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Passive behaviorale Daten im Public Mental Health-Bereich - Nutzung von Verhaltensdaten als Korrelate für eine depressive Symptomatik

Dissertation

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Abstract

This dissertation aimed to evaluate passive behavioural data as a new data source in the field of public mental health. To date, research in the field of public mental health has primarily used written or oral self-report data as a method, which requires great effort, is time-consuming, and is susceptible to report bias. The conceptualisation of prevention measures and needs in the space of public mental health requires data that are as up-to-date and precise as possible. The use of smartphone-assessed passive behavioural data has already been discussed as additional objective measurement method to identify symptoms of mental disorders. Standardised parameters of passive behavioural data do not yet exist within the public mental health context. However, before passive behavioural data can be integrated as a new data source in the field of public mental health research, it must be evaluated on the basis of quality criteria. The evaluation of passive behavioural data is accompanied by essential ethical (and data protection) questions. Due to the currently high prevalence of depressive disorders worldwide and their tremendous individual and social consequences, the evaluation of passive behavioural data in the present dissertation was carried out by using depressive symptoms as the example.

The three research projects in this dissertation were based on data collection aiming to predict depressive symptoms with the help of passive behavioural data. The results from Research Project 1 suggested that passive behavioural smartphone data offered added content value compared to survey data of established self-reported predictors of depressive symptoms. Of the included passive behavioural smartphone data, messenger use and video calls, as correlates of social interaction, contributed significantly to the prediction of depressive symptoms. The results of Research Project 1 suggested that passive behavioural data could be used as measures of depressive

symptoms; a precise attribution of passive behavioural data points to individual depressive symptoms is still pending. This would enable continuous data collection in the public mental health sector and thus early identification of trends in the prevalence of depressive symptoms. This, in turn, provides the basis for the equally timely planning and implementation of preventive measures.

In addition, Research Project 2 investigated the contribution of regional data derived from official statistics based on GPS location to the prediction of individual depressive symptoms. The results showed that regional information could be helpful in identifying risk groups in the public mental health sector. The results were not transferable to the postpandemic period due to the survey being conducted during the COVID-19 pandemic but, at the same time, provide valuable information on groups particularly at risk for depressive symptoms during a pandemic.

Research project 3 investigated the extent to which characteristics of passive behavioural data are valid as correlates of depressive symptoms across individuals. To this end, we tested the extent to which personality facets and perceived social support were associated with the relationship between media use and physical activity levels (measured as behavioural data) and depressive symptoms.

Some behavioural data points were found to be related to depressive symptoms independently of individual characteristics, while others were related to depressive symptoms in differential ways. Thus, the results of Research Project 3 highlighted the relevance of interindividual differences in the assessment of passive behavioural data. Overall, the results indicated that defining consistent behavioural data measures for the public mental health field is challenging, as some behavioural data measures show different strengths of associations with depressive symptoms between individuals. As a practical implication, both an individual-centred approach and the inclusion of person-specific control variables are recommended.

Zusammenfassung

Die vorliegende Arbeit widmet sich der Evaluation passiver behavioraler Daten als neue Datenquelle im Public Mental Health-Bereich. Die bisherige psychologische Forschung im Public Mental Health-Bereich bedient sich primär der Erhebungsmethode der schriftlichen oder mündlichen Selbstauskunft, welche aufwendig, zeitintensiv und anfällig für Verzerrungen der Antworten ist. Die Konzeptualisierung von Präventionsmaßnahmen und -bedarfen im Public Mental Health-Bereich erfordert möglichst aktuelle wie präzise Daten. Smartphone-basierte passive behaviorale Daten wurden bereits als objektive Messdaten zur Identifikation von Symptomen psychischer Störungen diskutiert. Standardisierte Parameter passiver behavioraler Daten gibt es im Public Mental Health-Bereich jedoch noch nicht. Vor einer Integration passiver behavioraler Daten als neue Datenquelle in die Forschung im Public Mental Health-Bereich bedarf es allerdings der Evaluation anhand von Gütekriterien. Diese Evaluation von passiven behavioralen Daten geht mit wesentlichen ethischen (und datenschutzrechtlichen) Fragestellungen einher. In der vorliegenden Dissertation wurde die Evaluation am Beispiel depressiver Symptome vorgenommen, aufgrund der weltweit hohen Prävalenz depressiver Störungen und ihrer enormen individuellen wie gesellschaftlichen Folgen.

Die drei Forschungsprojekte dieser Dissertation basieren auf Datenerhebungen zur Vorhersage von depressiven Symptomen mithilfe passiver behavioraler Daten.

Die Ergebnisse vom Forschungsprojekt 1 deuteten darauf hin, dass passive behaviorale Smartphone-Daten im Vergleich zu etablierten selbstberichteten Prädiktoren für depressive Symptome, die aus Umfragedaten gewonnen wurden, einen inhaltlichen Mehrwert boten: Von den einbezogenen passiven behavioralen Smartphone-Daten trugen die Nutzung von Messengern und Videoanrufe als Korrelate sozialer Interaktion signifikant zur Vorhersage von depressiven Symptomen bei. Die

Ergebnisse des Forschungsprojekts 1 legten nahe, dass passive behaviorale Daten als Messwerte depressiver Symptome herangezogen werden könnten, eine genaue Zuordnung passiver behavioraler Datenpunkte zu einzelnen depressiven Symptomen steht noch aus. Perspektivisch würde dies eine kontinuierliche Datenerhebung im Public Mental Health-Bereich und somit frühzeitige Identifikation von Trends in der Verbreitung depressiver Symptome ermöglichen. Dies bietet die Grundlage für ebenso zeitige Planung und Umsetzung von Präventionsmaßnehmen.

Darüber hinaus untersuchte Forschungsprojekt 2 den Beitrag regionaler Daten, die aus amtlichen Statistiken auf der Grundlage des GPS-Standorts abgeleitet wurden, zur Vorhersage individueller depressiver Symptome. Die Ergebnisse zeigten, dass regionale Informationen bei der Identifikation von Risikogruppen im Public Mental Health-Bereich hilfreich sein können. Die Ergebnisse waren aufgrund der Erhebung während der COVID-19 Pandemie nicht übertragbar auf die postpandemische Zeit, gaben gleichzeitig wertvolle Hinweise auf für depressive Symptome besonders gefährdete Gruppen während einer Pandemie.

Das Forschungsprojekt 3 untersuchte inwiefern Kennwerte passiver behavioraler Daten personenübergreifend Gültigkeit als Korrelate depressiver Symptome haben. Zu diesem Zweck wurde getestet, inwiefern Persönlichkeitsfacetten und wahrgenommene soziale Unterstützung mit dem Zusammenhang zwischen Mediennutzung bzw. körperlicher Aktivität (als behavioralen Daten) und depressiven Symptomen korrelieren. Es zeigte sich, dass manche behavioralen Datenpunkte unabhängig von individuellen Eigenschaften einen Zusammenhang mit depressiven Symptomen aufweisen und andere individuell verschieden mit depressiven Symptomen zusammenhängen. Damit verdeutlichten die Ergebnisse des Forschungsprojekts 3 die Relevanz interindividueller Unterschiede bei der Bewertung passiver Verhaltensdaten. Die Ergebnisse wiesen insgesamt darauf hin, dass die

Definition einheitlicher Kennwerte behavioraler Daten für den Public Mental Health-Bereich herausfordernd ist, da einige Kennwerte behavioraler Daten zwischen Personen unterschiedlich starke Zusammenhänge mit depressiven Symptomen aufwiesen. Als praktische Implikation ist sowohl ein personalisiertes Vorgehen als auch der Einschluss von personenspezifischen Kontrollvariablen angeraten.

Kapitel 1

Einleitung

Herausforderung im Bereich Public Mental Health

Der Public Health-Bereich kann als Teil des öffentlichen Gesundheitssystems verstanden werden, der die Gesundheit der Bevölkerung verstehen, schützen und fördern will (World Health Organization. Regional Office for Europe, 1999). Das Ziel von Public Health ist es, Krankheiten zu verhindern, Leben zu verlängern und durch gesellschaftliche Anstrengung mentale wie physische Gesundheit zu fördern. Der Begriff „Public Health" beschreibt daher ein Feld, das sich aus Wissenschaft und Präventionsmaßnahmen zusammensetzt (Childress et al., 2002).

Public Mental Health konzentriert sich auf die Themen Wohlbefinden und psychische Störungen, deren Epidemiologie, Ätiologie und die sich daraus ergebenden Präventionsmaßnahmen (Wahlbeck, 2015). Primäre Präventionsmaßnahmen haben dabei das Ziel, die Entstehung von psychischen Störungen zu verhindern, sekundäre Präventionsmaßnahmen versuchen durch Früherkennung von Krankheiten frühestmögliche Behandlung zu ermöglichen (Franzkowiak, 2022). Public Mental Health hat daher zum einen die Aufgabe soziale Determinanten (zum Beispiel Risikofaktoren) und gesundheitliche Ungleichheit (zum Beispiel Hochrisikogruppen) zu identifizieren, um zum Beispiel Präventionsmaßnahmen gezielt adressieren zu können. Zum anderen ist es die Aufgabe von Public Mental Health durch epidemiologische Studien die Verteilung von psychischer Gesundheit und psychischen Störungen in der Bevölkerung zu beschreiben und zu erklären, sowie neue Entwicklungen in der Verteilung zu erkennen, zum Beispiel als Datengrundlage zur Identifikation von Bedarf an Behandlungskapazitäten (World Health Organization. Regional Office for Europe, 2012).

Zur Umsetzung dieser Aufgaben bedarf es Datenerhebungen, deren Qualität und Quantität den Rahmen für die Entwicklung oder Anpassung späterer Public Mental Health Maßnahmen setzen.

Die vorliegende Arbeit widmet sich am Beispiel depressiver Symptomatik der Fragestellung, inwiefern die Erhebung von passiven behavioralen Daten als eine neue und möglicherweise ergänzende Methodik der Datenerhebung und Auswertung einen Mehrwert im Public Mental Health-Bereich bieten kann.

Relevanz neuer Datenquellen im Public Mental Health-Bereich

Die Aktualität der Daten im Public Mental Health-Bereich bestimmt den Zeitpunkt, zu dem Veränderungen - zum Beispiel in der Verbreitung von psychischen Erkrankungen - identifiziert und gezielt (Präventions-) Maßnahmen ergriffen werden können (Fried & Nesse, 2015). Die Detailtiefe der Daten, mit denen im Public Mental Health-Bereich die Symptome psychischer Störungen abgebildet werden, bestimmt, ab welchem Maß eine Veränderung (zum Beispiel eine Zunahme) in der Verbreitung einer psychischen Störung in der Bevölkerung erkannt wird.

Frühzeitiges Erkennen von Symptomen psychischer Störungen ermöglicht Maßnahmen, durch welche die Entwicklung des Vollbildes einer psychischen Störung und somit individuelles Leiden verhindert werden kann; dies wird auch mit dem Begriff der primären Prävention zusammengefasst (Franzkowiak, 2022). Zudem liegen die Kosten von Präventionsmaßnahmen unter der Summe von Behandlungskosten, Kosten aufgrund von Arbeitsausfällen, anschließender Rehabilitation sowie indirekten Kosten möglicher familiärer Belastung (Lépine & Briley, 2011; McDaid et al., 2019; Zechmeister et al., 2008). Aufgrund des steigendenden Kostendrucks in der Gesundheitsversorgung gewinnt dieses ökonomische Argument zunehmend an Gewicht (O’Doherty et al., 2016).

Depression, der inhaltliche Untersuchungsgegenstand dieser Arbeit, zählt weltweit zu den häufigsten psychischen Erkrankungen (World Health Organisation, 2023). Depression gehört heute sogar zu den drei Hauptdiagnosen im weltweiten Ranking des *Global Burden of Disease* Projektes, das sich die Quantifizierung von Todesfällen, Krankheitslast und Behinderung zur Aufgabe gemacht hat (Lépine & Briley, 2011; World Health Organisation, 2023). Da Depression also zu einer der häufigsten Ursachen für gesundheitliche Einschränkungen und Verlust an Lebenszeit zählt, ist die Forschung dazu für den Public Mental Health-Bereich von großer Relevanz. Die Frage nach dem Mehrwert neuer Methodik der Datenerhebung und Auswertung im Public Mental Health-Bereich soll daher anhand dieser psychischen Störung untersucht werden.

Aktueller Stand und Zukunftsperspektiven der Datenerhebung im Public Mental Health-Bereich

Bei der Datenerhebung im Public Mental Health-Bereich geht es um quantitative Methoden, um Symptome psychischer Störungen in der Bevölkerung zu erfassen. Die Methoden sollen je nach Fragestellung das Erleben und Verhalten zum Beispiel Kognitionen, Gefühle und Motivationen und das Sozialverhalten quantifizieren. Die psychologische Forschung bedient sich hierzu grundsätzlich vier Verfahren der Datenerhebung: der Verhaltensbeobachtung, dem Selbstberichtsverfahren, dem Testen und Messungen (Moosbrugger & Kelava, 2012). Die methodische Herausforderung in der Erhebung von Symptomen psychischer Störungen besteht stets darin, dass es um mentale, also um nicht sichtbare Zustände geht. Alle genannten Verfahren stellen also lediglich Näherungswerte dar. Der Standard in der Datenerhebung im Public Mental Health-Bereich ist aktuell die Befragung mittels standardisierter Fragebögen. Standardisierte Fragebögen erfragen Symptome sowie einige Ein- wie Ausschlusskriterien psychischer Störungen entsprechend der Diagnosekriterien wie zum Beispiel der Patient Health Questionnaire-9 (PHQ-9) (Löwe et al., 2004) bei depressiven Symptomen. Im Unterschied zu einem willkürlichen Fragenkatalog hat ein standardisierter Fragebogen ein wissenschaftliches Fundament und entspricht den Gütekriterien psychologischer Forschung (Moosbrugger & Kelava, 2012).

Zur Stellung einer klinischen Diagnose bedarf es der Überprüfung durch ein klinisches Interview durch Fachpersonal, zum Beispiel das strukturierte klinische Interview (SCID-5-CV) (First et al., 2019). Daher wird in zahlreichen Studien, so auch den vorliegenden auf Selbstbericht basierenden Forschungsprojekten, von Symptomen psychischer Störungen und nicht von Diagnosen wie zum Beispiel einer depressiven Störung gesprochen.

Die abhängige Variable in den vorliegenden drei Forschungsprojekten sind depressive Symptome, die mithilfe des standardisierten Fragebogens PHQ-9 gemessen wurden (Löwe et al., 2004).

