a blended approach yields better outcomes. Consequently, the limited availability of in-person care during lockdowns may have hindered recovery or exacerbated mental health conditions.

Environmental determinants of mental health have also received considerable attention. Studies such as those by Abed Al Ahad et al. (2022), Lanza-León et al. (2021), and Bloemsma et al. (2022) emphasize the relevance of factors such as access to green spaces, exposure to air pollution, and ambient noise. Bloemsma et al. (2022) found a negative association between exposure to air pollution and mental well-being, while traffic noise did not show a significant relationship. Importantly, they observed that residential proximity to green spaces is linked to better mental health in adolescents. These findings suggest that restrictions during lockdown, which reduced access to outdoor environments, may have further compromised psychological well-being.

Socioeconomic conditions have emerged as another critical dimension in the analysis of mental health impacts during the pandemic. Raynor et al. (2022) explored how confinement measures affected the mental health of economically vulnerable populations, focusing on factors such as job loss, increased living costs, and changes in housing conditions. Their research identified group households with pre-existing socioeconomic precariousness as particularly susceptible to adverse mental health outcomes. Similarly, Curtis et al. (2021) underscored that individuals residing in deprived neighborhoods faced disproportionately higher risks of psychological decline. In the context of aging populations, Zhou et al. (2022) found a direct relationship between pension schemes and depression, concluding that China's New Rural Pension Plan not only reduced depressive symptoms among the elderly but also helped lower associated healthcare costs.

Gender also plays a key role in mental health disparities. Zamarro et al. (2021) revealed that women, particularly mothers of school-age children, assumed a greater share of household and caregiving responsibilities during the pandemic, even when employed, which contributed to a widening psychological distress gap compared to women without children. De Breij et al. (2022) further confirmed that both female gender and age were associated with heightened depressive symptoms, with older female workers reporting worse outcomes than their male peers. Likewise, Legas et al. (2022) identified a range of risk factors for common mental disorders, including female gender, substance use, unemployment, rural residence, family history of mental illness, and weak social support, highlighting their especially high prevalence in populations with these vulnerabilities.

In addition to gender-based disparities, racial and ethnic inequalities also warrant attention. Fan et al. (2022) examined mental health among adolescents in the United

States and found that racial and ethnic minority youth were more likely to experience major depressive episodes than their white counterparts, yet were less likely to seek or receive mental health services.

1.3 Data Description

We employ data from the SHARE, a comprehensive and multidisciplinary panel survey targeting individuals aged 50 and older. Conducted across 27 European countries and Israel, SHARE stands out for its longitudinal design and rich microdata, capturing a wide range of information related to health, socioeconomic status, and social and familial networks. With over 140,000 participants, the survey investigates how health, social, economic, and environmental factors, and the policies that influence them, affect European citizens throughout their lives. The dataset spans from 2004 to 2020 and includes two waves addressing the COVID-19 pandemic.

This study specifically uses the most recent available data at the time of analysis: the two special COVID-19 waves of SHARE, known as SCS1 and SCS2. These waves were conducted between June and September 2020, and June and August 2021, respectively. In contrast to the standard SHARE methodology, these COVID-19 waves were adapted for remote data collection through telephone interviews due to pandemic-related restrictions. A shortened questionnaire was developed to replace the face-to-face format, focusing on essential topics while specifically addressing the living conditions of individuals aged 50 and over during the pandemic.

A total of ten variables were selected from these waves to represent a range of clinical and socioeconomic characteristics. The independent variables used in the analysis include: year of birth, sex, sleep problems, feelings of loneliness, nervousness, canceled medical appointments, deaths due to COVID-19, and receiving help from others as a result of the pandemic. These variables were chosen based on insights from existing literature, where they are frequently used in studies of mental health, as well as based on their availability within the SHARE COVID-19 dataset. The sample comprises data from all countries included in the selected waves, with the aim of offering a general overview of the phenomenon rather than exploring cross-country differences, an aspect that, due to its relevance, is proposed for future research in the conclusions.

The dependent variable selected for this study is “mental problems,” understood as whether the respondent reported experiencing depression recently. This variable is widely used in similar research and is supported by prior findings on the prevalence of depression in relation to the aforementioned factors (Hao et al., 2021). Table 1.1 below presents the set of explanatory variables included in the analysis, along with the dependent variable used to evaluate mental health outcomes.

Tabla 1.1. Variables definition

Name		Definition
Dependente variable	Mental Problem	1 if mental problem (depression), 0 otherwise
Clinic factors	Trouble	1 if trouble sleeping recently, 0 otherwise.
	Lonely	1 if feels lonely often or sometimes, 0 otherwise
	Nervous	1 if suffering nerves in the last 3 months, 0 otherwise
	Postponed appointment	1 if postpone a medical appointment due to COVID-19, 0 otherwise
	Died	1 if someone has died as a result of COVID-19, 0 otherwise
	Helpme	1 if the person has received help to obtain basic needs, 0 otherwise
Sociodemographic	Ybirth	Individual´s year of birth
	Gender	1 if female, 0 otherwise
	Couple	1 if couple, 0 otherwise

Source: Authors' elaboration

Each variable used in the analysis refers to the respondent’s situation at the time of the interview during the corresponding wave. For wave SCS1, this period ranges from June to September 2020, while for wave SCS2, it spans from June to August 2021. The variables capture current or recent experiences as reported by participants during the interview, reflecting their status during those specific months. As such, the data provide a cross-sectional snapshot of individuals’ mental health and related factors during each of the two main phases of the COVID-19 pandemic covered by the survey.

The variables described in Table 1.1 provide an overview of key clinical and socioeconomic factors relevant to understanding the mental health impacts during the COVID-19 pandemic.

Among the clinical factors, the Trouble variable identifies whether the respondent has recently experienced difficulty sleeping. This is a dichotomous variable that takes the value of 1 if the person has reported sleep problems, and 0 otherwise. This variable is particularly relevant given that sleep disorders are a common symptom associated with mental health issues, especially in contexts of uncertainty or stress, such as those created by the pandemic. The Lonely variable, on the other hand, measures whether the individual has experienced feelings of loneliness, with "often" or "sometimes" being the key categories. This information offers insight into the degree of perceived social isolation, which is closely linked to mental health, particularly among older adults.

The *Nervous* variable assesses whether the respondent has reported experiencing nervousness during the past three months. This variable is understood to capture the presence of symptoms related to tension, anxiety, or emotional restlessness. As a more subjective measure, it helps to identify states of psychological distress that may not have been clinically diagnosed but still significantly affect an individual's sense of well-being. *The Postponed appointment* variable reflects whether the individual had to postpone any medical appointments due to COVID-19. The impact of postponing healthcare is considered both on physical and emotional well-being, adding to the burden of concern or uncertainty regarding health.

The *Died* variable indicates whether the respondent has lost a person close to them as a direct result of the pandemic, to the best of their knowledge at the time of the survey. This experience can have a profound emotional impact, often associated with grief, sadness, and post-traumatic stress, thus making it an important factor in understanding the emergence of depressive symptoms. Lastly, the *Helpme* variable captures whether the individual received external assistance to meet basic needs during the pandemic, such as support with food, medicine, or essential supplies. This variable is interpreted as an indicator of vulnerability or functional dependence, especially when access to services or support networks is limited.

In terms of socioeconomic factors, the *Ybirth* variable represents the respondent's year of birth and serves as a proxy for age. Given that the study population consists of older cohorts, this variable helps to identify variations within this group and offers insight into generational differences in experiencing emotional distress. The *Gender* variable records the respondent's sex, where 1 indicates female and 0 indicates male. Its inclusion is critical for analyzing the gendered dimension of the psychological impact of the pandemic, as previous research suggests that women have a higher prevalence of depressive symptoms. Finally, the *Couple* variable reflects whether the individual currently lives with a partner, which serves as an indirect indicator of emotional support and companionship, elements that can help mitigate the effects of stressors such as isolation or disruption of daily routines.

It is worth noting that the data required preprocessing to ensure consistency and accuracy. Respondents who did not complete the relevant sections of the questionnaire were excluded from the sample. Furthermore, some variables identified as potentially important for the analysis could not be included, as they were not available in the abbreviated COVID-19 SHARE questionnaires. As a result, the analysis was structured into two separate models. Model 1 corresponds to wave SCS1 (June to September 2020), and Model 2 to wave SCS2 (June to August 2021). Each model is further divided into three subsamples: the full sample (Model 1: n = 54,778; Model 2: n = 49,222), females only (Model 1: n = 31,608; Model 2: n = 28,663), and males only (Model 1: n = 23,170; Model 2: n = 20,559).

1.4 Methodology

There is a deterioration of mental health problems in individuals over time. Obviously, COVID-19 has important consequences for mental health. To test this hypothesis we will use the SHARE data and consider different socioeconomic variables that could explain the behavior of mental health. The analysis is based on logistic regression models.

The variable of interest is "Mental Problem" and expresses whether the individuals have suffered any mental health problem. A value of 1 is needed if the respondent had depression and a value of 0 if they did not have any problems. The probability that the variable of interest takes the value 1 or the value 0 is p and 1-p respectively. In this regard, the probability of having mental health problems and specifically, depression (p) is a function of two vectors: one of them is that of a set of independent variables that affect the variable of interest (x). The other vector is made up of a collection of unknown parameters (β) that will be estimated using econometric methods. Therefore, the discrete choice model to be used will be the following one:

$$\text{Prob}(y=1|x)=F(x,\beta), \quad (1)$$

$$\text{Prob}(y=0|x)=1- F(x,\beta), \quad (2)$$

It should be remembered that only one of the two decisions can be observed: a respondent can only have been in the situation of having depression or, on the contrary, not have suffered from it. It is considered that there is a situation with latent variables when this happens that could be represented as follows:

$$y=1 \text{ if } y^* > 0, \quad (3)$$

$$y=0 \text{ if } y^* \leq 0, \quad (4)$$

where

$$y^* = x'\beta + \varepsilon \quad (5)$$

Hence, equation (5) represents the discrete choice model that will be used in this study to estimate the β parameters mentioned above. Due to these parameters, the impact of the different independent variables on the likelihood of suffering from mental health problems is estimated. In this way, the parameters are estimated through logistic regression to disentangle the impact of the variables included in this study. In logistic models, the conditional probability allows the predicted probability of the event to be bounded between 0 and 1, and follows the following form:

$$p = Prob\ (X) = \frac{exp\ (X'\beta)}{1 - exp\ (X'\beta)} \quad (6)$$

In this class of models, one of the main problems is that they are not linear. This causes that the interpretation of the estimated coefficients is not direct. As a solution to this problem, the Odds Ratio is calculated, which are the probability ratio of success and failure. Adjusted Odds Ratios (OR) are used to measure the magnitude of the effects.

More, the ORs report the relationship between the mean probabilities of reporting the risk factor in the result. If an OR greater than 1 is obtained, it implies an increase in the risk factor variable when the outcome is measured (ie, an increased risk of depression). On the contrary, if an OR of less than 1 is obtained, it shows a decrease in the risk factor variable when the outcome is measured (ie, a lower probability of suffering from depression).

$$ln\left(\frac{p}{1-p}\right) = X'\beta \tag{7}$$

Due to the logistic model that is going to be estimated, it is possible to study the impact of the different characteristics of individuals on whether or not they lead to developing poor mental health in general in relation to depression.

1.5 Empirical Results

This section presents the empirical findings of the study, structured around the research objectives previously outlined. It begins with a descriptive analysis of the analytical sample, which includes data from all participating countries and is divided into two separate models based on the corresponding SHARE COVID-19 wave. Specifically, Model 1 shows the descriptive statistics derived from respondents interviewed during the SCS1 wave (June to September 2020), while Model 2 focuses on the responses collected during the SCS2 wave (June to August 2021).

Thanks to the extensive dataset provided by these special COVID-19 waves, the results of the variables related to mental health will subsequently be presented, providing an initial overview of key patterns.

Table 1.2. Descriptive statistics of the analytical sample.

		Model 1			Model 2		
Variables		Full sample (N=54,778)	Female (N=31,608)	Male (N=23,170)	Full sample (N=49,222)	Female (N=28,663)	Male (N=20,559)
Dependent variable	Mental problem	0.26	0.31	0.19	0.29	0.35	0.22
Clinic factors	trouble	0.28	0.32	0.22	0.32	0.37	0.25
	lonely	0.28	0.34	0.21	0.30	0.35	0.23
	nervous	0.30	0.35	0.24	0.32	0.37	0.26
	Postponed appointment	0.26	0.27	0.24	0.13	0.13	0.12
	died	0.03	0.02	0.09	0.84	0.83	0.84
	helpme	0.28	0.31	0.21	0.34	0.39	0.28
Socioeconomic factors	ybirth	1949.60	1949.81	1949.30	1949.88	1950.05	1949.64
	couple	0.70	0.61	0.82	0.69	0.60	0.82
	gender	0.58	1	0	0.58	1	0

Source: Authors' elaboration.

The descriptive statistics presented in Table 1.2 show a comprehensive overview of the analytical sample for both models, which correspond to the two special COVID-19 waves of the SHARE survey. These statistics are disaggregated by gender to facilitate an initial understanding of potential differences between women and men.

Beginning with the dependent variable, the prevalence of mental health problems, defined as having experienced depression, is notably higher among women than among men in both models. In Model 1 (June–September 2020), 26% of respondents reported mental health issues, with a higher proportion among women (31%) compared to men (19%). This gender gap persists in Model 2 (June–August 2021), where the overall prevalence increases to 29%, with 35% of women and 22% of men reporting symptoms of depression. These findings suggest that the mental health impact of the pandemic not only persisted over time but also disproportionately affected women.

Back to clinical factors, the trends align with those observed for mental health. Variables such as trouble sleeping, feelings of loneliness, and nervousness exhibit clear gendered patterns, with women consistently reporting higher rates. For example, in Model 2, about 37% of women reported trouble sleeping, compared to 25% of men. Similarly, 35% of women reported feeling lonely, versus 23% of men, and 37% of women reported nervousness compared to 26% of men. These differences may reflect a greater psychological vulnerability among women in response to the challenges posed by the pandemic.

The proportion of individuals who postponed medical appointments due to COVID-19 declined significantly from the first to the second wave (from 26% to 13% overall), likely reflecting the gradual adaptation of healthcare systems to the limitations imposed by the pandemic. This variable shows minimal gender differences in both models.

The variable died, which indicates whether the respondent experienced the death of someone close due to COVID-19, shows a marked change between waves. While only 3% of the sample reported such a loss in Model 1, the proportion rises sharply to 84% in Model 2. This dramatic increase may be attributed to differences in data collection or in public awareness, at the onset of the pandemic, individuals may have been less informed about the actual causes of death among their acquaintances.

The variable helpme, which captures whether the respondent received assistance with basic needs during the pandemic, also reveals a distinct gender disparity. In Model

2, 39% of women reported receiving help, compared to 28% of men, further highlighting women's greater exposure to pandemic-related vulnerabilities.

With respect to socioeconomic characteristics, the average year of birth across all groups is around 1949, indicating a relatively uniform age distribution. Men are more likely than women to report living with a partner, 82% of men versus approximately 60–61% of women in both waves. This difference may be attributed to demographic patterns such as higher female life expectancy and age gaps between partners.

Finally, the gender variable confirms that women represent 58% of the total sample in both waves, indicating a slight overrepresentation of females in the older adult population surveyed.

Table 1.3. Associations mental health of older europeans: logistic regressions models (odds ratios and 95% confidence intervals) for all countries.

			Model 1						Model 2					
Independent variables			Full sample (N= 54,778)		Female (N= 31,608)		Male (N= 23,170)		Full sample (N= 49,222)		Female (N= 28,663)		Male (N= 20,559)	
			OR	CI	OR	CI	OR	CI	OR	CI	OR	CI	OR	CI
Clinic factors	trouble	Yes	2.41***	[2.29-2.52]	2.32***	[2.19-2.46]	2.57***	[2.36-2.80]	2.28***	[2.17-2.39]	2.28***	[2.14-2.42]	2.26***	[2.08-2.46]
		No	1				1		1		1		1	
	lonely	Yes	3.43***	[3.26-3.3.61]	3.28***	[3.09-3.49]	3.73***	[3.41-4.07]	3.39***	[3.21-3.57]	3.30***	[3.10-3.52]	3.53***	[3.23-3.86]
		No	1				1		1		1		1	
	nervous	Yes	7.24***	[6.90-7.59]	6.90***	[6.51-7.31]	7.88***	[7.28-8.55]	7.70***	[7.33-8.08]	7.35***	[6.92-7.82]	8.37***	[7.71-9.09]
		No	1				1		1		1		1	
	Postponed appointment	Yes	1.19***	[1.13-1.26]	1.15***	[1.08-1.22]	1.28***	[1.17-1.39]	1.20***	[1.12-1.28]	1.23***	[1.13-1.51]	1.13***	[1.01-1.27]
		No	1				1		1		1		1	
	died	Yes	1.43***	[1.24-1.63]	1.50***	[1.26-1.79]	1.32*	[1.06-1.63]	1.38***	[1.27-1.50]	1.36***	[1.23-1.52]	1.42***	[1.24-1.62]
		No	1				1		1		1		1	
	helpme	Yes	1.35***	[1.28-1.43]	1.31***	[1.22-1.39]	1.46***	[1.33-1.61]	1.35***	[1.28-1.42]	1.36***	[1.28-1.45]	1.33***	[1.22-1.46]

		No	1				1		1		1		1	
Socioeconomic factors	ybirth		0.99***	[0.98-0.99]	0.99***	[0.99-0.99]	0.99***	[0.98-0.99]	0.99***	[0.98-0.99]	0.99***	[0.98-0.99]	0.98***	[0.98-0.99]
	couple	Yes	0.99	[0.93-1.04]	0.98	[0.91-1.04]	0.99	[0.92-1.08]	0.87***	[0.83-0.92]	0.89***	[0.83-0.95]	0.83***	[0.74-0.91]
		No	1		1		1		1		1		1	
	gender	Yes	1.44***	[1.37-1.52]					1.35***	[1.28-1.42]				
		No	1						1					

Source: Authors' elaboration. ***, ** and * indicate signifcance at 1%, 5% and 10%, respectively. Reference categories: woman, without couple, with sleep problems, with a feeling of loneliness, with a feeling of nervous, with a postponed consultation, with a known person deceased by COVID and with someone's help.

The results of the logistic regression models, presented in Table 1.3, offer robust insights into the factors associated with the likelihood of reporting mental health problems during the COVID-19 pandemic. Across both waves and all subgroups, several clinical and socioeconomic variables show strong, consistent associations with self-reported depression, the study's dependent variable.

Among the clinical factors, feeling nervous in the past three months emerges as the most powerful predictor of mental health problems across all specifications. In Model 1 (2020), the odds of reporting depression are more than seven times higher for those who reported nervousness (OR = 7.24; 95% CI: [6.90–7.59]), with slightly higher odds among men (OR = 7.88) than women (OR = 6.90). This association remains strong in Model 2 (2021), where the odds rise further (OR = 7.70), and again, are particularly high among men (OR = 8.37). These findings highlight the central role of anxiety-related symptoms in the deterioration of mental well-being during the pandemic.

Loneliness and sleep disturbances are also significantly associated with a higher probability of experiencing mental health problems. Individuals reporting frequent feelings of loneliness are more than three times as likely to report depression in both waves. In Model 2, for example, the odds ratio is 3.39 for the full sample, with slightly higher estimates among men (OR = 3.53) than women (OR = 3.30). Similarly, trouble sleeping is consistently associated with increased odds of depression (Model 2 OR = 2.28), again with men showing a slightly stronger association than women. These results suggest that social isolation and disrupted sleep patterns have remained critical factors in the emotional toll of the pandemic.

Other health-related disruptions, such as postponing medical appointments due to COVID-19, are also positively associated with mental health problems, though with smaller effect sizes. In both models, the odds of reporting depression are about 20% higher among those who delayed care (Model 2 OR = 1.20), reflecting the broader mental strain linked to unmet healthcare needs during the crisis.

Experiencing the death of someone due to COVID-19 is another significant factor. While the magnitude of the association is more modest compared to other clinical variables, it remains statistically significant. In Model 2, individuals who lost someone are 38% more likely to report depression (OR = 1.38), with little variation by gender. This suggests that grief and bereavement may have contributed substantially to the psychological burden experienced by older adults during the pandemic.

The variable capturing whether respondents received help for basic needs (helpme) also shows a consistent association with mental health issues. Those who received assistance were approximately 35% more likely to report depression across both models, with the effect slightly more pronounced among men. This pattern may point to the vulnerability or lack of autonomy that accompanies needing external help, and its possible psychological consequences.

Regarding sociodemographic factors, the year of birth shows a negative association with the probability of reporting depression. Although the effect size is small, it is consistent and statistically significant across all groups (OR < 1), indicating that younger individuals within this older cohort (i.e., those born more recently) are slightly more likely to experience mental health problems.

Living with a partner appears to play a protective role in the second wave. In Model 2, individuals living with a partner have significantly lower odds of reporting depression (OR = 0.87), with a slightly stronger effect among men (OR = 0.83). However, this association was not significant in Model 1, possibly reflecting changes in the social dynamics or stressors experienced across different stages of the pandemic.

Being female is associated with a higher likelihood of reporting mental health problems. In both waves, women had significantly higher odds of depression than men (Model 1 OR = 1.44; Model 2 OR = 1.35), even after controlling for clinical and socioeconomic factors. This finding confirms the gendered impact of the pandemic on psychological well-being, echoing patterns observed in the descriptive analysis.

Overall, the results underscore the multifaceted nature of mental health challenges during the pandemic, shaped by a combination of psychological symptoms, social circumstances, healthcare access, and gender disparities. They also highlight the need for tailored mental health interventions that address the specific vulnerabilities of older adults, particularly women.

1.6 Discussion

This paper explores the impact of poor mental health on individuals during the COVID-19 pandemic, with a particular focus on older adults. We use data from the COVID-19 special waves (waves SC1 and SCS2) of the SHARE survey, which capture a wide range of characteristics related to mental health within this population. The COVID-19 factors framework, as applied to mental health, incorporates both clinical and socioeconomic variables, with particular emphasis on individuals aged 50 and older.

Understanding the determinants of mental health is essential for advancing public health initiatives. Several authors, including Cheah et al. (2019), Irfan et al. (2021), and Zhou et al. (2022), highlight the importance of mental health and stress the need to comprehend its complexities for effective management. Mental health has gained increasing attention, especially in the aftermath of the global health crisis triggered by the pandemic. The concerning prevalence of mental health issues, with approximately one-third of the population reporting such problems, underscores the need for continued research and intervention. Our study builds upon recent data regarding the intersection of COVID-19 and mental health, aiming to identify both clinical and socioeconomic factors that influence the mental well-being of older Europeans (aged 50+). Additionally, we explore the role of gender and track changes over time using data from waves SC1 and SCS2.

To the best of our knowledge, this study represents one of the first attempts to analyze the spillover effects of COVID-19 on mental health across a large sample of European countries, with a specific focus on older populations. Moreover, it integrates variables pertinent to the COVID-19 context, addressing a gap in the current literature.

From our individual-level estimates, we can draw several conclusions: (i) there is a positive and significant association between mental health conditions and clinical factors for individuals aged 50 and older, suggesting that clinical factors have a detrimental impact on mental health during the pandemic; (ii) socioeconomic factors are significant in determining mental health outcomes for older individuals, with those living with a partner during COVID-19 showing a lower likelihood of experiencing mental health problems; (iii) gender differences in mental health outcomes are evident; and (iv) the results remain consistent across both waves and tend to intensify over time.

While research on mental health and COVID-19 factors is limited, particularly in relation to older populations, this study offers valuable insights to the existing body of knowledge. Notably, it identifies a range of COVID-19-related factors that are both statistically significant and highly relevant, but have not been fully explored in the literature.

Our findings suggest that the pandemic has introduced new factors that negatively influence mental health. The importance of mental health extends beyond its status as a public health issue; it also has substantial economic implications. International economic events, such as recessions, financial crises, and health crises, can exacerbate mental health problems and influence public policies and health service management. Therefore, mental health must be considered a critical issue from an economic perspective.

However, it is important to acknowledge the limitations of our study. Restrictions on data usage, such as the inability to include all desired variables, impose constraints on the generalizability of our findings and policy recommendations. Additionally, our analysis relies on a dichotomized variable and does not include suitable instrumental variables. Given that the study is based only on two waves of the SHARE survey (waves SC1 and SCS2), future research should account for differences between countries and incorporate additional socioeconomic and demographic variables, such as education.

Despite these limitations, the SHARE data and methodology used in this study provide valuable new insights into the impact of COVID-19 on mental health, contributing to a more comprehensive understanding of the broader effects of the pandemic.

1.7 Conclusions

In this study, the impact of mental health on individuals during the COVID-19 pandemic was examined, focusing on the population over 50 years old in Europe, using data from the special waves SC1 and SCS2 of the SHARE survey. The results show that clinical and socioeconomic factors significantly impact the mental health of older adults, with a clear association between mental health conditions and the presence of clinical factors such as sleep difficulties, feelings of loneliness, nervousness, and postponement of medical appointments, all of which were worsened by the pandemic.

This study contributes to the existing body of knowledge by being one of the first to analyze the effects of COVID-19 on the mental health of older adults in Europe, incorporating a variety of factors related to the pandemic. The findings highlight the urgent need for public health policies that not only address the physical effects of COVID-19 but also include interventions focused on mental health, particularly among vulnerable groups such as older adults. Based on the evidence, public policies could be designed to promote access to mental health services, improve outreach and support programs for those living alone, and strengthen social support networks. Moreover, targeted interventions could be developed for women and those who have suffered personal losses or faced difficulties in accessing basic services, ensuring that psychological support is integrated into emergency response planning.

The analysis revealed that the risk of developing mental health issues during the pandemic is higher among older individuals, especially those who experienced the loss of a close person or faced difficulties in accessing basic services. On the other hand, the presence of a partner has been identified as a protective factor, reducing the likelihood of experiencing mental health problems. Additionally, significant differences between men and women were observed, with women showing a higher prevalence of mental health problems, emphasizing the importance of considering gender in mental health approaches.

Although the results provide valuable insights into the determinants of mental health during times of crisis, the study has some limitations, such as restrictions on the use of certain variables, the lack of broader longitudinal analysis and self-reported variables. However, the implications of these findings are clear: mental health should be considered not only as a public health challenge but also as a key issue from an economic perspective. The impact of the global health crisis on psychological well-being is widespread and, therefore, should be integrated into public policies and health services to mitigate the long-term impact.

In conclusion, this work provides an important understanding of how the pandemic has affected the mental health of older adults in Europe and underscores the importance of addressing the social and clinical factors that contribute to psychological well-being during times of crisis.

Chapter 2. Age, technology, and digital divide. Directly related to mental health problems?

2.1. Introduction

The evolution and integration of technology into our daily lives has become increasingly evident in recent decades. Beyond its ubiquity, the widespread use of technology, particularly Information and Communication Technologies (ICT), has brought about substantial improvements in comfort, efficiency, and overall societal well-being.

The enhancement of individual and collective welfare is closely linked to the growing presence of ICT in everyday life. According to the author at the time of publication, over the past 70 years, ICT have progressively reshaped society, particularly in the context of successive industrial revolutions (Santangelo, 2001).This transformation has enabled governments and institutions to embed digital tools into a wide range of domains, from healthcare management and social services to education and information access. ICT has also helped eliminate geographical barriers, boost productivity, and simplify complex tasks (Emmens et al., 2010), reinforcing its role as a key driver of social and economic development.

At the same time, demographic trends show a rapid increase in the proportion of older adults, especially in European countries. According to the World Health Organization (2022), the global share of people aged 65 and over is expected to double between 2015 and 2050. This demographic shift underscores the importance of ensuring that older adults can benefit from technological advancements. However, despite the many advantages ICT offers, a significant portion of the older population continues to face difficulties in adapting to digital technologies.

While the overall use of the Internet is high, approximately 99% of Europeans surveyed reported having used the Internet in the past three months (Eurostat, 2020), these figures mask important age-related disparities. In Spain, for example, 92.9% of individuals aged 16 to 74 used the Internet frequently in 2022 (INE, 2022). Yet, internet use is significantly more common among younger adults, with usage rates steadily declining with age, for both men and women.

This phenomenon is often referred to as the "digital divide." Although commonly associated with unequal access to ICT due to economic barriers, the concept encompasses much broader inequalities. The OECD (2001) defines it as the gap between individuals, households, businesses, and geographic areas of different socioeconomic levels in terms of their access to and effective use of ICT. These disparities can manifest both between countries and within them. Scholars such as Yu et al. (2016) have further categorized the digital divide into different levels, emphasizing the complexity of the issue.

This study focuses specifically on the dimension of age-related inequality within the digital divide. Understanding why many older adults, despite often having positive attitudes toward ICT, exhibit lower usage rates is key to facilitating their adaptation to the digital world and promoting their social inclusion.

The main aim of this research is to explore how the use of ICT has influenced the mental health of older adults over time. Starting from the premise that digital technologies have become an integral part of everyday life, we seek to examine whether the limited use or unfamiliarity with ICT, driven by the age-related digital divide, may be associated with mental health challenges among the older population.

The structure of this paper is as follows: Section 2 reviews the relevant literature and presents the current state of research. Section 3 outlines the methodology and data used. Section 4 discusses the main findings based on the regression analyses. Finally, Section 5 provides a discussion of the results and concludes the study.

2.2. Literature review

This section presents a review of existing research on the digital divide among older adults, with a particular focus on how age-related factors influence access to and use of ICT, and how this, in turn, relates to well-being and mental health. The aim is to contextualize the study within current academic debates and highlight key findings from recent literature.

Fast transformations experienced by modern societies, including the increasing integration of smart technologies into everyday services and the ongoing demographic shift toward an aging population, have contributed to a growing sense of information overload. This phenomenon has further complicated the ability of older adults to adapt to the demands of digital life, making their integration into the digital world increasingly difficult (Liu et al., 2021). As a result, public concern over the deepening digital divide affecting older individuals has become more pronounced.

Attitudes toward ICT play a critical role in shaping not only material access and digital skills, but also broader health outcomes (Van Deursen et al., 2022). Despite the wide-ranging benefits that digital technology brings to everyday life, patterns of ICT use vary substantially across population groups. This study focuses specifically on older adults, particularly those aged 55 and above, among whom difficulties in using ICT are frequently reported (Augner et al., 2022). These challenges are often linked to the digital divide, a concept widely discussed in the literature (Weldon et al., 2022). Barriers to ICT use in this age group may arise from usability issues, cognitive limitations, or learning difficulties associated with aging (Petros et al., 2022). Identifying the sociodemographic traits that facilitate ICT use is therefore essential to enhance the impact of digital health interventions and reduce the gap in digital engagement.

Several studies have examined the underlying factors that contribute to this digital divide. For instance, Zhang et al. (2022) emphasize the persistent disparities in ICT access and use among rural residents, older individuals, and low-income groups. Likewise, Van Deursen et al. (2022) point to age and educational attainment as key determinants of digital inequality. Complementary findings by Holmberg et al. (2022) reveal that increasing age and residence in assisted living facilities tend to limit digital access. Moreover, individuals with psychotic disorders or functional impairments were found to have considerably lower access to digital technologies compared to the general population.

In terms of personal capabilities, Augner et al. (2022) provide evidence of a positive relationship between self-assessed computer skills and key health-related variables such as mental well-being, cognitive function, and physical health in older adults. These authors also identify factors like having a partner, higher education levels, and better self-rated writing skills as strong predictors of digital proficiency. Mental health appears to be particularly relevant in this context: Park et al. (2023) show that anxiety related to gerontechnology affects both the ability to use ICT and levels of self-efficacy among older adults in rural areas of Korea. On the other hand, Connolly et al. (2022) report that older adults with lower income levels tend to suffer more intensely from the consequences of digital exclusion.

In order words, the existing literature suggests that the ongoing process of digitalization, especially the incorporation of digital tools into everyday life, presents significant challenges for the aging population. These challenges, in turn, reinforce the digital divide and highlight the importance of targeted strategies to support digital inclusion among older adults.

2.3. Data and Methodology

2.3.1. Data Sample

The data used in this study come from the SHARE, a longitudinal and cross-national survey that collects rich information on more than 120,000 individuals aged 50 and over, across 27 European countries and Israel. SHARE provides comprehensive data across various dimensions, including household characteristics, sociodemographic factors, health status, lifestyle habits, cognitive functioning, mental health, social support, and the use of health and social care resources.

For the purposes of this analysis, we selected data from waves 5 (2013), 6 (2015), 7 (2017), and 8 (2019/20). These specific waves were chosen for several key reasons. Firstly, wave 5 marks the first time SHARE includes questions related to the use of ICT, making it the earliest point from which a longitudinal examination of digital engagement among older adults can begin. Secondly, wave 8 is considered the most recent pre-pandemic wave in which digital technology use is assumed to be fully integrated into everyday life for a majority of the population. As such, wave 8 serves as our reference point for a "digitally established" society.

By comparing wave 8 with earlier waves (5, 6, and 7), we are able to analyze the progression and integration of digital life among older adults over time. This design allows us to explore not only the evolution of ICT use, but also how the digital divide has persisted or changed across different stages of digital development.