(Online-) Befragungen als Forschungsmethode setzen die Teilnahmebereitschaft der Befragten voraus, welche sowohl vom Interesse am Thema wie auch von der benötigten Bearbeitungsdauer abhängt (Wagner-Schelewsky & Hering, 2022). Langzeiterhebungen sind im Public Mental Health-Bereich noch selten (Müters & Lampert, 2020) und eine kontinuierliche Erhebung von Daten zu psychischer Gesundheit ist auch durch (Online-) Befragungen aufgrund der aufgeführten Hürden nur schwer umsetzbar. Bei Befragungen kann es zudem zu methodisch bedingten Ergebnisverzerrungen kommen, wie beispielsweise durch soziale Erwünschtheit. Dies meint den Versuch, sich durch angepasstes Antwortverhalten passend zu subjektiven sozialen Normen darzustellen (Paulhus, 2017). Auch Wahrnehmungs- und Gedächtniseffekte beeinflussen die Ergebnisse von Befragungen (Gaupp et al., 2006).

So können lediglich Aspekte berichtet werden, die von der Person bewusst wahrgenommen und erinnert werden. Psychische Erkrankungen können eine veränderte Wahrnehmung des eigenen Verhaltens mit sich bringen, was eine Verzerrung der Antworten beim Selbstbericht zu psychischer Gesundheit mit sich bringen könnte (Place et al., 2017; Torous et al., 2017).

Die Arbeit mit Befragungsdaten als Grundlage für den Public Mental Health-Bereich ist somit begrenzt durch ökonomische Eigenschaften wie Zeit- und Kostenaufwand sowie durch die Fähigkeiten und Bereitschaft der Teilnehmenden Auskunft über innere Prozesse zu geben.

Mit der Digitalisierung sind Möglichkeiten der Datenerhebung und neue Datenquellen entstanden: Passive behaviorale Daten meint digitale Verhaltensdaten, die ohne Zutun des Untersuchungsobjekts beobachtet und gesammelt werden können (Birk & Samuel, 2022; Onnela & Rauch, 2016; Zarate et al., 2022) zum Beispiel über das Smartphone. Passive Smartphone-Daten können wiederum unterteilt werden in Sensordaten, Aktivitätsdaten und Daten aus sozialen Netzwerken (Birk & Samuel, 2022). Sensordaten sind die Daten, die über zum Beispiel im Smartphone verbaute Sensoren erhoben werden können (zum Beispiel Daten des Global Positioning Systems (GPS), Daten des Akzelerometers). Aktivitätsdaten beschreiben die Aktivität am Smartphone (zum Beispiel Bildschirmzeit, Nutzungsdauer spezifischer Apps, Anrufdauer). Daten aus sozialen Netzwerken sind der Definition nach in den Netzwerken geteilte Inhalte wie Posts (Birk & Samuel, 2022).

Zu untersuchende Themen, nach denen einst gefragt werden musste, wie das individuelle Schlafverhalten, können heute über Schlaftracker auf der Smartwatch automatisiert gemessen werden (Robbins et al., 2020); die täglich zu Fuß zurückgelegte Distanz dokumentiert auf Wunsch der Schrittzähler im Smartphone

(Amagasa et al., 2019). In vielen alltäglichen Bereichen wie Navigationsdiensten und personalisierter Werbung ist die Erhebung und Auswertung dieser Daten in Echtzeit gängige Praxis (Puglisi et al., 2017). Im Public Mental Health-Bereich haben diese neuen Datenquellen und die Erhebung wie Auswertung in Echtzeit noch nicht Einzug gehalten.

Dabei wird die Nutzung passiver behavioraler Daten in Kombination mit maschinellem Lernen bereits als vielversprechende Methode im Mental Health-Bereich diskutiert (Shakeri Hossein Abad et al., 2021), zum Beispiel indem Symptomveränderungen im Rahmen einzelner nicht repräsentativer Pilotstudien automatisiert identifiziert oder vorhergesagt werden (Ben-Zeev et al., 2015; Dogan et al., 2017; Han et al., 2021; Kilgallon et al., 2022; Rohani et al., 2018; Zarate et al., 2022).

Passive behaviorale Daten sind als neue Datenquelle ebenfalls bereits Bestandteil der klinischen Forschung zu psychischen Erkrankungen (Rohani et al., 2018; Zarate et al., 2022). Inwiefern deren Nutzung auch im Public Mental Health-Bereich einen Mehrwert bietet, untersucht und diskutiert die vorliegende Arbeit - auch unter ethischen Gesichtspunkten.

Passive behaviorale Daten - Verwendung im Alltag

Über die Erhebung passiver behavioraler Daten wird eine Dokumentation von Verhalten im Alltag möglich, denn dank fortgeschrittener Digitalisierung findet ein großer Teil des menschlichen Verhaltens heute digital statt oder hinterlässt zumindest digitale Spuren (Golder & Macy, 2014). Ein großer Teil der sozialen Interaktionen passiert heute online (Lieberman & Schroeder, 2020); das im Smartphone integrierte Akzelerometer misst als Bewegungssensor körperliche Aktivität (Lu et al., 2017) zum Beispiel für Fitnessapps; das Mobilitätsverhalten wird über das GPS-Signal von Navigationsanwendungen analysiert (Birenboim & Shoval, 2016); das GPS-Signal verrät auch, an welchen Orten der individuelle Alltag stattfindet, wieviel Zeit zuhause und außer Haus verbracht wird (Birk & Samuel, 2022; Onnela & Rauch, 2016). Eine Vielzahl passiver behavioraler Smartphone-Daten machen somit soziale Interaktionen, körperliche Aktivität und Mobilitätsroutinen sichtbar. Am Beispiel der Forschung zu depressiven Symptomen gibt es zahlreiche Studien, die auf Basis von passiven behavioralen Smartphone-Daten aus den Bereichen soziale Interaktion, Aktivität oder Mobilität rechnerisch auf das Vorliegen depressiver Symptome schließen (Rohani et al., 2018; Saeb et al., 2016; Zarate et al., 2022).

Passive behaviorale Daten - von der Befragung zur Verhaltensmessung

Die psychiatrische Arbeit kennt das Spannungsfeld zwischen Selbstbericht von Patient*innen und externer Realität (Fisher & Appelbaum, 2017). Es werden objektive Messdaten für depressive Symptome gefordert (Fried & Nesse, 2015). Therapeut*innen nutzen daher bereits ergänzende Informationen jenseits des Selbstberichtes (zum Beispiel Angehörigengespräche), dies zeigt auch hier ein fachliches Interesse an Informationen, die aufgrund der Digitalisierung zum Beispiel in Form passiver behavioraler Daten bereits verfügbar sind (Fisher & Appelbaum, 2017). Auch als mögliche Antwort auf die bereits vorgestellten Limitationen der Befragungsmethode finden sich in der bestehenden Forschung zwei Zukunftsperspektiven: Die eine sieht passive behaviorale Daten als objektive Messwerte depressiver Symptome (Place et al., 2017); die andere Perspektive betont die Möglichkeit, mithilfe dieser engmaschigen digitalen Dokumentation menschlichen Verhaltens in naturalistischem Setting (Onnela & Rauch, 2016) explorativ ein tieferes Verständnis des depressiven Störungsbildes zu gewinnen (Mohr et al., 2017).

Nachfolgend sollen anhand bestehender Forschungsarbeiten die unterschiedlichen Perspektiven vorgestellt und gegeneinander abgewogen werden. Es ergeben sich daraus die in der vorliegenden Dissertation adressierten Forschungsfragen, mit deren Vorstellung die Einleitung endet.

Bei der Sichtung des aktuellen Forschungsstandes zeigen sich Ergebnisse, die nahelegen, dass passive behaviorale Daten mit Symptomen psychischer Störungen zusammenhängen (Opoku Asare et al., 2021; Saeb et al., 2016; Seppälä et al., 2019; Zarate et al., 2022). Nicht untersucht wurde bis dato, inwiefern konkrete depressive Symptome passiven behavioralen Datenparametern entsprechen (Renn et al., 2018). Ernala und Kolleg*innen beschreiben dies als fehlendes theoretisches Fundament (Ernala et al., 2019). Während standardisierte Fragebögen entwickelt wurden, um eine depressive Symptomatik via Selbstbericht zu erheben (Beck et al., 1996), gibt es bisher jedoch keine anerkannten Standardparameter (passiver) behavioraler Smartphone-Daten, die in bevölkerungsrepräsentativen Untersuchungen für die Forschung zu depressiven Symptomen evaluiert, definiert und repliziert worden wären (Batra et al., 2017; Mohr et al., 2017; Place et al., 2017; Rohani et al., 2018; Zarate et al., 2022).

Zur Übersetzung depressiver Symptome in solche per Smartphone beobachtbaren Merkmale soll im ersten Schritt das Störungsbild beschrieben werden. Laut Diagnosekriterien zeigt sich eine depressive Symptomatik anhand von gedrückter Stimmung, vermindertem Antrieb und Aktivität, Freud- und Interessenlosigkeit, Konzentrationsschwierigkeiten, Müdigkeit, gestörtem Schlaf und Appetit (ICD-10) (2019). Zu depressiven Symptomen zählen auch ein reduzierter Selbstwert und reduziertes Selbstvertrauen, Schuldgefühle und Gedanken über die eigene Wertlosigkeit (ICD-10) (2019). Somatische Symptome wie psychomotorische Hemmung, Agitiertheit, Libidoverlust können ebenso mit depressiven Symptomen einhergehen (ICD-10) (2019).

In einem zweiten Schritt soll dargestellt werden, inwiefern einige der aufgeführten depressiven Symptome oder deren Korrelate im Alltag beobachtbar sind. Depressive Symptome können sich in veränderter Mimik (Girard et al., 2014; Girard et al., 2013) und Sprache (Savekar et al., 2023) ausdrücken; Veränderung oder Verlust der Alltagsroutinen (Li et al., 2022) und vermehrtem Bericht von Krankentagen (Bretschneider et al., 2018) können mit reduzierter Aktivität und Antrieb auftreten; Interessenlosigkeit hängt zum Beispiel bei College-Studierenden mit reduzierten Freizeitaktivitäten zusammen (Blanco & Barnett, 2014); Konzentrationsschwierigkeiten korrelieren mit vermehrten Fehlern und Vergesslichkeit im Alltag (Dehn & Beblo, 2019); Schlafstörungen als Symptom psychischer Störungen (Nutt et al., 2008) sind ebenso sichtbar; wie auch veränderter Appetit als Symptom (Simmons et al., 2020) in Gewichtszu- oder abnahme sichtbar sein könnte; reduziertes Selbstvertrauen und Freudlosigkeit können sich zudem in sozialer Isolation zeigen (Ge et al., 2017). Welche passiven behavioralen Daten diesen beobachtbaren Parametern einer depressiven Symptomatik entsprechen könnten, wird im folgenden Abschnitt thematisiert.

Passive behaviorale Daten - in der Forschung zu depressiven Symptomen

Übergreifende Aussagen aus aktueller Forschung sind nicht möglich, da Studien sich in Bezug auf die Wahl der passiven behavioralen Parameter, der statistischen Verfahren und der Teilnehmenden unterscheiden (Dogan et al., 2017; Seppälä et al., 2019; Zarate et al., 2022). In den Forschungsarbeiten wurden zudem in der Regel datenbasierte Vorgehen bei der Suche nach Verhaltensparametern gewählt (Chekroud et al., 2021), die einzeln oder in Kombination eine depressive Symptomatik mit möglichst geringer Fehlerwahrscheinlichkeit vorhersagen. Bei der Verwendung passiver Daten findet dabei die Auswertung oft mithilfe automatisierter

Rechenverfahren, so genanntem maschinellen Lernen, statt (Birk & Samuel, 2022; Chekroud et al., 2021). Dies zeigt, dass die Forschungslogik zu passiven behavioralen Daten oft explorativ und nicht hypothesengeleitet vorgeht (Chekroud et al., 2021). Nachfolgend werden die Ergebnisse dieser Untersuchungen dargestellt und die darin identifizierten Korrelationen zwischen gemessenen Merkmalen und möglichen depressiven Symptomen erläutert.

Körperliche Aktivität. Körperliche Aktivität wird als beobachtbarer Parameter depressiver Symptome diskutiert, wie zum Beispiel für das depressive Symptom eines reduzierten Antriebs oder verminderten Interesses an Aktivitäten. Der Zusammenhang von körperlicher Aktivität und Gefühlszuständen zeigte sich in empirischer Forschung (Dogan et al., 2017), auch konkret zu depressiven Symptomen (Difrancesco et al., 2022; Jakobsen et al., 2020). Eine systematische Übersichtarbeit von Zarate und Kolleg*innen benannte konkret wenig körperliche Aktivität gemessen mittels passiver behavioraler Daten (via Smartphone oder um Brustkorb getragenes Akzelerometer) war in den meisten Studien mit mehr depressiven Symptomen korreliert (Zarate et al., 2022). Eine andere Arbeit von Moshe und Kolleg*innen bestätigte einen Zusammenhang für die mittels Smartwatch gemessene körperliche Aktivität und depressive Symptome (Moshe et al., 2021). Die Messung körperlicher Aktivität mithilfe des in diesem Fall im Smartphone verbauten Akzelerometers korrelierte in einer anderen Studie nicht mit Veränderungen der depressiven Symptomatik (Ben-Zeev et al., 2015). Eine Erklärung für diese widersprüchlichen Ergebnisse könnte sein, dass die Tragedauer des Smartphones mit der akzelerometrischen Messung über dieses Endgerät zusammenhängen könnte (Burns et al., 2011; Renn et al., 2018). Personen mit und ohne eine depressive Störung schienen sich jedoch in ihrer körperlichen

Aktivität zu unterscheiden (gemessen mit Schrittzähler und metabolischem Umsatz der Aktivität) (Opoku Asare et al., 2022).

Das Bild in der aktuellen Forschung von körperlicher Aktivität als beobachtbarem Merkmal einer depressiven Symptomatik gemessen zum Beispiel via Smartphone ist somit insgesamt nicht eindeutig und nicht spezifisch genug. Viele Studien zeigen Zusammenhänge, einige nicht, aufgrund der Unterschiede in der Operationalisierung sind die Ergebnisse methodisch schwer zu vergleichen (Seppälä et al., 2019). Zudem ist nicht ersichtlich, aus welchen Gründen eine Person zum Beispiel nur eine geringe körperliche Aktivität aufweist, vorstellbar sind alternativ zu einer depressiven Symptomatik weitere Gründen wie eine sitzende berufliche Tätigkeit.

Mobilitätsverhalten. Zu den depressiven Symptomen zählen ein reduzierter Antrieb und Interessenlosigkeit. Zu klären ist, inwiefern sich diese Symptome im Mobilitätsverhalten widerspiegeln. Eine Langzeitstudie von Meyerhoff und Kolleg*innen zeigte, dass GPS-Parameter mit depressiven Symptomen korrelierten. Konkret stellten die Autor*innen fest, dass die Dauer der verbrachten Zeit an Orten sozialer Aktivitäten mit Veränderungen depressiver Symptome zusammenhing (Meyerhoff et al., 2021). Auch eine längere Verweildauer zuhause zeigte sich in einer systematischen Übersichtsarbeit als positiv mit depressiven Symptomen in Verbindung stehend (in einer nicht-klinischem Stichprobe) (Rohani et al., 2018). Die via Smartphone erhobene Anzahl besuchter Orte und wie oft das Haus verlassen wurde korrelierte in der Studie von Di Matteo und Kolleg*innen mit einer reduzierten Wahrscheinlichkeit für ein positives Screening depressiver Symptome (Di Matteo et al., 2021). Die Veränderungen im Mobilitätsverhalten zeigten auch Veränderungen in depressiven Symptomen an (Ben-Zeev et al., 2015). Letzteres kann als erster Hinweis für den folgenden Abschnitt dienen, dass der Schweregrad depressiver Symptome mit sich verändernder Alltagsroutinen korreliert.

Alltagsroutinen. Neben den Symptomen des reduzierten Antriebs und der Interessenlosigkeit kann auch ein veränderter Schlaf zu einer depressiven Symptomatik gehören. Eine Theorie ist, dass derlei Symptome ursprüngliche Alltagsroutinen verändern können. Mobilitätsroutinen sind mithilfe passiver behavioraler Daten (konkret GPS) abbildbar (Saeb et al., 2016).

In ihrer systematischen Übersichtsarbeit analysierten Forschende mittels GPS-Daten die Verteilung der an verschiedenen Orten verbrachten Zeit, die sogenannte Entropie. Eine hohe Regelmäßigkeit dieses Mobilitätsmusters im Alltag korrelierte in nicht-klinischen Stichproben mit besserer Stimmung (Rohani et al., 2018). Auch andere Forschungsarbeiten fanden einen Zusammenhang zwischen höherer Entropie und geringeren depressiven Symptomen (Moshe et al., 2021; Saeb et al., 2015). Ein Erklärungsansatz für diese beobachtete Korrelation ist, dass dieses via Smartphone gemessene Mobilitätsverhalten einen Surrogatparameter für Aktivitäten außer Haus darstellt und mehr solcher Aktivitäten mit weniger depressiven Symptomen korreliert (Rohani et al., 2018). Eine Forschungsarbeit zeigte, dass tägliche Mobilitätsroutinen (gemessen mithilfe von GPS über das Smartphone), die einem 24-Stunden-Rhythmus folgten, mit weniger depressiven Symptomen einhergingen (Saeb et al., 2016; Saeb et al., 2015). Einen ähnlichen Zusammenhang gab es in selbiger Forschungsarbeit zwischen der Varianz der über zwei Wochen besuchten Orte und der Entropie, welche beide negativ mit depressiven Symptomen zusammenhingen, selbes galt für weniger zuhause verbrachte Zeit (Saeb et al., 2016; Saeb et al., 2015). Personen mit und ohne eine depressive Störung unterschieden sich also in ihrer Mobilität (zum Beispiel Anzahl besuchter Orte und durchschnittliche Verweildauer an Orten mittels GPS) (Opoku

Asare et al., 2022). Di Matteo und Kolleg*innen untersuchten Alltagsroutinen mittels Audioaufnahmen via Smartphone und prüften, inwiefern diese einem wiederkehrenden 24-Stunden-Rhythmus folgten. Es zeigte sich ein positiver Zusammenhang mit einem Screening für depressive Symptome (Di Matteo et al., 2021). Veränderte Alltagsroutinen können somit mithilfe passiver behavioraler Daten sichtbar gemacht werden und die Evidenz für Zusammenhänge mit depressiven Symptomen nimmt stetig zu.

Soziale Aktivität. Sowohl der reduzierte Antrieb als auch die Interessen- und Freudlosigkeit und das negative Selbstbild, welche mit einer depressiven Symptomatik einhergehen können, könnten in sozialen Aktivitäten sichtbar sein. Eine systematische Übersichtsarbeit beschreibt soziale Aktivitäten, die zum Beispiel mittels Telefonnutzung gemessen wurde, als mit depressiven Symptomen in Zusammenhang stehend (Burns et al., 2011; Seppälä et al., 2019; Zarate et al., 2022). Hierzu passt, dass mit depressiven Symptomen oft ein reduziertes Bedürfnis nach sozialer Interaktion und reduzierte soziale Fähigkeiten einhergingen (Grünerbl et al., 2015). Ein Gefühl von Einsamkeit kann die Folge sein, Depression und Einsamkeit standen in jedem Fall im Zusammenhang (J. Wang et al., 2018). Letzteres korrelierte in der Arbeit von Currey und Torous negativ mit passiven behavioralen Daten (zum Beispiel der Anzahl eingehender Anrufe) (Currey & Torous, 2022). Das Symptom Interessenverlust schien sich in Form reduzierter sozialer Aktivität zu zeigen (Fried & Nesse, 2015). Auch zeigte sich ein Zusammenhang in der Kommunikation via Smartphone mit depressiven Symptomen, zum Beispiel in der Dauer von Telefonanrufen (Currey & Torous, 2022). In einer klinischen Stichprobe erwies sich die Nutzung von Kommunikationsapps allgemein als negativ korreliert mit depressiven Symptomen (Rohani et al., 2018). Die Autor*innen dieser Studie wiesen jedoch darauf hin, dass soziale Applikationen des

Smartphones sehr individuellen Nutzungsmustern unterliegen und der Zusammenhang mit depressiven Symptomen eher intraindividuell analysiert werden sollte, auch geschlechterspezifische Unterschiede schlossen sie nicht aus (Rohani et al., 2018). Demgegenüber zeigte die Studie von Razavi und Kolleg*innen, dass sich die soziale Aktivität via Smartphone von Menschen mit depressiven Symptomen von derer ohne oder mit wenigen depressiven Symptomen systematisch unterschied: Menschen mit depressiven Symptomen wiesen eine höhere Smartphone-Nutzungsdauer auf, empfingen und erhielten weniger Anrufe, ihre Anrufdauer war kürzer, sie schickten mehr Textnachrichten und verbrachten mehr Zeit auf Plattformen sozialer Netzwerke (Razavi et al., 2020).

Es lässt sich zusammenfassend feststellen, dass sich soziale Aktivitäten als beobachtbare und mithilfe passiver behavioraler Daten messbare Parameter operationalisieren und messen lassen, sowohl allgemein als auch konkret Kommunikationsverhalten via Smartphone. Darüber hinaus scheinen sie in enger Verbindung mit depressiven Symptomen zu stehen.

Schlafverhalten. Ein veränderter Schlaf (Einschlaf-, Durchschlafstörung, frühes Aufwachen) ist per se ein mögliches depressives Symptom. Auch stellten zahlreiche Studien bereits unterschiedliche Operationalisierungen von Schlaf über passive behaviorale Daten dar (Ben-Zeev et al., 2015; Currey & Torous, 2022; Di Matteo et al., 2021; Difrancesco et al., 2022; Moshe et al., 2021). Unter anderem zeigte eine systematische Übersichtsarbeit die Korrelation erhöhter Schlafvariabilität (gemessen mithilfe passiver Daten) mit depressiven Symptomen (R. Wang et al., 2018; Zarate et al., 2022). Andere Studien beobachteten eine Korrelation zwischen der Schlafdauer (in einer Studie gemessen mithilfe der Bildschirmaktivität des Smartphones, in anderer Studie mittels Akzelerometer des Smartphones) und Veränderungen in depressiven

Symptomen (Ben-Zeev et al., 2015; Currey & Torous, 2022). Diese Ergebnisse konnten in einer systematischen Übersichtsarbeit (für klinische Stichproben) bestätigt werden (Rohani et al., 2018). Eine andere Studie erhob die Daten mithilfe eines sogenannten Smart Rings (Oura Ring) und identifizierte ebenso die Schlafdauer und die im Bett verbrachte Zeit als Korrelate depressiver Symptome (Moshe et al., 2021). Difrancesco und Kolleg*innen untersuchten Schlaf und dessen Zusammenhang mit einzelnen Dimensionen depressiver Symptome: Mittels Akzelerometer gemessene längere Schlafdauer korrelierte mit der somatischen und vegetativen Dimension depressiver Symptome, eine geringe Schlafeffektivität mit der Dimension Schlaf im Screening depressiver Symptome (Difrancesco et al., 2022). Schlafstörungen, gemessen als Umgebungslautstärke zwischen Mitternacht und 6 Uhr morgens via Smartphone, hingen positiv mit depressiven Symptomen zusammen (Di Matteo et al., 2021). Personen mit und ohne eine depressive Störung unterschieden sich auch in den Schlafparametern Schlafeffektivität und Schlafdauer (Opoku Asare et al., 2022).
Schlaf als ohnehin beobachtbares Verhalten, lässt sich offenbar auch über digitale Endgeräte wie das Smartphone messen und hängt mit einer depressiven Symptomatik zusammen.

Weitere Nutzungsmuster. Forschungsarbeiten zeigten zudem weitere passive behaviorale Datenparameter und Kombinationen derer, die eine depressive Symptomatik vorhersagen können, ohne dass diese explizit einem depressiven Symptom zuzuordnen wären.
Die aktive Bildschirmzeit wurde in diversen Arbeiten in nicht-klinischen Stichproben als mit depressiven Symptomen positiv in Zusammenhang stehend beschrieben (Rohani et al., 2018). Auch aktive App-Nutzung korrelierte in einer Langzeitstudie mit Veränderungen in depressiven Symptomen (Meyerhoff et al., 2021). Grund für die

Untersuchung auch diagnostisch fernerer passiver behavioraler Datenparameter und deren Zusammenhang mit depressiven Symptomen ist, dass - wie bereits beschrieben - die Forschung hier oft dem Ziel folgt, datenbasiert eine möglichst treffsichere Vorhersage depressiver Symptome zu erhalten. So zeigte zum Beispiel eine Forschungsarbeit die Vorhersage depressiver Symptome auf Basis passiver behavioraler Daten anhand von Parametern wie Anrufverhalten, Smartphone-Nutzung und Smartphone-Aktivitäten der Nutzer*innen (zum Beispiel Sperrzeiten des Bildschirms, Schlaf) und der GPS-Daten mit einer 77% Genauigkeit (He et al., 2022).

Die Darstellung bestehender Forschung zeigt zahlreiche Versuche, depressive Symptome mithilfe passiver behavioraler Daten vorherzusagen und präsentiert unterschiedliche Verhaltensparameter, welche mit depressiven Symptomen zusammenhingen. Mit Blick auf die Methodik der vorgestellten Forschungsarbeiten wurden bisher jedoch lediglich Korrelationen mit depressiven Symptomen dargestellt. Es ist auf Basis der bestehenden Ergebnisse nicht von Messung einer depressiven Störung (im diagnostischen Sinne) durch passive behaviorale Daten zu sprechen, sondern zum Beispiel von der Vorhersage depressiver Symptome mithilfe passive behaviorale Daten. Dies entspricht eher der Perspektive, mithilfe passiver behavioraler Daten im Public Mental Health-Bereich eine alltagsnahe digitale Dokumentation menschlichen Verhaltens zu umzusetzen (Onnela & Rauch, 2016), um depressive Symptome vorherzusagen oder ein tieferes Verständnis des Störungsbildes zu erlangen (Mohr et al., 2017).

Passive behaviorale Daten – Einordnung anhand von Gütekriterien

Unterschiedliche passive behaviorale Daten scheinen also mit depressiven Symptomen zu korrelieren. Standardisierte Verhaltensparameter, welche direkt depressive Symptome (und nicht deren Korrelate) über das Smartphone messen, wurden bisher jedoch nicht definiert (Mohr et al., 2017; Rohani et al., 2018). Für eine solche standardisierte Erhebung depressiver Symptome in Form passiver behavioraler Daten würde es der Einhaltung von Gütekriterien psychologischer Messungen bedürfen (Lind et al., 2018; Mohr et al., 2017). Zu diesen Gütekriterien zählen als Hauptkriterien Validität, Objektivität und Reliabilität. Hinzu kommen die Nebenkriterien Skalierung, Normierung, Testökonomie, Zumutbarkeit, Unverfälschbarkeit und Fairness (Moosbrugger & Kelava, 2012). Nachfolgend werden passive behaviorale Daten daher anhand von diesen Gütekriterien darstellt, um deren möglichen Zukunftsperspektiven im Public Mental Health-Bereich noch weiter einordnen zu können - es ergibt sich daraus, welcher Zukunftsperspektive folgend die vorliegende Dissertation an bestehende Forschung anknüpft.

Validität. Validität beschreibt die Gültigkeit einer Messung, also inwiefern diese Messung misst, was sie messen soll (Moosbrugger & Kelava, 2012). Bei einer hohen Validität der Messung von Depressivität hieße das zum Beispiel, dass das Messergebnis eine Aussage ermöglicht, wie depressiv eine Person im Alltag tatsächlich ist, und somit eine Übertragbarkeit der Messergebnisse auf Momente außerhalb der Messsituation gewährleistet wird.

Um die Validität zu sichern, bedient man sich den Unterkategorien Inhaltsvalidität, Konstruktvalidität, Kriteriumsvalidität und Augenscheinvalidität.

Inhaltsvalidität gibt an, inwieweit ein Messwert das zu messende Merkmal repräsentativ abbildet (Moosbrugger & Kelava, 2012). Diese könnte typischerweise berücksichtigt werden, indem die Methode einen Ausschnitt des zu messenden Merkmals erhebt. Die Überlegung ist, dass passive behaviorale Daten einen großen Teil von alltäglichen Aktivitäten sichtbar machen. Das depressive Symptom verminderten Antriebs würde so zum Beispiel anhand eines Ausschnitts alltäglicher Aktivität gemessen.

Eine weitere Unterkategorie der Validität ist die Konstruktvalidität. Sie beschreibt, inwiefern der Rückschluss von einer Messung (hier Messwerte passiver behavioraler Daten) auf ein Merkmal (zum Beispiel depressive Symptome) theoretisch fundiert ist (Moosbrugger & Kelava, 2012). Im Kontext der Anwendungsperspektive passiver behavioraler Daten zur Messung depressiver Symptome ist dieses Qualitätskriterium eingeschränkt, da die Erhebung mit unterschiedlichen Faktoren zusammenhängt: Die individuelle Nutzungsfrequenz des Smartphones korreliert zum Beispiel mit der Bildschirmzeit, die persönlichen Präferenzen im Teilen von Informationen korreliert mir der Nutzung sozialer Netzwerke, der Beruf hat einen Einfluss auf das Mobilitätsmuster im Alltag von Personen. All diese Faktoren korrelieren mit den absoluten Werten passiver behavioraler Daten. Offen ist die Frage, inwiefern die festgelegten Messwerte depressive Symptome abbilden oder aber indirekt jene aufgeführten Faktoren.