The initial pooled sample for the selected waves includes approximately 65,733 European respondents. However, after applying selection criteria, such as availability of relevant variables, completeness of data across waves, and consistency in individual-level information, the final working sample is reduced to a smaller but robust set of observations suitable for longitudinal analysis.

2.3.2. Variable Selection

The dependent variable in this study is labeled MentalHealth and is used to measure the presence of mental health problems among older adults. This variable is derived from the EURO-D depression scale, a widely used short scale designed to assess depressive symptoms in older populations across Europe (Tomas et al., 2022). The EURO-D scale includes a range of items that capture common indicators of depression, such as sleep disturbances, feelings of sadness, loss of interest, irritability, and concentration difficulties, among others. However, it is important to note that the scale does not offer a universally accepted definition of what constitutes a "normal" or "healthy" score. As pointed out by Cobos (2005), the concept of normality in health is often equated to the absence of symptoms, yet such a criterion lacks fixed or absolute thresholds. Consequently, we rely on the established literature to define poor mental health based on validated cut-off points.

Following previous studies by Castro-Costa et al. (2007) and Guerra et al. (2015), who used clinical benchmarks such as the DSM-IV and GMS/AGECAT, a score of four or more on the EURO-D scale is considered indicative of poor mental health. These studies also confirm the internal consistency and validity of the EURO-D scale within the context of the SHARE dataset. Therefore, in our analysis, we define an individual as experiencing poor mental health if their EURO-D score is equal to or greater than four. Based on this threshold, we generate a binary dependent variable that takes the value 1 if the respondent has poor mental health (EURO-D ≥ 4) and 0 otherwise.

In addition to mental health, the analysis includes a set of explanatory variables relevant to both the digital divide and mental well-being. These include age (age at the time of responding to the survey), sex, education level (classified according to the ISCED-97 codes into no formal education, low, medium, and high), number of children, area of residence (urban or rural), and, most notably, digital skills. These variables are consistently available across the selected waves of the SHARE dataset (waves 5 to 8), ensuring comparability over time.

The variable measuring digital skills is constructed by combining two key indicators available in the SHARE survey. First, we include the respondent's self-assessed computer skills, which offer insight into the individual's subjective perception of their own digital competence. Second, we incorporate a measure of frequent internet use, which captures actual behavioral engagement with digital technologies. The decision to integrate both variables into a single composite indicator is based on the recognition that neither self-perception nor usage alone is sufficient to fully reflect a person's functional digital literacy. For example, an individual may report high confidence in using technology without actively engaging in digital environments, while another may use the internet frequently but feel unskilled or insecure in doing so.

By combining these two dimensions, we generate a more robust and representative measure of digital skills, one that captures both attitudinal and behavioral aspects of digital engagement. This composite variable thus allows us to better understand the relationship between digital literacy and mental health outcomes. It also facilitates a more nuanced analysis of how different levels of digital proficiency might influence psychological well-being in an increasingly digital society. A detailed description of all variables included in the analysis is provided in Table 2.1.

Table 2.1. List of variables and codes

Variable	Label	Coding
Mental Health	Respondent's mental health status	1: respondent has suffered from mental health problems; 0: otherwise.
Ability	Digital skills of the respondent	1: respondent has digital skills; 0: otherwise.
Education	Education Code ISCED-97	0: No education; 1: low educational level; 2: level of secondary education; 3: high level of education.
Area	Location area (residence)	1: respondent has lived in a rural area; 0: in the rest.
Gender	Respondent gender	1: female; 0: man.
Age 50 to 65	Respondent's age	1: the respondent's age is between 50 and 65; 0: otherwise.
Age 65 to 80	Respondent's age	1: the respondent's age is between 65 and 80; 0: otherwise.
Age 80 plus	Respondent's age	1: the respondent's age is over 80 years; 0: otherwise.
Children	Number of children	1: respondent has one or more children; 0: otherwise.

Author: Own elaboration based on SHARE survey.

2.3.3. Statistical analysis

In this study, to evaluate the effect of ICT management and use on mental health, a Differences-in-Differences (DID) approach is applied.

The DID methodology allows for the estimation of causal effects by comparing changes in outcomes over time between a treatment group and a control group, before and after a specific intervention (Meyer, 1995). A well-known example of this technique is the study by Card and Krueger (1993) on minimum wage effects in New Jersey. DID is thus a widely accepted method in policy evaluation and longitudinal analysis of treatment effects. This method allows us to estimate the causal impact of a treatment, in our case, digital skills, by comparing changes in mental health outcomes over time between individuals who possess ICT skills (treatment group) and those who do not (control group).

In the context of this study, the "treatment" is defined as having digital skills, which reflects the individual's ability and proficiency in using ICT. The treatment group consists of individuals who report ICT skills, while the control group includes those without such skills. The analysis compares these groups across different time periods, specifically, before and after the widespread establishment of digital life in society. This setup allows us to test whether the presence or absence of ICT skills is associated with differences in mental health outcomes over time.

This approach is particularly suitable because it helps mitigate issues related to unobserved time-invariant heterogeneity and time trends that could bias the estimation. Nevertheless, it relies on the key identification assumption of parallel trends, that is, in the absence of treatment, the treated and control groups would have followed similar trends over time. Given the evolving nature of digital technology and its adoption, we address this by carefully selecting time periods in which digital life was still developing (waves 5–7) and a period in which digital life is considered to be fully established (wave 8). This comparison helps isolate the effect of ICT skills on mental health while accounting for broader temporal trends.

Following Rosenbaum and Rubin (1983), the average treatment effect can be expressed as:

$$ATE = E(Y_1|w = 1) - E(Y_0|w = 1) \quad (1)$$

where Y_0 and Y_1 represent mental health outcomes for individuals with and without ICT skills, respectively.

To formally estimate this, we use the following linear specification, based on the model proposed by Wooldridge (2015):

$$MentalHealth_{it} = \alpha + \delta ability_{it} + \lambda t_t + \gamma(ability_{it} * \lambda t_t) + \beta^{'} X_{it} + \epsilon_{it} \quad (2)$$

Here, $MentalHealth_{it}$ denotes the mental health status of individual i at time t, $ability_{it}$ is a binary variable indicating ICT skills, t_t represents the wave (time period), and X_{it} is a vector of individual-level control variables. $\epsilon_{it}$is the error term. The coefficient λ on the interaction term captures the DID estimator, the differential effect of ICT ability on mental health after digital life becomes established.

The empirical strategy is implemented through three model specifications. Model 1 includes time dummies, the ICT ability variable, and the interaction term between time and ICT ability. It also controls for age and sex. Model 2 expands on this by adding educational level and whether the respondent has children. Model 3 further adjusts for residential context, introducing a variable indicating whether the respondent lives in a rural area.

2.4. Results

2.4.1. Summary Statistics

Table 2.2 presents the descriptive statistics of the main covariates included in the analysis, disaggregated by wave. The proportion of individuals experiencing mental health problems shows an increasing trend over time. In 2013 (wave 5), 27.2% of respondents reported symptoms consistent with poor mental health, as measured by the EURO-D scale. This percentage gradually rose, reaching 29.9% in the most recent wave available (2019/20, wave 8). This upward trajectory suggests that, as the digitalization of everyday life has expanded, the prevalence of mental health issues among older adults has also slightly increased. It is worth noting, however, that in wave 7 (2017), this proportion experienced a minor decline compared to wave 6 (2015), before resuming its upward trend in wave 8.

Table 2.2. Main statistics (mean)

	Wave 5 (N=41021)	**Wave 6 (N=41713)**	**Wave 7 (N=9307)**	**Wave 8 (N=7258)**
MentalHealth	0.272	0.288	0.285	0.299
Ability	0.535	0.515	0.477	0.505
Age				
Age 50 to 65	58.511	58.856	62.684	62.839
Age 65 to 80	72.228	72.288	72.478	72.432
Age 80 +	85.254	85.297	85.739	85.784
Gender	0.586	0.600	0.603	0.611
Education				
No Education	0.041	0.040	0.037	0.038
Low Education	0.353	0.355	0.420	0.380
Medium Education	0.372	0.380	0.336	0.340
High Education	0.234	0.225	0.207	0.231
Children	0.889	0.891	0.892	0.896
Area	0.311	0.323	0.321	0.285

Source: Authors´ elaboration. Reference categories: with technology skills, woman, with children and rural area.

Regarding digital ability, a key variable in this study, the percentage of respondents reporting ICT skills decreased slightly over time, from 53.5% in 2013 to 50.5% in 2019/20. This gradual decline suggests a widening digital divide within the older population, possibly due to generational differences or unequal access to digital tools and training. Although the decline is not abrupt, it reflects persistent inequalities in digital engagement that may have implications for mental health and access to services.

Most of the other covariates show relatively stable patterns across waves. The gender distribution indicates a consistent predominance of women in the sample, with the proportion increasing slightly over time to 61.1% in wave 8. This trend reflects demographic realities in older populations, where women tend to live longer than men.

Educational attainment shows moderate variability. The proportion of respondents with no formal education remains low and stable across waves, at around 4%. In contrast, the distribution among low and medium education categories is more substantial, fluctuating between 33% and 42%. Respondents with higher education constitute a smaller segment, around 20% to 23%, though this group remains relatively stable throughout the period.

The presence of children among respondents is also stable, with approximately 89% to 90% reporting having children in all waves. This variable may play a role in social support networks, which are relevant to both digital inclusion and mental well-being.

Concerning area of residence, the percentage of respondents living in rural areas covers around 30%, with minor fluctuations between waves. This variable is important to consider given that rurality may be associated with lower access to digital infrastructure and healthcare services.

Table 2.3. Proportion of people without ICT skills

	Wave 8	**Wave 7**	**Wave 6**	**Wave 5**
Age to 50-65	23.02	30.31	28.74	27.86
Age to 65-80	43.75	50.39	57.45	57.32
Age 80 +	78.99	82.04	85.04	85.87

Author: Authors´ elaboration.

Finally, to a better understanding the relationship between age and digital skills, Table 2.3 shows the proportion of respondents without ICT abilities, disaggregated by age group and wave. A clear gradient is observed: the older the age group, the higher the proportion of individuals lacking digital skills. In wave 8, only 23% of respondents aged

50–65 reported having no ICT skills, compared to 44% among those aged 65–80 and nearly 79% among individuals aged 80 or older. This pattern persists across all waves, confirming the existence of an age-related digital divide that may contribute to social exclusion and affect mental health outcomes. However, conclusions regarding the digital divide related to age should be interpreted with caution, as they should not rely solely on row percentages; group sizes also play a crucial role and must be taken into account.

2.4.2. Regression Results

The results of the Difference-In-Differences (DID) analysis, applied to examine the relationship between digital skills and mental health among older adults, are presented in Table 2.4. This methodology allows for the estimation of the differential effect of technology use on mental health over time by comparing how this relationship changes between individuals with and without digital skills as the digitalization of daily life progresses. The DID approach relies on the key assumption that, in the absence of the factor of interest, in this case, the consolidation of digital life in 2019, the evolution of mental health in both groups would have followed a parallel trend. This assumption is considered plausible, as digital ability is a relatively stable characteristic in the short term, and the digital environment underwent a structural transformation during the study period.

Table 2.4. Results of the Analysis of Differences in Differences on mental health and the digital divide

	2019-2013			2019-2015			2019-2017		
Variables	**Coefficients Model 1**	**Coefficients Model 2**	**Coefficients Model 3**	**Coefficients Model 1**	**Coefficients Model 2**	**Coefficients Model 3**	**Coefficients Model 1**	**Coefficients Model 2**	**Coefficients Model 3**
γ (Interacción)	2.296 ***	2.362 ***	2.355 ***	2.203 ***	2.295 ***	2.305 ***	2.258 ***	2.310 ***	2.326 ***
	(0.113)	(0.133)	(0.135)	(0.108)	(0.129)	(0.131)	(0.138)	(0.162)	(0.166)
δ (Ability)	0.490 ***	0.553 ***	0.553 ***	0.507 ***	0.552 ***	0.549 ***	0.487 ***	0.545 ***	0.536 ***
	(0.001)	(0.014)	(0.015)	(0.010)	(0.014)	(0.014)	(0.02)	(0.028)	(0.028)
λ (Year)	0.728 ***	0.730 ***	0.737 ***	0.707 ***	0.688 ***	0.694 ***	0.740 ***	0.732 ***	0.732 ***
	0.026	0.029	0.030	0.025	0.027	0.028	0.031	0.035	0.035
Age									
Age 65 to 80	0.943 ***	0.890 ***	0.894 ***	0.943 ***	0.916 ***	0.904 ***	1.033 ***	0.975 ***	0.97
	(0.019)	(0.025)	(0.022)	(0.018)	(0.021)	(0.022)	(0.042)	(0.047)	(0.047)
Age 80 +	1.363 ***	1.212 ***	1.188 ***	1.335 ***	1.198 ***	1.183 ***	1.333 ***	1.232 ***	1.213 ***
	(0.038)	(0.04)	(0.04)	(0.035)	(0.038)	(0.039)	(0.066)	(0.071)	(0.071)
Gender	1.941 ***	1.935 ***	1.914 ***		1.960 ***	1.953 ***	1.989 ***	2.023 ***	2.009 ***
	(0.035)	(0.042)	(0.043)		(0.042)	(0.043)	(0.062)	(0.075)	(0.076)
Education									
Low Education		0.676 ***	0.670 ***		0.739 ***	0.740 ***		0.691 ***	0.684***
		(0.032)	(0.032)		(0.036)	(0.035)		(0.056)	(0.056)
Medium Education		0.530 ***	0.529 ***		0.589 ***	0.586 ***		0.561 ***	0.559 ***
		(0.026)	(0.026)		(0.029)	(0.029)		(0.048)	(0.047)
High Eduaction		0.461 ***	0.457 ***		0.544 ***	0.538 ***		0.516 ***	0.519 ***
		(0.024)	(0.024)		(0.028)	(0.028)		(0.047)	(0.047)

(*Continued*)

	2019-2013			2019-2015			2019-2017		
Variables	**Coefficients Model 1**	**Coefficients Model 2**	**Coefficients Model 3**	**Coefficients Model 1**	**Coefficients Model 2**	**Coefficients Model 3**	**Coefficients Model 1**	**Coefficients Model 2**	**Coefficients Model 3**
Children		0.868 ***	0.870 ***		0.904 ***	0.900 ***		0.951	0.944
		(0.028)	(0.029)		(0.029)	(0.029)		(0.053)	(0.053)
Area			0.932 ***			0.958 *			1.058
			(0.021)			(0.021)			(0.049
N (Observations)	72.527	50.632	48.293	73.473	51.572	48.986	23.176	17.075	16.580
Log-pseudolikehood	-40171.221	-28438.638	-27144.114	-41515.513	-29715.596	-28154.402	-13241.078	-9890.16	-9598.3029
Prob>chi2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Clustered standard errors at the individual level in parentheses. *** $p < 0.01$. ** $p < 0.05$. *$p<0.1$. Reference categories: with technology skills, from 50 to 65 years old, woman, without studies, with children and rural area of residence. Source: own elaboration.

In this context, the DID design makes it possible to identify whether differences in mental health between individuals with and without digital skills widened or narrowed over time, attributing such changes to the interaction between technological advancement and individual capacity to navigate it. The econometric specification used is represented in equation (2), where the main parameter of interest is γ, which captures the interaction effect between the 2019/20 period and the lack of digital skills. This coefficient quantifies whether the mental health gap between the two groups widened in the most recent period compared to 2013, 2015, and 2017. Alongside this key parameter, the model also estimates δ, which reflects the average difference in mental health between individuals with and without digital skills regardless of time, and λ, which represents the specific effect of the time period on the sample as a whole.

The models also incorporate a vector of control variables (X) to capture relevant heterogeneities among individuals. These variables include age, gender, educational level, presence of children, and type of residential area. Their inclusion helps isolate the specific effect of digital skills, reducing the likelihood that the results are biased due to systematic differences in group composition.

As shown in Table 2.4, in all estimated models, the interaction coefficient γ is positive and statistically significant. This indicates that the negative impact of lacking digital skills on mental health intensified in 2019 compared to previous years, which can be interpreted as a direct consequence of the consolidation of digital environments across all areas of life. Older adults without technological skills face greater barriers to adaptation, access to services, and social connection, which may lead to increased levels of anxiety, depression, or emotional isolation.

Moreover, the empirical results show that age is significantly associated with mental health in almost all models, with a lower risk of mental health issues among younger groups, but a substantial increase in risk among those over 80 years old. Regarding gender, the estimated coefficients suggest that women are more likely to report mental health problems compared to men, which is consistent with previous literature. Educational level shows statistically significant associations, although there is no clear pattern indicating that higher education consistently protects against mental health problems. Similarly, variables related to having children or living in rural versus urban areas do not show consistent effects across the different models.

These findings support the hypothesis that the digitalization of daily life, combined with a lack of digital skills, may be exacerbating mental health inequalities among older adults, particularly within groups that are more vulnerable due to age or gender. This evidence highlights the need for public policies that address the digital divide not only from the perspective of access and digital literacy, but also in terms of its potential impact on emotional well-being and health equity in later life.

2.5. Discussion and conclusions

This study set out to evaluate the impact that the evolution and integration of digital technologies into the daily lives of older adults has had on their mental health. By using four waves of the SHARE survey, we examined whether, and to what extent, the increasing digitalization of everyday life has influenced the psychological well-being of the elderly population in Europe. Through the use of a longitudinal DID approach, our findings provide new evidence.

First, we compared mental health outcomes across different time periods, enabling us to isolate the effects of the progressive digitalization of society. This temporal perspective helps disentangle the distinct contributions over time and compensates for the limitations of survey-based research when longer-term comparisons are constrained by data availability. Second, we provide empirical evidence on the association between digital engagement and mental health outcomes among older adults in 27 European countries over a seven-year span, from 2013 (when data on technology use first became available in SHARE to 2019/20, a period that reflects the consolidation of digital life.

Our results indicate that technological evolution has had a substantial and growing impact on the likelihood of reporting mental health problems among older adults. While the magnitude of the individual coefficients varies slightly across years and model specifications, the overall trend is robust. In particular, we find that the lack of digital skills significantly increases the probability of suffering from mental health issues, and this effect becomes stronger in more recent waves. This is particularly relevant for policymakers, as digital technologies are increasingly shaping how older individuals interact with health systems, public services, and social networks (Quizi, 2021). Our findings suggest that digital life has become integral to daily functioning, and thus, it would be beneficial to offer targeted digital training programs for older adults and provide support in contexts where technology use is essential. In this regard, appropriate policies are needed to ensure that health management, social service delivery, and information access do not create additional barriers for the elderly (Gong et al., 2020). Designing flexible and adaptive strategies will be crucial to respond to the evolving needs of ageing populations.

Although digital technologies were initially heralded as tools to improve well-being and inclusion, our findings caution against assuming universally positive effects. The lack of digital skills can produce adverse outcomes, especially in a context where digital tools have become ubiquitous. Contrary to the prevailing view that technological advances enhance individual well-being, our results highlight the negative mental health effects experienced by older adults who are unable to manage or adopt these tools. In this regard, the technological transformation of society may be exacerbating existing vulnerabilities. We find that the digital divide, particularly that linked to age, is emerging as a relevant social determinant of mental health. The evidence from 2019/20 clearly shows that older adults without digital competence are more susceptible to isolation, anxiety, and depressive symptoms.

In fact, rather than improving overall well-being, the expansion of technology use may impose a greater burden on older individuals who are less digitally engaged. As digital tools are increasingly required for a wide range of activities—from accessing services to maintaining social connections—the inability to use them effectively can widen the gap in health outcomes. This highlights the social cost of digital exclusion, and the age-related barriers in learning and using new technologies must be acknowledged as a public health concern. Governments should recognize that while advancing digitalization may be appealing from an efficiency and innovation standpoint, its implications for older populations must not be overlooked, especially given the rising costs associated with longevity and population ageing at both national and European levels. In this context, public policies must proactively address the challenges posed by digital transformation to avoid reinforcing existing health disparities.

While our analysis focuses on European data, literature has emphasized, age plays a critical role in determining mental health, and according to the United Nations (2017), Spain is expected to become the second oldest country in the world by 2050. This demographic shift underscores the urgency of developing policies that are responsive to the needs of older adults in an increasingly digital world.

Nevertheless, several limitations should be noted. First, the reference to digital ability and internet use is only available from wave 5 onwards, which restricts our capacity to evaluate the long-term evolution of these effects. Additionally, the digital ability variable used in this analysis was constructed by combining two closely related indicators, which, while informative, may not fully capture the complexity of digital competence. Nonetheless, the SHARE dataset remains a valuable source for generating new evidence on the impact of technology use on older adults and for identifying emerging inequalities linked to digital transitions.

This study opens promising avenues for future lines of research. Given that the intersection of ageing, mental health, and technology remains a relatively novel field, further investigation is needed to understand the mechanisms at play. Future work could explore, for instance, how cognitive functioning, social support, or the availability of digital infrastructure may moderate these effects. Cross-country comparisons would also be useful to examine how national digital strategies influence outcomes among older populations.

In conclusion, as Europe's population continues to age, the intersection between digitalization and mental health will become increasingly important. The success of digital transformation must not be measured solely by technological adoption, but also by the extent to which it includes and protects vulnerable groups. Effective and inclusive policies will be important to ensure that the digital shift contributes to reducing, not exacerbating, health and social inequalities among older adults.

Chapter 3. Is lack of activity in free time a problem on psychological health care? A propensity score matching analysis

3.1 Introduction

The promotion of health and the prevention of disease are widely recognized as fundamental pillars in the design and implementation of public policies. Adopting a life course and equity-oriented approach is essential to prevent the onset of conditions that may lead to disability and dependence, thereby contributing to the reduction of health inequalities across the population. In this context, preventing the progression or worsening of disability is particularly important to ensure that all individuals can live under conditions of equity and dignity (Ministry of Social Rights and Agenda 2030, 2022).

In Spain, as in many other European countries, the demographic structure is undergoing a significant transformation, characterized by a steady increase in the proportion of older adults. This demographic shift is closely associated with a growing prevalence of disability, as ageing is a major risk factor for developing functional limitations (INE, s.f.). Consequently, an ageing and increasingly frail population faces greater exposure to chronic diseases and disabilities as life expectancy increases.

According to official data, Spain had a total population of 47.37 million in 2020 (INE, s.f.-c). The Disability, Personal Autonomy, and Dependency Survey (EDAD 2020), conducted by the National Institute of Statistics (INE), revealed that approximately 4.38 million individuals reported having some form of disability, representing 9.25% of the population (INE, 2022). These figures highlight the growing importance of safeguarding the rights of people with disabilities and ensuring their access to adequate support and services.

This study focuses on the complex and multidimensional relationship between disability and mental health. Evidence suggests that people with disabilities face a significantly higher risk of experiencing mental health problems compared to the general population. In fact, Austin et al. (2018) found that individuals with disabilities are twice as likely to suffer from depression and anxiety disorders as those without such conditions.

Several interconnected factors may help explain this strong association. Social isolation and stigma often surround disability, leading to reduced opportunities for social participation, barriers to employment, and difficulties in accessing healthcare. These limitations can foster feelings of loneliness, marginalization, and hopelessness.

Furthermore, societal prejudices and negative attitudes toward disability may generate internalized shame, thereby exacerbating mental health issues.

In addition to social and structural barriers, the physical and emotional challenges associated with living with a disability also play a critical role. Chronic pain, fatigue, limited mobility, and a loss of autonomy can generate a significant psychological burden, often manifesting as frustration, sadness, or anger. In some cases, individuals may also experience trauma related to the origin of their disability, such as serious illness, injury, or medical interventions.

Despite these challenges, Spain has developed a range of resources to support the mental health of people with disabilities. These include mental health professionals, peer support groups, and advocacy organizations that provide both emotional assistance and practical guidance. Moreover, policies aimed at improving accessibility and fostering inclusion in all areas of society can contribute to mitigating the stigma and social isolation frequently experienced by this population.

Understanding the relationship between disability and mental health is thus a pressing issue that requires a multifaceted response. This study aims to contribute to this field by analyzing how participation in leisure activities influences the use of mental health services, specifically psychologists, psychotherapists, and psychiatrists, among people with disabilities in Spain.

By examining this relationship, we want to generate empirical evidence that can inform public policy and help address the healthcare needs of individuals with disabilities and those in situations of dependence. The ultimate goal is to support the development of more effective and equitable policies that improve the accessibility and quality of psychological care services.

The structure of this paper is as follows: Section 2 reviews the relevant literature; Section 3 outlines the methodology and data used in the analysis; Section 4 presents the main results; and Section 5 discusses the conclusions and policy implications derived from our findings.

3.2 Literature Review

Disability represents a major social and public health issue in Spain, affecting millions of individuals across the country. According to the latest data from INE, 4.38 million people in Spain reported having some form of disability in 2020, compared to just over 3.5 million in 1999. These disabilities, whether physical, sensory, intellectual, or related to mental health, can have a substantial impact on individuals’ daily functioning, limiting their ability to engage in education, employment, and social or recreational activities.

Despite progress in public policies and legislative frameworks aimed at improving the lives of people with disabilities, significant challenges persist. For example, the accessibility of public spaces and infrastructure remains uneven, often hindering the autonomy and mobility of individuals with disabilities. Moreover, persistent barriers in accessing education and employment opportunities continue to restrict personal development and social inclusion. These structural limitations can contribute to the deterioration of mental health among people with disabilities, a connection that has been increasingly recognized in academic literature.

Several studies have explored the links between disability and mental health, underscoring the multifaceted nature of this relationship. Schlüter et al. (2018) identify a heightened risk of depression and anxiety among people with disabilities, attributing this in part to experiences of social exclusion and stigma. The study also emphasizes the physical and emotional burden of living with a disability, often exacerbated by chronic pain or trauma. Complementarily, Theis et al. (2021) stress the importance of adequately addressing mental health needs within this population, noting that such issues are frequently overlooked. They call for improved accessibility to mental health services and initiatives to combat social isolation and promote inclusion. In a similar vein, the World Health Organization (2019) highlights the critical role played by advocacy organizations, peer support networks, and self-advocacy in advancing the mental health of people with disabilities, while also urging action to dismantle systemic barriers to care.

Beyond these structural and psychosocial factors, other risk elements affecting mental health have also been identified. Research points to the negative impact of prolonged sedentary behavior, limited engagement in organized or physical activities, and insufficient social interaction (Swed et al., 2022; Peng et al., 2022). These are precisely the conditions many individuals with disabilities face, as functional limitations, such as reduced mobility, difficulties in communication or learning, or challenges in self-care and interpersonal relationships, can restrict their ability to participate in leisure activities that are known to support mental well-being (Parmenter, 2021).

Leisure, as considered in the EDAD 2020 survey, includes a broad range of activities such as watching television, browsing the internet, using social networks, listening to music or the radio, exercising, reading, playing video games, socializing with friends or family, attending cultural or sporting events, and traveling. Numerous studies affirm the positive role these activities play in enhancing individuals' quality of life, overall well-being, and mental health (Mutz et al., 2021; Small et al., 2022; Krause et al., 2021; Naslund et al., 2020).

In this regard, several authors have emphasized that policies supporting mental health should promote active lifestyles, access to outdoor environments, and culturally sensitive mental health services for all individuals, including those with disabilities (Goldman-Mellor et al., 2023). In Spain, the promotion of mental health for people with disabilities is addressed in national legislation and policy frameworks. The General Law on the Rights of Persons with Disabilities and their Social Inclusion, approved by Royal Decree 1/2013 of September 29, affirms that the right to health protection encompasses disease prevention and health promotion, including mental health, without discrimination on the basis of disability (art. 10). Similarly, the Spanish Disability Strategy 2022–2030 incorporates specific measures to prevent mental health problems by promoting non-discrimination, enhancing accessibility, monitoring service provision, and providing support to individuals with disabilities and their families.

However, it is essential that mental health promotion efforts do not focus exclusively on individuals with psychosocial or intellectual disabilities, but rather encompass the entire population of people with disabilities (Cree et al., 2020). Numerous studies have documented the presence of mental health problems, such as depression, suicidal ideation, and anxiety, across diverse types of disability. Most of these analyses examine how various forms of impairment influence the prevalence of mental health conditions (Nguyen et al., 2023; Kimura et al., 2023; Sousa-Santos et al., 2023; Pessin et al., 2023; Castellvi Obiols et al., 2023).

In conclusion, awareness of the need to improve the situation of people with disabilities in Spain has grown in recent years. Initiatives have emerged to foster inclusion, improve accessibility, and raise awareness of the specific challenges this population faces. Nonetheless, much remains to be done to ensure that people with disabilities can fully participate in all areas of social life and, in doing so, reduce their exposure to mental health problems.

3.3 Data and methods

3.3.1 Data

In recent years, the number of individuals with disabilities in Spain has grown significantly, reflecting demographic changes and increased longevity, among other factors. Within this context, the relationship between mental health service utilization, particularly consultations with psychologists, psychiatrists, and psychotherapists, and participation in leisure activities among people with disabilities emerges as a relevant area of inquiry.

To explore this relationship, we rely on microdata from the 2020 edition of the EDAD 2020 conducted by the Spanish INE (INE, s.f.-b). This survey was designed to collect detailed information about the living conditions, needs, and support systems of people with disabilities, as well as the impact of caregiving on their environment. It gathers information both from individuals with disabilities and their caregivers, offering valuable insights into the time devoted to care and its implications for work, personal life, and leisure time.

The EDAD 2020 dataset, the most recent of its kind, is structured into multiple questionnaires, household, disability, limitations, and caregivers, each contributing specific and complementary dimensions to the analysis. A summary of the main variables used in this study, along with their definitions and descriptive statistics, is provided in Table 3.1.

Table 3.1. Variables definition and summary of statistics

Variables	Definition	Coding	Mean	Std.Dev
Personal characteristics				
Gender	Gender of respondent	1: whether respondent gender is female; 0 otherwise (male)	0.582	0.493
Age	Age of respondent	Age in years	66.217	19.965
FreeTime	Free time activity of respondent	1: respondent does *not* engage in any leisure activity; 0: respondent engages in at least one activity.	0.040	0.196
Health Care Utilization				
Care	Receive care at home	1: whether respondent receives care at home; 0 otherwise	0.415	0.493
Use of Psychological Healthcare Services	Psychological health use	1: whether respondent use of psychological health services; 0 otherwise	0.134	0.341
Health Status				
SAGHS	Self-Assessed Good Health Status	1: if respondent' Self-Assessed Good Health Status is very good or good; 0 otherwise	0.338	0.473
ADL	Number of limitations in Activities of Daily Living (ADLs)	Number of limitations in ADLs	1.203	1.496

Source: Authors' calculations based on disability, personal autonomy and dependency situation 2020 survey.

The primary variable of interest in our analysis is “Use of Psychological Healthcare Services”, which identifies whether the respondent with a disability uses psychological healthcare services. This binary variable is constructed from a set of four survey questions addressing the use of public, private, or other types of psychological support. Specifically, it takes a value of 1 if the respondent reports having accessed any psychological service, and 0 otherwise.

In addition to “Use of Psychological Healthcare Services”, several other variables are included to capture individual characteristics and contextual factors associated with mental health and leisure. These include age, gender, health status, care received at home, and the extent of limitations in performing ADLs. Among these, the variable FreeTime, indicating whether the respondent engages in leisure activities, plays a central role in our analysis as the key explanatory or treatment variable.

The definition of FreeTime is based on responses to questions about participation in a wide range of leisure activities, including but not limited to watching television, browsing the internet, using social media, listening to music or the radio, reading, exercising, playing video games, socializing with friends or family, attending cultural or sporting events, and traveling. These activities serve as a proxy for social engagement and stimulation, both of which are relevant to mental health outcomes.

Meanwhile, the ADL variable captures the number and nature of functional limitations the individual experiences in everyday life. This includes difficulties related to vision, hearing, mobility, communication, learning, self-care, and the management of domestic and interpersonal responsibilities. For instance, this could involve challenges in organizing household tasks, handling finances independently, or expressing emotions and maintaining relationships.

Preliminary descriptive results show that approximately 13.5% of people with disabilities reported using psychological healthcare services. Given the aging population in Spain and its implications for chronic illness and disability, these findings underscore the importance of monitoring access to and demand for mental health services among people with disabilities in the coming years.

3.3.2 Methods

Engaging in leisure activities is widely associated with improved mental health and may help reduce the need for psychological support, such as visits to psychologists, psychiatrists, or psychotherapists. As outlined previously, the variable *FreeTime* is defined using two complementary perspectives: individuals with disabilities who participate in various leisure activities, and those who do not. The classification of individuals is based on information collected in the EDAD 2020 survey, which employs a standardized definition of leisure activity participation.

The growing number of people with disabilities in Spain is increasingly viewed as a challenge, especially due to its impact on healthcare utilization, affecting both waiting lists and public healthcare expenditures. To test the hypothesis that leisure activity engagement influences the use of mental health services among this population, we use data from the EDAD 2020 survey and control for several sociodemographic characteristics that may confound this relationship.