Kriteriumsvalidität würde im selben Kontext bedeuten, dass die ausgewählten Werte passiver behavioraler Daten mit dem interessierenden Merkmal einer depressiven Symptomatik in der Realität zusammenhängen. Das ließe sich prüfen, indem die Werte passiver behavioraler Daten zu depressiven Symptomen mit der Einschätzung eines strukturierten klinischen Interviews (zum Beispiel SCID-5-CV) (First et al., 2019) von Fachpersonal verglichen würden (Moosbrugger & Kelava, 2012). Nach aktuellem Stand besteht jedoch keine solche Evaluation der Kriteriumsvalidität.

Darüber hinaus gibt die Augenscheinvalidität beispielsweise die Akzeptanz auf Seiten der Teilnehmenden gegenüber der Messung depressiver Symptome mittels passiver behavioraler Daten an (Moosbrugger & Kelava, 2012). Studien, welche die Augenscheinvalidität dieser Datenerhebung mittels passiver behavioraler Daten explizit erfragen, finden sich nach aktuellem Stand nicht. Eine systematische

Übersichtsarbeit gibt an, dass in einigen Studien die Einhaltung der Teilnahmebedingungen eine Limitation darstellte, es sei nicht vollständig kontrollierbar, inwiefern eine Person das Smartphone bei sich getragen oder mit einer weiteren Person geteilt habe (Dogan et al., 2017). Hinweise zur Akzeptanz der Methodik zur Messung depressiver Symptome finden sich jedoch in Arbeiten zur allgemeinen Akzeptanz der Erhebung passiver behavioraler Daten: Die Erhebung passiver behavioraler Daten via Smartphone wird als gering invasiv erlebt und es zeigen sich insbesondere hohe Akzeptanzwerte bei den Nutzer*innen, wenn die Daten für Forschungseinrichtungen erhoben werden (Batra et al., 2017; Garrison et al., 2016). Die Validität passiver behavioraler Daten zur Messung depressiver Symptome ist bisher also ungeklärt, was die Zukunftsperspektive unterstützt, passive behaviorale Daten aktuell lediglich als Korrelate depressiver Symptome einzuordnen, die eine digitale Dokumentation menschlichen Verhaltens im naturalistischen Setting ermöglichen (Onnela & Rauch, 2016).

Objektivität. Objektivität bezeichnet im Kontext psychologischer Tests die Unabhängigkeit des Testergebnisses von der Testleitung (Durchführungsobjektivität) und der auswertendenden Person (Auswertungsobjektivität) (Moosbrugger & Kelava, 2012). Hierfür notwendig ist das Vorliegen eines definierten Regelwerks, wie Ergebnisse objektiv zu interpretieren sind (Interpretationsobjektivität) (Moosbrugger & Kelava, 2012). Da es sich im Falle passiver behavioraler Daten um Messwerte handelt, ist die Erhebung und Auswertung unabhängig von Personen und somit objektiv. Was jedoch nicht existiert ist eine Anleitung zur inhaltlichen Interpretation der Ergebnisse, was die Interpretationsobjektivität mindert, dies spiegeln auch die beiden unterschiedlichen Zukunftsperspektiven wider. Nach bisherigem Forschungsstand sollten aus Ergebnissen lediglich Aussagen über das digital dokumentierte Verhalten und mögliche in der jeweiligen Studie sichtbare Zusammenhänge mit depressiven Symptomen getätigt werden. Auch die Objektivität mindernd ist die Selektion der zu erhebenden Parameter passiver behavioraler Daten zum Beispiel aufgrund technischer oder datenschutzrechtlicher Einschränkungen.

Reliabilität. Reliabilität bezeichnet die Genauigkeit der Messung eines Merkmals. Eine Messung desselben unveränderbaren Merkmals bei derselben Person sollte also in zwei Messungen denselben Wert ergeben, diese Reliabilitätsprüfung wird als Retest-Reliabilität bezeichnet (Moosbrugger & Kelava, 2012). Bei der Verwendung passiver behavioraler Daten sind die absoluten Werte zum Beispiel der Smartphone-Nutzung abhängig von der Nutzung an dem Tag, die Erhebung besuchter Orte mittels GPS ist möglicherweise abhängig vom Wochentag. Die Retest-Reliabilität scheint bei Verwendung absoluter Werte passiver behavioraler Daten gering zu sein, es gilt zu prüfen inwiefern andere Kennwerte (Durchschnittswerte, Veränderungsmaße, standardisiere Werte o.ä.) diesem Qualitätskriterium entsprechen. Es wird hier die Relevanz deutlich, das Gütekriterium der Skalierung genau zu definieren. Damit beschäftigt sich der nächste Abschnitt. Ergebnisse zur Reliabilitätsprüfung passiver behavioraler Daten bestehen keine, was - unabhängig von den Zukunftsperspektiven – in der Bewertung von Forschungsergebnissen zu passiven behavioralen Daten zu berücksichtigen ist.

Skalierung. Dem Gütekriterium der Skalierung wird eine Messung gerecht, wenn die Verhältnisse der Messwerte denen der realen Merkmalsausprägung entsprechen (Moosbrugger & Kelava, 2012). Diese Relationen sollten sowohl innerhalb einer Person als auch zwischen Personen gegeben sein. Der Perspektive folgend, dass passive behaviorale Daten depressive Symptome messen könnten, sollte einer

Person mit situativ stark ausgeprägten depressiven Symptomen demnach ein höherer Messwert mittels passiver behavioraler Daten entsprechen als in einer Phase schwächer ausgeprägter Symptomatik. Eine Person mit stärker ausgeprägter depressiver Symptomatik sollte zudem einen höheren Messwert passiver behavioraler Daten aufweisen als eine Person mit situativ schwächerer Symptomausprägung. In einigen Forschungsarbeiten wird die Anrufdauer oder Anzahl verschickter Nachrichten zur Vorhersage depressiver Symptome herangezogen (Razavi et al., 2020). An diesem Beispiel lässt sich veranschaulichen, dass die Relation der Messwerte zwischen Personen nicht zwingend die Relation depressiver Symptome abbildet, da eine Person möglicherweise ohnehin mehr telefoniert als eine andere unabhängig von der individuellen depressiven Symptomatik. Die interpersonellen Verhältnisse der absoluten Messwerte passiver behavioraler Daten entsprechen nicht dem Gütekriterium der Skalierung, so man sie als Messinstrument depressiver Symptome einordnen würde. Demgegenüber entspricht das Konstrukt der Entropie eben jenen Anforderungen der Skalierung, da eine Abweichung vom durchschnittlichen individuellen Mobilitätsverhalten gemessen wird (Rohani et al., 2018).

Normierung. Die Forderung nach dem Gütekriterium der Normierung ist die nach repräsentativen Vergleichswerten in Bezug auf relevante Merkmale wie Soziodemografie, um die erhobenen Werte einordnen zu können (Moosbrugger & Kelava, 2012). Derlei steht zu passiven behavioralen Smartphone-Daten als Korrelaten depressiver Symptome noch aus, möglicherweise auch, da nach aktuellem Stand noch keine einheitlichen Kennwerte definiert wurden (Batra et al., 2017; Place et al., 2017; Rohani et al., 2018; Zarate et al., 2022), die normiert werden könnten.

Testökonomie. Dem Kriterium der Ökonomie wird ein Verfahren gerecht, wenn der inhaltliche Mehrwert den Zeit- und Kostenaufwand überwiegt (Moosbrugger & Kelava, 2012). Unabhängig von der Perspektive, ob zur Messung depressiver Symptome oder Erhebung von Verhaltensdaten im naturalistischen Setting - im Falle passiver behavioraler Daten ist der technische Aufwand mit Blick auf die benötigten Ressourcen vergleichsweise gering: 62,6 Millionen Menschen nutzen in Deutschland ein Smartphone (Tenzer, 2023), durch die Verbreitung über soziodemografische und Altersgrenzen hinweg (Tenzer, 2023) ist die Erhebung passiver behavioraler Daten niedrigschwellig in breiter Bevölkerung möglich. Eine großangelegte Datenerhebung ist entsprechend leichter umsetzbar als beim Einsatz spezieller Forschungsgeräte (Onnela & Rauch, 2016; Opoku Asare et al., 2021). Hinzu kommt - wie in der Bezeichnung passiver behavioraler Daten ersichtlich - dass die Datenerhebung passiv erfolgt, das heißt nach umfangreicher Aufklärung und informierter Zustimmung der Teilnehmenden ist die Datenerhebung ohne weiteres Zutun der jeweiligen Person möglich (Ben-Zeev et al., 2015; He et al., 2022). Durch die technische Einbettung in den Alltag und das passive Format findet die Datenerhebung in naturalistischem Setting statt (Onnela & Rauch, 2016; Torous et al., 2016; Torous et al., 2017). Die Datenerhebung erfolgt nahezu in Echtzeit (Batra et al., 2017; Mohr et al., 2017; Torous et al., 2017) und kann nach Einwilligung ohne Mehraufwand kontinuierlich erfolgen, wodurch longitudinale Veränderungen einfach und in hoher temporaler Auflösung erfasst werden können (Han et al., 2021; He et al., 2022). Dies sind deutliche Vorteile, welche für die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich sprechen. Das Gütekriterium der Ökonomie sollte jedoch nicht über die Hauptkriterien Validität, Objektivität und Reliabilität gestellt werden (Moosbrugger & Kelava, 2012).

Zumutbarkeit. Eine Messung ist zumutbar, wenn der aus den Ergebnissen gewonnene Nutzen den Aufwand überwiegt, den man den Teilnehmenden zeitlich, körperlich oder psychisch zumutet (Moosbrugger & Kelava, 2012; World Medical Association, 2013). Wie der Begriff beschreibt, erfordert die Erhebung passiver behavioraler Daten nach Bearbeitung der Einwilligungserklärung keine weitere Zeitinvestition der Teilnehmenden. Auch ist die Erhebung nicht mit einer körperlichen Belastung verbunden. Was bisher jedoch unbeantwortet ist, ist die Frage nach unerwünschten Nebenwirkungen der Erhebung mittels passiver behavioraler Daten (Birk & Samuel, 2022; Dogan et al., 2017; Onnela & Rauch, 2016), welche für die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich äußerst relevant ist und auf die daher als ethischen Aspekt in der Diskussion näher eingegangen wird.

Unverfälschbarkeit. Wenn eine Messung nicht vorsätzlich durch Teilnehmende verfälscht werden kann, ist das Kriterium der Unverfälschbarkeit erfüllt (Moosbrugger & Kelava, 2012). Bei der Verwendung von passiven behavioralen Daten ist eine Verfälschung grundsätzlich möglich; das hieße jedoch, dass Verhaltensweisen im Alltag modifiziert werden müssten. Voraussetzung für das bewusste Verfälschen wäre die Kenntnis der Hypothesen wie zum Beispiel, dass reduzierte Aktivität in sozialen Netzwerken zur Messung einer depressiven Symptomatik herangezogen wird (Cunningham et al., 2021). Bei der Anwendung im Public Mental Health-Bereich gilt es im Rahmen der Einwilligungserklärung abzuwägen, wie viel Information für eine informierte Einwilligung notwendig ist und wo das Risiko entsteht Verfälschung durch Informationen zu ermöglichen.

Fairness. Fairness bezeichnet das Vermeiden von (systematischer) Ungleichheit oder Benachteiligung aufgrund spezifischer Eigenschaften und Merkmalen (Moosbrugger

& Kelava, 2012). Überlappende Themen finden sich in der ethischen Diskussion zur Verwendung passiver behavioraler Daten zum Beispiel der Gleichwertigkeit, Modellgleichwertigkeit und Transparenz und Fairness.

Im Kontext der Verwendung passiver behavioraler Daten wird Gleichwertigkeit vor allem im Sinne der soziodemographischen wie generationalen Gerechtigkeit diskutiert (Kilgallon et al., 2022). Unterschiedliche soziodemografische wie generationale Gruppen sollten gleichermaßen von der Verwendung passiver behavioraler Daten profitieren. Im Kontext von Public Mental Health hieße das, alle Gruppen in Datenerhebungen zu berücksichtigen. Eine Herausforderung dabei besteht u.a. darin, dass ältere Nutzer*innen eine weniger intensive Smartphone-Nutzung aufweisen (Andone et al., 2016; Bundesministerium für Familie, Senioren, Frauen und Jugend, 2020) und somit weniger Daten für die präzise Vorhersage einer depressiven Symptomatik zur Verfügung stehen würden. Mehr verfügbare Daten führen zu einer besseren Vorhersageleistung in den rechnerischen Modellen (Tuarob et al., 2017). Somit wäre der Nutzen aufgrund ungenauerer Ergebnisse für ältere Bevölkerungsgruppen geringer und die Forderung nach Gleichwertigkeit nicht gewährleistet.

Adler und Kolleg*innen beschrieben zudem das Problem der Modellgleichwertigkeit, die Anforderung an ein rechnerisches Vorhersagemodell mit Blick auf unterschiedliche Gruppen eine gleichwertige Performance über die Zeit zu gewährleisten. Zur Erstellung eines solchen Modells sind jedoch große (auch klinische) Datensätze notwendig, deren Erhebung einen großen Mehraufwand bedeuten würde (Adler et al., 2022; Kambeitz-Ilankovic et al., 2022), zum Beispiel durch erhöhten Rekrutierungsaufwand, nach Rekrutierung die Koordination der verschiedenen klinischen Einrichtungen oder das Einholen gesonderter Ethikvoten.

Im Fall der Analyse von Smartphone-Nutzungsdaten haben die Vorhersagemodelle aufgrund sich ändernder Nutzungsgewohnheiten von Smartphones zudem ohnehin eine Halbwertszeit allein aufgrund der verwendeten Datenquelle (passive behaviorale Daten) (Mohr et al., 2017). Deutlich wird dies anhand der Geschichte des Smartphones: vor 15 Jahren begann deren Verbreitung durch die Einführung erster Geräte namhafter Hersteller (Apple, Google). Hätte man zu der Zeit Kennwerte zum Beispiel für soziale Interaktion via Smartphone festgelegt, wären diese heute aufgrund technischer Neuerungen nicht mehr aussagekräftig, da sich zum Beispiel durch neue Apps sozialer Netzwerke das Nutzungsverhalten verändert hat.

Transparenz und Fairness beziehen sich ebenso auf die Auswertung der erfassten Daten mithilfe rechnerischer Vorhersagemodelle. Letztere sind für die wissenschaftliche Verwendung passiver behavioraler Daten essenziell, da wie beschrieben oft die Forschungslogik verfolgt wird, datenbasiert eine Kombination von Datenparametern zu identifizieren, die eine möglichst verlässliche Vorhersage zum Beispiel depressiver Symptome ermöglichen (Birk & Samuel, 2022; Chekroud et al., 2021). Auch aufgrund der großen Datenmengen werden neue statistische Verfahren des maschinellen Lernens genutzt (Bzdok & Meyer-Lindenberg, 2018; Chekroud et al., 2021). Manche dieser statistischen Verfahren wie das neuronale Netz sind in der Lage sehr komplexe nicht-lineare Zusammenhänge zu erkennen und daraus präzise Vorhersagen zu erstellen (Dao & Lee, 2020), andere wie Regressionen bilden lineare Zusammenhänge ab und ermöglichen die Interpretation eingeschlossener Variablen (Aleem et al., 2022). Bei der Wahl des statistischen Verfahrens besteht die Herausforderung darin, dass eine Abwägung zwischen Präzision der Vorhersage und Interpretierbarkeit der Ergebnisse im Sinne der Transparenz zur Sicherung der Fairness getroffen werden muss (Jacobson et al., 2020).

Zur Sicherung der Fairness als übergeordnetem Gütekriterium bei der Verwendung passiver behavioraler Daten im Public Mental Health-Bereich bedarf es der Berücksichtigung dieser Details bei der methodischen Umsetzung.

Die Darstellung passiver behavioraler Daten anhand der Gütekriterien zeigt zum einen, dass es ganz allgemein zum Beispiel forschungsökonomische Gründe für die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich gibt. Zum anderen wird auch anhand der Gütekriterien deutlich, dass nach aktuellem Stand passive behaviorale Daten als Korrelate depressiver Symptome einzuordnen sind und nicht von einer Messung depressiver Symptome zu sprechen ist. Entsprechend nimmt sich auch die vorliegende Dissertation dieser Perspektive an, passive behaviorale Daten als Korrelate depressiver Symptome für den Public Mental Health-Bereich näher zu untersuchen.

Die Zukunftsperspektive hinter der Verwendung passiver behavioraler Daten besteht dabei darin, im Public Mental Health-Bereich zum Beispiel durch ein früheres Erfassen von individuellen Verhaltensänderungen das Auftreten zum Beispiel von depressiven Symptomen in Hochrisikogruppen schneller zu erkennen (He et al., 2022; Kambeitz-Ilankovic et al., 2022; Mohr et al., 2020; Mohr et al., 2017; Seppälä et al., 2019). Übertragen auf zum Beispiel repräsentative Kohortenstudien im Public Mental-Health Bereich könnte das frühzeitige Erkennen individueller Änderungen kumuliert ebenso mit Änderungen in der Prävalenz von Symptomen psychischer Störungen korrelieren und wäre somit auch für epidemiologische Studien äußerst wertvoll.

Auch wäre im nächsten Schritt bei dieser Art der Datenerhebung (aufgrund automatisierter Auswertung in Echtzeit) eine rasche Reaktion im Falle von identifizierten Symptomverschlechterungen denkbar (Batra et al., 2017; Seppälä et al., 2019). Die Gesundheitsversorgung liegt jedoch außerhalb des Verantwortungsbereichs von Public Mental Health. Für den beschriebenen Fall, dass

durch die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich ein punktueller Versorgungsbedarf sichtbar wird, bedarf es einer Vernetzung mit der Gesundheitsversorgung.
Zu der Zukunftsperspektive gehört gleichermaßen die Assoziation möglicher Risiken und unerwünschter Nebenwirkungen der Verwendung passiver behavioraler Daten im Public Mental Health-Bereich (Birk & Samuel, 2022; Wykes et al., 2019). Die Gegenüberstellung von forschungsökonomischen und inhaltlichen Chancen versus mögliche individuelle oder gesellschaftliche Risiken erzeugt ethische Fragestellungen. Bisher wurden die Folgen einer umfangreichen Sammlung persönlicher Daten (nicht explizit die Gesundheit betreffend) wie von Gesundheitsdaten jedoch wenig diskutiert (O'Doherty et al., 2016), umso relevanter ist die Darstellung der eigenen Forschungsergebnisse innerhalb der Diskussion auch unter ethischen Gesichtspunkten.

Die bisherige Einleitung hat dargestellt, dass die Bewertung passiver behavioraler Daten als Korrelate depressiver Symptome im Public Mental Health-Bereich eine methodische Abwägung ist. Die vorliegende Arbeit hat zum Ziel, sich mit eigener empirischer Forschung Fragen zu passiven behavioralen Daten als Korrelaten depressiver Symptome zu stellen, um diese Ergebnisse abschließend auch unter ethischen Gesichtspunkten zu diskutieren.

Herleitung eigener Forschung

Vor einer Integration passiver behavioraler Daten als neue Datenquelle in die Forschung im Public Mental Health-Bereich bedarf es der Evaluation (Batra et al., 2017). In Bezug auf passive behaviorale Smartphone-Daten in der Forschung zu depressiven Symptomen im Public Mental Health-Bereich ergeben sich im ersten Schritt die folgenden Fragen:

Im Vergleich zur Befragung, dem bisherigen methodischen Standard für Forschung im Public Health-Bereich, versprechen passive behaviorale Daten mindestens ökonomische Vorteile (Zachary et al., 2017). Diese allein sind jedoch nicht ausreichend als Begründung, um eine neue Methode zu verwenden; hierzu bedarf es eines inhaltlichen Mehrwertes (Moosbrugger & Kelava, 2012). Offen ist die Frage, inwiefern passive behaviorale Smartphone-Daten unter Einbezug bewährter Prädiktoren aus Befragungsdaten ebenso einen Beitrag zur Vorhersage depressiver Symptome leisten. Diese Fragestellung wurde in dem folgenden Forschungsprojekt der vorliegenden Dissertation adressiert:

1. Welchen Mehrwert bieten passive Smartphone-Daten sozialer Interaktion (u.a. Videotelefonie, Nutzung von Apps sozialer Medien) bei der Vorhersage einer depressiven und Angstsymptomatik unter Berücksichtigung bewährter selbst-berichteter Risikofaktoren während der COVID-19 Pandemie?

   Titel der Publikation zu dem Thema:

   Messenger use and video calls as correlates of anxiety and depressive symptoms – Results from the CORONA HEALTH App Study with German adults during the COVID-19 pandemic.

Vielversprechend erscheinen passive behaviorale Daten, insbesondere mit Blick auf die Forschungsökonomie (Zachary et al., 2017). Dies gilt sowohl für passive behaviorale Daten, welche Verhalten dokumentieren, als auch für verfügbare rein passive Daten wie Details zur Wohnumgebung, welche zum Beispiel durch das GPS-

Signal des Smartphones automatisiert Personen zugeordnet werden können. Es liegt daher die Frage nahe, inwiefern es einen Mehrwert der Verwendung dieser Daten im Public Mental Health-Bereich gibt, konkret wie präzise die Vorhersageleistung allein auf Basis passiver (nicht behavioraler) Daten ist. Diese Fragestellung wurde in dem zweiten Forschungsprojekt der vorliegenden Dissertation adressiert:

2. Wie genau ist die Vorhersage depressiver Symptome allein auf Basis über GPS ermittelter regionaler Daten zur Soziodemografie, Wohnverhältnissen und COVID-19 Infektionsgeschehen zum Zeitpunkt der Erhebung?

   Titel der Publikation zu dem Thema:
   Predicting depressive symptoms using GPS-based regional data: A feasibility study with the CORONA HEALTH APP during the COVID-19 pandemic in Germany.

Die bestehende Forschung zu passiven behavioralen Daten stellt immer wieder die Frage nach der Verallgemeinerbarkeit einzelner Verhaltensparameter als Prädiktoren zum Beispiel für depressive Symptome (Mohr et al., 2017; Place et al., 2017; Rohani et al., 2018; Zarate et al., 2022). Ein Argument hinter dieser Frage ist, dass eine depressive Symptomatik interindividuell sehr verschieden aussehen kann (Lux & Kendler, 2010) und somit die Festlegung einheitlicher beobachtbarer Verhaltensparameter, welche mich depressiven Symptomen korrelieren, schwierig scheint. Dies würde die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich erschweren, so keine personenübergreifend gültige Aussage möglich ist, da Public Mental Health sich Gesundheitsthemen der Gesamtbevölkerung widmen soll (World Health Organization. Regional Office for Europe, 1999). Es ergibt sich daraus die Frage, welche Rolle interindividuelle Unterschiede bei der Interpretation passiver behavioraler Daten spielen. Diese Frage wird in dem dritten Forschungsprojekt dieser Dissertation adressiert:

3. Welche Rolle spielen wahrgenommene soziale Unterstützung und Persönlichkeit für Zusammenhänge von depressiven Symptomen und Gesundheitsverhalten wie körperliche Aktivität und Mediennutzung?

   Titel der Publikation zu dem Thema:

   The role of personality traits and social support in relations of health-related behaviours and depressive symptoms.

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Kapitel 2

Messenger use and video calls as correlates of depressive and anxiety symptoms: Results from the CORONA HEALTH APP study of German adults during the COVID-19 pandemic

Edler, J.-S., Terhorst, Y., Pryss, R., Baumeister, H. & Cohrdes, C. (2024). Messenger use and video calls as correlates of depressive and anxiety symptoms: Results from the CORONA HEALTH APP study of German adults during the COVID-19 pandemic. *Journal of Medical Internet Research*, 26. https://www.jmir.org/2024/1/e45530

Original Paper

Messenger Use and Video Calls as Correlates of Depressive and Anxiety Symptoms: Results From the Corona Health App Study of German Adults During the COVID-19 Pandemic

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Abstract

Background: Specialized studies have shown that smartphone-based social interaction data are predictors of depressive and anxiety symptoms. Moreover, at times during the COVID-19 pandemic, social interaction took place primarily remotely. To appropriately test these objective data for their added value for epidemiological research during the pandemic, it is necessary to include established predictors.

Objective: Using a comprehensive model, we investigated the extent to which smartphone-based social interaction data contribute to the prediction of depressive and anxiety symptoms, while also taking into account well-established predictors and relevant pandemic-specific factors.

Methods: We developed the Corona Health App and obtained participation from 490 Android smartphone users who agreed to allow us to collect smartphone-based social interaction data between July 2020 and February 2021. Using a cross-sectional design, we automatically collected data concerning average app use in terms of the categories *video calls and telephony*, *messenger use*, *social media use*, and *SMS text messaging use*, as well as pandemic-specific predictors and sociodemographic covariates. We statistically predicted depressive and anxiety symptoms using elastic net regression. To exclude overfitting, we used 10-fold cross-validation.

Results: The amount of variance explained (R^2) was 0.61 for the prediction of depressive symptoms and 0.57 for the prediction of anxiety symptoms. Of the smartphone-based social interaction data included, only messenger use proved to be a significant negative predictor of depressive and anxiety symptoms. Video calls were negative predictors only for depressive symptoms, and SMS text messaging use was a negative predictor only for anxiety symptoms.

Conclusions: The results show the relevance of smartphone-based social interaction data in predicting depressive and anxiety symptoms. However, even taken together in the context of a comprehensive model with well-established predictors, the data only add a small amount of value.

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KEYWORDS

passive data; depression; anxiety; predicting mental health; mobile phone

Introduction

Background

Depression and anxiety are common disorders, with depression having a prevalence of 15.7% in Germany in 2017 before the COVID-19 pandemic [1,2]. In 2023, after the pandemic, approximately 19% of the adult population in Germany showed elevated rates of depressive symptoms; in addition, the burden of anxiety symptoms was notable for 12% to 15% of the German population in 2022 [3]. People with major depression show leading symptoms such as depressed mood, loss of interest, or lack of drive, whereas persistent excessive worry and restlessness concerning everyday issues are leading symptoms in people with general anxiety disorder. Both depression and anxiety often incur high individual and societal costs [4]. Accurate and real-time measurement of depressive and anxiety symptoms allows for the identification of current risk factors (eg, pandemic-related factors) [5] as well as the design of preventive and treatment measures. Through digitalization and the spread of smartphones, new possibilities have arisen for flexible, cost-effective, and high-quality data collection on symptoms of mental disorders such as depression and anxiety [6,7]; for example, smartphone data (use data and survey data) can be collected in real time using ecological momentary assessment methodology [8]. Technological advances have enabled passive collection of smartphone use data (without user intervention), reducing interviewer and recall bias. In addition, it is useful to record depressive symptoms via behavioral measurement using objective digital data. With behavioral measurement (such as smartphone use data), it is not necessary for users to be aware of the changes in their behavior. Persons with depressive or anxiety symptoms may only become aware of a behavior change when it reaches a certain level, whereas passive behavior measurement captures each slow change over time, regardless of user awareness; for example, in the context of depressive symptoms, possible behavioral changes such as reduced activity or social withdrawal could be an indicator of a change toward depressive symptoms. Previous studies have shown that depressive symptoms [9-14] and anxiety symptoms [10,11,15] correlate with various smartphone-based social interaction data, such as the duration of phone calls, Facebook use, the number of SMS text messages sent, or total smartphone use time. Furthermore, the high proportion of interpersonal communication that is conducted via mobile devices allows for the measurement of an indicator of social interaction. Specifically, the pandemic showed that perceived social connectedness improved when smartphone use increased, resulting in improved well-being [16]. Social interaction, as indicated by the use duration or frequency of various smartphone social media apps, has been identified as a significant predictor of depressive and anxiety symptoms [17,18]. While time spent on Facebook positively correlates with depressive symptoms [18], social smartphone use is a negative predictor [19]. Excessive smartphone use in general is positively associated with depressive symptoms [10]. Moreover, during the COVID-19 pandemic, daily face-to-face or video calls correlated with decreased depressive symptoms [20]. Anxiety symptoms are only positively related to consumption-related smartphone use and not to social interaction–related smartphone use [11].

Overall, studies analyzing smartphone data have mainly investigated isolated predictors and combinations of only a few predictors [21,22]. The question remains concerning the extent to which smartphone-based social interaction data will continue to a comprehensive model for the prediction of depressive and anxiety symptoms. Answering this question is of great importance for achieving an up-to-date, ecologically valid, and economic assessment of high-quality epidemiological data.

Mental Health During the COVID-19 Pandemic

During the COVID-19 pandemic and the associated restrictions on social life, both the importance of digital social interaction and concerns about depressive and anxiety symptoms increased as the situation worsened [16,23]. Due to the dramatic increase in COVID-19 infections in Germany in March 2020, the German government implemented pandemic action plans to limit the spread of SARS-CoV-2, including quarantine measures, reduction of social contact, and restrictions on mobility. Over the following 18 months, social distancing measures were gradually eased, social contacts were restored, and restrictions on mobility were lifted, culminating in the reopening of shops, playgrounds, and schools in summer 2021 due to the decreased number of COVID-19 infections. In Germany, as in other countries, this period represented a balancing act between universal protection against a growing number of new COVID-19 infections and the preservation of individual psychological and physical health in the face of severe restrictions in daily life [23].

We mapped these pandemic-related changes in daily life in terms of internal and external aspects. Internal aspects refer to perceptions of the pandemic situation and resulting emotions such as fears and worries, which could be stressors. External aspects include changes in daily life due to pandemic control measures, which can also act as potential stressors.