Our empirical strategy is based on matching techniques. This approach allows us to estimate causal effects by comparing the outcomes of treated and untreated individuals who are similar in observable characteristics. In line with the potential outcomes framework (Angrist and Imbens, 1995), we define the causal effect of the treatment (engaging in leisure activities) as the difference between potential outcomes: y1 for the treated and y0 for the untreated. Specifically, we focus on estimating the effect as y1- y0 .

To ensure the validity of this approach, we assume the Stable Unit Treatment Value Assumption (SUTVA), which implies that the treatment assigned to one individual does not affect the potential outcomes of others, and that the treatment and control groups are independent and identically distributed (Wooldridge, 2002).

We define two groups of individuals with disabilities: those who engage in leisure activities ($T = 1$) and those who do not ($T = 0$). These mutually exclusive groups allow us to identify the treatment variable, *FreeTime*, as binary. Let $T \in \{0,1\}$ be the treatment indicator, and let (y0,y1,T) denote the potential outcomes and treatment assignment for each individual in the population.

Following Rosenbaum and Rubin (1983), we define two causal estimands:

The Average Treatment Effect (ATE):

$$ATE = E(y_1 - y_0) \tag{1}$$

The Average Treatment Effect on the Treated (ATET):

$$ATET = E(y_1 - y_0 | T = 1) \quad (2)$$

Since treatment assignment may be influenced by observed characteristics, we condition these effects on a vector of covariates xxx (e.g., age, gender, health status). Thus, we define the conditional ATET as:

$$E(y_1 - y_0 | x, T = 1) \quad (3)$$

However, in practice, we can only observe the actual outcome y, which depends on treatment status:

$$y = Ty_1 + (1 - T)y_0 = \{y_0,\ \ if\ T = 0;\ \ y_1,\ \ if\ T = 1 \quad (4)$$

Matching methods aim to estimate the counterfactual outcomes by pairing treated and untreated individuals with similar characteristics. This involves selecting a control group that closely resembles the treatment group in terms of observable covariates.

To satisfy the conditional independence assumption (or selection on observables), we invoke the ignorability condition (Rubin, 1978):

$$(y_o, y_1 \perp T) | b(x) \quad (5)$$

where b(x) is a balancing score. In practice, the propensity score is the most commonly used balancing score. It represents the probability of receiving the treatment given the observed covariates:

$$e(x) = P[T = 1 | x] \quad (6)$$

Under the assumptions stated above, the ATET can be estimated as:

$$ATET = E_{e(x)}(E(e(x), T = 1) - E(e(x)x, T = 0)) \quad (7)$$

To implement this strategy, we apply *nearest neighbor matching*, a widely used matching algorithm that pairs each treated individual with the untreated individual whose propensity score is closest. This is formalized as (Becker and Ichino 2002):

$$C(i) = min\ \ ||e_i - e_j|| \quad (8)$$

This method allows us to construct counterfactual outcomes for treated individuals and estimate the causal effect of leisure activity engagement on the use of mental health services, while controlling for observed confounders.

3.4 Empirical Results

As anticipated, in the Spanish context, individuals with disabilities who do not participate in leisure activities present significant challenges for the healthcare system. Specifically, the lack of engagement in such activities is associated with an increased demand for psychological services. This phenomenon carries important implications for government healthcare expenditures, particularly in relation to mental health programs at both the national and regional levels, and must be considered by public policy makers when designing effective mental health strategies.

To empirically test this hypothesis, we used data from the 2020 EDAD survey, incorporating a range of sociodemographic variables to understand the differences between individuals with disabilities who engage in leisure activities and those who do not. Prior research has consistently shown that participation in leisure activities can play a key role in improving the mental health of individuals, which in turn may reduce the use of psychological care services. In line with this literature, we constructed a set of variables to capture these dynamics and applied a matching technique to estimate the causal effect of leisure participation on the use of psychological care.

The results of the estimation, conducted using STATA 17.0, are presented in Table 3.2. Overall, the ATE is small and not statistically significant, suggesting no generalizable effect across the full population. However, subgroup analyses reveal noteworthy patterns when disaggregated by gender and geographic region.

Table 3.2. Nearest Neighbor Matching results on psychological care by gender and Spain region

	ATE	Std.Err	z
Total	-0.002	0.018	-0.09
According to gender			
Male	0.022	0.030	0.75
Female	-0.014	0.022	-0.65
According to Spanish region			
Northern Spain	0.055	0.123	0.45
Southerm Spain	-0.029	0.028	-1.03

Source: Authors' calculations based on disability, personal autonomy and dependency situation 2020 survey.

When examining subgroups, clear differences emerge. In terms of gender, the results suggest that women with disabilities who do not participate in leisure activities may experience worse mental health outcomes, as evidenced by a greater need for psychological care. Conversely, for men, the estimated effect is positive, albeit not statistically significant, indicating a different pattern of association.

A similar divergence is observed when analyzing results by region. In southern Spain, individuals with disabilities who do not engage in leisure activities exhibit higher reliance on psychological services compared to their counterparts in the north. These regional disparities may reflect differences in healthcare access, availability of community programs, or cultural factors influencing leisure participation and help-seeking behavior.

In summary, the findings highlight the importance of promoting inclusive leisure opportunities for people with disabilities as part of broader mental health and social care policies, especially for women and in less-favored geographic regions.

3.5 Conclusion

The prevalence of disability in Spain has been gradually increasing over time, posing significant challenges not only for physical health but also for mental well-being. Disabilities often disrupt daily functioning and limit individuals' capacity to lead what is perceived as a "normal" life, which can, in turn, contribute to the development of mental health problems. Addressing these issues requires the design and implementation of public policies that actively promote and facilitate the participation of people with disabilities in leisure activities as a means to enhance their quality of life and psychological well-being.

While many individuals with disabilities express a willingness to participate in leisure activities, their ability to do so is often constrained by inadequate infrastructure, inaccessible programming, or social discrimination. These structural and attitudinal barriers can lead to frustration, exclusion, and the internalization of stigma, further exacerbating the risk of developing mental health problems. Thus, even when motivation exists, opportunities for participation may remain out of reach.

Our research has explored the relationship between engagement in leisure activities and mental health outcomes among people with disabilities in Spain, with a particular focus on the use of psychological care services. Drawing on data from the 2020 EDAD survey, we identified that approximately 4% of people with disabilities report not engaging in any leisure activities, and around 14% of this group access psychological care services. These figures highlight the relevance of leisure participation as a potential protective factor for mental health.

There is a pressing need in Spain to improve support systems for individuals with disabilities, particularly by enhancing accessibility and mobility in both private and public spaces. The results of our empirical analysis provide compelling evidence that the absence of leisure activity participation is associated with greater use of psychological services. These findings underscore the importance of removing practical and social barriers that prevent people with disabilities from accessing leisure opportunities, which are essential for mental and emotional well-being.

Employing the most recent data from EDAD and applying propensity score matching techniques, our analysis confirms that individuals with disabilities who do not engage in leisure activities are more likely to experience mental health challenges and, consequently, to use psychological care. This pattern is particularly pronounced among women and residents of southern Spanish regions, suggesting that sociodemographic factors mediate the relationship between leisure and mental health.

In sum, our findings contribute to the growing body of empirical evidence linking leisure engagement with mental health in vulnerable populations. Policymakers should consider these insights when designing mental health strategies, recognizing that promoting inclusive and accessible leisure opportunities is a critical complement to the provision of clinical psychological services. Addressing the root causes of exclusion and enhancing everyday participation could alleviate pressure on mental health systems and significantly improve the quality of life for people with disabilities.

Chapter 4. Our lifestyle as a mental health problem.

4.1 Introduction

In contemporary society, the pursuit of a healthy and balanced lifestyle has gained unprecedented prominence. Healthy habits have become essential not only for the preservation of physical well-being but also for sustaining emotional and mental health. These habits include proper nutrition, regular physical activity, restorative sleep, and the avoidance of harmful behaviors such as smoking and excessive alcohol consumption (Kris-Etherton et al., 2021; Firth et al., 2020).

However, it is important to emphasize that health encompasses more than just the physical dimension. Mental health is a critical component of overall well-being, encompassing emotional, psychological, and social aspects. Its proper balance is fundamental for coping with everyday challenges, managing stress, and fostering meaningful interpersonal relationships (Venkatesh & Edirappuli, 2020).

In our fast-paced and increasingly demanding world, a worrying rise has been observed in the prevalence of mental health disorders, particularly stress, anxiety, and depression. These conditions are often linked to lifestyle factors, including poor diet, physical inactivity, and other behavioral patterns. As a result, promoting mental health has become a public health priority for governments, healthcare professionals, and society at large.

The COVID-19 pandemic has further underscored the relevance of this issue, triggering a global health crisis that has profoundly affected lifestyle habits and mental health across populations. The resulting social isolation, uncertainty, and disruption of routines have emphasized the protective role of healthy behaviors in maintaining psychological resilience (Lee et al., 2020).

Nevertheless, despite growing awareness, recent findings from the Annual Report of the National Health System 2020–21 in Spain reveal that unhealthy lifestyles remain prevalent. One-third of the population aged 15 and over consumes alcohol regularly (at least once a week), with men being twice as likely as women to engage in this behavior. Moreover, two out of every ten adults are classified as obese, and five out of ten are overweight. Notably, 36% of individuals in this age group report sedentary behavior during their leisure time (Ministry of Health, 2022).

A robust body of literature supports the positive relationship between healthy lifestyle habits, such as maintaining a balanced diet, engaging in regular physical activity, avoiding tobacco and alcohol use, and achieving a healthy body mass index, and improved mental health outcomes (Ruiz-Hernández et al., 2022; Blom et al., 2021). In light of this evidence, it is imperative to further examine the potential link between unhealthy lifestyle habits and the prevalence of mental health problems in Spain. According to the Subdirectorate General of Health Information (2021), approximately 27.4% of the population reports experiencing mental health issues, with psychotropic medication being prescribed to 34.3% of women and 17.7% of men.

This study aims to explore the influence of healthy lifestyle habits on both physical and emotional well-being, analyzing how these behaviors affect mental health, and, conversely, how good mental health can promote the adoption of positive health-related practices. Special focus will be given on regional disparities across Spain's autonomous communities, as well as to variations based on specific types of mental disorders.

By deepening our understanding of the interplay between physical and mental health, we seek to raise awareness about the importance of holistic care and offer insights that contribute to improving individuals' quality of life and fostering a more balanced and fulfilling existence.

The structure of this study is as follows. After this introduction, a literature review will provide an overview of the key findings related to lifestyle habits, body mass index, and their connection to mental health. Subsequently, the dataset used for the empirical analysis will be described, followed by the presentation of the methodology and main results. The final section will provide conclusions and policy implications derived from the analysis.

4.2 Literature Review

Mental health constitutes a cornerstone of overall well-being and should be regarded as a top priority both within healthcare systems and in broader societal discourse

(Wasserman, 2023). Far from being a concern limited to specific populations, mental health affects individuals across all age groups, genders, races, and socioeconomic backgrounds. To foster mental well-being, it is essential to promote healthy lifestyle habits—including a balanced and nutritious diet, regular physical activity, sufficient rest, and effective stress management strategies.

The promotion of healthy behaviors has emerged as a subject of growing interest in the context of achieving a fulfilling and balanced life. A broad range of studies has demonstrated the positive effects that certain lifestyle choices can have on both physical and psychological health. This literature review synthesizes empirical findings that highlight the relationship between healthy habits and mental health, offering an integrated perspective on how these practices contribute to emotional stability and psychological resilience. Collectively, the studies reviewed underscore a consistent association between the adoption of healthy behaviors and improvements in mental well-being.

One of the most recurrent themes in the literature is the connection between physical activity and mental health. Wong et al. (2023), for instance, identify a positive correlation between physical activity and both physical and psychological health among older Chinese adults. Their findings suggest that regular engagement in exercise is associated with lower levels of depression and anxiety, along with a general enhancement in mental well-being among this demographic.

Conversely, the presence of obesity has been identified as a risk factor for deteriorating mental health. Leutner et al. (2023) report that individuals with obesity are more likely to develop mood disorders, anxiety, and other mental health conditions throughout their lives. Beyond its metabolic implications, obesity appears to exert a considerable burden on psychological health.

Other lifestyle-related variables, such as substance use, also play a critical role. Lien et al. (2021) examined hospitalized individuals receiving treatment for substance use disorders and observed that tobacco consumption was strongly associated with diminished mental health and a lower perceived quality of life.

Social factors are equally relevant in this domain. Matias et al. (2023) emphasize the importance of addressing social isolation when promoting healthy lifestyles among adolescents. Their study highlights that social interactions and participation in group activities not only benefit mental health directly but also encourage health-positive behaviors such as physical activity and healthy eating. Promoting social inclusion, regardless of weight status, emerges as a valuable strategy for enhancing overall well-being in this age group.

The specific types and intensities of physical activity also matter. According to Da Costa et al. (2023), engaging in vigorous exercise and resistance training is linked to better mental health outcomes among adolescents and young adults. Similarly, He et al. (2023) explore how the domain in which physical activity occurs influences mental health. Their findings indicate that leisure-time physical activity, in particular, is inversely associated with depressive symptoms, while physical exertion related to work or domestic responsibilities does not appear to confer the same psychological benefits. This perspective is reinforced by Zhang et al. (2023), who report that adolescents who engage in higher levels of physical activity experience greater life satisfaction and subjective well-being.

Dietary patterns also show a significant impact on mental health. Ardekani et al. (2023) investigate the relationship between the Mediterranean-DASH Diet Intervention for Neurodegenerative Delay (MIND diet), mental well-being, and cardiometabolic markers among individuals with obesity. Their results suggest that adherence to this dietary pattern is linked to improved mental health and reduced cardiometabolic risk, pointing to the dual physical and psychological benefits of healthy eating. In contrast, food insecurity has emerged as a factor that exacerbates psychological distress. Koob et al. (2023) find that individuals experiencing food insecurity report elevated stress levels compared to those with stable access to food, highlighting the mental health toll of material deprivation.

In summary, the existing body of research demonstrates the intricate relationship between mental health and various modifiable lifestyle factors—including physical activity, body weight, dietary habits, substance use, social connectedness, and food security. These findings underscore the importance of adopting a holistic approach to health promotion that addresses both physical and psychological dimensions across the life course.

4.3 Data and Methodology

4.3.1 Data Sample

This study draws upon detailed microdata from the most recent edition of the European Health Survey in Spain (EHSS), corresponding to the year 2020. The EHSS is conducted by the INE and constitutes the Spanish component of the broader European Health Interview Survey (EHIS), coordinated by Eurostat. This initiative is conduced by Regulation (EC) No 1338/2008 and Commission Regulation No 141/2013, which establish the framework for health statistics collection across the European Union.

The EHSS is administered every five years and is aimed at private households. Its overarching objective is to gather comprehensive health-related information from individuals aged 15 years and older residing in Spain, using a standardized questionnaire that facilitates comparability at both national and European levels. The data collected serve as a critical tool for the planning, implementation, and evaluation of public health policies, and allow for monitoring population health and associated risk factors over time.

In Spain, the survey's questionnaire was jointly adapted by the INE and the Ministry of Health to ensure comparability with the key indicators of the National Health Survey (ENSE). In addition, specific variables were added to address the particular needs of the national health information system. The methodological design of the EESE also ensures the continuity of health indicators over successive waves, providing consistency for longitudinal analyses.

The initial sample for the 2020 edition comprised approximately 22,072 individuals, with data collection conducted between July 15, 2019, and July 24, 2020. The sample was stratified and distributed across all Autonomous Communities (AC), combining a uniform allocation with a proportional component based on the population size of each region. Interviews were primarily conducted face-to-face, although telephone interviews were used in exceptional circumstances.

The adult questionnaire consists of several sections, including: identification data, perceived health status and accidents, use of health services, lifestyle habits, and sociodemographic characteristics. This rich dataset provides insights not only at the national level but also disaggregated by Autonomous Community, enabling regional comparisons of health status, service utilization, preventive practices, and health-related behaviors, such as physical activity, diet, smoking, and alcohol consumption, based on age, gender, and other sociodemographic variables.

For the purposes of this study, we focus exclusively on individuals aged 15 years and older. The final analytical sample includes all adult respondents who provided complete information relevant to the research questions. Table 4.1 presents the distribution of the adult sample by Autonomous Community, highlighting the representativeness of the data across Spain's territorial structure.

Table 4.1. Composition of the adult sample in the EHSS

AC	EHSS 2020	AC	EHSS 2020
Andalucía	2,820	C.Valenciana	1,870
Aragón	821	Extremadura	923
Asturias	979	Galicia	1,304
Baleares	396	Madrid	2,327
Canarias	1,138	Murcia	1,007
Cantabria	929	Navarra	747
Castilla León	1,124	País Vasco	1,229
Castilla-Mancha	1,146	La Rioja	648
Cataluña	2,138	Ceuta y Melilla	526

Note: AC (Autonomous Community); EHSS (European Health Survey in Spain). Source: Authors' calculations based on European Health Survey in Spain 2020.

Table 4.1 presents the distribution of the adult sample across Spain's Autonomous Communities, illustrating a relatively balanced representation. The largest samples correspond to more populous regions such as Andalucía (2,820 respondents), Madrid (2,327), and Cataluña (2,138), which is consistent with their demographic weight in the national population. In contrast, smaller regions such as La Rioja (648) and the autonomous cities of Ceuta and Melilla (526) have proportionally smaller sample sizes. This distribution ensures regional comparability.

4.3.2 Variable Selection

The dependent variables in this study are based on responses to three distinct questions included in the EESE 2020. These questions aim to capture whether individuals have experienced depression, anxiety, or other mental health disorders. The responses are self-reported and consist of a simple dichotomous format, where individuals indicate with a "Yes" or "No" whether they have ever experienced each of the aforementioned mental health conditions.

To explore the association between mental health and other factors, we include a set of independent variables or covariates that provide detailed information on the respondents' sociodemographic characteristics, health status, and lifestyle habits. Specifically, the selected covariates include: age, gender, marital status, nationality, level of education, self-perceived health status, presence of chronic diseases, physical activity, dietary habits, smoking, and alcohol consumption.

All the explanatory variables have been recoded into dichotomous variables to facilitate analysis and interpretation. To ensure clarity and consistency, each variable has been renamed and clearly defined in the table below:

Table 4.2. Variables defination

Variable	**Label**	**Coding**
Age	Number of years	
Gender	Gender of the respondent	1 if female, 0 otherwise.
Nationality	Spanish or foreign nationality	
NoEducation	Education level	1 if illiterate or uneducated, , 0 otherwise.
Marital status	Marital status of the respondent	1 if single, 0 otherwise.
SAGHS	Perceived health status	1 if respondents Self-Assessed Health Status is Good or very good, 0 otherwise.
Chronic disease	Have chronic diseases	1 if the respondent has chronic diseases, 0 otherwise.
Physical activity	Frequency with which you perform physical activity	1 if physical activity is performed with high frequency, 0 otherwise.
Diet Habits	Consumption frequency of dairy products: fruits, meet, eggs, fish, rice, corn, vegetables, legumes, cold meat, dairy, sweets, sugary soft drinks, fast food, appetizers and natural juice.	1 if you eat each of the foods with high frequency, 0 otherwise.
DrinkDaily	Frequency with which you consume alcohol.	1 if respondent drinks alcoholic beverages daily, 0 otherwise.
Smoke	Frequency with which you consume tobacco.	1 if ever smoked daily, 0 otherwise.

Source: Authors' calculations based on European Health Survey in Spain 2020.

In relation to the chosen explanatory variables, we have organized them into distinct conceptual groups para facilitar su análisis. The first group comprises several sociodemographic characteristics that may influence mental health outcomes. The variable "age" represents the age in years of each respondent, while "gender" is coded as 1 for female respondents and 0 otherwise. Nationality is also treated as a dichotomous variable, taking the value 1 for Spanish nationals and 0 for foreign nationals. The education level variable captures whether the respondent has no formal education or is illiterate (coded as 1), while all other levels of education are coded as 0. Marital status is represented by a variable coded as 1 for individuals who are single and 0 for those who are married, separated, divorced, or widowed.

The second group gathers information related to the health status of individuals, which is essential for understanding their overall well-being. The variable SAGHS (Self-Assessed General Health Status) captures the individual's subjective perception of their health. It is coded as 1 when the respondent reports having good or very good health and 0 when their self-assessed health is fair, poor, or very poor. Alongside this, the presence of chronic conditions is recorded through the variable "chronic disease," which is assigned a value of 1 if the individual reports having one or more chronic illnesses and 0 if none are reported.

Lastly, the third group reflects lifestyle habits that may have a significant impact on mental health. Physical activity is included as a variable that takes the value 1 when individuals report engaging in physical exercise frequently, and 0 otherwise. The smoking variable identifies whether the respondent has ever smoked daily (coded as 1), while the alcohol consumption variable ("DrinkDaily") is coded as 1 for those who consume alcoholic beverages on a daily basis and 0 for others.

Dietary habits are addressed through the consumption frequency of fifteen specific food groups, such as fruits, meats, fish, vegetables, legumes, cold cuts, dairy products, sweets, sugary soft drinks, fast food, snacks, and natural juices. Each food item is categorized as high consumption if it is consumed three or more times per week. This classification helps to identify healthier dietary patterns and their potential association with mental health outcomes.

4.4 Methodology

In this study, to conduct the empirical analysis, probit models are estimated, with results reported alongside their corresponding levels of statistical significance. The choice of the probit model is justified by the binary nature of the dependent variables, indicating whether individuals have experienced depression, anxiety, or other mental disorders, and by the need to model the probability of these outcomes as a function of several explanatory factors.

This modeling approach is especially useful given the individual-level nature of the data and the objective of analyzing how mental health outcomes are associated with lifestyle habits and personal characteristics. By adopting a probit model, we are able to consider the latent decision process that leads an individual to experience a mental health condition. Moreover, as highlighted by Heckman (1978), this approach allows us to distinguish between individuals based on unobserved propensities, thereby improving the interpretability and consistency of the estimated relationships.

The dependent variables used in this analysis take the value of 1 ($y = 1$) if the individual reports having experienced a specific mental health issue (depression, anxiety, or other disorders), and 0 ($y = 0$) otherwise. The probability of observing $y = 1$ is modeled as a function of a set of explanatory variables (x) and a vector of parameters (β) to be estimated. The general specification of the model is as follows:

$$E(y|x) = F(x, \beta)$$

Where F(.) denotes the cumulative distribution function of the standard normal distribution. The vector β captures the effect of each covariate on the latent probability of reporting mental health problems. The use of the normal distribution in this context ensures that the resulting probability predictions remain bounded between 0 and 1, avoiding the inconsistencies that arise in linear probability models.

Importantly, only one of two mutually exclusive outcomes can be observed for each individual: either they have reported experiencing mental health problems or they have not. This implies the existence of a latent variable y^*, which reflects the unobserved continuous propensity to suffer from such issues. The model is thus specified as:

$$y=1 \text{ si } y^* > 0,$$

$$y=0 \text{ si } y^* \leq 0,$$

$$y^* = x^{'} \beta + \varepsilon$$

Where ε is the error term, assumed to follow a standard normal distribution. This assumption, combined with the use of a probit link function, leads to the following probability function:

$$\Pr(y = 1|x) = F(x^{'} \beta)$$

The estimation of the parameters β is carried out through Maximum Likelihood Estimation (MLE). The log-likelihood function for a sample of n independent observations is given by:

$$ln\ L = \sum_{i=1}^{n} \{y_i lnF(x_i^{'}\beta) + (1 - y_i) ln\ [1 - F(x_i^{'}\beta)]\ \}$$

This technique yields consistent and efficient estimators for the effects of the explanatory variables on the likelihood of mental health problems.

Based on this specification, we estimate three separate probit models—one for each mental health outcome: depression, anxiety, and other disorders. These models allow us to evaluate the role of various lifestyle habits and sociodemographic factors in shaping mental health status in the Spanish population. Furthermore, the analysis is also disaggregated by AC, enabling us to explore potential regional differences in these relationships, which is highly relevant for designing public health interventions adapted to the territorial context (Muthén, 1979).

The probit model is particularly appropriate given that the dependent variable represents the occurrence of a dichotomous event (the presence or absence of a mental health disorder), and it allows for an adequate modeling of the latent decision-making process underlying such manifestation. Moreover, its probabilistic structure facilitates the interpretation of results in terms of relative risks associated with various sociodemographic and lifestyle factors, providing useful evidence to guide mental health prevention policies.

4.5 Results

Given that the variables of interest are binary, the probit model technique was chosen for this study due to its inherent advantages. The results presented in the Appendix were obtained using the statistical software STATA 17.0, where the log-likelihood function was maximized.

It is crucial to highlight that, in the majority of cases, the signs of the coefficients of the explanatory variables remain stable in relation to the AC and largely align with the prior expectations. Specifically, explanatory variables related to personal characteristics, such as age, gender, nationality, and education level, exhibit a high degree of stability across AC. In contrast, the explanatory variables associated with dietary habits show less stability in relation to the AC. This variability can be attributed to differences in food consumption patterns and dietary habits that vary by region due to various influences such as local traditions, geographic location, food availability, and regional culinary preferences.

It is important to remember that our variables of interest, i.e., the dependent variables (depression, anxiety, and other mental health conditions), take on the value 1 in the presence of these conditions and 0 otherwise. Therefore, the sign of the explanatory variables reflects their qualitative effect in relation to the presence or absence of these conditions.

The results are presented in three tables, each corresponding to a specific variable of interest: depression, anxiety and other mental health problems.

The first table shows the results of the probit model in relation to depression for all AC.

Table 4.3. Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	All		Andalucía		Aragón	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.3366	0.0292	0.1836	0.0928	0.3633	0.1945
age	0.0035	0.0010	0.0004	0.0035	0.0037	0.0068
nationality	0.0807	0.0670	-0.0330	0.2340	0.0000	(omitted)
maritalstatus	0.0258	0.0363	0.1190	0.1189	0.0159	0.2918
NoEducation	0.0040	0.0396	0.1119	0.1125	0.0197	0.2960
Health Status						
saghs	-0.7233	0.0291	-0.8603	0.0972	-0.7471	0.1833
chronicdisease	0.8544	0.0452	0.9688	0.1564	0.0000	(omitted)
Lifestyle						
physicalactivity	0.0930	0.0371	0.0729	0.1428	0.3456	0.3234
smoke	0.2383	0.0351	0.2268	0.1090	-0.0256	0.2959
drinkdaily	0.0102	0.0395	0.0310	0.1360	-0.2030	0.2487
Diet Habits						
fruit	-0.0724	0.0460	-0.3282	0.1340	0.3167	0.5617
meet	-0.0391	0.0293	-0.1813	0.0915	-0.1956	0.2095
egg	-0.0110	0.0274	0.2481	0.0891	-0.0606	0.1832
fish	-0.1349	0.0278	-0.2823	0.0905	0.1433	0.1876
rice	0.0518	0.0292	0.1202	0.0881	-0.0229	0.1865
corn	-0.0943	0.0492	0.0202	0.1870	-0.3234	0.2500
vegetables	-0.0728	0.0444	0.1518	0.1698	0.3668	0.5637
legums	0.0303	0.0279	0.0390	0.0856	-0.0157	0.2671
coldmeet	-0.0426	0.0296	-0.0125	0.0945	0.0648	0.1896
dairy	0.0089	0.0493	-0.1332	0.1558	0.2783	0.2766
sweets	0.0552	0.0273	0.1358	0.0956	0.0897	0.1922
sugarysoftdrinks	0.0721	0.0460	0.0631	0.1456	0.2265	0.4033
fastfood	-0.0224	0.0670	-0.0304	0.2181	0.0000	(omitted)
appetizers	0.0977	0.0620	-0.1474	0.2025	0.7454	0.3991
naturaljuice	0.0906	0.0321	-0.0695	0.1124	-0.1341	0.2089
Cons	-1.9852	0.1219	-1.7654	0.4257	-2.2656	0.8814
Observations Number	21,773		2,775		469	
LR chi2	2556.09		348.5		41.47	
Prob > chi2	0		0		0.0072	
Pseudo R2	0.1858		0.2383		0.1286	
Log likelihood	-5601.7146		-557.09078		-140.54301	

Data source: Own elaboration from EHSS.

Table. 4.3 (continuation): Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	Asturias		Balears, Illes		Canarias	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.4194	0.1297	0.3970	0.2410	0.1541	0.1256
age	0.0050	0.0043	0.0044	0.0075	0.0089	0.0047
nationality	0.6558	0.5458	-0.0359	0.3545	1.1653	0.4893
maritalstatus	-0.1660	0.1732	0.4535	0.2727	0.1367	0.1612
noeducation	0.0267	0.2429	0.4577	0.3671	-0.1745	0.1596
Health Status						
saghs	-0.5351	0.1199	-1.0134	0.2452	-0.8016	0.1436
chronicdisease	1.2046	0.2260	0.9001	0.3393	0.9070	0.2645
Lifestyle						
physicalactivity	0.2873	0.1292	0.0000	(omitted)	0.1323	0.2200
smoke	0.3726	0.1514	-0.3713	0.3196	0.3946	0.1477
drinkdaily	0.2171	0.1606	-0.1309	0.3746	-1.1293	0.4797
Diet Habits						
fruit	0.2074	0.2239	0.1775	0.2772	0.0505	0.2155
meet	-0.2707	0.1287	-0.2910	0.2413	-0.3481	0.1246
egg	0.0055	0.1189	-0.3240	0.2482	0.1128	0.1206
fish	-0.1712	0.1349	-0.2383	0.2285	-0.3100	0.1498
rice	-0.0304	0.1230	0.6726	0.2843	0.0961	0.1406
corn	0.0239	0.2189	-0.2761	0.2666	-0.3171	0.2271
vegetables	-0.0053	0.1883	0.0312	0.3095	-0.0362	0.2015
legums	0.1071	0.1278	0.0297	0.2482	-0.1014	0.1254
coldmeet	-0.2449	0.1409	0.0640	0.2562	-0.0830	0.1238
dairy	0.0783	0.2626	0.0095	0.2675	0.1169	0.2473
sweets	0.1222	0.1183	-0.0370	0.3103	-0.0199	0.1470
sugarysoftdrinks	-0.1385	0.2464	-0.2717	0.4322	0.2110	0.2374
fastfood	0.5989	0.3388	0.0266	0.6282	-0.4875	0.5698
appetizers	0.0419	0.3512	0.3286	0.5054	-0.6548	0.5344
naturaljuice	-0.0727	0.1474	0.0649	0.2641	0.1359	0.1291
Cons	-3.2423	0.7590	-1.8275	0.6926	-3.2556	0.7453
Observations Number	955		371		1,131	
LR chi2	184.95		80.13		183.81	
Prob > chi2	0		0		0	
Pseudo R2	0.2209		0.3058		0.2289	
Log likelihood	-326.08311		-90.959263		-309.50831	

Data source: Own elaboration from EHSS.

Table. 4.3 (continuation): Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	Cantabria		Castilla y León		Castilla - La Mancha		
	Coef	Std.Err.	Coef	Std.Err.	Coef	Std.Err.	
Personal Characteristics							
gender	0.2330	0.1570	0.4145	0.1095	0.4084	0.1447	
age	0.0009	0.0055	0.0058	0.0039	-0.0004	0.0053	
nationality	0.0000	(omitted)	-0.4381	0.2884	-0.0969	0.3496	
maritalstatus	0.1787	0.2031	0.0063	0.1346	0.2252	0.1808	
noeducation	0.5536	0.3689	0.1091	0.1520	0.2467	0.1637	
Health Status							
saghs	0.8447	0.1687	-0.6004	0.1087	-0.8000	0.1568	
chronicdisease	0.7541	0.2310	0.8197	0.1990	0.5936	0.2053	
Lifestyle							
physicalactivity	0.0919	0.2202	-0.0534	0.1620	0.4806	0.2426	
smoke	0.3381	0.1847	0.3952	0.1375	0.3463	0.1669	
drinkdaily	0.2342	0.2034	-0.0076	0.1293	-0.0117	0.2155	
Diet Habits							
fruit	0.2820	0.2205	-0.4380	0.1807	-0.4902	0.4178	
meet	0.1188	0.1627	-0.0090	0.1315	0.8447	0.1911	
egg	0.0363	0.1511	-0.0616	0.1026	-0.1376	0.1320	
fish	0.0065	0.1529	0.0036	0.1045	-0.1123	0.1356	
rice	0.0396	0.1976	0.1091	0.1170	-0.1736	0.2827	
corn	0.6754	0.2991	-0.1951	0.2401	-0.4853	0.3927	
vegetables	0.0180	0.2282	-0.0312	0.2045	0.2692	0.2671	
legums	0.4124	0.2110	0.1570	0.1046	-0.3173	0.1365	
coldmeet	0.1926	0.1886	-0.1728	0.1181	0.0689	0.1623	
dairy	0.3879	0.2314	0.2174	0.2289	-0.0911	0.3073	
sweets	0.5907	0.1692	0.0056	0.1129	-0.0629	0.1360	
sugarysoftdrinks	0.0000	(omitted)	-0.0439	0.1998	0.2551	0.2090	
fastfood	0.0000	(omitted)	-0.2416	0.3365	-0.0153	0.3683	
appetizers	0.7875	0.5653	0.2677	0.2338	-0.3338	0.4430	
naturaljuice	0.1350	0.2251	0.2538	0.1278	0.3041	0.2746	
Cons	0.3525	0.6196	-1.3476	0.5177	-1.6556	0.7878	
Observations Number	830		1,112		1,144		
LR chi2	123.35		149.91		138.55		
Prob > chi2	0		0		0		
Pseudo R2	0.2384		0.1549		0.2215		0.2439
Log likelihood	196.99		-409.087		-243.4443		-503.41

Data source: Own elaboration from EHSS.

Table. 4.3 (continuation): Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	**Cataluña**		**Comunitat Valenciana**		**Extremadura**	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.4388	0.0994	0.2191	0.0958	0.3839	0.1790
age	0.0030	0.0034	0.0032	0.0034	0.0073	0.0067
nationality	-0.0061	0.1846	-0.1284	0.1876	0.0000	(omitted)
maritalstatus	-0.1108	0.1254	0.0877	0.1242	0.4105	0.2063
noeducation	-0.1904	0.1521	0.0094	0.1386	-0.6208	0.2174
Health Status						
saghs	-0.8989	0.0974	-0.8349	0.0989	-0.7289	0.1753
chronicdisease	0.7771	0.1246	0.6737	0.1485	0.9334	0.2588
Lifestyle						
physicalactivity	0.0345	0.1183	0.0458	0.1134	0.9033	0.4927
smoke	0.1710	0.1187	0.3329	0.1138	-0.0218	0.2104
drinkdaily	-0.0810	0.1394	-0.0239	0.1393	-0.2185	0.2690
Diet Habits						
fruit	0.0621	0.1740	0.1356	0.1518	0.2879	0.3101
meet	-0.0929	0.1119	-0.1646	0.1004	-0.2005	0.1888
egg	-0.0969	0.0966	0.1553	0.0907	-0.0317	0.1945
fish	-0.3089	0.0951	-0.1543	0.0950	0.1302	0.1843
rice	0.0164	0.1110	-0.0259	0.1140	-0.0581	0.1784
corn	-0.0620	0.1690	-0.1778	0.1389	0.0428	0.3818
vegetables	-0.2744	0.1627	-0.2419	0.1464	-0.4700	0.2233
legums	0.0351	0.0992	0.0229	0.0999	0.2657	0.1581
coldmeet	0.0879	0.0974	0.0359	0.0964	-0.0595	0.1934
dairy	-0.1671	0.1375	-0.0074	0.1535	0.1293	0.4921
sweets	0.1677	0.0944	-0.0221	0.0946	-0.2672	0.1615
sugarysoftdrinks	0.2471	0.1323	0.1020	0.1461	0.3601	0.2498
fastfood	-0.1903	0.1743	0.0578	0.1487	-0.6396	0.6634
appetizers	0.1891	0.2036	0.3133	0.1661	0.5967	0.4277
naturaljuice	0.1181	0.1054	0.0213	0.1099	0.2456	0.2168
Cons	-1.3218	0.3728	-1.3050	0.3722	-3.2102	0.9450
Observations Number	2,109		1,849		906	
LR chi2	324.85		219.51		115.58	
Prob > chi2	0		0		0	
Pseudo R2	0.2439		0.1768		0.2418	
Log likelihood	-503.41		-511.0735		-181.162	

Data source: Own elaboration from EHSS.

Table. 4.3 (continuation): Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	Galicia		Madrid		Murcia	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.3924	0.1115	0.3715	0.1061	0.3769	0.1439
age	0.0023	0.0041	-0.0021	0.0034	-0.0012	0.0052
nationality	0.3584	0.3822	0.1526	0.1938	0.4003	0.3211
maritalstatus	0.0680	0.1431	0.0914	0.1255	-0.3530	0.2079
noeducation	0.2431	0.1439	0.3920	0.1475	0.0154	0.1704
Health Status						
saghs	0.7748	0.1101	-0.7799	0.1037	-0.6814	0.1382
chronicdisease	0.7141	0.1759	0.8976	0.1728	1.6082	0.3762
Lifestyle						
physicalactivity	0.0791	0.1389	0.1199	0.1201	0.2212	0.1948
smoke	0.1478	0.1562	0.1036	0.1308	0.2096	0.1629
drinkdaily	0.0638	0.1359	-0.0793	0.1585	-0.1361	0.1821
Diet Habits						
fruit	0.0944	0.1553	-0.0904	0.1606	-0.3923	0.2360
meet	0.2076	0.1132	0.0575	0.1065	-0.0859	0.1371
egg	0.1285	0.1093	-0.1578	0.0982	-0.1358	0.1257
fish	0.4293	0.1097	-0.0841	0.1007	0.0631	0.1411
rice	0.0174	0.1258	-0.0484	0.1007	-0.2953	0.1712
corn	0.2098	0.2014	0.0291	0.1560	-0.4089	0.2126
vegetables	0.1024	0.1283	-0.0611	0.1565	-0.1824	0.2698
legums	0.2155	0.1291	0.0422	0.1075	0.2990	0.1286
coldmeet	0.0696	0.1203	-0.0898	0.1025	-0.3299	0.1515
dairy	0.0263	0.1867	-0.0406	0.2060	0.4120	0.2730
sweets	0.1865	0.1067	0.1106	0.0975	-0.0111	0.1370
sugarysoftdrinks	0.1076	0.2209	0.1089	0.1413	0.1866	0.2098
fastfood	0.1500	0.2144	-0.1619	0.2524	-0.1345	0.3625
appetizers	0.4704	0.2359	0.0142	0.1681	-0.2582	0.3787
naturaljuice	0.1700	0.1138	-0.0118	0.1073	-0.0281	0.1433
Cons	1.2310	0.5410	-2.0516	0.4235	-1.9912	0.7205
Observations Number	1,250		2,316		1,001	
LR chi2	190.98		228.42		197.86	
Prob > chi2	0		0		0	
Pseudo R2	0.1943		0.2066		0.2652	
Log likelihood	395.98		-438.69622		-274.059	

Data source: Own elaboration from EHSS.

Table. 4.3 (continuation): Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	Navarra,		Basque Country		Rioja, La	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.2232	0.1706	0.3958	0.1284	0.6363	0.1993
age	-0.0001	0.0059	0.0143	0.0048	0.0003	0.0063
nationality	0.0138	0.4336	-0.8080	0.2619	0.3527	0.4228
maritalstatus	-0.1216	0.1942	0.1803	0.1458	-0.1482	0.2340
noeducation	-0.5557	0.4154	0.2172	0.1957	0.5744	0.2974
Health Status						
saghs	-0.6563	0.1676	-0.7681	0.1257	-0.7749	0.1786
chronicdisease	1.0614	0.2466	0.8251	0.2091	1.0176	0.2623
Lifestyle						
physicalactivity	0.1432	0.1918	0.2079	0.1397	-0.1749	0.2018
smoke	0.4219	0.1979	0.1284	0.1627	-0.1264	0.2359
drinkdaily	-0.2186	0.2290	0.0372	0.1523	0.5461	0.2105
Diet Habits						
fruit	-0.0982	0.2941	-0.3227	0.2113	0.1568	0.3159
meet	-0.0845	0.1951	-0.1626	0.1303	-0.3566	0.2006
egg	0.0541	0.1694	-0.0522	0.1232	0.1750	0.1772
fish	-0.0399	0.1679	-0.0340	0.1244	-0.0408	0.1753
rice	0.0678	0.1660	0.0422	0.1251	-0.2607	0.1776
corn	0.4933	0.3644	0.0995	0.2437	0.0464	0.2979
vegetables	-0.5871	0.4175	-0.1117	0.1875	-0.4134	0.2799
legums	0.1529	0.1696	-0.0401	0.1250	0.2923	0.1905
coldmeet	-0.0874	0.1775	-0.0963	0.1410	0.0722	0.2017
dairy	-0.3125	0.2697	0.3849	0.2854	0.4248	0.4412
sweets	-0.0159	0.1664	0.2195	0.1202	0.0212	0.1705
sugarysoftdrinks	-0.4652	0.4426	-0.0790	0.2359	0.6329	0.2476
fastfood	0.1796	0.7110	-0.4886	0.6528	0.3879	0.5372
appetizers	0.3898	0.4374	0.3784	0.3097	-0.2015	0.4141
naturaljuice	0.0916	0.1947	0.2242	0.1384	0.0696	0.1887
Cons	-1.5791	0.6879	-2.0930	0.5246	-2.5078	0.7863
Observations Number	732		1,215		631	
LR chi2	84.08		218.68		107.02	
Prob > chi2	0		0		0	
Pseudo R2	0.2049		0.2659		0.2611	
Log likelihood	-163.09396		-301.86		-151.4	

Data source: Own elaboration from EHSS.

Table. 4.3 (continuation): Estimation of probit model on suffering from depression. Spain. Year 2019-2020.

Variable	Ceuta y Melilla	
	Coef	**Std.Err.**
Personal Characteristics		
gender	0.0040	0.4553
age	-0.0189	0.0179
nationality	0.0000	(omitted)
maritalstatus	-5.6327	586.4675
noeducation	-0.8061	0.7229
Health Status		
saghs	-0.5985	0.4307
chronicdisease	18.5186	1339.1620
Lifestyle		
physicalactivity	0.0000	(omitted)
smoke	0.0987	0.6556
drinkdaily	-5.7500	636.9514
Diet Habits		
fruit	-0.2186	0.6006
meet	-1.1846	0.7548
egg	-0.2098	0.6505
fish	-0.5467	0.4993
rice	-0.7386	0.5070
corn	0.0000	(omitted)
vegetables	-0.0581	0.7161
legums	-1.0679	1.1014
coldmeet	1.8672	0.6007
dairy	0.0000	(omitted)
sweets	-0.0059	0.6055
sugarysoftdrinks	0.2197	0.7790
fastfood	0.0000	(omitted)
appetizers	18.6525	1339.1620
naturaljuice	0.4620	0.4855
Cons	-18.3126	1339.1610
Observations Number	310	
LR chi2	59.84	
Prob > chi2	0	
Pseudo R2	0.5245	
Log likelihood	-27.12247	

Data source: Own elaboration from EHSS.

The second table shows the results of the probit model in relation to anxiety for all AC.

Table. 4.4. Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	All		Andalucía		Aragón	
	Coef	Std.Err.	Coef	Std.Err.	Coef	Std.Err.
Personal Characteristics						
gender	0.3720	0.0306	0.1857	0.0997	0.7513	0.1910
age	-0.0088	0.0011	-0.0123	0.0038	0.0021	0.0059
nationality	0.3204	0.0746	0.2263	0.2864	0.1949	0.4443
maritalstatus	-0.0280	0.0372	-0.0552	0.1288	0.1214	0.2305
noeducation	0.0434	0.0432	-0.0830	0.1293	0.5030	0.3546
Health Status						
saghs	-0.6461	0.0304	-0.7420	0.1017	0.7399	0.1678
chronicdisease	1.0652	0.0489	1.8402	0.3045	1.0136	0.2813
Lifestyle						
physicalactivity	0.0936	0.0375	0.1728	0.1491	0.1539	0.2235
smoke	0.2314	0.0356	0.2072	0.1127	0.2120	0.2320
drinkdaily	0.0216	0.0422	0.0187	0.1443	0.1942	0.2371
Diet Habits						
fruit	-0.0750	0.0466	-0.4305	0.1375	0.2721	0.3734
meet	-0.0506	0.0308	-0.0699	0.0993	0.3619	0.1868
egg	0.0217	0.0285	0.0970	0.0962	0.0124	0.1667
fish	-0.0570	0.0289	-0.0629	0.0950	0.0992	0.1692
rice	0.0458	0.0305	0.0312	0.0934	0.3646	0.1686
corn	-0.0802	0.0503	-0.3736	0.1721	0.2010	0.2525
vegetables	0.0450	0.0474	0.1129	0.1733	0.3009	0.3756
legums	-0.0402	0.0293	-0.0399	0.0925	0.6026	0.2821
coldmeet	-0.0046	0.0305	-0.0942	0.1023	0.1062	0.1662
dairy	0.0036	0.0508	-0.0308	0.1687	0.4404	0.2616
sweets	0.0056	0.0285	0.1869	0.1042	0.0324	0.1693
sugarysoftdrinks	-0.0061	0.0475	-0.1087	0.1540	0.0694	0.3260
fastfood	0.0408	0.0655	0.2273	0.2122	0.5234	0.4178
appetizers	0.1132	0.0620	-0.0315	0.1990	0.0067	0.3918
naturaljuice	0.0298	0.0336	-0.2690	0.1305	0.0330	0.1784
Cons	-1.9200	0.1300	-1.8022	0.5219	2.3009	0.7469
Observations Number	21,769		2,774		813	
LR chi2	2081.51		314		105.03	
Prob > chi2	0		0		0	
Pseudo R2	0.1697		0.2445		0.237	
Log likelihood	5092.23		-485.09		169.11	

Data source: Own elaboration from EHSS.

Table. 4.4. (continuation): Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	Asturias		Balears, Illes		Canarias	
	Coef	Std.Err.	Coef	Std.Err.	Coef	Std.Err.
Personal Characteristics						
gender	0.3472	0.1490	0.6648	0.2821	0.2328	0.1201
age	-0.0033	0.0052	0.0116	0.0095	0.0016	0.0044
nationality	0.4127	0.5808	0.4607	0.5218	1.2212	0.4751
maritalstatus	-0.1163	0.1973	0.2762	0.3183	0.0913	0.1517
noeducation	0.0512	0.2871	0.7681	0.4237	0.0279	0.1527
Health Status						
saghs	-0.7023	0.1415	1.0072	0.2872	0.7316	0.1328
chronicdisease	1.4629	0.3994	0.0000	(omitted)	1.2637	0.2879
Lifestyle						
physicalactivity	-0.0067	0.1443	0.0000	(omitted)	0.0208	0.2059
smoke	0.3251	0.1728	0.4287	0.3113	0.3504	0.1407
drinkdaily	-0.0711	0.2012	0.5293	0.3613	1.1550	0.4735
Diet Habits						
fruit	0.0737	0.2581	0.5030	0.3152	0.0812	0.1982
meet	-0.1967	0.1484	0.4317	0.2739	0.2859	0.1170
egg	0.0347	0.1370	0.0141	0.2935	0.1201	0.1147
fish	-0.0296	0.1518	0.7780	0.2843	0.2838	0.1425
rice	-0.0276	0.1411	0.7733	0.3084	0.0273	0.1311
corn	0.0237	0.2505	0.4948	0.3039	0.1482	0.2195
vegetables	0.1748	0.2310	0.3874	0.3732	0.0787	0.1934
legums	-0.0993	0.1489	0.2147	0.2837	0.0014	0.1193
coldmeet	-0.0729	0.1621	0.2304	0.2893	0.0389	0.1181
dairy	-0.0102	0.2916	0.6594	0.3166	0.0114	0.2235
sweets	0.0195	0.1376	1.2593	0.4841	0.1207	0.1398
sugarysoftdrinks	0.0053	0.2781	0.7170	0.5715	0.0394	0.2270
fastfood	-0.1913	0.5291	0.8601	0.9209	0.0389	0.4260
appetizers	0.0000	(omitted)	0.5355	0.7816	0.0420	0.3567
naturaljuice	-0.1781	0.1749	0.1602	0.3144	0.0329	0.1254
Cons	-2.6815	0.8735	0.9024	0.8865	3.0997	0.7206
Observations Number	918		213		1,131	
LR chi2	114.07		54.28		195.96	
Prob > chi2	0		0.0002		0	
Pseudo R2	0.1908		0.2717		0.2195	
Log likelihood	-241.828		-72.75		-348.4	

Data source: Own elaboration from EHSS.

Table. 4.4 (continuation): Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	Cantabria		Castilla y León		Castilla - La Mancha	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.0895	0.2052	0.3536	0.1228	0.2969	0.1675
age	0.0196	0.0074	0.0112	0.0042	-0.0345	0.0064
nationality	0.0000	(omitted)	0.1607	0.3129	0.8936	0.5489
maritalstatus	0.0361	0.2556	0.1172	0.1508	-0.6783	0.2355
noeducation	0.1452	0.4413	0.1299	0.1681	0.4297	0.2004
Health Status						
saghs	0.5509	0.2248	0.4784	0.1191	-0.8366	0.1857
chronicdisease	0.8032	0.3127	0.9453	0.2322	0.6518	0.2179
Lifestyle						
physicalactivity	0.4227	0.3318	0.4350	0.2079	0.8908	0.2979
smoke	0.1939	0.2419	0.0621	0.1599	0.0484	0.1894
drinkdaily	0.3155	0.3031	0.1287	0.1438	-0.5027	0.3417
Diet Habits						
fruit	0.3209	0.2734	0.0903	0.2220	-0.0762	0.4931
meet	0.3198	0.2144	0.0367	0.1498	0.2666	0.2105
egg	0.0004	0.1994	0.0123	0.1136	-0.2246	0.1527
fish	0.3002	0.2107	0.1636	0.1163	0.1867	0.1589
rice	0.0353	0.2595	0.1977	0.1338	0.2610	0.3816
corn	0.3601	0.3997	0.0684	0.2843	-0.2957	0.4994
vegetables	0.1518	0.3062	0.0195	0.2331	0.4960	0.3329
legums	0.0578	0.2826	0.0124	0.1170	-0.4873	0.1587
coldmeet	0.6109	0.3083	0.1491	0.1294	0.2351	0.1803
dairy	0.3405	0.2853	0.2301	0.2329	0.2211	0.4464
sweets	0.5438	0.2231	0.2144	0.1313	-0.1199	0.1576
sugarysoftdrinks	0.1215	0.4311	0.2122	0.2365	0.1150	0.2302
fastfood	0.0000	(omitted)	0.3379	0.3897	0.2716	0.3587
appetizers	0.7663	0.7628	0.1567	0.2604	0.0432	0.4403
naturaljuice	0.6308	0.3991	0.1481	0.1435	-0.3580	0.3968
Cons	0.5909	0.8762	1.8512	0.5989	-2.0651	1.0657
Observations Number	865		1,112		1,144	
LR chi2	57.16		90.59		126.8	
Prob > chi2	0.0001		0		0	
Pseudo R2	0.2139		0.1232		0.26	
Log likelihood	-105		322.31		-180.48	

Data source: Own elaboration from EHSS.

Table. 4.4 (continuation): Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	Cataluña		Comunitat Valenciana		Extremadura	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.4258	0.1002	0.3404	0.0963	0.7797	0.2048
age	0.0125	0.0034	-0.0094	0.0035	-0.0070	0.0069
nationality	0.2578	0.1895	0.1771	0.2123	0.0566	0.7765
maritalstatus	0.0248	0.1208	-0.1041	0.1254	0.2085	0.2142
noeducation	0.0208	0.1572	0.1636	0.1437	-0.3310	0.2368
Health Status						
saghs	0.8617	0.0990	-0.5308	0.0974	-0.5161	0.1821
chronicdisease	0.8809	0.1240	1.3413	0.1869	1.0547	0.2532
Lifestyle						
physicalactivity	0.3148	0.1245	0.0097	0.1106	0.5692	0.3710
smoke	0.1380	0.1166	0.4394	0.1119	0.4821	0.1968
drinkdaily	0.0475	0.1410	0.0673	0.1364	0.1395	0.2856
Diet Habits						
fruit	0.0298	0.1686	-0.1717	0.1434	0.1044	0.2988
meet	0.0887	0.1152	-0.1196	0.1015	0.0215	0.1909
egg	0.0258	0.0961	0.0980	0.0910	0.0363	0.2012
fish	0.0806	0.0944	-0.1026	0.0947	0.5396	0.1853
rice	0.0976	0.1158	0.0701	0.1169	-0.1680	0.1951
corn	0.0495	0.1759	-0.0593	0.1399	-0.0986	0.4050
vegetables	0.0901	0.1705	0.1211	0.1594	-0.3908	0.2367
legums	0.0423	0.0998	0.1724	0.0984	0.3413	0.1650
coldmeet	0.1003	0.0983	0.0485	0.0957	-0.2125	0.1980
dairy	0.0236	0.1450	0.0096	0.1556	-0.0413	0.4376
sweets	0.1473	0.0952	-0.0851	0.0953	-0.1128	0.1763
sugarysoftdrinks	0.0410	0.1385	0.0438	0.1486	-0.0007	0.2612
fastfood	0.2174	0.1688	-0.1437	0.1531	0.5880	0.4493
appetizers	0.3748	0.1950	0.2707	0.1647	0.2693	0.4181
naturaljuice	0.0893	0.1087	0.0350	0.1094	0.2320	0.2151
Cons	1.5681	0.3868	-1.9525	0.4077	-2.6795	1.1375
Observations Number	2,109		1,850		920	
LR chi2	286.73		211.23		103.89	
Prob > chi2	0		0		0	
Pseudo R2	0.227		0.1701		0.24	
Log likelihood	-488.2		-515.3228		-164.5	

Data source: Own elaboration from EHSS.

Table. 4.4 (continuation): Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	**Galicia**		**Madrid**		**Murcia**	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.5010	0.1138	0.4696	0.1171	0.3064	0.1363
age	-0.0142	0.0041	-0.0081	0.0037	-0.0052	0.0051
nationality	-0.2307	0.3639	0.6067	0.2593	0.2673	0.2980
maritalstatus	-0.1458	0.1408	0.0527	0.1342	-0.2429	0.1883
noeducation	0.2202	0.1515	-0.0370	0.1867	-0.2208	0.1768
Health Status						
saghs	-0.5728	0.1113	-0.8269	0.1131	-0.7869	0.1364
chronicdisease	0.9747	0.1792	0.9252	0.1835	1.3136	0.2520
Lifestyle						
physicalactivity	0.0496	0.1329	-0.1784	0.1182	-0.1175	0.1668
smoke	0.1415	0.1376	0.2108	0.1340	0.3128	0.1510
drinkdaily	0.1888	0.1391	0.1456	0.1591	-0.0598	0.1747
Diet Habits						
fruit	0.0542	0.1471	-0.0213	0.1671	-0.0989	0.2266
meet	-0.1964	0.1147	0.0001	0.1157	0.0338	0.1373
egg	0.0110	0.1080	-0.0285	0.1050	-0.1490	0.1221
fish	-0.1999	0.1080	-0.2050	0.1111	-0.0298	0.1375
rice	-0.1222	0.1223	-0.0959	0.1078	-0.1139	0.1706
corn	0.1799	0.1862	-0.1378	0.1546	-0.2609	0.2005
vegetables	-0.1668	0.1288	-0.0256	0.1711	0.0708	0.2601
legums	0.0188	0.1243	0.0173	0.1184	0.0789	0.1270
coldmeet	-0.1234	0.1195	-0.0475	0.1094	-0.0947	0.1435
dairy	-0.0915	0.1729	0.4018	0.2619	-0.1702	0.2164
sweets	-0.0578	0.1053	0.0553	0.1047	-0.0052	0.1324
sugarysoftdrinks	0.0278	0.1978	0.1183	0.1520	-0.1943	0.2032
fastfood	0.0845	0.2083	-0.0514	0.2488	0.2687	0.2793
appetizers	0.0723	0.2416	-0.0011	0.1802	0.4013	0.2933
naturaljuice	-0.0335	0.1157	-0.0219	0.1154	0.0562	0.1374
Cons	-0.6426	0.5247	-2.3927	0.4952	-1.2976	0.6165
Observations Number	1,249		2,316		1,001	
LR chi2	141.86		185.22		152.38	
Prob > chi2	0		0		0	
Pseudo R2	0.1527		0.1999		0.2087	
Log likelihood	-393.54		-370.67966		-288.865	

Data source: Own elaboration from EHSS.

Table. 4.4 (continuation): Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	Navarra		Basque Country		Rioja, La	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.1965	0.1725	0.5017	0.1372	0.4401	0.2436
age	-0.0080	0.0059	0.0041	0.0048	0.0216	0.0080
nationality	0.0000	(omitted)	0.1050	0.3240	0.3652	0.4734
maritalstatus	0.1109	0.1897	0.3091	0.1477	0.3478	0.2631
noeducation	-0.2625	0.4420	0.3496	0.2090	0.2238	0.4103
Health Status						
saghs	-0.7544	0.1842	0.6042	0.1300	0.9222	0.2403
chronicdisease	0.9177	0.2246	1.4630	0.2840	1.1918	0.3619
Lifestyle						
physicalactivity	0.2442	0.1979	0.3154	0.1461	0.0543	0.2522
smoke	0.1964	0.2106	0.0816	0.1660	0.1044	0.3014
drinkdaily	-0.2280	0.2459	0.0749	0.1671	0.4712	0.2771
Diet Habits						
fruit	0.0180	0.3075	0.3940	0.2123	0.3518	0.5045
meet	-0.0914	0.2034	0.1224	0.1447	0.5656	0.2554
egg	0.1073	0.1712	0.1377	0.1270	0.4205	0.2318
fish	-0.5154	0.1816	0.0433	0.1291	0.3745	0.2180
rice	-0.0427	0.1695	0.1410	0.1313	0.4156	0.2279
corn	0.2696	0.3814	0.0490	0.2344	0.3788	0.3986
vegetables	0.1604	0.5339	0.1225	0.2068	0.0000	(omitted)
legums	-0.1180	0.1835	0.0575	0.1304	0.1562	0.2541
coldmeet	-0.0043	0.1752	0.0061	0.1424	0.7010	0.3235
dairy	-0.3547	0.2857	0.2039	0.2617	0.0757	0.4158
sweets	0.4200	0.1813	0.0314	0.1237	0.3983	0.2280
sugarysoftdrinks	-0.5010	0.4371	0.1774	0.2305	0.9153	0.3026
fastfood	0.0000	(omitted)	0.4760	0.6132	0.1521	0.8538
appetizers	0.6814	0.3767	0.0564	0.3211	0.0560	0.5275
naturaljuice	0.3322	0.1881	0.1098	0.1469	0.0142	0.2283
Cons	-1.6246	0.7495	2.9338	0.5938	1.8548	0.8999
Observations Number	696		1,215		565	
LR chi2	83.77		153.48		83.89	
Prob > chi2	0		0		0	
Pseudo R2	0.215		0.2176		0.307	
Log likelihood	-152.92136		275.94		94.677	

Data source: Own elaboration from EHSS.

Table. 4.4 (continuation): Estimation of probit model on suffering from anxiety. Spain. Year 2019-2020.

Variable	Ceuta y Melilla	
	Coef	**Std.Err.**
Personal Characteristics		
gender	0.4298	0.3231
age	0.0198	0.0110
nationality	0.1300	0.6112
maritalstatus	0.6703	0.5138
noeducation	0.6126	0.3507
Health Status		
saghs	0.6006	0.3123
chronicdisease	1.6054	0.5336
Lifestyle		
physicalactivity	0.6078	0.5110
smoke	0.8933	0.3510
drinkdaily	0.0000	(omitted)
Diet Habits		
fruit	0.6078	0.4571
meet	0.5177	0.3787
egg	0.3200	0.3581
fish	0.1120	0.3049
rice	0.0680	0.3064
corn	0.1493	0.6835
vegetables	0.3012	0.4099
legums	0.2882	0.4373
coldmeet	0.3409	0.3119
dairy	0.8835	0.5864
sweets	0.6251	0.3353
sugarysoftdrinks	0.5497	0.4826
fastfood	0.0000	(omitted)
appetizers	0.0000	(omitted)
naturaljuice	0.0090	0.3494
Cons	2.2557	1.3083
Observations Number	453	
LR chi2	50.07	
Prob > chi2	0.0006	
Pseudo R2	0.3055	
Log likelihood	-56.92	

Data source: Own elaboration from EHSS.

The third table shows the results of the probit model in relation to other mental health problems for all AC.

Table. 4.5. Estimation of probit model on suffering from others mental health problems. Spain. Year 2019-2020.

Variable	All		Andalucía		Aragón	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	-0.1554	0.0487	0.4561	0.1816	-0.5136	0.4080
age	0.0069	0.0017	0.0107	0.0068	0.0593	0.0223
nationality	0.2335	0.1360	0.1897	0.3952	0.0000	(omitted)
maritalstatus	0.5407	0.0578	0.7285	0.2209	1.6378	0.5606
noeducation	0.2727	0.0588	0.1255	0.2036	-0.0361	0.5236
Health Status						
saghs	-0.5213	0.0523	1.0121	0.2470	-1.3574	0.5015
chronicdisease	1.0864	0.1261	0.0000	(omitted)	0.0000	(omitted)
Lifestyle						
physicalactivity	0.2459	0.0750	0.9320	0.5668	-0.7427	0.6728
smoke	-0.0264	0.0656	0.4980	0.2822	0.0152	0.6549
drinkdaily	-0.4384	0.0837	0.0659	0.2732	-0.9850	0.6756
Diet Habits						
fruit	-0.0973	0.0776	0.8055	0.2590	0.0000	(omitted)
meet	0.0893	0.0519	0.2752	0.1843	0.6207	0.5520
egg	0.0430	0.0476	0.0528	0.1730	-0.2878	0.3898
fish	-0.1305	0.0489	0.0531	0.1752	0.1287	0.3955
rice	0.0065	0.0513	0.0870	0.1733	-0.5337	0.3828
corn	-0.2506	0.0808	0.4196	0.3109	0.0000	(omitted)
vegetables	0.0090	0.0744	0.3028	0.3494	0.0000	(omitted)
legums	0.0449	0.0480	0.1891	0.1732	0.3527	0.5566
coldmeet	-0.0604	0.0520	0.1626	0.2012	-0.5060	0.4019
dairy	0.0990	0.0915	0.2165	0.2724	-0.3108	0.5069
sweets	0.1558	0.0471	0.3847	0.1841	0.1785	0.4221
sugarysoftdrinks	0.1396	0.0756	0.1880	0.2974	0.8130	0.6368
fastfood	0.2041	0.1028	0.3080	0.4362	0.0720	1.0107
appetizers	0.0173	0.1075	0.0000	(omitted)	0.6552	0.7453
naturaljuice	0.1098	0.0556	0.1897	0.1969	0.3035	0.4228
Cons	-3.6114	0.2427	2.1852	0.8614	-5.2795	1.6677
Observations Number	21,787		1,457		388	
LR chi2	736.14		76.25		42.69	
Prob > chi2	0		0		0.0022	
Pseudo R2	0.1812		0.2211		0.3749	
Log likelihood	1662.99		134.31		-35.5835	

Data source: Own elaboration from EHSS. Note: No observations in Ceuta and Melilla on which to perform probit model.

Table. 4.5 (continuation): Estimation of probit model on suffering from others mental health problems. Spain. Year 2019-2020.

Variable	Asturias		Balears, Illes		Canarias	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	-0.0665	0.2412	0.1832	0.4854	0.2142	0.2301
age	0.0253	0.0081	0.0134	0.0152	0.0167	0.0082
maritalstatus	0.7842	0.2955	0.6426	0.5943	0.9157	0.2718
noeducation	0.4098	0.3226	1.0427	0.5760	0.1737	0.2525
Health Status						
saghs	-0.4531	0.2468	0.3066	0.4738	1.0236	0.3514
chronicdisease	0.6966	0.4519	0.0000	(omitted)	0.0000	(omitted)
Lifestyle						
physicalactivity	0.3363	0.2783	0.0000	(omitted)	0.3531	0.5338
smoke	0.2109	0.3387	0.2329	0.6633	0.1541	0.2768
drinkdaily	-0.3628	0.3432	0.0000	(omitted)	0.1757	0.5313
Diet Habits						
fruit	0.6404	0.5859	0.1625	0.5554	0.1617	0.4439
meet	0.1737	0.2802	0.4994	0.4912	0.1097	0.2193
egg	0.2021	0.2336	0.0585	0.4808	0.0217	0.2228
fish	-0.3803	0.2936	0.0249	0.4295	0.0583	0.2558
rice	-0.0868	0.2508	0.6547	0.4891	0.3038	0.2467
corn	-0.8160	0.3250	0.4380	0.5533	0.0000	(omitted)
vegetables	-0.1439	0.3561	1.3172	0.5989	0.0064	0.3572
legums	-0.0793	0.2583	0.6721	0.5013	0.2829	0.2308
coldmeet	0.1720	0.2639	0.2998	0.5011	0.1184	0.2262
dairy	0.0000	(omitted)	0.7793	0.5398	0.0000	(omitted)
sweets	-0.2244	0.2458	0.0661	0.5653	0.2506	0.2488
sugarysoftdrinks	0.0000	(omitted)	0.6675	0.7498	0.0762	0.4148
fastfood	0.9548	0.4694	0.0000	(omitted)	0.4336	0.8255
appetizers	0.1567	0.6311	0.0000	(omitted)	0.7560	0.5378
naturaljuice	0.1881	0.2904	0.4621	0.5209	0.5994	0.2256
Cons	-4.1977	1.0081	2.7139	1.3057	3.3637	0.9208
Observations Number	808		151		640	
LR chi2	53.32		16.17		37.84	
Prob > chi2	0.0002		0.6459		0.0135	
Pseudo R2	0.2468		0.237		0.174	
Log likelihood	-81.37446		-26.02		89.834	

Note: The variable "nationality" was omitted from the estimation for Asturias, the Balearic Islands, and the Canary Islands because the model automatically excluded it due to collinearity or lack of variability. No observations in Ceuta and Melilla on which to perform probit model. Data source: Own elaboration from EHSS.