Specifically, internal aspects within the scope of this study include the expected stigmatization of individuals with COVID-19 infection [24] and various related concerns; for example, previous research has revealed increased concerns about not receiving adequate medical care in case of COVID-19 infection due to lack of medical capacity [25] as well as concerns about infecting others with COVID-19 [24,25]. Pandemic-related social distancing also seemed to have altered social interaction, as suggested by reports of increased loneliness [26] and negative family climate [27,28]. Correspondingly, there is evidence showing an increase in psychosocial stress [29] and domestic violence during the pandemic [30].

Regarding external aspects, recent studies have discussed pandemic-related working conditions (eg, short-term work, reduced performance capacity due to home office work and home schooling of children, and increased workloads in the health sector) as stressful changes in daily routines [31-33].

In addition to these internal and external pandemic-specific changes, there are individual differences (reliable predictors existing before the pandemic) that may also be related to mental well-being during the pandemic and that could be considered stressors; for example, general health status should be considered a possible pandemic-related stress factor because this factor poses a potentially increased risk of severe disorder progression in the event of COVID-19 infection [34]. The same point applies to chronic conditions [30]. In addition, due to the pandemic, the availability of support services for treating mental disorders was temporarily limited, which placed a particular burden on people with preexisting diagnoses of mental disorders [35]. Finally, the risk of contracting COVID-19 infection should also be considered a potential stressor. The general population had to cope with this large number of possible stressors related to the COVID-19 pandemic and social restriction measures; therefore, individual coping strategies became increasingly important. In this context, early investigations in Germany showed an increase in adverse coping techniques, such as alcohol consumption [36]. Likewise, the restriction of sporting activities (in gyms or clubs) can be seen as a potential loss of a resource and method for adaptive coping [37].

According to the vulnerability-stress model [38], an accumulation of stressors is believed to increase the risk of depressive and anxiety symptoms. Quarantine and contact restriction measures result in a reduction in personal encounters, possible additional stress factors at work (eg, job loss and home schooling of children), and restrictions concerning personal lifestyle (eg, due to the closure of gyms and cinemas). Accordingly, the pandemic might have been a high-risk situation for the development or intensification of depressive and anxiety symptoms with the accumulation of multiple stressors in an individual [30,39]. In view of these findings, investigating depressive and anxiety symptoms during the COVID-19 pandemic may add new insights into the validity and predictive value of smartphone-based social interaction data. To date, the relative importance of such predictors in the context of a comprehensive model of established public health indicators has not yet been fully explained.

Objectives of This Study

This study aimed to validate the predictive value of smartphone-based social interaction data in relation to depressive and anxiety symptoms via a comprehensive, data-driven approach, including well-established predictors (eg, chronic conditions and partnership status) from survey data collected during the COVID-19 pandemic. In many existing studies on the topic, smartphone data have been considered in isolation [21,22]. However, to evaluate these objective (smartphone-based social interaction) data as predictors, we opted for a data-based approach that integrates all reliable predictors into a holistic model and automatically identifies the optimal set of predictors. In this way, we were able to test the extent to which various smartphone-based social interaction parameters (eg, video calls and social media) contribute to the prediction of depressive and anxiety symptoms alongside, or instead of, empirically well-established predictors. Due to the ongoing COVID-19 pandemic during data collection, we also considered pandemic-specific factors (eg, COVID-19 infection and short-term work situations).

Methods

Sample and Procedure

The study is part of the Corona Health App project, a collaboration between the Robert Koch Institute, the University of Würzburg, the University of Ulm, and the University of Regensburg in Germany. The project includes an extensive cross-sectional app-based baseline survey, followed by a reduced weekly ongoing longitudinal survey for adults. The collection of both smartphone data and survey data was carried out via the Corona Health App, which is why it was necessary for participants to download and install the app from the Google Play Store or the Apple App Store to participate in the study. Recruitment was carried out through press releases by the participating institutions, media reports, and social networks. Before they took part in the study, participants were provided comprehensive information about the collection of select passive smartphone-based social interaction data and anonymized storage of the data; in addition, they were asked to provide informed consent. We collected passive smartphone-based social interaction data for 1 week before administering the questionnaire. Duration of use was recorded as the time during which the app was running in the foreground.

The cross-sectional analyses included 490 German residents who completed the baseline questionnaire between July 2020 and February 2021 and consented to the collection of smartphone-based social interaction data. During this period, Germany experienced a summer with very low COVID-19 infection numbers and eased restrictions on public life. In the autumn, a second wave of infections started, which worsened as autumn passed into winter and led to lockdown measures starting in mid-December. These measures continued until the end of the survey period for this study. Participants ranged in age from 18 to 78 (mean 42.46, SD 13.33) years, and the gender ratio was relatively balanced, with 52.9% (259/490) of the participants being women, 45.9% (225/490) being men, and 1.2% (6/490) being transgender individuals. Whereas 7.8% (38/490) of the participants had no school-leaving certificate or had lower than a secondary school certificate with or without training, 64.5% (316/490) had a technical college or university degree. A clinician-based lifetime diagnosis of mental disorder was reported by 43.7% (214/490) of the participants. As the recording of app use is not allowed on Apple devices, our reporting sample was limited to Android smartphone users, who, with a market share of 64.7% in Germany [40], constitute the clear majority of users. From the original sample of 1760 participants, 18 (1.02%) were excluded for failing the plausibility check, which assessed correspondence between similar items, straightlining, intraindividual response variability, and extreme outliers. Of the remaining 1742 participants, 1052 (60.39%) were Android smartphone users. Of these 1052 participants, 490 (46.58%) consented to the collection of data concerning social interaction app use. A detailed description of the sample and descriptive statistics of all variables can be found in Multimedia Appendix 1.

Ethical Considerations

Ethics approval was granted by the ethics committee of the University of Würzburg (130/20-me). Furthermore, the app was developed in accordance with the regulations for medical devices. Participants were given comprehensive information about the type of data collected as well as the data collection, processing, and dissemination procedures and were asked to provide consent. Data storage was anonymized. The study protocol with details on the data collection, processing, and dissemination procedures has been described previously [41]. The study fulfils the criteria of the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) statement [42]. Participation was voluntary and not financially compensated.

Measures

Depressive and Anxiety Symptoms

Depressive and anxiety symptoms were measured with the German version of the Patient Health Questionnaire, German version (PHQ-D) [43]. Depressive symptoms (9 items; eg, the stem question "Over the last week, how often have you been bothered by" followed by "little interest or pleasure in doing things?" "depression, melancholy, or hopelessness?" "difficulty falling asleep or staying asleep, or increased sleep?" "tiredness or feeling of having no energy?" "reduced appetite or excessive desire to eat?" "a bad opinion of yourself; feeling of being a failure or having disappointed the family?" "difficulties concentrating on something, eg, when reading the newspaper or watching television?" "thoughts that you would rather be dead or want to harm yourself?" as well as "Were your movements or speech so slowed down that others would notice? Or were you on the contrary 'fidgety' or restless and therefore had a stronger urge to move than usual?") were rated on a 4-point scale: 0=*not at all*, 1=*on single days*, 2=*on more than half of the days*, and 3=*almost every day*. The 7 anxiety symptoms (eg, the stem question "Over the last week, how often have you been bothered by" followed by "not being able to stop or control worrying?" "nervousness, anxiety, or tension?" "excessive worries regarding various matters?" "difficulties to relax?" "restlessness, making it difficult to sit still?" "quick annoyance or irritability?" "a feeling of fear, as if something bad is going to happen?") were answered on a 4-point scale: 0=*I haven't been doing this at all*, 1=*I've been doing this a little bit*, 2=*I've been doing this a medium amount*, and 3=*I've been doing this a lot*. We summarized the answers for each scale as a total score ranging from 0 (minimum) to 27 (maximum) for depressive symptoms and 21 (maximum) for anxiety symptoms [44]. The Cronbach α values for the internal consistency of the scales for depressive and anxiety symptoms were 0.89 and 0.85, respectively.

Smartphone-Based Social Interaction Data

As smartphone-based indicators of social interaction, we included a selection of communication data for apps open in the foreground over the past 7 days (video calls, phone calls, social media, SMS text messaging use, and messenger apps) and total smartphone use duration. Use times were averaged on a weekly basis in minutes. The following selection of communication apps was included: Skype, Skype Messenger, Zoom, Facebook, Facebook Messenger, Instagram, Snapchat, WhatsApp, and Telegram. Skype and Zoom belong to the category *video calls*. Phone calls were recorded by the device-specific phone app and included as a separate category. Facebook, Instagram, and Snapchat were grouped into the category *social media*. *SMS text messaginguse* was also captured via the device-specific app and included as a separate category. Facebook Messenger, WhatsApp, and Telegram were combined into the category *messenger*.

COVID-19–Related Factors

As pandemic-related variables, we made use of an in-house–developed item indicating COVID-19 status and differentiating between the 3 categories of *tested positive for COVID-19*, *tested positive for COVID-19 but already recovered*, and *did not test positive for COVID-19*. Other variables included were stigmatization because of (suspected) COVID-19 infection using a modified version of the inventory of subjective experience of stigmatization [45]. Two items each were collected as indicators of the expectation and actual experience of stigmatization. Expectation of stigmatization experience (eg, "Do you think people will value you less if they know that you are infected with COVID-19 or if you were?") was scored on a 5-point scale ranging from 1=*always* to 5=*never*, and for the actual experience of stigmatization (eg, "Have you ever been teased, bullied, or harassed because you were infected with COVID-19, or have you seen such behavior toward others?"), participants answered on a dichotomous scale (yes or no). We calculated sum scores for the expectation and experience of stigmatization, and the Pearson r values for the interitem correlations were 0.41 and 0.43, respectively. Furthermore, we assessed pandemic-related concerns (concern about inadequate medical treatment in case of COVID-19 infection due to lack of medical capacity and concern about infecting others with COVID-19). The items were rated on a 3-point scale ranging from 0=*not bothered* to 2=*bothered a lot*. As employment status may have changed due to the measures implemented to combat the spread of SARS-CoV-2, participants answered several items that were developed in-house regarding employment status (ie, short-term work, unemployed, currently unable to pursue regular profession due to health protection measures, or on sick leave), wage loss (none, slight, or high), predominant workplace (home office, regular working location, or a combination of both), and employment as a health care professional (yes or no). Nominal categories were converted to dummy variables. We also used items developed in-house to ask about COVID-19 infections among relatives and friends (no, currently ill, or recovered). Those who reported COVID-19 infections in their social environment were asked whether they had lost relatives or friends to COVID-19 (no or yes). Both categorial variables were dummy coded and included in the analyses.

Reliable Predictors of Depressive and Anxiety Symptoms

As indicated by previous research, feelings of loneliness [46-48], psychosocial distress [49], family climate [50], physical abuse [51], general health status or chronic conditions [52], coping [53], alcohol consumption [54], and physical activity [55] are correlated with depressive or anxiety symptoms. We measured loneliness using the 3-item Socio-Economic Panel loneliness scale [56]. The answers were rated on a 5-point scale ranging from 1=*very often* to 5=*never*. An example item was "How often do you feel left out?" We calculated a sum score, and the Cronbach α value for internal consistency was 0.79. Family climate was assessed using 2 different items developed in-house: the actual climate rated on a 5-point scale ranging from 0=*very bad* to 4=*very good* and the perceived change in family climate since the beginning of the COVID-19 pandemic answered using 1 of 3 options: 0=*yes, it got worse*; 1=*no, it remained unchanged*; and 2=*yes, it improved*. Aspects of psychosocial distress were addressed by the PHQ-D stress module [57], comprising 10 items that were answered on a 3-point scale ranging from 0=*not bothered* to 2=*bothered a lot*. An example item was "In the past week, how much have you been bothered by stress at work outside of the home or at school?" We measured physical abuse using the PHQ-D [57] and an additional item developed in-house. The first item asked about experience of physical abuse in the past week, and the second item asked about experience of abuse approximately 12 months previously (yes or no). General health status was assessed using the first 3 items of the Minimum European Health Module (self-perceived health, chronic conditions, and long-term activity limitation) [58]. Moreover, participants reported a clinician-based lifetime diagnosis of a mental disorder (yes or no). Situational coping strategies (during the COVID-19 pandemic) were measured using the Coping Orientation to Problems Experienced Inventory (Brief-COPE) [59]. This instrument comprises a total of 28 items assessed on a 4-point scale ranging from 1=*I haven't been doing this at all* to 4=*I've been doing this a lot*. As a result of an exploratory factor analysis and a confirmatory factor analysis, the 4 coping factors were formed in accordance with the categories *problem-focused coping* (eg, "I've been taking action to try to make the situation better"), *support-focusedcoping* (eg, "I've been getting help and advice from other people"), *escape-avoidant–focused coping* (eg, "I've been using alcohol or other drugs to make myself feel better"), and *meaning-focusedcoping* (eg, "I've been trying to see things in a different light, to make things seem more positive") [60] following previous studies [60-62]. We summed the respective items and calculated a mean score for the 4 subscales problem-focused coping, support-focused coping, escape-avoidant–focused coping, and meaning-focused coping. The Cronbach α values for the internal consistency of the 4 subscales were 0.77, 0.84, 0.69, and 0.74, respectively. In addition, we explored the frequency of alcohol consumption per week with an item developed in-house that was answered on a 5-point scale ranging from 0=*none* to 4=*six to seven times a week*. Moreover, we included an item developed in-house to indicate levels of physical activity during the past week that was answered on a 5-point scale ranging from 1=*no sporting activity* to 5=*regularly more than 4 hours per week*. We assessed personality with the German version of the Big Five Inventory-10 [63], which was answered on a 5-point scale ranging from 1=*disagree strongly* to 5=*agree strongly*. In line with the Big Five Inventory-10 scoring manual [63], we constructed 5 subscales with 2 items each for the dimensions of openness (eg, active imagination), conscientiousness (eg, doing a thorough job), extraversion (eg, being outgoing and sociable), agreeableness (eg, being generally trusting), and neuroticism (eg, easily becoming nervous). The Pearson *r* values for the interitem correlations of the 5 subscales were 0.31, 0.26, 0.60, 0.07, and 0.41, respectively. The level of education was determined by the general school-leaving certificate and the highest vocational qualification. These 2 areas were combined into 3 levels according to the Comparative Analysis of Social Mobility in Industrial Nations classification [64]. The first level includes the range from no school-leaving certificate to a lower secondary school certificate, the second level includes the range from a secondary school certificate to a general qualification for university entrance or a general or subject-linked higher education entrance qualification, and the third level includes technical school certificates and university degrees. We included each category as a dummy-coded variable. In addition, household size and the number of children were included as sociodemographic variables, each as a metric variable. We asked about marital status and living environment, specifically about the type of housing (house or apartment; with garden, with balcony, or with terrace). Multiple choices were allowed for this variable, and the response categories were integrated into the analyses, each as a separate dummy variable. We also included the participant's age as a continuous predictor and the participant's gender based on the 3 categories *woman, man,* and *transgender*. Categorical variables were included as dummy-coded variables in the analyses.