Table. 4.5 (continuation): Estimation of probit model on suffering from others mental health problems. Spain. Year 2019-2020.

Variable	Cantabria		Castilla y León		Castilla - La Mancha	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.1900	0.2753	-0.3866	0.2733	-0.6020	0.2704
age	0.0094	0.0092	0.0109	0.0101	-0.0211	0.0095
maritalstatus	0.7586	0.3090	0.5503	0.3277	0.4362	0.3227
noeducation	0.5568	0.5593	0.3826	0.3051	0.2296	0.3296
Health Status						
saghs	1.0703	0.3371	0.0555	0.2815	-0.9197	0.3348
chronicdisease	0.0000	(omitted)	0.0000	(omitted)	1.0894	0.4988
Lifestyle						
physicalactivity	0.0000	(omitted)	0.0000	(omitted)	0.6379	0.4784
smoke	0.1315	0.3287	0.0000	(omitted)	-0.1744	0.3611
drinkdaily	0.4183	0.3613	-0.7639	0.4238	0.0000	(omitted)
Diet Habits						
fruit	0.0694	0.3825	0.0000	(omitted)	0.0000	(omitted)
meet	0.0107	0.2634	-0.3077	0.3330	-0.0650	0.3446
egg	0.1956	0.2530	0.2085	0.2767	-0.2521	0.2569
fish	0.0545	0.2600	-0.5766	0.2754	-0.2965	0.2561
rice	0.1991	0.2997	0.2552	0.3447	0.0000	(omitted)
corn	0.5470	0.5064	-0.6662	0.5746	0.0000	(omitted)
vegetables	0.0914	0.3623	0.0000	(omitted)	0.5204	0.5709
legums	0.6289	0.4202	0.4852	0.2740	0.2999	0.2652
coldmeet	0.4074	0.3128	0.0575	0.2949	0.1168	0.2907
dairy	0.1509	0.4048	0.0837	0.5477	0.0000	(omitted)
sweets	0.3071	0.2692	-0.0076	0.3078	0.2612	0.2802
sugarysoftdrinks	0.1887	0.6527	0.8956	0.4212	-0.0518	0.3958
appetizers	0.0000	(omitted)	0.1053	0.7564	0.7835	0.7033
naturaljuice	0.0825	0.4341	-0.6017	0.6085	0.6809	0.5124
Cons	2.3620	1.0525	-2.1441	0.9580	-2.3238	1.0085
Observations Number	414		556		775	
LR chi2	30.84		31.62		40.63	
Prob > chi2	0.0574		0.0244		0.0017	
Pseudo R2	0.1793		0.2179		0.2485	
Log likelihood	-70.55		-56.73		-61.4297	

Note: The variables "nationality" and "fast food" were omitted from the estimation for Cantabria, Castilla y León, and Castilla-La Mancha because the model automatically excluded them due to collinearity or lack of variability. No observations in Ceuta and Melilla on which to perform probit model. Data source: Own elaboration from EHSS.

Table. 4.5 (continuation): Estimation of probit model on suffering from others mental health problems. Spain. Year 2019-2020.

Variable	**Cataluña**		**Comunitat Valenciana**		**Extremadura**	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.2229	0.1749	-0.1460	0.1466	0.1215	0.3239
age	0.0009	0.0060	-0.0018	0.0050	0.0049	0.0135
nationality	0.3845	0.4068	-0.1723	0.3011	0.0000	(omitted)
maritalstatus	0.4316	0.2083	0.4815	0.1868	0.0326	0.4409
noeducation	0.2699	0.2494	0.5883	0.1785	0.3478	0.3953
Health Status						
saghs	0.5510	0.1874	-0.3454	0.1518	0.4407	0.3874
chronicdisease	1.0506	0.2974	1.0800	0.3126	0.5899	0.4792
Lifestyle						
physicalactivity	0.3281	0.2774	0.5321	0.2295	0.0525	0.5244
smoke	0.1523	0.2079	-0.1559	0.2046	0.0105	0.4208
drinkdaily	0.7156	0.4207	-0.3978	0.2776	0.0000	(omitted)
Diet Habits						
fruit	0.0025	0.2947	-0.3903	0.2026	0.1199	0.5652
meet	0.1112	0.2272	-0.0524	0.1572	0.1472	0.3720
egg	0.4572	0.2101	0.1455	0.1427	0.0412	0.4125
fish	0.8056	0.2182	-0.1702	0.1517	0.2476	0.3479
rice	0.1961	0.2023	0.1505	0.2042	0.2728	0.3776
corn	0.1518	0.3036	0.1634	0.2499	1.1900	0.4848
vegetables	0.1391	0.2667	-0.2529	0.2122	0.2237	0.4486
legums	0.0187	0.1935	0.1477	0.1539	0.4041	0.3025
coldmeet	0.1944	0.1870	-0.1963	0.1557	0.0387	0.3957
dairy	0.0730	0.2777	-0.1548	0.2227	0.0000	(omitted)
sweets	0.2049	0.1753	0.3965	0.1455	0.4329	0.3889
sugarysoftdrinks	0.2984	0.2215	-0.4283	0.2658	0.3611	0.4547
fastfood	0.1079	0.2748	0.0359	0.2430	0.0000	(omitted)
appetizers	0.4170	0.4412	0.4094	0.2404	0.0000	(omitted)
naturaljuice	0.0179	0.2043	0.2592	0.1656	0.1698	0.3702
Cons	2.6750	0.7412	-2.6557	0.5998	1.7121	1.2610
Observations Number	2,109		1,851		698	
LR chi2	99		108.65		23.18	
Prob > chi2	0		0		0.2802	
Pseudo R2	0.2716		0.2194		0.2049	
Log likelihood	132.73		-193.239		44.978	

Note: No observations in Ceuta and Melilla on which to perform probit model. Data source: Own elaboration from EHSS.

Table. 4.5 (continuation): Estimation of probit model on suffering from others mental health problems. Spain. Year 2019-2020.

Variable	Galicia		Madrid		Murcia	
	Coef	**Std.Err.**	**Coef**	**Std.Err.**	**Coef**	**Std.Err.**
Personal Characteristics						
gender	0.2908	0.1913	0.0258	0.1775	0.1549	0.2620
age	0.0009	0.0075	0.0142	0.0060	0.0003	0.0082
nationality	0.7292	0.5841	-0.1410	0.3478	0.4363	0.6460
maritalstatus	0.3294	0.2405	0.6940	0.2083	0.8947	0.3025
noeducation	0.6633	0.2279	0.3136	0.2190	0.4967	0.2582
Health Status						
saghs	0.8231	0.2190	-0.4839	0.1813	-0.4023	0.2520
Lifestyle						
physicalactivity	0.1440	0.2575	0.2073	0.2231	0.3765	0.3970
smoke	0.1396	0.2864	0.1765	0.2312	0.1285	0.2989
drinkdaily	0.4991	0.2940	-0.3743	0.3223	-0.2962	0.3752
Diet Habits						
fruit	0.0373	0.2632	0.2794	0.3535	0.5772	0.5212
meet	0.0164	0.2049	-0.0331	0.1861	-0.1613	0.2517
egg	0.0159	0.1920	0.1053	0.1702	-0.1265	0.2257
fish	0.0596	0.1970	0.0114	0.1764	0.1404	0.2492
rice	0.3198	0.2637	-0.1513	0.1733	0.1002	0.3698
corn	0.2860	0.3163	-0.1975	0.2688	0.5302	0.5817
vegetables	0.0398	0.2257	0.1532	0.3061	-0.2666	0.4157
legums	0.0030	0.2127	0.3485	0.1731	-0.1404	0.2440
coldmeet	0.0089	0.2212	0.1361	0.1732	-0.2104	0.2676
dairy	0.2579	0.3828	0.0000	(omitted)	0.0000	(omitted)
sweets	0.1349	0.1817	0.1022	0.1685	-0.1184	0.2368
sugarysoftdrinks	0.0639	0.3662	0.3586	0.2253	0.3391	0.3357
fastfood	0.2060	0.3607	0.7691	0.3424	0.8675	0.4604
appetizers	0.4455	0.4013	-0.6163	0.4216	-0.6069	0.6044
naturaljuice	0.3255	0.2315	0.0567	0.1813	-0.4422	0.2963
Cons	1.0649	0.8711	-3.3792	0.6896	-3.4007	1.2371
Observations Number	898		1,321		584	
LR chi2	47.24		51.14		43.98	
Prob > chi2	0.0031		0.0007		0.0053	
Pseudo R2	0.167		0.1548		0.2068	
Log likelihood	117.79		-139.63156		84.3308	

Note: The variable "chronicdisease" was omitted from the estimation for Cantabria, Castilla y León, and Castilla-La Mancha because the model automatically excluded them due to collinearity or lack of variability.No observations in Ceuta and Melilla on which to perform probit model. Data source: Own elaboration from EHSS.

Table. 4.5 (continuation): Estimation of probit model on suffering from others mental health problems. Spain. Year 2019-2020.

Variable	Navarra		País Vasco		Rioja, La	
	Coef	Std.Err.	Coef	Std.Err.	Coef	Std.Err.
Personal Characteristics						
gender	-1.6439	0.5999	0.2560	0.2506	0.2934	0.5537
age	0.0107	0.0164	0.0217	0.0091	0.0106	0.0146
maritalstatus	0.1340	0.4833	0.9486	0.2609	0.9100	0.6531
noeducation	1.2141	0.7032	0.4060	0.3175	0.3129	0.6249
Health Status						
saghs	-0.6321	0.5246	0.8060	0.2704	1.1349	0.6561
Lifestyle						
physicalactivity	-0.1936	0.5273	0.4637	0.3141	0.0000	(omitted)
smoke	0.1468	0.6357	0.5412	0.3051	0.0000	(omitted)
drinkdaily	-0.3905	0.5337	1.2708	0.5099	0.1895	0.5425
Diet Habits						
fruit	0.0000	(omitted)	0.5815	0.4122	0.6477	0.6453
meet	0.0000	(omitted)	0.4267	0.2824	1.0585	0.6816
egg	1.6075	0.7690	0.0475	0.2442	0.1314	0.4827
fish	0.0422	0.4349	0.0551	0.2483	0.6137	0.4897
rice	0.3037	0.4674	0.1641	0.2384	0.3152	0.4769
corn	-0.9275	0.8028	1.3124	0.3534	0.3797	0.7693
vegetables	0.0000	(omitted)	0.9973	0.5047	0.1015	0.7186
legums	-0.2300	0.4312	0.0641	0.2423	0.0203	0.5197
coldmeet	-0.2917	0.4506	0.5457	0.3166	0.5269	0.5586
dairy	0.0000	(omitted)	0.0000	(omitted)	1.2230	0.8413
sweets	-0.1182	0.4252	0.3449	0.2404	0.0691	0.4641
sugarysoftdrinks	0.8338	1.0211	0.1008	0.4688	0.0000	(omitted)
appetizers	0.0000	(omitted)	1.0873	0.4977	0.0000	(omitted)
naturaljuice	0.3475	0.5179	0.1010	0.2683	0.2790	0.5032
Cons	-2.1039	1.4828	3.1132	0.7827	1.9819	1.7020
Observations Number	263		666		182	
LR chi2	26.48		77.97		17.23	
Prob > chi2	0.0661		0		0.5071	
Pseudo R2	0.3377		0.3269		0.2626	
Log likelihood	-25.976181		80.262		-24.2	

Note: The variables "nationality", “chronicdisease” and "fast food" were omitted from the estimation for Navarra, Basque Country and Rioja because the model automatically excluded them due to collinearity or lack of variability. No observations in Ceuta and Melilla on which to perform probit model. Data source: Own elaboration from EHSS.

The table 4.3, detailed in the appendix, focuses on outcomes derived from probit models concerning the incidence of depression. Looking at personal characteristics, the gender variable consistently shows a positive sign across all outcomes, indicating that women in Spain and all AC are more likely to experience depression than men. Similarly, the results suggest that, overall, higher age increases the likelihood of depression in Spain and most communities. In communities where the sign is negative, the effect is relatively small. Regarding nationality, results vary among communities, but on a national level, individuals with Spanish nationality are more likely to experience depression.

Results concerning marital status exhibit some instability across AC, but, overall, being single increases the likelihood of experiencing depression in Spain. It's essential to note that this instability may be due to the presence of other marital statuses, such as separated, divorced, or widowed.

In terms of education, it is observed that in most communities and for Spain as a whole, being illiterate or having no formal education increases the probability of experiencing depression.

Health status indicators show a high degree of stability with respect to depression. Individuals who perceive their health as good or very good have a lower probability of experiencing depression in Spain and all AC. Conversely, those reporting chronic illnesses have a higher probability of experiencing depression.

Lifestyle-related variables exhibit relatively consistent patterns. Individuals who do not engage in physical activity and smoke daily have a greater likelihood of experiencing depression in both Spain and all AC. Daily alcohol consumption in Spain is generally associated with a higher probability of depression, although results vary across AC, possibly due to cultural differences in wine consumption during meals.

Moreover, regarding dietary habits, there is a lack of consistency across AC, so we rely on results for Spain as a whole. Foods that do not significantly increase the likelihood of depression include fruits, meat, eggs, fish, cereals, vegetables, processed meats, and fast food. Conversely, foods associated with a higher likelihood of depression include rice, legumes, dairy products, sweets, sugary beverages, salty snacks, and natural juices. Notably, fast food consumption has particular significance in dietary habits.

Analyzing the information in Table 4.4, which outlines the results of a probit model examining chronic anxiety and lifestyles across various autonomous regions, the key findings can be summarized as follows.

The observed signs in the results, indicating the probability of experiencing anxiety, align with expectations and remain relatively stable across all AC concerning personal characteristics, respondent health status, and lifestyle factors. However, the results show more variability when it comes to dietary habits across these regions.

At both the national level (Spain) and across AC, the following findings emerge regarding chronic anxiety and personal characteristics. The "gender" variable consistently exhibits a positive coefficient, suggesting that women have a higher likelihood of experiencing chronic anxiety compared to men. Additionally, it is noted that, both in Spain and many autonomous regions, as an individual's age increases, the likelihood of suffering from chronic anxiety decreases. This pattern holds true in most AC when considering marital status, with singles being less prone to anxiety in Spain and many autonomous regions, although there are exceptions in some areas.

Regarding education, diverse results are observed. In the context of Spain, individuals with no formal education or those who are illiterate show a higher probability of experiencing anxiety. However, differences in this regard are noted when examining results by AC.

Consistent results are found in both Spain and across the AC when assessing health status. Specifically, respondents who perceive themselves to be in good health have a lower probability of experiencing anxiety, while individuals with chronic illnesses have a higher probability.

Results related to the lifestyles of respondents show some instability in both Spain and the AC. Generally, in both Spain and the majority of autonomous regions, frequent engagement in physical activity, as well as excessive tobacco and alcohol consumption, is associated with a higher likelihood of anxiety.

Regarding dietary habits, instability is observed in both Spain and the AC. In Spain, a high consumption of fruits, meat, fish, cereals, legumes, processed meats, and sugary beverages does not result in a higher likelihood of experiencing anxiety. Conversely, a high consumption of eggs, rice, vegetables, dairy products, sweets, fast food, snacks, and natural fruit juices is associated with a greater likelihood of experiencing anxiety.

From the results obtained regarding the presence of other mental illnesses in relation to independent variables, it is noteworthy to highlight the stability of the signs of the coefficients of the explanatory variables associated with health status and personal characteristics, both at the level of the AC and in the entirety of Spain. In particular, these results reveal that some variables are frequently omitted in the models. In summary, when analyzing the results of all the explanatory variables, the following is obtained.

Within personal characteristics, the gender variable indicates that being female in Spain does not have a higher probability of suffering from other mental illnesses;

However, this result is not consistent across different AC. With increasing age, there is a higher likelihood of experiencing other mental illnesses both in Spain and in all AC.

This is also observed in the case of being single. Single individuals have a higher likelihood of experiencing other mental health disorders both in Spain and in the majority of AC.

Similarly, individuals with no education are at a higher risk of suffering from other mental health issues in Spain and virtually in all AC.

Regarding self-perceived health status, respondents who consider themselves to have poor health are at a greater risk of facing other mental health problems, which also occurs in the presence of chronic diseases. In the case of smoking and frequent alcohol consumption, it does not seem to generate a higher probability of experiencing other mental health problems in Spain and some AC.

Dietary habits and their impact on the likelihood of experiencing other mental health issues vary across AC. When examining the case of Spain as a whole, it is observed that the frequent consumption of fruits, fish, cereals, and cured meats is not associated with a higher likelihood of experiencing other mental health problems. In contrast, the frequent consumption of other foods does show such an association.

4.6 Conclusions

A healthy lifestyle is crucial for maintaining and improving physical and mental health over time. Given the significant impact of prevention and improvement policies on this matter, it is necessary to identify factors that contribute to a higher risk of mental health issues. This study aims to delve into and differentiate how lifestyle-related factors affect various mental health problems such as depression, anxiety, and other mental health issues. The proposed model utilizes microdata from the EHSS, revealing that different factors associated with lifestyles have varying effects depending on the mental health problem under examination. It is crucial to consider the specific nature of mental illness when developing and implementing measures or policies, as our results demonstrate that the relevant factors for these initiatives have differentiated effects. Each mental disorder exhibits distinctive characteristics that necessitate individualized approaches, underscoring the importance of tailoring interventions to the unique features of each condition. Furthermore, there is an emphasis on the need to conduct studies that identify the factors and their mechanisms of action to provide more accurate information and enable the development of intervention strategies. In conclusion, a healthy lifestyle not only helps prevent diseases but also contributes to overall well-being, both physically and mentally, enhancing the quality and duration of life and enabling more precise actions based on the specific mental health issue.

Chapter 5. Urban Bustle vs Rural Serenity: Analysis of Disparities in Mental Health Based on Residential Environment

5.1 Introduction

The environment in which individuals live can exert a profound influence on their quality of life and overall well-being, particularly in relation to their physical and mental health. While personal preferences undoubtedly play a key role in the decision of where to reside, the choice between living in a rural or urban area often involves more than individual inclination, it reflects a broader set of lifestyle differences and contextual factors. As highlighted by Jansen (2020), both rural and urban settings offer a range of advantages and disadvantages, which may vary depending on socioeconomic status, cultural background, or life stage.

In this context, a growing number of studies have documented significant disparities in the prevalence of mental health symptoms and disorders between countries with different levels of income (López-Díaz et al., 2022). However, even within a single country, meaningful differences can be found across geographical áreas, urban, semi-urban, and rural, due to variations in income distribution, employment opportunities, and access to essential services (Thiede et al., 2020). These economic differences are closely linked to disparities in mental health outcomes and general well-being (Nasrudin & Resosudarmo, 2023).

Rural life is often associated with a quieter, more serene environment, which contrasts sharply with the fast-paced rhythm of city living. The relative absence of noise, pollution, and social overstimulation can foster a sense of peace and relaxation, making rural areas particularly attractive to those seeking relief from urban stress. Moreover, smaller populations in these settings often promote stronger interpersonal relationships and a closer connection to the community, which have been linked to enhanced emotional and psychological well-being (Batterham et al., 2022). In economic terms, rural areas also tend to offer a lower cost of living, housing, food, and basic services are generally more affordable, contributing to a more sustainable and less pressured lifestyle (Lagakos, 2020).

Conversely, urban areas offer a distinct set of benefits, including greater access to healthcare services, education, cultural activities, entertainment, and a broader range of professional opportunities. These features represent key attractions for many individuals, particularly younger populations and those seeking to expand their personal or professional horizons (Burger et al., 2020).

In recent decades, global trends indicate a steady migration of populations from rural to urban and semi-urban areas. Projections by Jiang and O'Neill (2017) suggest that by 2050, the global population could reach between 8.5 and 9.9 billion, with as much as 78% residing in urban environments. This rapid and ongoing urbanization is reshaping not only the physical structure of cities but also the social dynamics and lifestyles of their inhabitants. In parallel, semi-urban zones have emerged as hybrid spaces that combine the amenities of city life with certain elements of rural tranquility, offering a perceived “best of both worlds.”

Although rural environments may offer benefits related to psychological well-being and mental health, urbanization continues to draw a growing share of the population. However, this process has been associated with complex and sometimes adverse effects. For instance, Ventriglio et al. (2021) and van der Wal et al. (2021) highlight a nonlinear and positive relationship between urbanization levels and the prevalence of mental health disorders, particularly in highly urbanized countries.

Against this backdrop, the aim of this study is to examine how an individual’s place of residence, be it urban, semi-urban, or rural, affects their mental health, and to identify the specific factors that are most influenced by geographical location.

The structure of this study is organized as follows: Section 2 presents a review of the relevant literature; Section 3 describes the methodology and data used; Section 4 outlines the results obtained from the regression models; and Section 5 discusses the main findings and concludes.

5.2 Review literature

The relationship between individuals' mental health and their residential environment has attracted considerable academic attention, largely due to its multifaceted nature and growing relevance in public health discourse. A growing body of evidence suggests that individuals residing in urban areas are more susceptible to experiencing mental disorders compared to those living in rural or semi-rural settings (Alcañiz et al., 2020). However, it is essential to recognize that the determinants of mental health are not uniform; rather, they encompass a wide array of social, environmental, and personal factors that can vary significantly from one individual to another.

Several studies have highlighted a consistent association between urban living and an elevated risk of mental health issues. Over recent decades, the interplay between the physical environment and emotional well-being has become increasingly prominent in research. Variables such as access to green spaces, levels of pollution, and proximity to natural landscapes have emerged as key factors influencing psychological and emotional health (Krabbendam et al., 2021). These environmental components do not act in isolation; instead, they interact with social conditions and individual characteristics, shaping the mental health landscape in distinct ways across geographic settings.

For instance, Lanza-León et al. (2023) found that exposure to, usage of, and proximity to green areas positively impact mental health across different population groups, including older adults, students, and individuals with pre-existing health conditions. In contrast, long-term exposure to air pollution, particularly that stemming from urban traffic, has been shown to correlate with worsening mental health outcomes, as evidenced by the findings of Bakolis et al. (2021).

In line with this, research by Zhu et al. (2021) underscores the mental health benefits of living in nature-rich rural environments. These settings offer not only aesthetic and recreational advantages but also measurable psychological benefits, reinforcing the notion that contact with nature is a protective factor for mental health. On the other hand, densely populated urban areas are more prone to outbreaks of infectious diseases, due to close human interaction and easier pathogen transmission, which adds another layer of public health concern in urban epidemiology.

Beyond the physical environment, social and framework elements also play a pivotal role. Neighborhood safety, perceived comfort, and the sense of community belonging can deeply influence individuals' psychological well-being. Baranyi et al. (2021), for example, demonstrated that exposure to neighborhood crime is a significant predictor of mental health disorders. Similarly, a strong sense of security and emotional attachment to one's residential environment is associated with positive mental health outcomes, whereas chronic exposure to environmental stressors—such as noise pollution—can lead to increased stress, emotional discomfort, and reduced feelings of belonging (Kou et al., 2021).

Social connectedness also emerges as a critical determinant of mental health. While urban areas typically offer more opportunities for social interaction, they may also foster superficial relationships or exacerbate feelings of loneliness when meaningful connections are lacking. Importantly, this issue is not exclusive to cities; rural environments, due to their lower population density and reduced access to services, may also present barriers to social inclusion, potentially leading to social isolation (Evans & Fisher, 2022).

In summary, mental health is shaped by a complex and dynamic interaction of environmental, social, and individual-level factors. Understanding these relationships is essential for informing public health strategies that aim to promote psychological well-being across diverse residential contexts.

5.3 Data and Methodology

5.3.1 Data

This study draws on data from the SHARE, a rich and comprehensive source of information widely used in social and health research.

SHARE targets individuals aged 50 and over and is conducted across 27 European countries, as well as Israel. One of the main strengths of this survey lies in its longitudinal and multidisciplinary design, which allows for the collection of detailed microdata on a broad range of dimensions, including health status, socioeconomic conditions, and social and family networks. With a panel of over 140,000 individuals, SHARE facilitates the analysis of how health, social, economic, and environmental factors interact over time and across countries. Since its launch in 2004, the survey has collected multiple waves of data, with continuous updates until 2020, including two special waves dedicated to capturing the impact of the COVID-19 pandemic.

For the purposes of this study, we use the most recent and complete data available at the time of analysis: the beta version of wave 8, which corresponds to interviews conducted during 2019 and the early part of 2020. Although later waves exist, they are more limited in scope, focusing specifically on the effects of the pandemic, and do not provide the same breadth of information as wave 8.

Despite the international scope of SHARE, our analysis focuses exclusively on data from Spain. The decision to use this survey is justified not only by its extensive geographic coverage and high-quality data but also by its ability to provide a large, harmonized dataset that reflects the contemporary socioeconomic and health landscape. This makes it particularly suitable for analyzing complex phenomena such as the relationship between place of residence and mental health.

The original sample size for wave 8 across all participating countries is approximately 66,065 respondents. However, once we apply selection criteria to retain only those individuals with complete and valid responses for all variables of interest, the final analytical sample for Spain is reduced to 3,168 observations.

5.3.2 Variables Selection

The dependent variable in this study is designed to address the main objective: estimating the likelihood of an individual experiencing mental health problems based on a range of personal, contextual, and environmental characteristics. This variable, referred to as "Mental Health", is constructed using information from the SHARE survey, which asks respondents whether they have experienced symptoms associated with mental health disorders. To operationalize this, the study relies on the EURO-D scale, a validated tool for measuring depressive symptoms in older European populations (Tomas et al., 2022). The EURO-D scale assesses the presence or absence of twelve specific symptoms, such as sadness, sleep disturbances, lack of interest, irritability, and loneliness, assigning a value of 1 or 0 to each. The total score ranges from 0 (no symptoms) to 12 (presence of all symptoms).

However, interpreting this score poses certain challenges, as there is no universally accepted threshold that defines what constitutes "normal" or "abnormal" mental health. The same score may reflect different levels of emotional well-being across individuals. This lack of consensus highlights the complexity of defining mental health "normality", which goes beyond the mere absence of symptoms and includes aspects of functionality and subjective well-being. Given this ambiguity, we follow criteria established in the literature to define mental health problems. Specifically, studies by Castro-Costa et al. (2007) and Guerra et al. (2015) identify a score of four or higher on the EURO-D scale as the optimal cut-off point for detecting poor mental health, as it aligns with clinical diagnoses from both the DSM-IV and the GMS/AGECAT classification systems. These studies also confirm the internal consistency and validity of the EURO-D scale within the context of the SHARE survey. Based on this evidence, we classify individuals as having poor mental health when their EURO-D score is equal to or greater than four. The dependent variable is then constructed as a binary indicator: it takes the value 1 if the individual suffers from poor mental health, and 0 otherwise.

In addition to this primary variable, we include several explanatory variables to capture predisposing, enabling, and need-related factors that may influence mental health outcomes. These variables span four main dimensions: sociodemographic characteristics, health status, lifestyle factors, and perceptions of the residential environment. Regarding sociodemographic variables, we include age, categorized into three groups (50–64, 65–80, and over 80 years), sex, coded as 1 for female and 0 for male, and educational attainment based on the ISCED-97 international classification. This classification defines seven education levels, which we group into four categories for this analysis: no education (level 0), low (levels 1 and 2), medium (levels 3 and 4), and high (levels 5 and 6). Education is treated as a categorical variable.

Health-related variables include self-perceived health status, classified into three levels: poor (value 1), fair/good (value 2), and very good/excellent (value 3). Physical inactivity is represented as a binary variable, where 1 indicates no physical activity and 0 indicates that the individual is physically active. Limitations in ADLs are captured by another binary variable, with 1 denoting the presence of functional limitations and 0 their absence. The number of chronic conditions is similarly coded: 1 if the respondent suffers from at least one chronic illness, and 0 otherwise.

Finally, we incorporate variables related to the respondent's living environment, as existing research has shown the relevance of residential context for mental health. These include the sense of belonging to the neighborhood, the perception of receiving help from others in emergencies, and views on local conditions such as cleanliness, vandalism or crime, and general comfort. Additional indicators capture the ease of access to basic services, including supermarkets, banks, pharmacies, and health centers. As shown in Table 5.1, all variables are clearly defined and coded for inclusion in the econometric model, classified as binary, categorical, or continuous according to their structure.

Table 5.1. List of variables and codes

Variable	Label	Coding
Mental Health	Respondent's mental health status	1: respondent has suffered from mental health problems; 0: otherwise
Age	Respondent's age	0: the respondent's age is between 50 and 64; 1: the respondent´s age is between 65 and 80; and 2: the respondent´s age is over 80
Gender	Respondent´s gender	1: female; 0: man
Education	Education Code ISCED-97	0: No education; 1: low educational level; 2: level of secondary education; 3: high level of education
Health	Self-perceived health status	0: bad; 2: 1: fair and good; 2: very good and excellent
Phactiv	Physical inactivity	1: no physcical activity; 0: physical activity
ADL	Number of limitations in daily activity	1: limitations in ADL; 0: no limitations in ADL
Nchronic	Number of chronic diseases	1: suffering from a chronic disease; 0: in case of not suffering from any problem.
Feeling	Feeling part of this area	1: Agree; 0: Disagree
Vandal	Vandalism/Crime is a big problem in this area	1: Agree; 0: Disagree
Clean	Area is kept very clean	1: Agree; 0: Disagree
Help	If the respondent had problems, someone in the area would help them	1: Agree; 0: Disagree
Shops	How easy to get to the nearest grocery shop or supermarket	1: easy; 0: difficult
Bank	How easy to get to the nearest bank or cash point	1: easy; 0: difficult
Healthcentre	How easy to get to your general practitioner or the nearest health center	1: easy; 0: difficult
Pharma	How easy to get to the nearest pharmacy	1: easy; 0: difficult

Author: Own elaboration based on SHARE survey.

5.3.3 Methodology

In this study, the SHARE database is utilized. Based on this information and given the established objective, the dependent variable of our study is mental health, i.e., whether individuals suffer from mental health problems or not. On one hand, it is worth noting that, relative to the questions on the scale that lead to determining whether the respondent has mental health problems, SHARE refers to factors that could have been considered as independent variables. Therefore, 15 sociodemographic and health factors are considered explanatory variables. To analyze the potential factors associated with the place of residence of the respondents that affect their mental health among Spanish individuals over 50 years old, nonlinear models are employed using the statistical software package STATA.18. Specifically, binary logistic regressions are specified (Browne and Rasbash, 2004; Fairbrother, 2014). These types of models provide bounded results within a characteristic probability interval [0, 1]. Likewise, they can infer the causal effect of one or more treatments and are characterized by having a dependent variable that is a dichotomous variable taking the value one or zero depending on the chosen outcome. It is understood that they suffer from mental health problems if it takes the value one and zero otherwise. Therefore, the conditional expectation of Yi with respect to the explanatory variables, i.e., that they suffer from mental health problems, given the selected characteristics and considering that F is the selected logistic function, is represented as:

$$E[Y_i] = P_i = F(\beta_1 + \beta_2 X_{2i} + \cdots + \beta_k x_k) = \frac{\exp\,(\beta_1 + \beta_2 X_{2i} + \cdots + \beta_k x_k)}{1 + \exp\,(\beta_1 + \beta_2 X_{2i} + \cdots + \beta_k x_k)}$$

In this regard, adjusted odds ratios (OR) are calculated, which measure the magnitude of the effects. Likewise, 95% confidence intervals (CI) are established and we consider three different p-values significant: 0.01, 0.05, and 0.10. Therefore, the OR informs about the relationship between the average probabilities of reporting the risk factor in the outcome (in this case, suffering from mental health problems) and the average probabilities of reporting the risk factor when the individual suffers some consequences of the explanatory variables. If we obtain an OR greater than 1, it implies an increase in the risk factor variable when measuring the outcome (i.e., a higher probability of suffering from mental health problems). Conversely, if we obtain an OR less than 1, it shows a decrease in the risk factor variable when measuring the outcome (i.e., a lower probability of suffering from mental health problems).

5.4 Results

This section presents the findings of the logistic regression analysis, aimed at exploring how various independent variables relate to the probability of experiencing mental health problems within the studied population. Logistic regression enables us to assess the strength and direction of associations between a set of predictor variables and a binary outcome, in this case, the presence or absence of mental health issues.

Table 5.2. Descriptive statistics of the analytical sample

	All sample	City	Semi-rural	Rural
mental heatlh	0.318	0.293	0.323	0.328
age				
50-64	0.220	0.228	0.222	0.176
65-80	0.455	0.451	0.460	0.397
>80	0.325	0.321	0.318	0.426
Gender	0.575	0.636	0.561	0.564
Education				
No education	0.242	0.149	0.259	0.304
Low	0.546	0.559	0.542	0.564
Medium	0.104	0.136	0.100	0.064
High	0.107	0.156	0.099	0.069
Health				
Bad	0.128	0.142	0.124	0.132
Normal	0.689	0.650	0.695	0.735
Excellent	0.183	0.208	0.181	0.132
Phactiv	0.161	0.202	0.152	0.137
ADL	0.115	0.111	0.115	0.113
Nchronic	0.809	0.774	0.812	0.873
Feeling	0.958	0.955	0.959	0.961
Vandal	0.154	0.218	0.138	0.157
Clean	0.883	0.823	0.893	0.931
Help	0.905	0.935	0.898	0.907
Bank	0.826	0.952	0.831	0.417
Shops	0.872	0.966	0.881	0.500
Healthcentre	0.838	0.925	0.846	0.495
pharma	0.879	0.969	0.891	0.475

Source: Authors' calculations based on SHARE Survey.

Table 5.2 provides a descriptive overview of the sample, broken down by urban, semi-rural, and rural areas. A first glance reveals that the prevalence of reported mental health problems is slightly higher in rural settings compared to cities and semi-rural areas. This initial finding, though modest, sets the stage for more detailed analyses.

Age distribution also varies across settings. The proportion of individuals aged over 80 is significantly higher in rural areas, whereas the younger segments (50–64 and 65–80) are more prevalent in urban and semi-rural areas. Educational attainment follows a clear pattern: rural areas report the lowest levels of formal education, while cities show the highest proportion of individuals with medium and high levels of education.

Interestingly, despite having more chronic conditions, rural residents report higher levels of physical activity and better self-rated health. This may point to different health perceptions or lifestyle adaptations across geographic contexts. In terms of environmental and service-related variables, rural dwellers report greater difficulties accessing public services such as banks, shops, and healthcare facilities. However, they tend to perceive their surroundings as cleaner and express a stronger sense of social support.

Table 5.3. Logistic regression results.

	All sample (N=3,168)		City (N=583)		Semi-rural (N=2,381)		Rural (N=204)	
	OR	CI	OR	CI	OR	CI	OR	CI
Age								
65-80	0.754	[0.594-0.958]	1.171	[0.660-2.077]	0.76 **	[0.574-1.000]	0.165 ***	[0.053-0.515]
>80	0.815	[0.624-1.065]	1.373	[2.566-3.427]	0.82	[0.598-1.120]	0.25 **	[0.082-0.759]
Gender	2.154	[1.795-2.584]	2.169 ***	[1.373-23.427]	2.1 ***	[1.699-2.588]	3.803 ***	[1.686-8.580]
Education								
Low	0.64	[0.521-0.786]	0.551 *	[0.320-0.948]	0.667 ***	[0.526-0.845]	0.678	[0.291-1.580]
Medium	0.476	[0.334-0.677]	0.565	[0.261-1.225]	0.453 ***	[0.298-0.688]	0.374	[0.058-2.433]
High	0.293	[0.200-0.429]	0.224 ***	[0.973-0.514]	0.29 ***	[0.184-0.459]	1.07	[0.200-5.719]
Health								
Normal	0.252	[0.192-0.331]	0.365 ***	[0.204-0.654]	0.223 ***	[0.161-0.311]	0.156 ***	[0.042-0.580]
Excellent	0.145	[0.085-0.183]	0.26 ***	[0.117-0.580]	0.1 ***	[0.064-0.160]	0.088 **	[0.013-0.589]
Phactiv	1.743	[1.359-2.235]	1.015	[0.590-1.746]	2.11 ***	[1.559-2.848]	2.451	[0.805-7.465]
ADL	2.587	[1.935-3.460]	2.758 ***	[1.394-5.456]	2.41 ***	[1.716-3.385]	2.547	[0.644-10.069]
Ncronic	2.08	[1.563-2.768]	2.073 **	[1.102-3.898]	2.042 ***	[1.462-2.852]	3.176	[0.753-13.386]
Feeling	0.488	[0.321-0.742]	0.482	[0.179--1.295]	0.493 ***	[0.303-0.802]	0.371	[0.062-2.196]
Vandal	1.479	[1.181-1.898]	0.981	[0.582-1.652]	1.762 ***	[1.325-2.344]	2.677	[0.966-7.414]
Clean	0.776	[0.593-1.015]	0.806	[0.461-1.410]	0.751 *	[0.544-1.036]	0.248	[0.048-1.273]
Help	0.63	[0.469-0.848]	0.636	[0.270-1.497]	0.665 **	[0.476-0.930]	0.635	[0.180-2.240]
Bank	1.08	[0.759-1.536]	2.225	[0.487-10.162]	1.003	[0.687-1.464]	4.754	[0.429-52.707]
Shops	0.836	[0.540-1.294]	0.266	[0.036-1.973]	0.808	[0.503-1.298]	6.934 **	[0.791-60.762]
Healthcentre	0.808	[0.569-1.147]	0.609	[0.246-1.502]	0.908	[0.613-1.344]	0.08	[0.003-2.081]
pharma	1.274	[0.786-2.064]	1.468	[0.165-13.051]	1.193	[0.703-2.023]	0.617	[0.020-18.622]
cons	3.121	[1.593-6.111]	2.908	[0.450-18.794]	3.61 **	[1.623-8.028]	13.371	[0.597-299.468]

Note: OR (Odds Ratios); CI (confidence interval).*** , **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Source: own elaboration.

The results of the logistic regression models, summarized in Table 5.3, provide more nuanced insights into the factors associated with mental health outcomes.

Starting with sociodemographic characteristics, age appears to be inversely associated with the probability of experiencing mental health problems in the full sample. However, this relationship varies by area: in urban settings, older individuals tend to report worse mental health, whereas in semi-rural and rural areas, age is associated with a lower likelihood of mental health issues.

Gender consistently emerges as a significant predictor, with women facing a notably higher risk of mental health problems compared to men, regardless of their area of residence.

Educational level is another important factor. Individuals with low, medium, or high levels of education generally show a lower probability of experiencing mental health problems compared to those with no formal education. Nonetheless, this protective effect is more evident in cities and semi-rural areas; in rural settings, higher education does not seem to offer the same mental health advantage, and in some cases, the association is even reversed.

Self-perceived health status is strongly associated with mental well-being across all areas. Those reporting normal or excellent health have significantly lower odds of experiencing mental health problems. Similarly, a sedentary lifestyle, limitations in ADLs, and a higher number of chronic conditions are all robustly linked to a greater risk of poor mental health.

Moving to environmental characteristics, the sense of belonging to one's community does not show a statistically significant impact on mental health outcomes. In contrast, the presence of vandalism is positively associated with mental health problems, particularly in semi-rural and rural contexts. Cleanliness of the residential area and the perception of social support (i.e., being able to count on help when needed) are both associated with lower mental health risk.

Access to services plays a more complex role. In urban and semi-rural areas, proximity to banks is linked to a higher risk of mental health issues, a somewhat counterintuitive result that may reflect stress related to financial management or urban crowding. Conversely, in rural areas, this relationship is particularly strong and deserves further exploration.

Access to shops and supermarkets generally corresponds to better mental health outcomes in urban and semi-rural environments. However, in rural areas, greater access to these services is paradoxically associated with an increased risk of mental health problems, perhaps reflecting underlying structural differences in how these communities operate.

In terms of healthcare services, being near a health center is consistently associated with a reduced probability of mental health problems across all geographic contexts. Access to pharmacies, however, shows a differentiated effect: in cities and semi-rural areas, proximity is linked to higher risk, while in rural settings, it appears to be a protective factor.

In sum, these findings underscore the importance of considering both individual and contextual factors when analyzing mental health. The impact of age, education, and health status is relatively consistent, while the role of environmental characteristics and access to services varies markedly across urban, semi-rural, and rural areas. These nuances highlight the need for geographically sensitive policies and interventions tailored to the specific realities of different population groups.

5.5 Discussion and conclusions

The analysis of the results concerning the area of residence reveals significant variations that shed light on the complex interplay between environmental factors and mental health outcomes.

To begin with, age presents divergent trends across different residential contexts. In urban areas, advancing age appears to be associated with an increased risk of mental health problems, whereas in semi-rural and rural settings, the opposite trend is observed. This contrast suggests that different sociocultural and economic dynamics are at play in each environment, potentially influencing the way aging impacts mental well-being.

Gender also emerges as a consistently relevant determinant. Across all areas of residence, women exhibit a higher likelihood of experiencing mental health issues. This persistent disparity highlights the importance of addressing gender-based inequalities in mental health and underscores the need for targeted interventions that respond to the specific challenges faced by women in diverse contexts.

Educational level, another key factor, reveals nuanced effects depending on the area of residence. While higher education does not appear to significantly increase mental health risks in urban and semi-rural areas, individuals in rural areas with higher educational attainment seem to face a greater risk. This may point to underlying disparities in access to mental health services or differences in expectations and available opportunities, particularly in less urbanized settings.

Perceived health status is also a strong predictor across all contexts. Individuals reporting a better subjective health perception are less likely to report mental health problems, reaffirming the value of considering self-perceived health as an integral component in the assessment and promotion of mental well-being.

In contrast, certain characteristics of the physical and social environment, such as community belonging, perceived vandalism, and cleanliness of the neighborhood, exert a limited effect on mental health risk. Notably, the perceived availability of support from neighbors in times of need does not appear to significantly influence mental health outcomes, suggesting that other dimensions of social support, such as family ties or institutional support networks, may play a more central role.

When considering access to services, proximity to healthcare centers is consistently associated with a lower risk of mental health issues, regardless of the area of residence. However, the effects of access to pharmacies and financial institutions vary depending on the type of area, reflecting the need to account for broader socioeconomic and geographical factors when designing mental health service networks.

In summary, the findings underscore the multifactorial nature of mental health and the importance of incorporating both individual and contextual variables into mental health promotion strategies. Addressing geographical and socioeconomic inequalities in service provision is essential, as is adopting an integrated and territorially sensitive approach to intervention planning. Future research should consider income levels, as both geographic (rural vs urban) and economic (high vs low income) factors are related. High-income countries or areas tend to have better access to services.

In conclusion, the risk of experiencing mental health problems varies significantly depending on both the area of residence and the specific factors under consideration. Some variables, such as gender, physical activity, chronic illness, and perceptions of the residential environment, show consistent patterns that allow for robust conclusions. In rural areas, women, individuals with chronic conditions, those who are physically inactive, and those exposed to vandalism or with easier access to banks and shops appear particularly vulnerable. These findings suggest that rural populations may be more sensitive to certain environmental and lifestyle factors, resulting in comparatively poorer mental health outcomes than their urban and semi-rural counterparts. This calls for context-specific strategies that prioritize the most influential determinants of mental health in each type of setting.

Chapter 6. Transforming Healthcare with Chatbots: Uses and Applications. A scoping review

6.1 Introduction

The COVID-19 pandemic has led to an increased use of healthcare resources. In a context of budget constraints and higher demand for resources, as well as social distancing and remote work, this has resulted in a greater use of artificial intelligence and telemedicine, aiming for efficiency and efficacy in the delivery of care and promoting health (Almalki & Azeez, 2020; LeBrón et al., 2020; Mehraeen et al., 2022, 2023; Moutsana Tapolin, Liaskos, Zoulias, & Mantas, 2023). Efficiency is understood as better use of available resources and benchmarking, as established by public organizations with their well-known spending reviews, to focus resources on the most priority areas or activities.

In this way, despite the fact that many countries have a long tradition of evaluating public spending efficiency and have increasingly focused on this issue since the Great Recession fifteen years ago, it is generally observed that many have predominantly relied on linear spending cuts. This approach has persisted even after the lessons learned during the mentioned period, reflecting a global trend toward reducing expenditures without a thorough review of efficiency and effectiveness in resource allocation.

The use of chatbots in healthcare is also being driven by international collaborations and knowledge sharing. Organizations such as the WHO have recognized the potential of artificial intelligence to improve public health and have promoted the development of guidelines and standards for the implementation of these technologies. These initiatives aim to ensure that the benefits of healthcare chatbots are accessible globally, promoting equity and quality in healthcare (World Health Organization (WHO), 2021).

In this context, related to the search for efficiency and the growing advancements in artificial intelligence, the idea of applying these technologies to medical uses has emerged. Consequently, the use of chatbots in the healthcare sector has grown significantly, becoming an innovative tool to improve patient care and optimize health processes. Aggarwal et al (Aggarwal, Tam, Wu, Li, & Qiao, 2023) approximated the following definition for "chatbot" in healthcare: "*AI chatbots are conversational agents that mimic human interaction through written, oral, and visual forms of communication with a user*". This way of defining chatbots was based on the studies of Laranjo et al (Laranjo et al., 2018) and Oh et al (Oh, Zhang, Fang, & Fukuoka, 2021). This development can help create the potential to improve health outcomes, potentially alleviating some of the burdens on healthcare providers and systems from being the sole voices of public health outreach (Powell et al., 2023).

Chatbots offer various applications in the healthcare sector, from providing information on symptoms and treatments to scheduling appointments and medication reminders but their main focus till now is within mental health, screening and public health according to Afsahi et al (Afsahi et al., 2024). For example, some studies (Ahmed et al., 2023; Lim, Shiau, Cheng, & Lau, 2022; Zhu, Wang, & Pu, 2022) showed that chatbots can be effective in the field of mental health, providing clinical support and resources to individuals needing therapeutic conversations. This use can be especially beneficial in contexts where access to mental health professionals is limited. Other uses are related to the use of chatbots for changes in patients behaviour towards healthier lifestyles (Aggarwal et al., 2023) or even chatbots are helpful in the management of chronicity (Bin Sawad et al., 2022; Kurniawan, Handiyani, Nuraini, Hariyati, & Sutrisno, 2024).

Additionally, chatbots have the potential to monitor patient health and provide early interventions. Irfan et al. (Irfan & Zafar, 2023) in their article show that chatbots can monitor health parameters such as blood pressure and glucose levels, sending alerts to medical professionals when abnormal values are detected. This not only improves the quality of care but can also prevent serious complications by allowing for early intervention.

However, despite these benefits, a significant limitation in the literature is the lack of studies estimating the costs associated with the development and implementation of these systems. Evaluating the cost-effectiveness of chatbots is crucial to ensure that their use is not only clinically beneficial but also economically viable. Studies analysing the cost-benefit relationship will help justify the investment in these technologies and promote their adoption in healthcare systems with limited resources.

Chatbots also systematically collect data through specific queries and data retrieval, improving patient engagement and quality of life. Bergmo (Bergmo, 2015) emphasizes that comprehending the costs and benefits of eHealth interventions is crucial for several reasons: it helps to demonstrate cost-effectiveness, aids in decision-making, and is vital for creating business models and payment systems that can sustain widespread services. Integrating a cost-effectiveness analysis will allow for measuring not only the costs associated with the implementation and use of these platforms but also the economic benefits derived from improved health and reduced cardiovascular events.

Through this analysis, we aim to provide a comprehensive overview of how these interactive systems are being used to facilitate communication, diagnosis, patient follow-up, and medical information management, thereby contributing to more efficient and accessible care.

6.2 Methods

6.2.1. Search strategy and eligibility criteria

We have carried out this literature review following the guidelines of Preferred Reporting Items for Literature Review and Meta-Analyses (PRISMA) (Moher et al. 2009). This review is not registered, and a protocol has not been previously published.

We have used three different databases such as PubMed, Web of Science and Scopus for the search of relevant articles published during the last 5 years to identify the most current studies published regarding regarding the use and cost of chatbots in health. The search strategy is based on mainly three selected keywords: “Chatbots”, “Health” AND “Cost within the fields “title, abstract and keywords”, depending on the database consulted (Table 6.1). Nevertheless, although the word “Costs” was a keyword in our search, this survey did not estimate the cost or savings of the chatbot.

Studies are included if they meet the following inclusion criteria: (i) full-text articles; (ii) written in English or Spanish; (iii) published in peer-reviewed journals; (iv) published in the last 5 years; (v) focused on create a chatbot for the use in medicine. Meanwhile, studies are excluded from further review if (i) results are not reported; (ii) are non-English or non-Spanish publications; (iii) are review articles, conference presentations, abstracts, editorial letters or comments; (iv) are deemed outside of the scope of the present review, that is, they do not focus on on their application in medicine.

Table 6.1. Search strategy: PubMed, Web of Science and Scopus

#	Search term
	PubMed
#1.	Chatbot* [Title]
#2.	Health Title/Abstract]
#3.	Cost [Title/Abstract]
	Web of Science
#1.	Chatbot* [Title]
#2.	Health [Title]
#3.	Cost [Title]
#4.	Limit to: journal article; year of publication <= last 5 years; English or Spanish; Web of Science Core Collection; Open Access.
	Scopus
#1.	Chatbot* [Title]
#2.	Health [Title/Abstract/Keywords]
#3.	Cost [Title/Abstract/Keywords]
#4.	Limit to: journal article; year of publication <= last 5 years; English or Spanish; All Open Access.

Source: Authors' elaboration

6.2.2. Study selection and data extraction

Using the procedure and criteria mentioned above, 231 articles are identified by the search strategy in our databases. 58 studies are found in PubMed, 123 in Web of Science and 50 in Scopus. After the exclusion of the duplicates, 169 articles are screened. Titles and abstracts are reviewed, and 86 articles do not fulfil the inclusion criteria, so they are excluded. In total, 83 studies are included for full-text screening and reviewed, of which 50 are excluded, to do this, Figures (such as flowcharts) and tables were used to synthesize the data. Therefore, the final number of studies included in this review is 33. Figure 6.1 summarised the search selection procedure as Table 6.2 shows the results.

After removing duplicates, two independent reviewers performed the first selection of the screening process. To assess the quality of the articles selected in this systematic review, the authors applied a structured methodology to ensure the rigor and reliability of the included studies. On the one hand, studies were initially assessed against predefined inclusion criteria, such as the relevance of the approach to the use of chatbots in healthcare (communication, diagnosis, patient monitoring, and medical information management), their methodological design, and the availability of complete data. Articles that did not meet these criteria were excluded. On the other hand, studies that passed the initial review were assessed by at least two independent reviewers to reduce bias in the quality assessment. In case of disagreement, both researchers discussed the article with a third reviewer and a joint decision was reached (include or exclude the article). For each of the studies selected for inclusion, one author designed a data extraction procedure that was approved by the other review authors. The extraction form included the following data: authors and year of publication, country, study objectives, population characteristics and sample size, type of nudge, duration of intervention, setting, study outcome, and outcome.

Figure 6.1. Flow diagram for the search process for identifying and including references for the systematic review

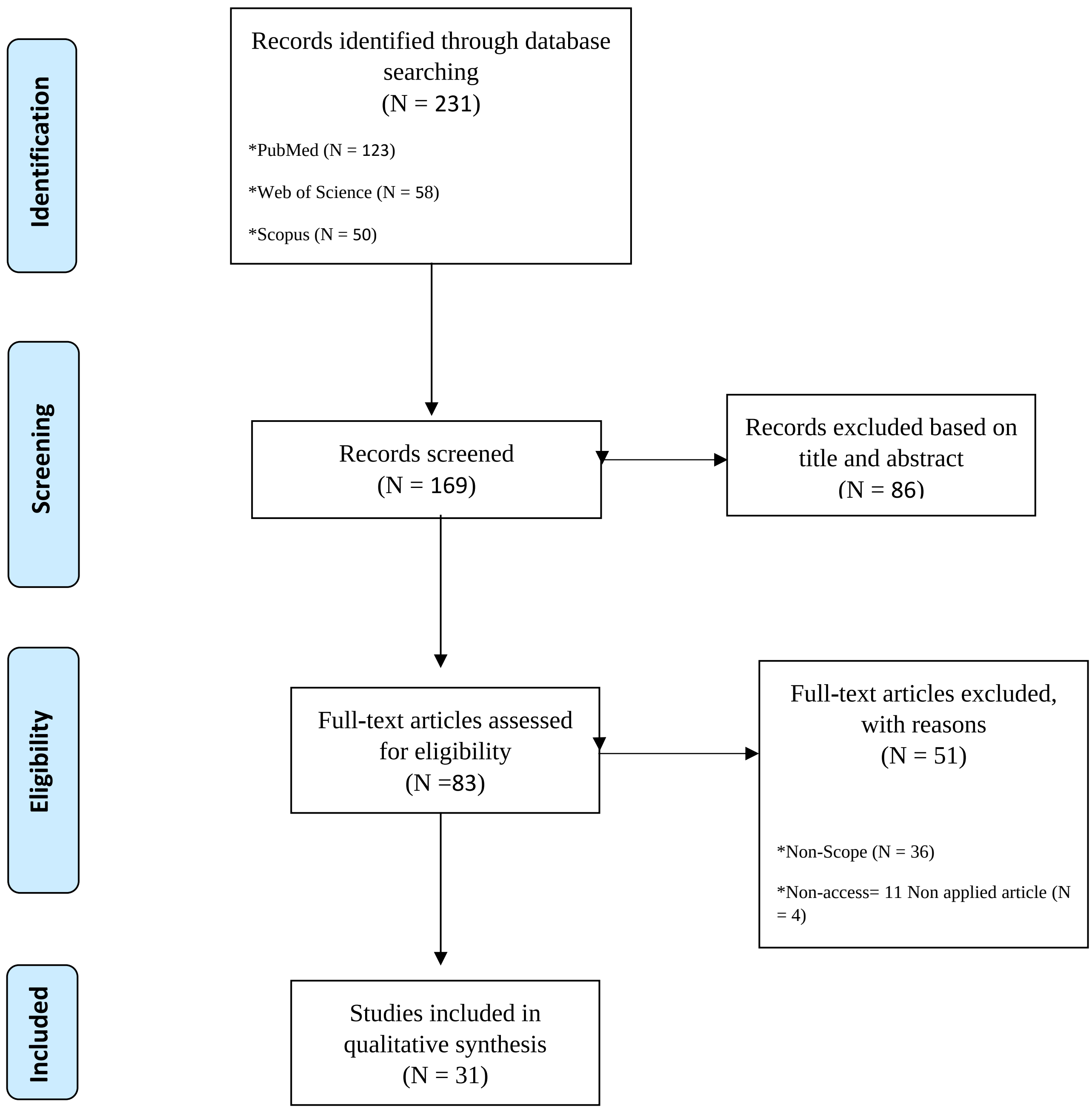


Table 6.2. Summary of the case studies

Article	Country	Objective	Population characteristics	Chatbot intervention	Intervention duration	Study outcome(s)	Results +/-
Anjum et al. (2023) (Anjum, Sameer, & Kumar, 2023)	India	To develop a health chatbot powered by AI and natural language processing, which can diagnose conditions and offer relevant information, improving healthcare accessibility while lowering expenses.	Potential patients.	Using a medical Chatbot which offers appropriate guidance on maintaining a healthy lifestyle.		NLP and machine learning are the most effective approaches for building chatbots.	Positive
Bhuvanesh et al. (2023) (Bhuvanesh Shathyan, Begam, Jashwanth, & Jayaprakash, 2023)	India	To create a chatbot that evaluates symptoms and categorizes the potential diseases the patient might be experiencing.	Patients with health issues.	A method based on knowledge graphs was proposed for developing health chatbots that evaluate patient symptoms and determine the disease based on the assessment.		The medical chatbot model based on knowledge graphs achieves 99% accuracy and can offer enhanced diagnoses as more knowledge bases are integrated.	Positive
Booth et al. (2023) (Booth et al., 2023)	Europe	The chatbot's log data is analysed to provide insights into usage patterns, identify different user types through clustering, and uncover associations	A total of 579 adult users (over 18 years old).	The onset of the COVID-19 outbreak.	A span of 12 weeks	This research has shed light on the demographics of ChatPal chatbot users, usage trends, and the relationships between different app features. These insights can guide future app development by highlighting which	Positive

						features are most frequently utilized.	
Goldnadel et al. (2023) (Monteiro, Pantani, Pinsky, & Hernandes Rocha, 2023)	USA	Create a digital chatbot capable of providing anonymous interactions with an unlimited number of users around the clock on topics related to alcohol, including strategies for reducing risks. It should be available in several languages, free of charge, and compatible with various devices.	No personal data was utilized, ensuring that all interactions remained anonymous.	Interactive chatbot for educating the general public about alcohol.	From November 9, 2021, to January 16, 2022.	Preliminary findings suggest a promising potential for leveraging artificial intelligence solutions to improve health education on the risks associated with alcohol consumption.	Positive
Hasnain (2023) (Hasnain, 2023)	Pakistan	Offering information on monkeypox (mpox) infections in Pakistan through ChatGPT.	People in general.	Utilize ChatGPT to deliver information on monkeypox infections in Pakistan.		There are potential drawbacks regarding the latest mpox situation in Pakistan and other countries, including ChatGPT's limitations in predicting trends with small datasets and concerns about its performance and reliability.	Negative
Irfan & Zafar (2023) (Irfan & Zafar, 2023)	India	Develop an AI-driven medical chatbot capable of diagnosing illnesses and offering fundamental information about diseases prior to seeking a doctor's consultation.	Individuals experiencing health concerns.	The suggested system is a text-based conversational agent designed to engage users in dialogue about their health concerns. It queries users about their symptoms to assist in		The chatbot is user-friendly and accessible to anyone who can write in their native language, whether on a mobile app or desktop version. It offers personalized diagnoses based on the	Positive

				diagnosing their condition.		symptoms provided by users.	
Kaywan et al. (2023) (Kaywan, Ahmed, Ibaida, Miao, & Gu, 2023)	India	To assess the practicality and efficacy of employing AI-powered chatbots for the early detection of depression. .	50 participants with an average age of 34.7 years.	Determining the levels of depression.		While the chatbot is not designed to replace mental health professionals, it demonstrates potential as a tool for supporting automation and providing discreet communication through validated scoring systems.	Limited
Potts et al. (2023) (Potts et al., 2023)	Northern Ireland, Scotland, the Republic of Ireland, Sweden, and Finland	To assess the impact of a multilingual mental health and well-being chatbot mental well-being.	348 participants from rural areas, with 73% being female, aged between 18 and 73 years (average age: 30).	A pre-and post-intervention study of the ChatPal chatbot.	A duration of 12 weeks	The study evaluated the Warwick-Edinburgh Short Mental Well-Being Scale (SWEMWBS) and observed enhancements in well-being scores. Additionally, the Satisfaction with Life Scale (SWLS) and the World Health Organization Well-Being Index (WHO-5) were assessed, with both showing improvements throughout the study period.	Positive
Prakasam et al. (2023) (S, Balakrishn	India	Machine learning algorithms designed to facilitate the process of scheduling, cancelling, and rescheduling doctor's	Patients	Development of a chatbot for managing the booking, cancellation, and rescheduling of doctor's appointments.		The WhatsApp chatbot allows patients to automatically book, cancel, and reschedule doctor appointments	Positive

an, T R, B, & S, 2023)		appointments based on users' preferred times.				without the need for human assistance, thereby streamlining continuous communication between patients and doctors.	
Rekik et al. (2023) (Rekik, Elamine, & Belguith, 2023)	Egypt	Develop a medical chatbot tailored for the Tunisian dialect. Based on users' symptoms, the chatbot will make health predictions, diagnose conditions using the identified symptoms, and suggest appropriate medical care. Users will be able to interact with the chatbot	356 patients who received the correct diagnosis.	To develop a medical chatbot tailored for the Arabic language, with a specific focus on the Tunisian dialect.		The latter approach achieved the highest performance, with an F1 score of 98.60%. Although the study utilized only 356 data pairs, the results highlighted the effectiveness of our implemented chatbot.	Positive
Sabour et al. (2023) (Sabour et al., 2023)	China	To evaluate the effectiveness of the conversational agent in alleviating symptoms of mental distress.	Patients with mental problems	A conversational agent offering cognitive support, known as Emohaa		Participants who utilized the chatbot saw notably greater improvements in symptoms of mental distress, such as depression, negative affect, and insomnia	Positive
Suharwardy et al. (2023) (Suharwardy et al., 2023)	California (USA)	To assess the acceptability and initial effectiveness of a mental health chatbot for managing mood in a broad postpartum population.	192 English-speaking postpartum women, aged 18 or older, who have had a live birth and have access to a smartphone.	Mental health chatbot intervention versus standard care alone	Assessment of symptoms of depression and anxiety during hospitalization (baseline) and at 2, 4, and 6 weeks postpartum	The sample showed no signs of depression at baseline, which constrained the chatbot's ability to address depressive symptoms effectively. However, 91% of users expressed satisfaction with the chatbot, and 80% felt at	Limited

						ease using a mobile app for managing their mood.	
Upadhyaya & Kaur (2023) (Upadhyaya & Kaur, 2023)	India	Creating a multilingual health awareness chatbot is proposed to assist individuals. This AI-driven chatbot aims to provide answers to questions about diseases, treatments, and preventive measures.	21 people.	The chatbot named SERMO is employed to address the rise in suicide attempts and deaths due to the shortage of mental health professionals. It uses Cognitive Behavioral Therapy (CBT) to assist individuals with mental health conditions in managing their emotions and coping with their thoughts and experiences.		The healthcare chatbot provides the advantage of easy implementation on user-friendly platforms like smartphones and tablets, enabling health-related updates to be received at any time and from any location.	Positive
Vera & Palaoag (2023) (Vera & Palaoag, 2023a)	Philippines	To offer design guidelines for creating a prototype system that collects current information on medicinal plants and their uses, with the aim of distributing this information to underserved regions with limited medical services.	150 participants from remote regions of Catanduanes, who predominantly depend on herbal remedies provided by local clinics.	A prototype of an intelligent interactive system is presented, integrating chatbot technology with artificial intelligence (AI) to address queries about treatment alternatives and the use of various medicinal plants for common health issues, thereby promoting alternative healing methods.		The MedPlantBot system prototype could significantly impact the healthcare industry by promoting sustainability and ethical practices.	Positive

Bhangdia et al. (2021) (Bhangdia, Bhansali, Chaudhari, Chandnani, & Dhore, 2021)	India	To utilize technology to enable more individuals to access support. The proposed approach involves the development of a responsive therapist robot that generates suitable responses based on the user's emotions.	Individuals with mental health conditions.	Developing a reliable and accurate method for detecting emotions.		Developing a multimodal therapy chatbot enables accurate detection of emotions, provision of appropriate responses, and suggestions of activities based on the user's mood. Incorporating facial recognition technology could further improve the effectiveness of the system.	Positive
Binh et al. (2022) (Vu et al., 2022)	Europe	Designing solutions to improve the lives of individuals who do not need body-specific benefits but could greatly benefit from an active lifestyle, especially those suffering from obesity, is the primary goal.	45 local communities throughout the European Union.	The creation of the platform (STOP KM-EP) will play a crucial role in applying strategies to enhance the quality of life for individuals living with obesity by promoting an active lifestyle.		STOP KM-EP platform is effective and appropriate for gathering data on fitness profiles, fitness information, knowledge resources, logs, and chatbot functions	Positive
Hakani et al. (2022) (Hakani, Patil, Patil, Jhunjhunwala, & Deulkar, 2022)	India	To combine these advanced technologies into a single system to deliver highly accurate outcomes. This project covers a broad range of areas, focusing on both identifying and addressing depression in individuals.	People with depression.	To develop a digital platform that identifies indicators of anxiety and provides recommendations for managing depression.		The system offers a comprehensive solution for detecting and managing depression, giving it an edge over current approaches. However, there could be cases where the user lacks sufficient tweets to accurately assess their depression score.	Limited