Data Analyses

To analyze the predictive value of smartphone-based social interaction data for depressive and anxiety symptoms, we opted for a data-driven approach, using ridge, least absolute shrinkage and selection operator (LASSO), and elastic net regression [65]. Hyperparameter optimization was implemented using a grid search. These analyses allow us to perform a statistics-based variable selection [66] and answer the question concerning the extent to which each smartphone-based social interaction parameter explains a relevant proportion of the variance or whether the parameter is automatically removed from the model as statistically irrelevant. In addition to the smartphone-based social interaction data, we considered other relevant and well-established predictors of depressive and anxiety symptoms (eg, coping strategies and physical activity) as well as pandemic-related factors (eg, concerns and stigmatization). To avoid overfitting, we split the data set into training and test sets. Within the training set, we performed 10-fold cross-validation with 5-fold repetition [65]. The model was then estimated in the training set, and the outcome variable was estimated (ie, predicted mathematically) based on this model in the test set to validate the model. Here, the term *prediction* refers to a statistical procedure and not a temporal prediction in the future. The model with the best fit in terms of estimating depressive and anxiety symptoms was chosen based on indicators of the amount of measurement error (primarily the root mean square error [RMSE] and secondarily the mean absolute error [MAE]) as well as the amount of variance explained (R^2). The predictive value was indicated for each significant predictor by means of the variable importance.

For the majority of questions, answers were required (forced choice); there were only 3 missing values in the data, all of which were related to items on the PHQ-9 scale. However, a precondition for the use of ridge, LASSO, and elastic net regression is a data set without missing values [67]. For this reason, missing data were imputed by single imputation with 500 iterations using the classification and regression trees method with the R package *mice* [68]. The continuous predictors were *z*-standardized, and the outcome variables remained in the original scaling.

Results

Overview

For the prediction of depressive symptoms, the model with the smallest MAE (3.04) was the LASSO regression (Table 1). The smallest RMSE (3.85) resulted from the elastic net regression, which also had the highest amount of variance explained (R^2=0.61). Accordingly, the elastic net regression proved to be the model with the best fit, reducing the data set from 76 to 28 significant variables.

The model with the best fit for predicting anxiety symptoms was also an elastic net regression (MAE=2.56, RMSE=3.22, R^2=0.57) and contained 30 significant predictors of anxiety symptoms (Table 2).

Table 1. Model fit indices for predicting depressive symptoms resulting from stepwise, ridge, least absolute shrinkage and selection operator (LASSO), and elastic net regression based on 50 replicate samples.

	Values, median (IQR; minimum-maximum)	Values, mean
Mean absolute error		
Linear model	3.299 (3.050-3.519; 2.665-4.222)	3.295
Ridge	3.133 (2.922-3.315; 2.511-3.797)	3.135
LASSO	2.973 (2.845-3.204; 2.617-3.812)	3.055
Elastic net[a]	*2.998 (2.813-3.189; 2.553-3.855)*	*3.045*
Root mean square error		
Linear model	4.088 (3.851-4.407; 3.346-5.145)	4.146
Ridge	3.940 (3.708-4.201; 3.220-4.663)	3.967
LASSO	3.787 (3.590-4.060; 3.245-4.672)	3.856
Elastic net[a]	*3.772 (3.594-4.060; 3.286-4.680)*	*3.849*
$\boldsymbol{R^2}$		
Linear model	0.558 (0.524-0.636; 0.265-0.713)	0.562
Ridge	0.587 (0.529-0.656; 0.300-0.776)	0.586
LASSO	0.619 (0.553-0.677; 0.265-0.819)	0.612
Elastic net[a]	*0.619 (0.554-0.676; 0.264-0.817)*	*0.612*

[a]The best model fit by parameter is highlighted in italics in each case; overall, elastic net regression has the best model fit due to the largest amount of variance explained (R^2) and the smallest mean absolute error and root mean square error.

Table 2. Model fit indices for predicting anxiety symptoms resulting from stepwise, ridge, least absolute shrinkage and selection operator (LASSO), and elastic net regression based on 50 replicate samples.

	Values, median (IQR; minimum-maximum)	Values, mean
Mean absolute error		
Linear model	2.683 (2.486-2.958; 1.917-3.534)	2.711
Ridge	2.608 (2.409-2.834; 1.866-3.235)	2.614
LASSO	2.605 (2.432-2.759; 1.814-3.120)	2.582
Elastic net[a]	*2.560 (2.402-2.745; 1.749-3.130)*	*2.564*
Root mean square error		
Linear model	3.395 (3.133-3.712; 2.438-4.395)	3.405
Ridge	3.273 (3.002-3.551; 2.442-3.939)	3.277
LASSO	3.319 (2.989-3.443; 2.344-3.873)	3.246
Elastic net[a]	*3.283 (3.004-3.409; 2.309-3.776)*	*3.216*
R^2		
Linear model[a]	*0.522 (0.450-0.610; 0.312-0.767)*	*0.528*
Ridge	0.536 (0.481-0.630; 0.366-0.787)	0.550
LASSO	0.561 (0.491-0.606; 0.359-0.814)	0.563
Elastic net	0.564 (0.498-0.625; 0.388-0.820)	0.569

[a]The best model fit by parameter is highlighted in italics in each case; overall, elastic net regression has the best model fit due to the largest amount of variance explained (R^2) and the smallest mean absolute error and root mean square error.

Smartphone-Based Social Interaction Data

Of the smartphone-based social interaction data included, only average weekly messenger use turned out to be a significant negative predictor of depressive and anxiety symptoms. The average weekly duration of video calls was a significant negative predictor only of depressive symptoms. In the model for the prediction of anxiety symptoms, the weekly average duration of SMS text messaging use remained a relevant negative predictor. The other smartphone-based social interaction parameters (weekly averaged use duration of phone calls and social media, as well as weekly averaged total smartphone use duration) were omitted from the best fit model.

Predictors of Depressive and Anxiety Symptoms

The final models overlap in terms of the following 19 predictors (in order of importance according to the model for depressive symptomatology): escape-avoidant–focused coping, loneliness, good current family climate, poor general health status, a clinician-based lifetime diagnosis of mental disorder, age, neuroticism, conscientiousness, expectation of no stigmatization due to (suspected) COVID-19 infection, agreeableness, meaning-focused coping, a chronic condition, wage loss, inability to pursue current occupation due to health protection measures, being a transgender individual, average weekly messenger use, no relatives or friends lost to COVID-19, household size, and concern about not receiving adequate medical care in case of COVID-19 infection due to lack of medical capacity.

The following predictors were found to be exclusively relevant for the prediction of depressive symptoms (in decreasing order of importance): physical abuse, extraversion, alcohol consumption, job seeking, short-term work (due to the COVID-19 pandemic), being married or in a stable relationship, divorce, and employment as a health care professional. Figure 1 presents the order and directions of unique correlates.

By contrast, the following predictors proved to be exclusively relevant for anxiety symptoms (in decreasing order of importance): concern about infecting others with COVID-19, experience of stigmatization, a living environment with a terrace, being male, being single, having relatives who recovered from COVID-19, being in a registered (same-sex) partnership but living separately, average weekly SMS text messaging use, physical activity, and being widowed. The order and directions of unique correlates are presented in Figure 2.

Figure 1. Total variable importance as an indicator of the contribution to the reduction of the estimation error in the prediction of depressive symptoms.

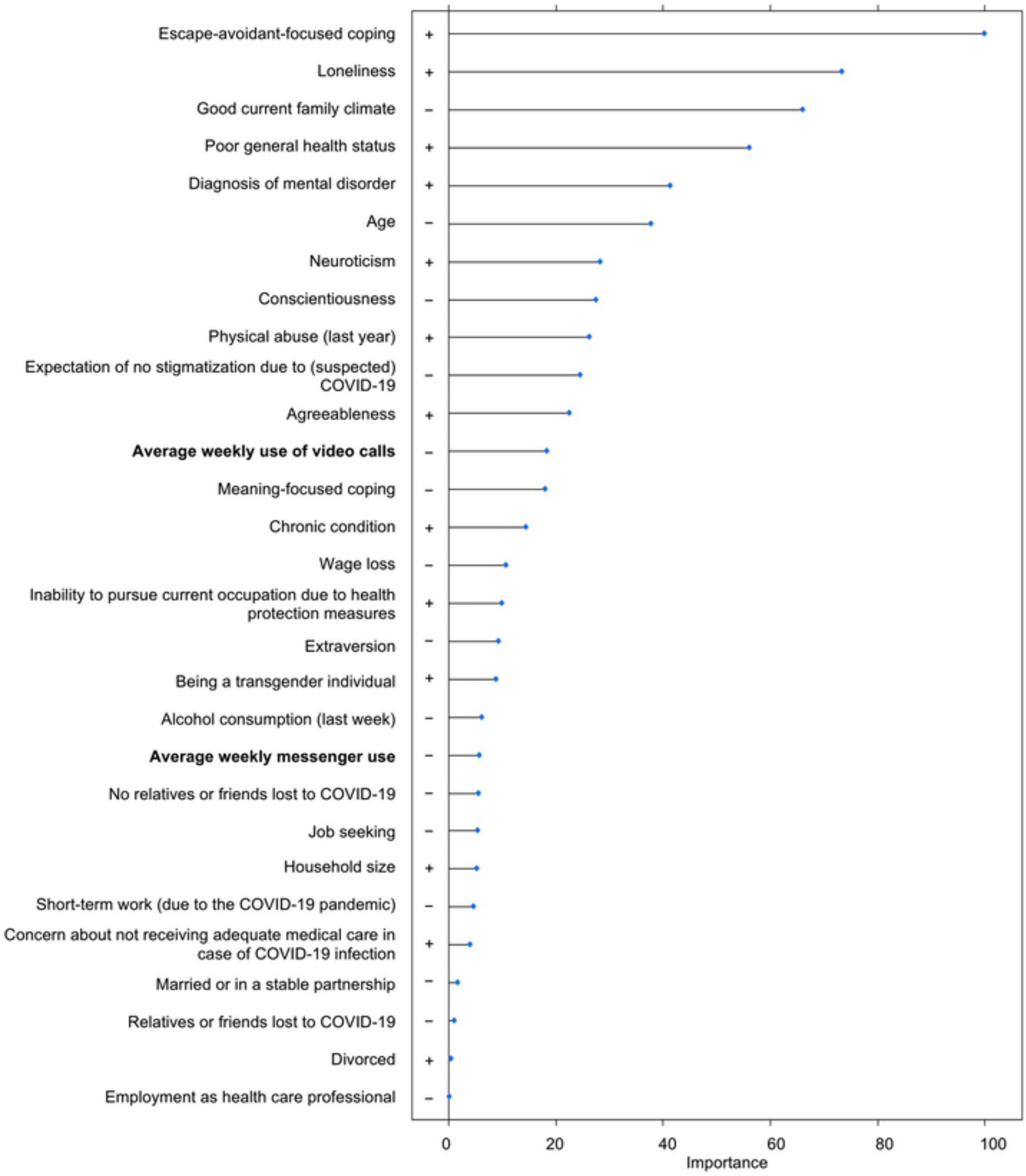
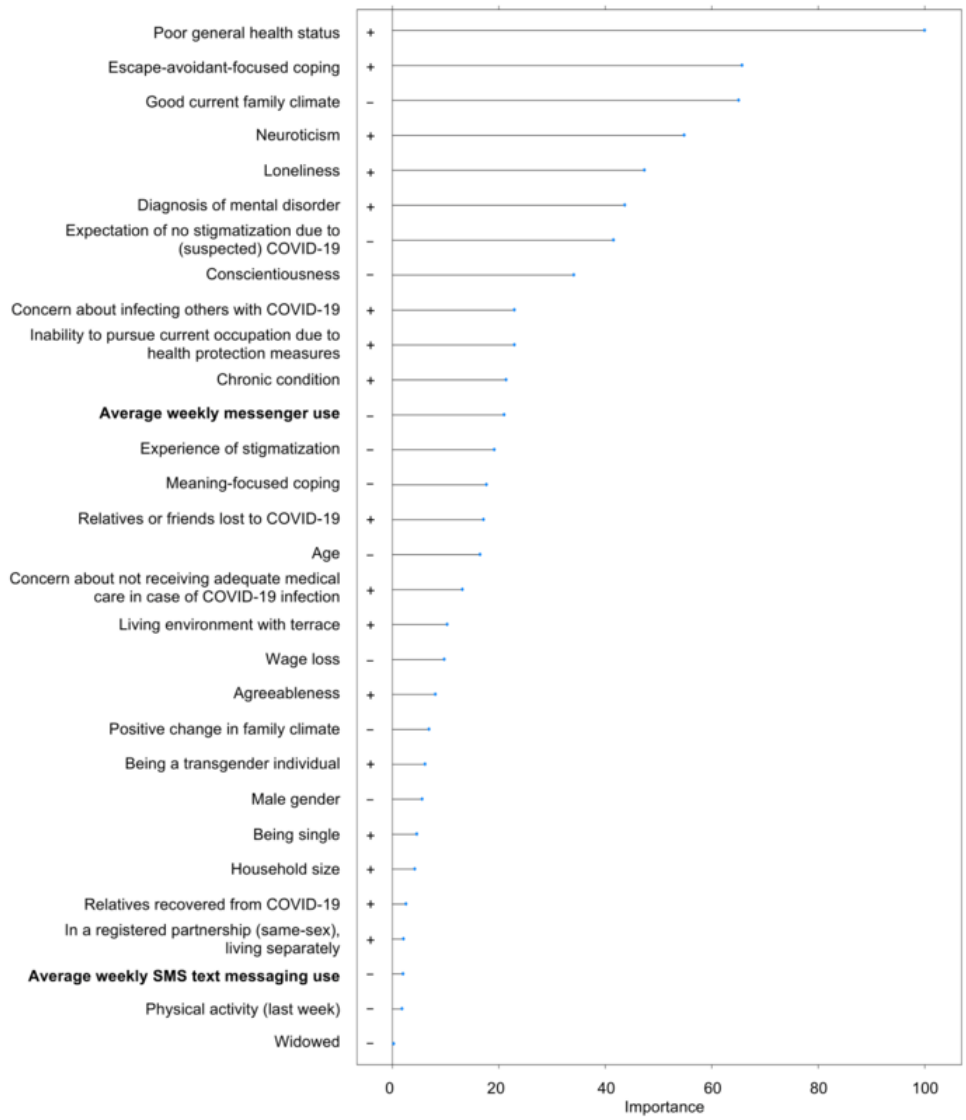


Figure 2. Total variable importance as an indicator of the contribution to the reduction of the estimation error in the prediction of anxiety symptoms.