Mehta & Singh (2022) (Mehta & Singh, 2022)	India	To demonstrate that the proposed medical robot can provide greater benefits compared to most chatbots currently used in the healthcare sector.	People in general.	To establish human-computer interaction through the use of NLP technology.		A supportive system has been designed for offices and medical facilities that offers treatment recommendations, identifies prescriptions, and integrates with a medication API.	Positive
Mellah et al. (2022) (Mellah, Bouchentouf, Rahmoun, & Rahmoun, 2022)	Morocco	Analysing and predicting whether a patient has COVID-19 using a chatbot.	50 patients.	The chatbot operates in both Arabic and French, providing guidance and actions to safeguard lives and curb the virus's transmission based on its analytical findings.		The system accurately identified high risk in 25 out of 25 COVID-19 patients and low risk in 20 out of 25 individuals without the virus, resulting in a precision rate of 90%.	Positive
Natsheh, & Jabed (2022) (Natsheh & Jabed, 2022)	Bahrein	Design a 24/7 helpline chatbot that offers users crucial support and information to handle the rising demand for COVID-19 care.	People with COVID-19.	Developing an AI-driven chatbot utilizing free and open-source tools and frameworks		This proposed chatbot model showcases its ability to address future demands in the healthcare sector as well.	Positive
Okonkwo et al. (2022) (Okonkwo, Amusa, & Twinomurinzi, 2022)	Johannesbourg	Develop a chatbot designed to assess students and verify their COVID-19 vaccination status.	106 university students.	The chatbot (COVID.Bot) is an advanced interactive system capable of engaging with students to ascertain their COVID-19 vaccination status for entry to the institution and		The results showed that most participants regarded the chatbot as effective (86.8%), well-suited to their devices and lifestyles (80.2%), capable of delivering accurate responses (81.1%), and user-friendly (80.2%). The	Positive

				participation in its activities.		average reliability score was .87, reflecting satisfactory reliability.	
Peng et al. (2022) (Peng et al., 2022)	Malaysia	Examine the obstacles and enablers affecting the uptake of an AI chatbot for HIV testing and prevention among men who have sex with men in Malaysia, highlighting perceived benefits, challenges, and preferred functionalities.	Five focus group interviews were carried out, each consisting of 5 to 9 participants.	An AI chatbot developed to support HIV testing and prevention.	July-September 2021	Barriers and facilitators for MSM's acceptance of an AI chatbot for HIV testing are identified. Concerns include the chatbot's accuracy, convenience, and social stigma. Facilitators include connections to healthcare and self-testing services. Recommendations include implementing anonymous settings, MSM-friendly platforms, and clear guidance on HIV-related topics.	Positive
Zhu et al. (2022) (Zhu et al., 2022)	China	Examine the factors influencing user satisfaction and their intention to continue using mental health chatbots.	371 users.	Mental health chatbot (Xiaolv).	1 week	An analysis of 371 Chinese users revealed that while personalization, enjoyment, learning, and the COVID-19 pandemic have some positive but weak effects on user satisfaction and the intention to keep using the chatbot, satisfaction itself has only a slight positive influence on continued	Positive

						use. Voice interaction did not significantly predict either satisfaction or continuance. This research underscores the relevance of the Theory of Consumption Values for understanding mental health chatbot usage.	
Bendig et al. (2021) (Bendig et al., 2021)	Germany, Austria, and Switzerland	Assess the clinical effectiveness and user acceptance of the brief IMI SISU software based on agents, in comparison to a control group that is on a waiting list.	120 Participants of the German language.	Develop a medical chatbot utilizing neural networks to offer diagnostic information and deliver essential details about various diseases.		SISU is regarded as a viable intervention with the potential to enhance participants' psychological well-being. In the feasibility trial, a dropout rate of 39% was observed during the study's course.	Positive
Dhinagaran et al. (2021) (Dhinagaran et al., 2021)	Singapore	Assess the practicality and appeal of a conversational agent created to promote healthy lifestyle behaviour changes within the general population of Singapore	60 Participants.	To support the design and development of a conversational agent centred on promoting healthy lifestyle changes.	August-September 2019.	Future digital solutions, such as conversational agents targeting healthy lifestyles and diabetes prevention, should tackle the obstacles revealed in this study and inspire individuals to embrace healthier habits.	Positive
Gabrielli et al. (2021) (Gabrielli et al., 2021)	Italy	Perform an initial evaluation to measure how well Atena, a psychoeducational chatbot, engages users and supports effective stress and anxiety	71 university students.	Psychoeducational chatbot designed to assist with managing	During the Covid-19 pandemic.	The benefits of employing a digital intervention, such as a chatbot, for promoting healthy coping strategies among university students	Positive

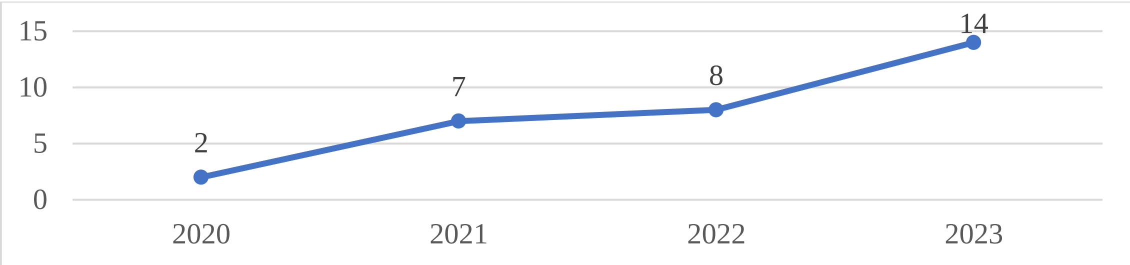
		management among university students.		stress and anxiety in a healthy way.		experiencing high levels of stress are demonstrated.	
Omarov et al. (2021) (Omarov, Zhumanov, Gumar, & Kuntunova, 2023)	Kazakhstan	Explore the design and deployment of the mobile chatbot psychologist, emphasizing the AIML-driven conversational engine and the incorporation of cognitive-behauvioral therapy (CBT) techniques.	Individuals facing psychological distress	An AI-powered mobile chatbot psychologist is introduced, utilizing Artificial Intelligence Markup Language (AIML) and Cognitive Behavioral Therapy (CBT) to deliver customized psychological support.		The AI-powered mobile chatbot psychologist marks a major advancement in mental health care by leveraging AI and evidence-based therapeutic methods to offer accessible, affordable, and tailored psychological support.	Positive
Larbi et al. (2021) (Larbi, Gabarron, & Denecke, 2021)	Switzerland/Norway	To evaluate the usability of the chatbot called MYA.	Thirty volunteers participated, including 15 males aged 18 to 69 years and 15 females aged 18 to 49 years.	To create MYA, a Telegram-based chatbot aimed at encouraging increased physical activity.		Although the results are promising, it is still uncertain whether the chatbot can effectively motivate individuals to boost their physical activity levels.	Limited
Pivithuru et al. (2021) (Ashan Pivithuru et al., 2021)	Sri.Lanka	Develop a versatile, user-friendly technology for an Integrated Electronic Patient Health Record System to replace traditional paper records with a comprehensive electronic system	Doctors	A smartcard-based Integrated e-Patient Card System		The proposed system, utilizing CNN and GradCAM with a transfer learning approach, attained an accuracy of 95.21%. It is capable of diagnosing lung diseases with over 90% accuracy.	Positive

						The system enables a radiographer to upload an X-ray image, which is then analyzed to provide the disease name, its probability, and its location.	
Daley et al. (2020) (Daley et al., 2020)	Brazil	Conduct a preliminary assessment of Vitalk, a mental health chatbot, to evaluate its engagement and effectiveness in reducing anxiety, depression, and stress.	3,629 Portuguese-speaking users from Brazil, all over 18 years old with internet access. Of these, 76% were female and 52% were aged 18–24 years.	To create Vitalk, an automated chatbot that provides mental health information through an innovative conversational format.	1 month period	Scores for anxiety, depression, and stress decreased from the initial assessment to the follow-up. Higher user engagement was associated with more significant improvements in anxiety and depression levels after the intervention.	Positive
(Srivastava & Singh, 2020)	India	Develop a diagnostic chatbot that interacts with patients to address their medical queries and issues, offering a personalized diagnosis based on their symptoms and profile.	Doctors and patients.	Develop a chatbot, named Medibot, to deliver personalized diagnoses.		For extracting diagnosed symptoms, correct symptoms were identified with a recall rate of 65% and a precision rate of 71%.	Positive

Note: Artificial Intelligence Markup Language (AIML); Cognitive Behavioral Therapy (CBL); Natural Language Processing Technology (NLP); Human Immunodeficiency Virus (HIV). Source: Authors' elaboration.

As shown in Figure 6.2, the first paper found on the use and cost of chatbots in healthcare was published in 2020, despite this literature review covering the last 5 years. In this document, a total of 31 articles are considered. The temporal evolution has been increasing from 2020 to 2023. Thus, in the first year, there were 2 articles, while the highest number of articles was published in 2023 (fourteen articles). The annual growth of articles has been as follows. From 2020 to 2021, articles analysing interactive systems to facilitate communication, diagnosis, patient follow-up and medical information management have increased by 250.00%, from 2 articles to 7. From 2021 to 2022, this percentage has grown to a lesser extent, by 14.29%, from 7 to 8 publications related to our objective. Meanwhile, from 2022 to 2023, the annual growth corresponds to 75.00%, increasing to 14 articles.

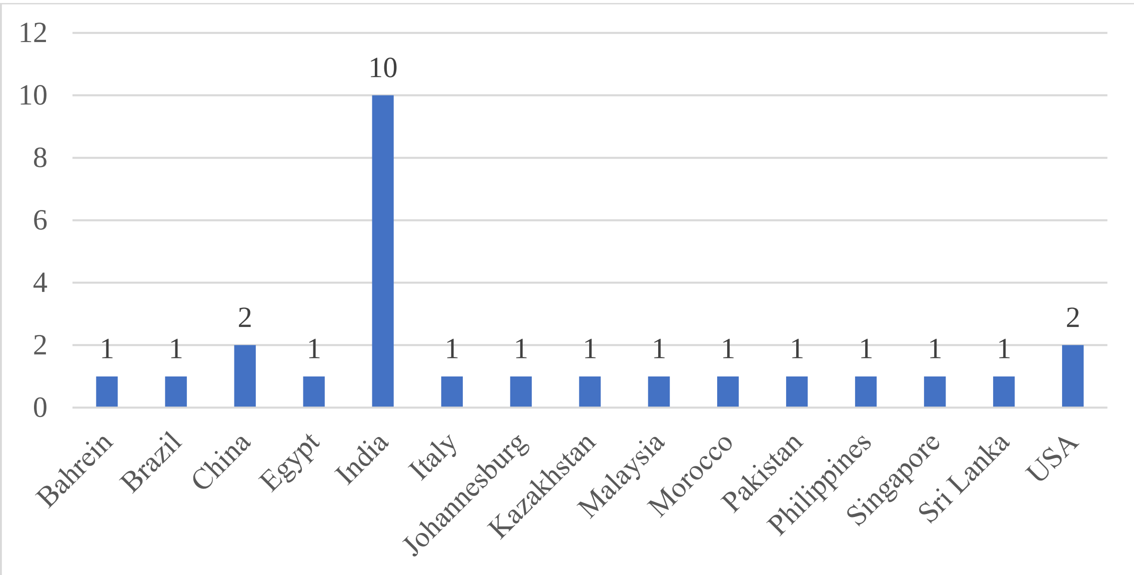
Figure 6.2. Evolution of published papers over time.



Source: Authors' elaboration.

Then, Figure 6.3 plotted the distribution of the selected studies by country. In this context, most studies were conducted in India (N = 10), followed by China (N = 2) and USA (N = 2). The remaining articles considered only one country, such as those listed below: Bahrein, Brazil, Egypt, Italy, Johannesburg, Kazakhstan, Malaysia, Morocco, Pakistan, Philippines, Singapore and Sri Lanka. Two other articles look at the European continent in general, while three other articles look at several countries at once.

Figure 6.3. Distribution of individual country articles by country.



Note: Three articles were multi-country (Potts et al. 2023; Bendig et al. 2021; Larbi et al. 2021) and two analysed Europe (Booth et al. 2023; Binh et al. 2022), and we could not classify them. Source: Authors' elaboration.

According to the applications of chatbots in health, here were a synthesis of the chatbot interventions described in the reviewed articles. The articles were grouped by similar types of interventions, demonstrating the diverse applications of chatbot interventions in healthcare, ranging from mental health support and medical information to appointment management and health education.

Several articles included mental health support and psychological well-being chatbots. Kaywan et al. (2023) assessed feasibility and effectiveness in detecting early and assisting depression through an artificial intelligence chatbot, which showed some potential for assisting with automation and discreet communication. Potts et al. (2023) evaluated a multilingual mental health and well-being chatbot called ChatPal, which aimed at improving mental well-being of the participants from rural areas. Meanwhile, Sabour et al. (2023) analysed effectiveness in reducing symptoms of mental distress through a conversational agent providing cognitive support (Emohaa), concluding significant improvements in symptoms of depression, negative affect, and insomnia. Suharwardy et al. (2023) evaluated acceptability and efficacy for mood management using a mental health chatbot intervention in postpartum women, showing results such as high user satisfaction but limited impact on depressive symptoms due to baseline conditions. In addition, Upadhyaya and Kaur (2023) assisted individuals using a chatbot that employs Cognitive Behavioural Therapy to provide mental health support, help manage emotions and cope with thoughts and experiences. Zhu et al. (2022) investigated determinants of user satisfaction, interaction and clinical support with mental health chatbots, designed for symptom collection, health status monitoring, medication reminders, and patient education on their health conditions and presenting positive influences on user satisfaction and continuance intention. In the case of Hakani et al. (2022), the authors detected signs of anxiety and suggest methods for controlling depression using a digital chatbot, but their results were limited due to lack of data for accurate predictions. Bendig et al. (2021) improved psychological well-being using agent-based software and they found positive results in psychological well-being. In particular, Gabrielli et al. (2021) managed stress and anxiety through a psychoeducational chatbot (Atena) and showed benefits for university students in stress management. Omarov et al. (2023) provided personalized psychological support using a mobile psychologist chatbot based on AIML and cognitive behavioral therapy, concluding significant advances in accessible psychological support. For example, Daley et al. (2020) evaluated the engagement and effectiveness of a mental health chatbot (Vitalk), delivering mental health content in a conversational format, showing a decreased anxiety, depression, and stress levels.

On one hand, other articles were focused on medical and health information chatbots. Anjum et al. (2023) provided accessible healthcare information using artificial intelligence and natural language processing technology (NLP) through a medical chatbot offering advice on healthy lifestyles, who demonstrated effective results in reducing costs and making healthcare accessible. In this context, Bhuvanesh et al. (2023) developed a chatbot for symptom assessment and disease classification, concluding that it presented high accuracy in disease diagnosis. In particular, Hasnain (2023) provided information about monkey pox infection using ChatGPT for disease information dissemination, highlighting potential disadvantages in prediction competency. Rekik et al. (2023) built a medical chatbot for health predictions and medical care based on symptoms for the Tunisian dialect and it also demonstrated high efficiency and accuracy. Vera and Palaoag (2023) provide information on medicinal plants and their applications using a chatbot for alternative healing methods, which made a significant contribution to healthcare with sustainable practices.

On the other hand, two articles were related to disease diagnosis and communication management chatbots. Irfan and Zafar (2023) diagnosed illnesses and provide basic disease information through a text-to-text conversational agent for health problem diagnosis, which was easy to use and offered personalized diagnoses. Prakasam et al. (2023) analysed a WhatsApp chatbot that facilitated managing, booking, cancelling, and rescheduling doctor appointments and enhanced communication between patients and physicians. Mehta and Singh (2022) used NLP, that is, a robot, for human-computer communication in medical contexts, showing the useful applications in offices and medical centers. In the case of Bhangdia et al. (2021), they evaluated symptoms and classify possible diseases based on symptoms and emotions, provided appropriate responses, and suggested activities based on the user's mood using a chatbot. Pivithuru et al. (2021) created a multifunctional, user-friendly technology for an Integrated Electronic Patient Health Record System, including, specifically, a chatbot for medical record management and showing 90% accuracy in lung disease diagnosis. Srivastava et al. (2020) built a diagnosis bot (Medibot) for engaging patients in medical queries and providing individualized diagnoses based on symptoms and patient profiles, presenting a recall of 65% and a precision of 71% in symptom identification.

In addition, health education and awareness were contexts covered by some articles considered. Goldnadel et al. (2023) and Monteiro et al. (2023) educated on alcohol-related topics with risk reduction strategies through digital conversational agent accessible 24/7, promising scenario for health education on alcohol harms. Peng et al. (2022) assisted in Human Immunodeficiency Virus (HIV) testing and prevention among marginalized populations using artificial intelligence chatbot for culturally sensitive health tool, and the results showed valuable insights into key features for design and implementation.

Two articles also analyzed chatbots for promoting healthy lifestyle changes. Binh et al. (2022) and Vu et al. (2022) improved the lives of people suffering from obesity through an active lifestyle using a specific platform, showing the positive usability and feasibility, suitable for collecting fitness data and logs. Similarly, Dhinagaran et al. (2021) promoted healthy lifestyle changes using a conversational agent, which made useful recommendations for improving future digital interventions. Larbi et al. (2021) tried to increase physical activity using a Telegram-based chatbot, but their results were inconclusive based on motivation to increase physical activity.

Related to COVID-19 management chatbots, we found some other articles. Booth et al. (2023) analyzed the chatbot's log data to provide information on usage patterns and different types of users during the beginning of the COVID-19 pandemic, presenting positive insights into user types and usage patterns, helping in further app development. In the case of Mellah et al. (2022), they suggested measures against COVID-19 using a bilingual chatbot (Arabic and French) with a 90% accuracy in risk prediction. Natsheh and Jabed (2022) provided 24/7 help to meet the increasing demand of COVID-19 patients, having the capability to meet future healthcare sector needs. Okonkwo et al. (2022) assessed the vaccination status of students against COVID-19 using an interactive system, with high levels of effectiveness and usability.

6.3. Discussion

This article aimed at summarizing the growing adoption and effectiveness of chatbots in health care systems. We demonstrate that chatbots are revolutionizing healthcare by providing accessible, efficient, and effective solutions across different domains, including mental health and patient management, disease diagnosis and health information dissemination. This fact indicates a significant shift towards digital health solutions.

The integration of AI and NLP in chatbots enhances their functionality and accuracy. Studies like those by Bhuvanesh et al. (Bhuvanesh Shathyan et al., 2023) and Rekik et al. (Rekik et al., 2023) demonstrate high diagnostic accuracy and a n improved access to healthcare, suggesting that AI-driven chatbots could become integral components of future healthcare systems. Moreover, chatbots have proven to be effective in engaging patients and providing health information in a user-friendly manner. The ability of chatbots to operate 24/7 and provide immediate responses makes healthcare more accessible, particularly for populations with limited access to traditional healthcare services as Natsheh and Jabed (Natsheh & Jabed, 2022) demonstrated.

Regarding costs, the fact that routine tasks such as appointment scheduling, management of medical records, and processing of administrative data, which reduces the workload of healthcare staff can be automatized and provide preliminary health assessments, chatbots can significantly reduce direct costs. Anjum et al. (Anjum et al., 2023) and Upadhyaya and Kaur (Upadhyaya & Kaur, 2023) highlighted the cost-reducing potential of healthcare chatbots, making systems more sustainable and efficient while chatbots improve the quality in healthcare delivery.

One the one hand, studies such as those by Kaywan et al. (Kaywan et al., 2023) and Sabour et al. (Sabour et al., 2023) provide clear evidence on the potential of AI-driven interventions in addressing mental health problems through accessible and discreet platforms. The evidence suggests that mental health chatbots can serve as valuable tools in extending mental health support, particularly in underserved areas. The success of multilingual and culturally sensitive chatbots, like ChatPal and those targeting rural populations, indicates that such technologies can bridge gaps in mental health care accessibility and equity. Moreover, the diverse applications of chatbots, from cognitive behavioural therapy (CBT) to psychoeducation, illustrate the flexibility and potential of these technologies in delivering personalized mental health care. This adaptability is crucial for developing tailored interventions that can cater to varied demographic and psychological needs.

The broader application of chatbots in health information dissemination, disease diagnosis, and lifestyle promotion demonstrates their potential to contribute significantly to overall health and well-being. Chatbots can offer personalized healthcare solutions by using patient data to provide tailored advice and interventions. This personalized approach is crucial for managing chronic diseases and improving patient outcomes, as demonstrated by Upadhyaya and Kaur (Upadhyaya & Kaur, 2023) and Bhangdia et al. (Bhangdia et al., 2021).

In the case of recent Large Language Models (LLMs), they have significantly surpassed their predecessors in the ability to understand and generate natural language, enabling much more fluid and accurate interactions with patients (Nazi & Peng, 2024). This improves the quality of communication and user satisfaction. Greater accuracy in language analysis and the generation of contextualised responses reduces errors and improves the reliability of diagnosis as well as treatment recommendations (Haltaufderheide & Ranisch, 2024). In addition, LLMs allow chatbots to better adapt to patients' needs, providing more personalised responses based on deeper analysis of available data. This not only increases effectiveness in monitoring and managing medical information, but also improves clinical outcomes (Clark & Bailey, 2024; Jiang et al., 2017) . Nevertheless, while previous studies showed that chatbots could reduce costs by alleviating the burden on healthcare staff, the new LLMs offer even greater efficiencies, allowing for better scaling without compromising service quality (Bohr & Memarzadeh, 2020; Topol, 2019). However, we recognise that the upfront costs of implementing LLMs can be higher due to their complexity and infrastructure requirements. We have also to add to this analysis the fast evolution of chatbots. It presents a challenge when interpreting conclusions from older studies and even possible replication in the near future. Early research in this field often relied on less sophisticated algorithms and limited computational resources, which constrained the functionality, accuracy, and scalability of chatbots. For example, earlier systems lacked the advanced natural language processing and adaptive learning capabilities that are now available in modern LLMs that are accessible to the wide public such as GPT-4 and Gemini. These newer models offer substantially improved contextual understanding and personalized interaction, enabling more effective applications in healthcare. As a result, while older studies provide valuable foundational insights, their relevance may be limited in the context of today's technological advancements. The lack of enough data from real-world applications of current-generation chatbots also poses a barrier to totally understand their potential. This discrepancy highlights the need for ongoing and continuously update research to evaluate the impact of brand new chatbots and ensure that conclusions drawn from earlier studies are appropriately contextualized.

As evidenced by studies on COVID-19 management and health education, chatbots can play a critical role in public health responses and preventive care. The studies by Mellah et al. (Mellah et al., 2022)and Okonkwo et al. (Okonkwo et al., 2022) highlight how chatbots can be rapidly deployed to support public health efforts and very useful disseminating information, assessing symptoms, and managing patient inquiries such as vaccination status. Chatbots can also play a key role in health education. Goldnadel et al. (Monteiro et al., 2023) and Peng et al. (Peng et al., 2022) showed promising results at this regard in educating the public on critical health issues, promoting preventive measures, and reducing the spread of misinformation.

Despite their benefits, the deployment of chatbots in healthcare comes with challenges such as ensuring data privacy, addressing ethical concerns, and managing user trust. Some studies like the one from Suharwardy et al. (Suharwardy et al., 2023) reveal some limitations in their study concerning baseline conditions of users. Additionally, Hakani et al. (Hakani et al., 2022) noted the importance of improving the accuracy of their depression predictive model in the case of the lack of extensive data.. These issues need to be carefully considered and addressed to fully realize the potential of chatbots in healthcare. Future research should explore the long-term impact of chatbot interventions on patient outcomes, the integration of chatbot technology with electronic health records, and the development of more sophisticated AI models to enhance chatbot capabilities. Additionally, cross-disciplinary collaboration might foster innovative solutions and address the current limitations.

Despite the strengths of this review, some limitations should be noted. First, the review includes studies published in English and Spanish, which may introduce some language bias and limit the generalizability of the findings. Although most of the newest advances in LLM and chatbots may be published in English. Secondly, although we include articles published within the last five years to ensure updated evidence, some of the first studies that could offer additional insights in the evolution of LLM and chatbots may have been not included in our paper. Thirdly, the heterogeneity of the included studies in terms of methodologies, sample sizes, and outcomes makes it challenging to draw definitive conclusions and propose policy recommendations. Furthermore, many studies provided limited details on the cost-effectiveness and real-world implementation challenges of chatbot technologies. Lastly, as chatbot technology continues to evolve rapidly, some findings from included studies may already be outdated, being necessary continuous updates to capture the impact of emerging innovations. Future research should address these limitations by incorporating broader language inclusivity, longitudinal assessments, and real-world data to provide a more comprehensive evaluation of chatbot applications in healthcare.

6.4. Conclusions

In summary, chatbots represent a transformative technology in healthcare, offering numerous benefits from increased accessibility and personalized care to cost savings and enhanced patient engagement and empowerment. Despite these benefits, challenges remain in integrating these tools into healthcare systems and assessing their long-term impact. In recent years, the development of LLMs, such as GPT-4 or Gemini among others, has significantly improved the effectiveness and accuracy of chatbots, enabling more fluid and contextualized interactions with patients. Additionally, recent advancements and optimizations in technological infrastructure, along with increasing market competition, have led to a substantial reduction in the costs associated with using LLMs. This decrease in costs can enhance the cost-effectiveness of chatbots in healthcare settings, enabling their use not only in large hospital systems but also in smaller clinics and rural environments, where access to healthcare is limited. However, the high costs of implementation and operation of these technologies should not be overlooked, as they have been a barrier to their widespread adoption.

To fully leverage the potential of this technology, it will be crucial to continue fostering innovation, supporting robust research, and developing supportive policies that regulate and evaluate the use of chatbots to ensure they meet the required quality and safety standards. Additionally, regulatory frameworks must evolve to ensure that advancements in AI and LLMs are integrated ethically and efficiently into clinical practice, safeguarding patient privacy and data security.

Finally, policymakers should develop frameworks to regulate and evaluate the use of chatbots in healthcare, ensuring they meet quality and safety standards. Support for research, evaluation and development in this field can accelerate the adoption of chatbot technology leading to improved healthcare delivery and outcomes.

Conclusiones

Esta tesis culmina con una sección que ofrece un análisis exhaustivo de los principales hallazgos obtenidos a lo largo de la investigación, haciendo hincapié en los resultados específicos de cada capítulo. En esta parte final, se busca no solo resumir las conclusiones clave, sino también discutir sus implicaciones más relevantes en el contexto de las políticas públicas, especialmente en el ámbito de la salud mental dentro de la economía de la salud.

Entendemos que los resultados alcanzados en esta investigación suponen un avance significativo en la materia, pero es importante señalar que aún existen numerosos aspectos que requieren tanto un análisis más profundo como mayor comprensión desde la perspectiva de la Economía de la Salud. Por tanto, esta sección también dedica un espacio a proponer futuras líneas de investigación que podrían derivarse o expandirse a partir de los capítulos presentados en esta tesis. Dichas propuestas buscan contribuir al desarrollar el campo temático que enmarca esta investigación.

Además, es relevante destacar que este estudio ha aportado nueva evidencia empírica que enriquece el conocimiento existente sobre la interrelación entre la salud mental y la economía de la salud. Los resultados obtenidos no solo fortalecen la base teórica, sino que también tienen el potencial de orientar decisiones en el diseño e implementación de políticas públicas más efectivas. Este trabajo, por tanto, no solo sienta las bases para futuras exploraciones académicas, sino que también aspira a tener un impacto tangible en la mejora de la salud mental desde una perspectiva económica, contribuyendo al bienestar general de la sociedad.

En el transcurso de esta investigación, se ha abordado de manera sistemática el análisis de la relación entre la salud mental y diversos factores como son los socioeconómicos o sociodemográficos, explorando cómo influyen mutuamente en contextos específicos. A través de un enfoque interdisciplinario, la tesis ha examinado no solo los impactos directos de la salud mental en la economía de la salud, sino también las implicaciones más amplias en términos de equidad y acceso. Dicho análisis ha permitido identificar patrones y tendencias que subrayan la necesidad de integrar consideraciones de salud mental en las políticas económicas para lograr una sociedad más equilibrada y justa.

Asimismo, los hallazgos presentados sugieren que la integración de la salud mental en el análisis económico podría abrir nuevas vías para mejorar la efectividad de las políticas públicas. Por ejemplo, la evidencia empírica recopilada en esta tesis resalta la importancia de diseñar intervenciones que no solo aborden los síntomas de los trastornos mentales, sino que también consideren las condiciones sociodemográficas subyacentes que los agravan. De este modo, las futuras investigaciones podrían enfocarse en desarrollar modelos económicos que incorporen factores psicológicos y sociales de manera más explícita, contribuyendo a diseñar políticas integrales que promuevan tanto la salud mental como el desarrollo económico sostenible.

1. Resultados e implicaciones de políticas pública

A lo largo de esta tesis, se han empleado varias encuestas de especial relevancia para la investigación en el ámbito de la economía de la salud, en particular para analizar los determinantes y consecuencias de la salud mental desde una perspectiva económica. Entre las encuestas utilizadas, destacan tres de manera especial: el SHARE, la Encuesta de Discapacidad, Autonomía personal y Dependencia (EDAD) del INE, y la Encuesta Europea de Salud, también del INE.

La encuesta SHARE ha sido la herramienta más utilizada a lo largo de los capítulos de esta tesis debido a sus características únicas y a la riqueza de los datos que proporciona en distintos países. SHARE es una encuesta longitudinal que recoge información detallada sobre la salud, la situación económica y social, y las redes familiares y sociales de personas mayores de 50 años en Europa. Su diseño permite un análisis profundo de las trayectorias de salud a lo largo del tiempo, lo que es especialmente valioso para estudiar la evolución de la salud mental en relación con distintos factores económicos. Además, la amplitud de variables y detalles que ofrece SHARE ha facilitado la implementación de modelos econométricos complejos que capturan la relación entre la salud mental y diversas dimensiones socioeconómicas, permitiendo obtener conclusiones robustas y generalizables para la población europea.

Por otro lado, la EDAD del INE ha proporcionado información crucial sobre la prevalencia y características de las discapacidades en la población española, así como sobre los recursos y necesidades de las personas con dependencia. Esta encuesta es especialmente valiosa para el análisis de la relación entre la discapacidad y la salud mental, ofreciendo datos que permiten evaluar cómo las limitaciones físicas y la dependencia pueden influir en el bienestar psicológico de las personas. La EDAD ha sido una fuente importante para poner en contexto los resultados obtenidos con SHARE, aportando una perspectiva nacional.

La Encuesta Europea de Salud, también administrada por el INE, ha aportado con datos sobre la salud percibida, estilos de vida, y uso de servicios de salud en la población general española. Esta encuesta ha sido fundamental para examinar cómo los factores de riesgo y los comportamientos de salud están asociados con la salud mental en diferentes grupos demográficos. La información obtenida de esta encuesta ha permitido contrastar los hallazgos obtenidos con SHARE y EDAD, proporcionando un marco más amplio y diverso para el análisis.

Es importante destacar que para el tratamiento de los datos obtenidos de estas encuestas y la aplicación de modelos econométricos se ha utilizado el software STATA, siendo elegido por su capacidad para manejar grandes volúmenes de datos y su flexibilidad para aplicar una amplia variedad de métodos estadísticos y econométricos. El uso de STATA ha sido crucial para llevar a cabo análisis descriptivos y multivariantes que permitan explorar las complejas relaciones entre la salud mental y los factores económicos y sociales estudiados en esta tesis. La capacidad de STATA para realizar análisis robustos ha asegurado la validez y fiabilidad de los resultados, contribuyendo de manera significativa al rigor metodológico de la investigación.

En resumen, el uso de las encuestas SHARE, EDAD, y la Encuesta Europea de Salud ha sido clave para la obtención de datos empíricos ricos y diversos, permitiendo un análisis profundo y comprensivo de la salud mental en el contexto de la economía de la salud. Entre ellas, SHARE ha sido la más empleada debido a su amplitud y riqueza de datos, mientras que STATA ha proporcionado las herramientas necesarias para el análisis detallado y la modelización de estos datos, asegurando la calidad y relevancia de los hallazgos presentados en esta tesis.

Aunque el uso de encuestas ha proporcionado una base empírica sólida para el análisis de la relación entre salud mental y economía de la salud, es fundamental reconocer las limitaciones inherentes a estas fuentes de datos. Estas limitaciones afectan tanto a la generalización de los resultados como la precisión de los análisis y deben ser consideradas al interpretar los hallazgos de esta tesis.

En primer lugar, una de las principales limitaciones de la encuesta SHARE radica en su diseño longitudinal, que, aunque es una de sus mayores fortalezas, también presenta desafíos específicos. Al tratarse de un estudio que sigue a los mismos individuos a lo largo del tiempo, puede surgir el problema de la pérdida de participantes a medida que avanza el tiempo, fenómeno conocido como atrition (abandono). Este “abandono” puede no ser aleatorio y estar relacionado con factores de salud, lo que puede sesgar los resultados. Por ejemplo, las personas con peor salud mental o mayores problemas económicos pueden ser más propensas a abandonar el estudio, lo que podría resultar en una subestimación de la verdadera magnitud de los problemas de salud mental en la población estudiada. Además, aunque SHARE cubre una amplia gama de países europeos, no todos los países están representados de manera uniforme en todas las olas de la encuesta, lo que puede limitar la comparabilidad entre países y la capacidad de generalizar los resultados a toda Europa.

Por otro lado, la Encuesta de Discapacidad, Autonomía personal y Dependencia (EDAD) del INE, aunque proporciona datos detallados sobre la población con discapacidad y dependencia en España, también presenta ciertas limitaciones. Una de ellas es su enfoque específico en personas con discapacidad, lo que puede limitar la aplicabilidad de los hallazgos obtenidos a la población general. Además, la EDAD está estructurada para recoger datos principalmente a nivel del hogar, lo que podría omitir información relevante sobre personas que viven en instituciones, como residencias para mayores, quienes a menudo presentan tasas más altas de problemas de salud mental. Esta limitación puede generar un sesgo en los análisis, subestimando la prevalencia y el impacto de la salud mental en grupos de población vulnerables. Asimismo, la naturaleza transversal de la EDAD, al igual que la de la Encuesta Europea de Salud, limita la capacidad de inferir relaciones causales, ya que no permite observar cómo cambian las condiciones de salud mental a lo largo del tiempo.

En cuanto a la Encuesta Europea de Salud, si bien es una fuente valiosa de información sobre la salud percibida y comportamientos relacionados con la salud en la población española, también enfrenta limitaciones. Al igual que la EDAD, es una encuesta de corte transversal, lo que significa que los datos se recopilan en un solo punto en el tiempo. Esto impide observar la evolución de la salud mental y su relación con factores económicos en un horizonte temporal, limitando la capacidad para establecer relaciones causales claras. Además, esta encuesta se basa en gran medida en la auto información, lo que puede introducir sesgos en los datos debido a la percepción subjetiva de los encuestados sobre su propia salud. Las personas pueden subestimar o sobreestimar sus problemas de salud mental, lo que puede afectar a la precisión de los resultados.

Otra limitación común a estas encuestas es la posible falta de uniformidad en las definiciones y medidas utilizadas para evaluar la salud mental. Dado que estas encuestas fueron diseñadas con diferentes propósitos y contextos, puede haber una variabilidad importante en cómo se definen y miden los problemas de salud mental, lo que dificulta la comparación directa de los resultados entre las diferentes encuestas. Además, aunque las encuestas incluyen una amplia gama de variables, es posible que no cubran todos los factores relevantes que influyen en la salud mental, como algunos determinantes sociales o económicos específicos, lo que puede limitar la profundidad del análisis.

Además de las limitaciones previamente mencionadas, es importante subrayar que la percepción de la salud mental en las encuestas utilizadas se basa en la autopercepción de los encuestados. Este enfoque puede introducir un sesgo significativo, ya que la autopercepción de la salud mental está influenciada por factores subjetivos y puede no reflejar con precisión la realidad clínica.

Finalmente, el uso de estas encuestas en combinación con el software STATA, si bien es una fortaleza en términos de capacidad analítica, también conlleva ciertas limitaciones técnicas. STATA, como cualquier software estadístico, requiere decisiones específicas por parte del investigador, como la selección de modelos, el manejo de datos no disponibles y la corrección de posibles sesgos. Estas decisiones, aunque informadas por la teoría y la práctica estadística, pueden influir en los resultados finales. Además, la complejidad de los modelos utilizados puede requerir simplificaciones que no capturen toda la heterogeneidad de la población estudiada.

En resumen, aunque el uso de las encuestas ha permitido realizar un análisis detallado y riguroso sobre la relación entre salud mental y economía de la salud, es crucial reconocer las limitaciones asociadas con estas fuentes de datos. Estas limitaciones incluyen problemas relacionados con el diseño de las encuestas, la representatividad de la muestra, la naturaleza transversal de algunos datos, y las decisiones técnicas en el análisis de datos. Al interpretar los resultados de esta tesis, es esencial considerar estos factores para una comprensión más matizada y precisa de los hallazgos e implicaciones.

A continuación, procedemos a sintetizar los resultados clave y las implicaciones derivadas de cada uno de los capítulos.

En este primer capítulo, se ha utilizado una muestra de adultos mayores obtenida de los datos más recientes del estudio SHARE para ofrecer un análisis detallado sobre la relación entre la COVID-19 y la salud mental en esta población. Los resultados muestran, en primer lugar, un impacto negativo significativo de la pandemia en el bienestar psicológico de los europeos de mayor edad. En segundo lugar, se ha identificado que ciertas características clínicas y socioeconómicas desempeñan un papel crucial en la explicación de las variaciones en la salud mental dentro de este grupo. El análisis revela la existencia de un gradiente social considerable, particularmente influenciado por el género, que afecta a la distribución de los efectos sobre la salud mental. En síntesis, estos hallazgos no solo son coherentes con la literatura existente, sino que también aportan nuevos conocimientos sobre la salud mental de los europeos mayores durante la pandemia. Los resultados estadísticos ponen de manifiesto la presencia de desigualdades significativas, subrayando la necesidad de abordarlas de manera integral. Las implicaciones de estos hallazgos son particularmente relevantes para la formulación de políticas públicas, que deberán integrar una perspectiva social y considerar los efectos indirectos de la COVID-19 en la salud mental de la población adulta mayor. Es imperativo que las políticas diseñadas respondan a las desigualdades identificadas, con el fin de mitigar posibles impactos adversos y promover el bienestar mental de esta población vulnerable.

En este segundo capítulo, se ha explorado el impacto de la evolución y adopción de la tecnología en la salud mental de los adultos mayores, utilizando datos de cuatro oleadas de la encuesta SHARE. Los resultados demuestran que, aunque la tecnología tiene el potencial de mejorar la vida de los mayores, también supone desafíos significativos, especialmente cuando las habilidades tecnológicas son insuficientes. A lo largo del período analizado, se constató un efecto positivo de la tecnología en la probabilidad de experimentar problemas de salud mental entre la población mayor, lo que subraya la importancia de cerrar la brecha digital. Las implicaciones de estos hallazgos son claras: los responsables de políticas (policymakers) deben desarrollar estrategias que no solo promuevan el uso de la tecnología entre los mayores, sino que también ofrezcan apoyo adecuado, como capacitación en habilidades digitales, para evitar que la brecha tecnológica exacerbe los problemas de salud mental en esta población vulnerable. Dado el envejecimiento de la población europea, es crucial que las políticas públicas se ajusten a esta nueva realidad para facilitar una integración más efectiva de los adultos mayores en la vida digital, optimizando así sus resultados de salud y bienestar.

En el tercer capítulo, se aborda el creciente problema de salud mental entre las personas con discapacidad en España, enfatizando cómo la falta de participación en actividades de ocio puede agravar esta situación. A lo largo del tiempo, la tasa de personas con discapacidad ha aumentado, y con ello, las dificultades para llevar una vida normal, lo que a menudo deriva en problemas de salud mental. El estudio analiza datos de la encuesta EDAD 2020 y encuentra que aproximadamente el 4% de las personas con discapacidad no participan en actividades de ocio, de las cuales un 14% recurre a servicios de atención psicológica. Los resultados demuestran que la falta de acceso adecuado a actividades de ocio incrementa significativamente la probabilidad de que las personas con discapacidad experimenten problemas de salud mental, especialmente entre mujeres y en Comunidades Autónomas del sur de España. Estos hallazgos subrayan la necesidad de mejorar la adaptabilidad y accesibilidad de las instalaciones de ocio para este grupo de población. Las políticas públicas deben enfocarse en eliminar las barreras que impiden la participación en actividades recreativas, ya que estas no solo mejoran el bienestar general, sino que también reducen la dependencia de servicios de atención psicológica. En resumen, este estudio aporta nueva evidencia empírica que refuerza la importancia de las actividades de ocio en la salud mental de las personas con discapacidad. Es crucial que los responsables de políticas consideren estos resultados para desarrollar estrategias que no solo mejoren los servicios de atención psicológica, sino que también aborden las necesidades de ocio de las personas con discapacidad, contribuyendo así a su bienestar integral y a la reducción de la discriminación y el estigma que enfrentan.

En el cuarto capítulo, se examina la relación entre el estilo de vida y la salud mental, destacando la importancia de identificar los factores que aumentan el riesgo de problemas como la depresión, la ansiedad y otros trastornos mentales. Utilizando microdatos de la Encuesta Europea de Salud en España, este estudio revela que los factores asociados con el estilo de vida impactan de manera distinta en cada tipo de problema de salud mental. Los resultados subrayan la necesidad de considerar la naturaleza específica de cada trastorno mental al desarrollar políticas y medidas preventivas. El estudio destaca que los enfoques de tipo general pueden ser ineficaces, ya que cada trastorno presenta características únicas que requieren intervenciones personalizadas. La investigación pone de relieve la importancia de adaptar las estrategias de prevención y tratamiento a las particularidades de cada condición mental, lo que puede mejorar significativamente la efectividad de las políticas de salud pública. Además, se enfatiza la necesidad de estudios adicionales que identifiquen con mayor precisión los factores de riesgo y sus mecanismos de acción, lo que permitirá desarrollar intervenciones más específicas y efectivas. En resumen, un estilo de vida saludable es clave no solo para prevenir enfermedades físicas, sino también para mejorar el bienestar mental. Los hallazgos de este capítulo sugieren que políticas de salud bien diseñadas y adaptadas a las características individuales de los trastornos mentales pueden contribuir a una mejor calidad de vida y a reducir la incidencia de problemas de salud mental en la población.

En el quinto capítulo, se explora cómo el área de residencia impacta sobre la salud mental, mostrando variaciones significativas según el entorno. En las zonas urbanas, el riesgo de problemas de salud mental aumenta con la edad, mientras que en las áreas rurales y semirrurales, este riesgo tiende a ser menor a medida que envejece la población. Este contraste sugiere que las diferencias socioculturales y económicas entre dichos entornos (rural y urbano) influyen en la salud mental de manera diversa. Además, se observa que las mujeres tienen un mayor riesgo de problemas de salud mental en todas las zonas residenciales, destacando la necesidad de abordar y combatir las desigualdades de género. En términos educativos, mientras que en las zonas urbanas y semirrurales el nivel educativo no afecta significativamente sobre el riesgo de problemas de salud mental, en las áreas rurales sí se observa una mayor probabilidad de experimentar estos problemas, indicando disparidades en el acceso a servicios de salud mental. La percepción subjetiva de la salud tiene una relación inversa con el riesgo de problemas de salud mental en todas las áreas, subrayando su importancia como predictor. Aunque factores como el vandalismo y la limpieza del entorno tienen un impacto limitado, la proximidad a centros de salud se asocia con un menor riesgo de problemas mentales, aunque el acceso a farmacias y bancos varía según la zona. En conclusión, los resultados sugieren que los determinantes de la salud mental son complejos y varían según el entorno. Las políticas públicas deben ser adaptadas a las características específicas de cada área, especialmente para las zonas rurales, donde ciertos factores como la falta de actividad física y la exposición al vandalismo tienen un impacto más pronunciado en la salud mental.

El sexto capítulo de esta tesis doctoral presenta una revisión sistemática sobre el uso de chatbots en el sector sanitario, especialmente en el contexto de la pandemia de COVID-19, que ha intensificado la demanda de recursos de salud y ha resaltado la necesidad de soluciones eficientes bajo restricciones presupuestarias. En este contexto, el uso creciente de la inteligencia artificial y telemedicina ha emergido como una estrategia clave para optimizar la atención y los recursos de salud, siendo los chatbots una herramienta innovadora en diversas áreas, como la salud mental y la monitarización de pacientes. Este capítulo examina los estudios más relevantes publicados en los últimos cinco años, recopilados en bases de datos como PubMed, Web of Science y Scopus, y analiza las aplicaciones y efectividad de los chatbots en diferentes ámbitos de la atención sanitaria. Los resultados destacan su amplio potencial en el apoyo a la salud mental, la gestión de citas, la educación en salud, los cambios en el estilo de vida y la gestión del COVID-19. Sin embargo, también se identifican diversos desafíos relacionados con la implementación y compatibilidad con otros sistemas así como las consideraciones éticas que podrían surgir en diferentes entornos de atención médica. Abordar estos desafíos será esencial para maximizar los beneficios de los chatbots, mitigar riesgos y garantizar un acceso equitativo a estas innovaciones en salud.

2. Futuras líneas de investigación

La tesis ofrece una visión integral sobre diversos aspectos de la salud mental, pero también abre múltiples caminos para futuras investigaciones. A nivel general, una dirección consiste en profundizar acerca de cómo interactúan los diversos factores sociales, económicos y ambientales en la salud mental, integrando variables adicionales como el contexto cultural y las políticas locales específicas. Es fundamental explorar cómo estos factores pueden influir de manera conjunta o aislada en diferentes poblaciones para ofrecer recomendaciones más precisas y adaptadas a contextos específicos.

Además, sería muy valioso ampliar el alcance geográfico de este tipo de estudios, incorporando datos de regiones menos representadas o países con características socioeconómicas y culturales distintas. Esto permitiría una comprensión más global y comparativa de los determinantes de la salud mental y sus implicaciones para las políticas públicas. Además, la integración de estudios longitudinales podría proporcionar una visión más dinámica y evolutiva de cómo los factores de riesgo y protección influyen en la salud mental a lo largo del tiempo.

Para continuar con la línea de investigación del primer capítulo, se podría realizar un análisis longitudinal para observar cómo el impacto de la COVID-19 en la salud mental de los adultos mayores ha evolucionado con el tiempo. Sería útil investigar tanto la duración como la intensidad de la pandemia han modificado las experiencias y percepciones acerca de la salud mental en esta población. Adicionalmente, futuros estudios podrían explorar el papel de las intervenciones específicas, como programas de apoyo psicológico y social, y evaluar su eficacia en la mitigación de los efectos negativos de la pandemia. Investigaciones comparativas entre diferentes países europeos podrían ofrecer perspectivas adicionales sobre las estrategias más efectivas para abordar los problemas de salud mental en contextos diversos.

Una futura línea de investigación sobre el capítulo 2 podría centrarse en la evaluación del impacto de las nuevas tecnologías emergentes, como las aplicaciones de salud mental y las plataformas de telemedicina en la salud mental de la población mayor. Sería relevante investigar cómo la adopción de tecnologías avanzadas, como la realidad virtual para la terapia o las tecnologías de asistencia, afecta al bienestar mental. También se podría explorar cómo las barreras tecnológicas, como la falta de formación o accesibilidad, influyen en la efectividad de estas herramientas y en la salud mental de los mayores. Además, estudios de intervención podrían analizar el impacto de programas de capacitación tecnológica en la reducción de la brecha digital y la mejora de la salud mental.

Para futuras investigaciones sobre la temática del capítulo 3, se podría examinar cómo la calidad y la accesibilidad de las actividades de ocio afectan de manera específica a diferentes tipos de discapacidades. Sería beneficioso investigar el impacto de programas específicos de ocio adaptados para diversas discapacidades y evaluar cómo estos programas pueden mejorar el bienestar mental. Asimismo, se debería explorar la relación entre la participación en actividades de ocio y otros factores como el soporte familiar y comunitario. Estudios comparativos entre diferentes tipos de discapacidades y regiones geográficas podrían proporcionar información valiosa sobre la eficacia de distintas políticas y programas de ocio en la mejora de la salud mental.

Futuros estudios relacionados con el capítulo 4 podrían investigar cómo intervenciones específicas en el estilo de vida, como programas de ejercicio físico, dietas equilibradas y prácticas de mindfulness, afectan de manera diferenciada a diversos trastornos mentales. Además, sería útil explorar cómo factores como el entorno laboral y las condiciones de vivienda influyen en la relación entre estilo de vida y salud mental. Este tipo de investigación podría beneficiarse de enfoques interdisciplinares que combinen conocimientos de psicología, sociología y medicina para desarrollar estrategias de prevención y tratamiento más efectivas. También se podría estudiar el impacto de diversas políticas públicas que promuevan estilos de vida saludables en diferentes poblaciones y cómo estas políticas afectan a la salud mental a nivel poblacional.

Una línea de investigación futura para el capítulo 5 podría enfocarse en cómo las características específicas del entorno urbano versus rural, como la densidad poblacional, la infraestructura y el acceso a servicios, influyen en la salud mental. Sería relevante investigar el papel de las redes de apoyo social y los programas comunitarios en la mitigación de los riesgos asociados a diferentes entornos residenciales. Adicionalmente, estudios longitudinales podrían analizar cómo los cambios en el entorno residencial, como las mejoras en la infraestructura o las políticas urbanas, afectan a la salud mental de los residentes. Asimismo, la investigación podría beneficiarse de enfoques de política pública que integren las necesidades y características de salud mental específicas de cada tipo de área residencial.

Finalmente, las futuras investigaciones sobre el uso de chatbots en la atención de la salud, deben centrarse en varias áreas clave para abordar las limitaciones actuales y maximizar su potencial. Dichas futuras investigaciones sobre chatbots en la atención de la salud, como se analiza en el Capítulo 6, deben centrarse en evaluar su impacto a largo plazo en los resultados de los pacientes, en particular en el manejo de enfermedades crónicas y la atención preventiva. Investigar la integración de chatbots con Registros Médicos Electrónicos (RME) también es crucial para mejorar la gestión del paciente y la atención personalizada. A medida que los Modelos de Lenguaje Amplio (MLA) continúan evolucionando, estudios adicionales deben explorar su potencial para mejorar la precisión de los chatbots y las interacciones conscientes del contexto. Se considera pues esta nueva línea de investigación también debe evaluar la relación coste-efectividad y la escalabilidad de las tecnologías de chatbots, en particular en entornos de bajos recursos, como las áreas rurales.

Conclusions

This thesis concludes with a section that provides a comprehensive analysis of the main findings obtained throughout the research, emphasizing the specific results of each chapter. In this final part, the aim is not only to summarize the key conclusions but also to discuss their most relevant implications in the context of public policies, particularly in the area of mental health within health economics.

The results obtained in this research provide novel insights and contribute to a better understanding of the relationship between mental health and different population groups and contexts. But it is important to note that there are still numerous aspects that require deeper analysis and greater understanding from the perspective of Health Economics. Therefore, this section also dedicates space to proposing future lines of research that could be derived from or expanded upon the chapters presented in this thesis. These proposals aim to contribute to the continued development of the thematic field that frames this doctoral research.

Additionally, it is important to highlight that this research has provided new empirical evidence that enriches existing knowledge about the interrelationship between mental health and health economics. The results not only strengthen the theoretical foundation but also have the potential to guide decisions in the design and implementation of more effective public policies. Therefore, this work not only lays the groundwork for future academic explorations but also aspires to have a tangible impact on improving mental health from an economic perspective, contributing to the overall well-being of society.

Along this research, the relationship between mental health and various factors, such as socioeconomic or sociodemographic ones, has been systematically addressed, exploring how they mutually influence each other in specific contexts. This thesis, employing an interdisciplinary approach across its various chapters, examines not only the direct effects of mental health on health economics, but also the broader implications for equity and access to care. It explores the impact of COVID-19, the role of technology, and the limitations individuals face in engaging in leisure activities. Additionally, it considers lifestyle factors, regional differences, and the influence of artificial intelligence on health outcomes. This analysis has allowed the identification of patterns and trends that underscore the need to integrate mental health considerations into economic policies to achieve a more balanced and just society.

Our findings also suggest that integrating mental health into economic analysis could open new avenues for improving the effectiveness of public policies. For example, the empirical evidence collected in this thesis highlights the importance of designing interventions that not only address the symptoms of mental disorders but also consider the underlying sociodemographic conditions that exacerbate them. In this way, future research could focus on developing economic models that incorporate psychological and social factors more explicitly, contributing to the creation of comprehensive policies that promote both mental health and sustainable economic development.

1. Results and Public Policy Implications

Throughout this thesis, several highly relevant surveys for research in the field of health economics have been employed, particularly to analyze the determinants and consequences of mental health from an economic perspective. Among the surveys used, three stand out in particular: the SHARE, the INE's Disability, Autonomy, and Dependency Survey (EDAD), and the European Health Survey, also from INE.

The SHARE survey has been the most utilized tool throughout the chapters of this thesis due to its unique characteristics and the richness of the data it provides. SHARE is a longitudinal survey that collects detailed information on the health, economic and social situation, and family and social networks of individuals aged 50 and over in Europe. Its design allows for an in-depth analysis of health trajectories over time, which is particularly valuable for studying the evolution of mental health in relation to different economic factors. Additionally, the breadth of variables offered by SHARE has facilitated the implementation of complex econometric models that capture the relationship between mental health and various socioeconomic dimensions, allowing for robust and generalizable conclusions for the European population.

On the other hand, the INE's Disability, Autonomy, and Dependency Survey (EDAD) has provided crucial information about the prevalence and characteristics of disabilities in the Spanish population, as well as the resources and needs of dependent individuals. This survey is especially valuable for analyzing the relationship between disability and mental health, offering data that allows for the evaluation of how physical limitations and dependency can influence individuals' psychological well-being. EDAD has been an important source for contextualizing the results obtained with SHARE, providing a national perspective.

The European Health Survey, also administered by INE, has contributed data on perceived health, lifestyles, and health service usage in the general Spanish population. This survey has been fundamental for examining how risk factors and health behaviors are associated with mental health in different demographic groups. The information obtained from this survey has allowed for a comparison of the findings obtained with SHARE and EDAD, providing a broader and more diverse framework for analysis.

It is important to note that STATA software was used to process the data obtained from these surveys and apply econometric models. Stata was chosen for its ability to handle large volumes of data and its flexibility in applying a variety of statistical and econometric methods. The use of STATA was crucial for conducting descriptive and multivariate analyses that explore the complex relationships between mental health and the economic and social factors studied in this thesis. STATA´S capacity for robust analysis has ensured the validity and reliability of the results, significantly contributing to the methodological rigor of the research.

In summary, the use of the SHARE, EDAD, and European Health Surveys has been key to obtaining rich and diverse empirical data, allowing for a deep and comprehensive analysis of mental health in the context of health economics. Among them, SHARE has been the most employed due to its breadth and richness of data, while Stata has provided the necessary tools for detailed analysis and modeling of this data, ensuring the quality and relevance of the findings presented in this thesis.

While the use of surveys has provided a solid empirical foundation for analyzing the relationship between mental health and health economics, it is essential to acknowledge the inherent limitations of these data sources. These limitations affect both the generalization of the results and the precision of the analyses and must be considered when interpreting the findings of this thesis.

First, one of the main limitations of the SHARE survey lies in its longitudinal design, which, while being one of its greatest strengths, also presents specific challenges. Since it is a study that follows the same individuals over time, there may be an issue of participant attrition as time progresses, a phenomenon known as "attrition." This dropout may not be random and could be related to health factors, which may bias the results. For example, individuals with poorer mental health or more severe economic problems may be more likely to leave the study, which could result in an underestimation of the true magnitude of mental health issues in the studied population. Furthermore, while SHARE covers a wide range of European countries, not all countries are equally represented in all waves of the survey, which may limit comparability between countries and the ability to generalize results across Europe.

On the other hand, the INE's Disability, Autonomy, and Dependency Survey (EDAD), while providing detailed data on the population with disabilities and dependency in Spain, also presents certain limitations. One of them is its specific focus on individuals with disabilities, which may limit the applicability of the findings to the general population. Additionally, EDAD is structured to collect data primarily at the household level, which may omit relevant information about individuals living in institutions, such as nursing homes, who often have higher rates of mental health problems. This limitation may introduce bias in the analyses, underestimating the prevalence and impact of mental health issues in vulnerable population groups. Moreover, the cross-sectional nature of EDAD, like that of the European Health Survey, limits the ability to infer causal relationships, as it does not allow for observation of how mental health conditions change over time.

Regarding the European Health Survey, while it is a valuable source of information on perceived health and health-related behaviors in the Spanish population, it also faces limitations. Like EDAD, it is a cross-sectional survey, meaning that data is collected at a single point in time. This prevents observing the evolution of mental health and its relationship with economic factors over time, limiting the ability to establish clear causal relationships. Additionally, this survey relies heavily on self-reporting, which may introduce biases into the data due to respondents' subjective perceptions of their own health. People may underestimate or overestimate their mental health issues, which can affect the accuracy of the results.

Another common limitation of these surveys is the possible lack of uniformity in the definitions and measures used to assess mental health. Since these surveys were designed for different purposes and in different contexts, there may be variability in how mental health issues are defined and measured, making it difficult to directly compare results across the different surveys. Moreover, while the surveys include a wide range of variables, they may not cover all relevant factors influencing mental health, such as specific social or economic determinants, which could limit the depth of the analysis.

In addition to the previously mentioned limitations, it is important to underscore that the perception of mental health in the surveys used is based on the self-perception of the respondents. This approach can introduce significant bias, as self-perception of mental health is influenced by subjective factors and may not accurately reflect clinical reality.

Finally, the use of these surveys in combination with Stata software, while a strength in terms of analytical capacity, also faces certain technical limitations. Stata, like any statistical software, requires specific decisions by the researcher, such as model selection, handling missing data, and correcting for possible biases. These decisions, though informed by statistical theory and practice, can influence the final results. Additionally, the complexity of the models used may require simplifications that do not capture the full heterogeneity of the studied population.

In summary, while the use of surveys has enabled a detailed and rigorous analysis of the relationship between mental health and health economics, it is crucial to recognize the limitations associated with these data sources. These limitations include issues related to survey design, sample representativeness, the cross-sectional nature of some data, and technical decisions in data analysis. When interpreting the results of this thesis, it is essential to consider these factors for a more nuanced and accurate understanding of the findings and their implications.

Next, we proceed to synthesize the key results and implications derived from each of the chapters.

In this first chapter, a sample of older adults from the most recent SHARE study data was used to provide a detailed analysis of the relationship between COVID-19 and mental health in this population. The findings first show a significant negative impact of the pandemic on the psychological well-being of older Europeans. Secondly, certain clinical and socioeconomic characteristics have been identified as playing a crucial role in explaining variations in mental health within this group. Finally, the analysis revealed a considerable social gradient, particularly influenced by gender, that affects the distribution of mental health effects. In summary, these findings not only align with existing literature but also provide new insights into the mental health of older Europeans during the pandemic. The statistical results highlight significant dependencies and inequalities, emphasizing the need for a comprehensive approach to address them. The implications of these findings are particularly relevant for public policy formulation, which should integrate a social perspective and consider the indirect effects of COVID-19 on the mental health of the older population. It is imperative that the policies designed address the identified inequalities to mitigate adverse impacts and promote the mental well-being of this vulnerable population.

In this second chapter, the impact of technology evolution and adoption on the mental health of older adults is explored using data from four waves of the SHARE survey. The results show that while technology has the potential to improve the lives of older adults, it also presents significant challenges, especially when technological skills are insufficient. Over the period analyzed, a positive effect of technology was observed on the likelihood of experiencing mental health problems among older adults, underscoring the importance of closing the digital divide. The implications of these findings are clear: policymakers must develop strategies that not only promote the use of technology among older adults but also provide adequate support, such as digital skills training, to prevent the technology gap from exacerbating mental health problems in this vulnerable population. Given the aging of the European population, it is crucial that public policies are adjusted to facilitate a more effective integration of older adults into digital life, thereby optimizing their health and well-being outcomes.

The third chapter addresses the growing mental health problem among people with disabilities in Spain, emphasizing how a lack of participation in leisure activities can exacerbate this situation. Over time, the rate of people with disabilities has increased, and with it, the difficulties in leading a normal life, often resulting in mental health problems. The study analyzes data from the EDAD 2020 survey and finds that approximately 4% of people with disabilities do not participate in leisure activities, of whom 14% use psychological care services. The lack of access to leisure activities is associated with a higher likelihood of experiencing mental health problems, especially among women and in southern Spanish communities. These findings highlight the need to improve the adaptability and accessibility of leisure facilities for this population group. Public policies should focus on removing barriers to participation in recreational activities, as these not only improve overall well-being but also reduce the reliance on psychological care services. In summary, this study provides empirical evidence reinforcing the importance of leisure activities in the mental health of people with disabilities. It is crucial that policymakers consider these results to develop strategies that not only improve psychological care services but also address the leisure needs of people with disabilities, thereby contributing to their overall well-being and reducing the discrimination and stigma they face.

In the fourth chapter, the relationship between lifestyle and mental health is examined, highlighting the importance of identifying factors that increase the risk of problems such as depression, anxiety, and other mental disorders. Using microdata from the EHSS, this study reveals that lifestyle-associated factors impact different mental health problems in distinct ways. The results emphasize the need to consider the specific nature of each mental disorder when developing policies and preventive measures. The study highlights that generalized approaches may be ineffective, as each disorder presents unique characteristics that require tailored interventions. The research underscores the importance of adapting prevention and treatment strategies to the particularities of each mental condition, which can significantly improve the effectiveness of public health policies. Furthermore, the need for additional studies to more precisely identify risk factors and their mechanisms of action is emphasized, allowing for the development of more specific and effective interventions. In summary, a healthy lifestyle is key not only to preventing physical diseases but also to improving mental well-being. The findings of this chapter suggest that well-designed health policies tailored to the individual characteristics of mental disorders can contribute to a better quality of life and a reduction in the incidence of mental health problems in the population.

In the fifth chapter, the impact of residential area on mental health is explored, revealing significant variations according to the environment. In urban areas, the risk of mental health problems increases with age, while in rural and semi-rural areas, this risk tends to be lower as the population ages. This contrast suggests that sociocultural and economic differences between environments influence mental health in different ways. Additionally, women are found to have a higher risk of mental health problems in all residential areas, highlighting the need to address gender inequalities. In terms of education, while the educational level does not significantly affect the risk of mental health problems in urban and semi-rural areas, in rural areas, a higher probability of experiencing these problems is observed, indicating disparities in access to mental health services. The subjective perception of health has an inverse relationship with the risk of mental health problems in all areas, underscoring its importance as a predictor. Although factors such as vandalism and environmental cleanliness have a limited impact, proximity to health centers is associated with a lower risk of mental problems, although access to pharmacies and banks varies by area. In conclusion, the results suggest that the determinants of mental health are complex and vary according to the environment. Policies should be tailored to the specific characteristics of each area, especially for rural areas where certain factors, such as a lack of physical activity and exposure to vandalism, have a more pronounced impact on mental health.

Chapter 6 of this work presents a systematic review on the use of chatbots in the healthcare sector, particularly in the context of the COVID-19 pandemic, which has intensified the demand for healthcare resources and highlighted the need for efficient solutions under budgetary constraints. In this context, the growing use of artificial intelligence and telemedicine has emerged as a key strategy to optimize healthcare delivery and resources, with chatbots serving as an innovative tool in various areas such as mental health and patient monitoring. This chapter examines relevant studies published over the past five years, gathered from databases such as PubMed, Web of Science, and Scopus, and analyzes the applications and effectiveness of chatbots in different healthcare settings. The findings highlight their potential in supporting mental health, appointment management, health education, lifestyle changes, and COVID-19 management, showcasing their broad potential. However, challenges related to implementation, compatibility with other systems, and ethical considerations that may arise in various healthcare environments are also identified. Addressing these challenges will be crucial to maximizing the benefits of chatbots, mitigating risks, and ensuring equitable access to these healthcare innovations.

2. Future research lines

The thesis provides a comprehensive overview of various aspects of mental health but also opens multiple avenues for future research. At a general level, one direction is to delve deeper into how various social, economic, and environmental factors interact with mental health, integrating additional variables such as cultural context and specific local policies. It is essential to explore how these factors may influence different populations either jointly or in isolation to provide more precise recommendations tailored to specific contexts.

Moreover, it would be valuable to expand the geographical scope of studies by incorporating data from less-represented regions or countries with different socioeconomic and cultural characteristics. This would allow for a more global and comparative understanding of the determinants of mental health and their implications for public policy. Finally, the integration of longitudinal studies could provide a more dynamic and evolutionary view of how risk and protective factors influence mental health over time.

To continue the research line of the first chapter, a longitudinal analysis could be conducted to observe how the impact of COVID-19 on the mental health of older adults has evolved over time. It would be useful to investigate how the duration and intensity of the pandemic have altered experiences and perceptions of mental health in this population. Additionally, future studies could explore the role of specific interventions, such as psychological and social support programs, and assess their effectiveness in mitigating the negative effects of the pandemic. Comparative research between different European countries could offer additional perspectives on the most effective strategies for addressing mental health issues in varied contexts.

A future research direction on the topic of Chapter 2 could focus on evaluating the impact of emerging technologies, such as mental health apps and telemedicine platforms, on the mental health of older adults. It would be relevant to investigate how the adoption of advanced technologies, such as virtual reality for therapy or assistive technologies, affects mental well-being. Additionally, the influence of technological barriers, such as lack of training or accessibility, on the effectiveness of these tools and on the mental health of older adults could be explored. Intervention studies could also analyze the impact of technology training programs in reducing the digital divide and improving mental health.

For future research on the theme of Chapter 3, the focus could be on examining how the quality and accessibility of leisure activities specifically affect different types of disabilities. It would be beneficial to investigate the impact of specific leisure programs tailored to various disabilities and assess how these programs can improve mental well-being. Additionally, the relationship between participation in leisure activities and other factors such as family and community support should be explored. Comparative studies between different types of disabilities and geographical regions could provide insights into the effectiveness of various leisure policies and programs in improving mental health.

Future studies related to Chapter 4 could investigate how specific lifestyle interventions, such as physical exercise programs, balanced diets, and mindfulness practices, differentially affect various mental disorders. Additionally, it would be useful to explore how factors such as the work environment and housing conditions influence the relationship between lifestyle and mental health. Research could benefit from interdisciplinary approaches that combine insights from psychology, sociology, and medicine to develop more effective prevention and treatment strategies. The impact of public policies promoting healthy lifestyles in different populations and how these policies affect mental health at the population level could also be studied.

A future research direction for Chapter 5 could focus on how the specific characteristics of urban versus rural environments, such as population density, infrastructure, and access to services, influence mental health. It would be relevant to investigate the role of social support networks and community programs in mitigating the risks associated with different residential environments. Additionally, longitudinal studies could analyze how changes in residential environments, such as infrastructure improvements or urban policies, affect residents' mental health. Finally, research could benefit from public policy approaches that integrate the specific mental health needs and characteristics of each type of residential area.

Future research on chatbots in healthcare, as discussed in Chapter 6, should focus on evaluating their long-term impact on patient outcomes, particularly in managing chronic conditions and preventive care. Investigating the integration of chatbots with Electronic Health Records (EHRs) is also crucial for enhancing patient management and personalized care. As LLMs continue to evolve, further studies should explore their potential to improve chatbot accuracy and context-aware interactions. Empirical research should also assess the cost-effectiveness and scalability of chatbot technologies, particularly in low-resource settings such as rural areas.

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