Discussion

Principal Findings

This study investigated the prediction of depressive and anxiety symptoms on the basis of smartphone-based social interaction data supplemented by a comprehensive set of well-established predictors, while also taking into account relevant pandemic-specific factors. The results show that when well-established predictors are considered, only the average weekly duration of messenger use as a negative predictor adds significant value to the prediction of both depressive and anxiety symptoms. In only 1 of the 2 prediction models, the average weekly duration of video calls (depressive symptoms) and SMS text messaging use (anxiety symptoms) remained relevant.

These findings are based on data collected during the COVID-19 pandemic and underscore the importance of messenger, video call, and SMS text messaging use for maintaining social contact. This interpretation aligns with the fact that social contact is considered a preventive factor for depressive and anxiety symptoms in general [69,70] as well as during the COVID-19 pandemic in particular, as already discussed by several studies that have reported an increase in digital face-to-face interactions [71]. This point is particularly relevant in view of the social distancing measures imposed to reduce COVID-19 infection rates because in times of lockdown, digital interactions were sometimes the only means to achieve face-to-face contact and group meetings [16]. It is also conceivable that as depressive symptoms increase, accompanied by social withdrawal, smartphone-based interaction is also reduced.

In contrast to previous findings [21,22], other smartphone-based social interaction parameters (weekly averaged use duration of phone calls and social media, as well as weekly averaged total smartphone use duration) did not contribute to the prediction of depressive or anxiety symptoms in the context of the COVID-19 pandemic. One possible explanation is that prior studies examined individual or only a few nonsmartphone-based social interaction parameters; for example, loneliness is a well-established correlate of depressive symptoms [46-48]. Consistent with previously published results from this study

[72] and other research [73], certain social interaction parameters, such as messenger use, are negatively correlated with loneliness. Thus, if loneliness is not taken into consideration, various smartphone parameters might seem to be significant correlates of depressive symptoms through spurious correlation. To avoid this effect, we included a comprehensive set of reliable predictors to provide insights into the additional value of smartphone-based social interaction data as predictors of depressive and anxiety symptoms. Future studies should also explicitly investigate the predictive value of smartphone-based social interaction data in isolation because these data are particularly attractive and accessible from a research economic point of view.

Another aspect that should be considered is the poor resolution of smartphone-based social interaction data. Whereas some studies have analyzed individual use patterns or changes over time [15,74], we decided to use a comprehensive but coarse-grained model and thus were unable to take into consideration more detailed information on, for example, content, motivation, or satisfaction with interactions. However, it has been found that the correlation between (social) media use and the symptoms of mental disorders varies according to use motives [75] and apps used [76]. A more detailed high-resolution analysis might help clarify associations between smartphone-based social interaction data and the symptoms of mental disorders in more detail.

Moreover, by taking into account a large number of proven predictors of depressive and anxiety symptoms, the results highlight the relevance of pandemic-related changes as additional predictors. The pandemic-related variables that remained significant in both our final models can be divided into internal aspects (cognitive appraisal processes and emotions) and external aspects (changes in daily life due to pandemic control measures).

The remaining internal aspects include expected stigmatization due to (suspected) COVID-19 infection and concern about not receiving adequate medical care in case of COVID-19 infection due to lack of medical capacity. In addition, the pandemic may have exacerbated the impact of other internal aspects of social interaction on feelings of loneliness [26] and family climate [27], which were already considered risk factors for the development of depressive and anxiety symptoms before the COVID-19 pandemic [46-48]. Correspondingly, loneliness and family climate were among the most important predictors of depressive and anxiety symptoms in our research. This result seems understandable if we view loneliness as an expression of an unmet need for attachment, which might increase the risk for developing depressive or anxiety symptoms. Similarly, social withdrawal can be an aspect of depressive symptoms and lead to family problems. By contrast, a subjective feeling of social connection prevents depressive symptoms. Family climate could be an indicator of the number of conflicts or tasks to be managed and thus an additional stressor that favors the development of psychopathological symptoms. Similarly, having a positive family climate as a resource could prevent the development of psychopathological symptoms.

The external aspect experienced in everyday life that predicts symptoms of depression and anxiety is the inability to pursue one's current occupation due to health protection measures (eg, due to the closure or suspension of work activities). With this study, we were able to replicate previous findings in a more comprehensive statistical model that also included passive smartphone-based social interaction data [24-26]. The fact that the accumulation of stressors during the COVID-19 pandemic, along with the accompanying changes and limitations, can lead to an increase in depressive and anxiety symptoms was discussed [29,77]. Our data also showed high wage loss as a positive predictor of both depressive and anxiety symptoms, whereas a stable income seemed to correlate negatively with the development of psychopathological symptoms.

In contrast to other studies [78], our data indicated that losing relatives or friends to COVID-19 was a negative predictor of depressive and anxiety symptoms. In line with previous research findings, general health status, such as individual differences, chronic conditions, and a lifetime diagnosis of a mental disorder, showed particular relevance in relation to depressive and anxiety symptoms [29,30]. In addition, relations may have become even stronger in the context of the COVID-19 pandemic [79] because treatment services for people with both physical and mental health problems were temporarily reduced due to contact restrictions [80,81]. At the same time, willingness to seek help decreased, presumably due to concerns about contracting COVID-19 infection [79,82]. It can also be assumed that persons with poor physical health status have an increased risk of severe illness if infected with COVID-19 [34], possibly leading to increased health concerns that favor depressive and anxiety symptoms [83].

Coping strategies also played a role in predicting depressive and anxiety symptoms [53]. In line with previous findings [84], our results showed a positive association of escape-avoidant–focused coping with depressive and anxiety symptoms as well as a negative association with meaning-focused coping. The fact that coping strategies are gaining relevance is particularly understandable in view of the COVID-19 pandemic [53]: it is only when major stress arises in one's life that the functionality and benefits of one's coping strategies become evident; for example, Fullana et al [84] were able to show that reduced consumption of news concerning COVID-19 and pursuing hobbies were negatively related to depressive symptoms.

In addition, the personality facets of conscientiousness, agreeableness, and neuroticism proved to be significant predictors of depressive and anxiety symptoms, consistent with previous findings [85]. Due to the pandemic-related dissolution of work boundaries, it is conceivable that conscientiousness may have become even more relevant; for example, mandatory work from home shifted the responsibility for organizing work time entirely to the employee [86]. In this context, conscientiousness is particularly valuable for meeting professional requirements as well as managing tasks such as home schooling children or caring for underage children. By contrast, neuroticism was a positive predictor of depressive and anxiety symptoms, which is to be expected [87-89] because neuroticism's core facet is trait anxiety [90]. In contrast to other research [87,88,91], our data showed that agreeableness was a positive predictor of depressive and anxiety symptoms.

Consistent with previous research [92], we found that older age was associated with lower depressive and anxiety symptoms. Younger age, already a risk factor for the development of depressive symptoms [93], seemed to play a particularly important role in the pandemic [92]. One of the reasons discussed is that younger people are much more connected via media and thus exposed to the news, which could have acted as a stressor during the COVID-19 pandemic and in the context of related news coverage [94]. Again, the task of analyzing this interaction effect remains an area for future studies. Another reason discussed is the greater vulnerability to stress and depressive symptoms associated with younger age [95]. If one also considers the restrictions in the everyday life of young people during the COVID-19 pandemic, it is noticeable that meeting friends, partying, dancing, attending vocational school in person, and collective studying suddenly disappeared due to contact restrictions. Accordingly, there was evidence of stressors such as feelings of loneliness and social isolation, especially among young adults [96]. Household size also proved to be a positive predictor of depressive and anxiety symptoms. This result is in line with previous findings that have discussed the fact that shared living space is associated with increased stress, depending on the number of residents [97].

The results provide initial indications that, taking established predictors into account, depressive and anxiety symptoms can be predicted using smartphone-based social interaction data. This represents an important step toward a future in which the early recognition of depressive symptoms via smartphones may become feasible. Even today, automated feedback based on smartphone-based social interaction data could enable early preventive health-promoting measures tailored to individual results.

Strengths and Limitations

A major strength of this study is the comprehensive set of data comprising smartphone-based social interaction app use data as well as survey data. These data allowed us to create a holistic model of mental health predictors during the COVID-19 pandemic. Moreover, big data methodology was used, which allowed us to investigate the value of passive smartphone-based social interaction parameters for the prediction of depressive or anxiety symptoms while taking into account a broad set of other well-established relevant factors. This approach made it possible to show that passive smartphone-based social interaction data contribute to the explanation of variance beyond established predictors, which emphasizes the relevance of these new data. Furthermore, by collecting data via smartphones, a large number of participants could be reached and interviewed despite contact restrictions.

A limitation of the study is the lack of representativeness of the data. The group with a high level of education and younger participants are overrepresented. In addition, the cross-sectional correlational study design is a limitation because it is not possible to investigate predictive direction for a large number of variables that are unlikely to be antecedents of depressive or anxiety symptoms (eg, household, age, and gender). The latter variables include all smartphone-based interaction data and a large share of putative internal predictors. The inclusion of established strong predictors (eg, chronic condition and partnership status) may have limited the explanatory power of the model with respect to weaker risk factors (eg, smartphone-based social interaction data). The collection of various sorts of smartphone-based social interaction data also presents a methodological challenge because many apps can be used to communicate in different ways (eg, written messages or video calls). Thus, the mode of communication cannot be clearly ascertained. Due to a lack of comparative data before the pandemic, potential changes over time could also not be taken into account.

Conclusions

This study indicates that data concerning the time spent engaging in smartphone-based social interaction adds only limited value regarding the prediction of depressive and anxiety symptoms among German adults during the COVID-19 pandemic. Although predictive direction cannot be established, these results are in line with models of the etiology of depression and anxiety.

Data Availability

The data sets generated and analyzed during this study are not publicly available because the participants' informed consent did not cover consent for making the data publicly available but are available from the corresponding author on reasonable request.

Authors' Contributions

JSE developed the research questions and methodology in consultation with CC. YT provided advice regarding the planning of the statistical analyses. RP developed the app and data collection processes. JSE performed the data analyses and wrote the manuscript in consultation with YT, RP, HB, and CC. All authors critically revised the paper and approved the final revision.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Descriptive statistics of the sample of German-speaking adults (n=490) in total and grouped by gender.
[DOCX File , 33 KB-Multimedia Appendix 1]

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Abbreviations

Brief-COPE: Coping Orientation to Problems Experienced Inventory
LASSO: least absolute shrinkage and selection operator
MAE: mean absolute error
PHQ-D: Patient Health Questionnaire, German version
RMSE: root mean square error
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

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Kapitel 3

Predicting depressive symptoms using GPS-based regional data in Germany with the CORONA HEALTH app during the COVID-19 pandemic: Cross-sectional study

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Original Paper

Predicting Depressive Symptoms Using GPS-Based Regional Data in Germany With the CORONA HEALTH App During the COVID-19 Pandemic: Cross-Sectional Study

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Abstract

Background: Numerous studies have been conducted to predict depressive symptoms using passive smartphone data, mostly integrating the GPS signal as a measure of mobility. Environmental factors have been identified as correlated with depressive symptoms in specialized studies both before and during the pandemic.

Objective: This study combined a data-based approach using passive smartphone data to predict self-reported depressive symptoms with a wide range of GPS-based environmental factors as predictors.

Methods: The CORONA HEALTH app was developed for the purpose of data collection, and this app enabled the collection of both survey and passive data via smartphone. After obtaining informed consent, we gathered GPS signals at the time of study participation and evaluated depressive symptoms in 249 Android users with the Patient Health Questionnaire-9. The only GPS-based data collected were the participants' location at the time of the questionnaire, which was used to assign participants to the nearest district for linking regional sociodemographic data. Data collection took place from July 2020 to February 2021, coinciding with the COVID-19 pandemic. Using GPS data, each dataset was linked to a wide variety of data on regional sociodemographic, geographic, and economic characteristics describing the respondent's environment, which were derived from a publicly accessible database from official German statistical offices. Moreover, pandemic-specific predictors such as the current pandemic phase or the number of new regional infections were matched via GPS. For the prediction of individual depressive symptoms, we compared 3 models (ie, ridge, lasso, and elastic net regression) and evaluated the models using 10-fold cross-validation.

Results: The final elastic net regression model showed the highest explained variance (R^2=0.06) and reduced the dataset from 121 to 9 variables, the 3 main predictors being current COVID-19 infections in the respective district, the number of places in nursing homes, and the proportion of fathers receiving parental benefits. The number of places in nursing homes refers to the availability of care facilities for the elderly, which may indicate regional population characteristics that influence mental health. The proportion of fathers receiving parental benefits reflects family structure and work-life balance, which could impact stress and mental well-being during the pandemic.

Conclusions: Passive data describing the environment contributed to the prediction of individual depressive symptoms and revealed regional risk and protective factors that may be of interest without their inclusion in routine assessments being costly.

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KEYWORDS

depression; COVID-19; mobile phone; geographic information systems; GPS-based data; mobile applications; mental health

Introduction

Background

Depression is a serious and widespread disease accompanied by a high individual burden [1]. Early detection of depressive symptoms facilitates care through early intervention and can thus prevent the development of severe symptoms such as suicidal ideation [2]. Therefore, knowledge of the current incidence and rapid recognition of trends in the prevalence of depressive symptoms is of great social relevance [3], for instance, for planning treatment strategies and identifying capacities.

To identify such trends in a timely manner, population-wide (broad) data collection in real time is pivotal. Collecting survey data requires the commitment of the participants, and they have to take the time and effort to answer questions. With the proliferation of smartphones, an alternative data source is available that does not require the effort of participants. Smartphone data have been used in research on mental health [4,5] and explicitly for depressive symptoms [6,7]. Analyses based on these smartphone data often aim to predict, for instance, depressive symptoms by including all available data [4,6,8,9]. A distinction is made between active and passive data collected via smartphones. Active smartphone data involve data that require the active involvement of the smartphone user (eg, survey data collected via the smartphone), and passive smartphone data include data that can be collected without the user's involvement [4]. Passive smartphone data can be divided into activity data, social media data, and sensor data [10]. A whole body of evidence investigates the predictive power of activity data (eg, text messages sent, calls made, and screen activity), which are understood as objective measures of behavior [11]. It has been shown that some of these activity data are clearly related to depressive symptoms [12-15]. Social media data include information about posts on social networks, and these aspects of social interaction are also associated with depressive symptoms [16]. Smartphone sensor data involve the data measured with the sensors integrated in smartphones, such as GPS [10]. Studies often use GPS to analyze mobility behavior and have been able to identify correlations with depressive symptoms as well [4,7,10,14,17-20]. However, by including GPS sensor data in research on depressive symptoms, it is further possible to describe the participants' environment in detail. Environmental factors include, for example, the sociodemographics of the population living in the surrounding area, economic conditions, social affairs, or living conditions (Table S1 in Multimedia Appendix 1). These environmental factors are external factors that affect people's living conditions. For example, urbanization and population density are controversially discussed as risk factors for depressive symptoms [21]. In addition, different types of noise and air pollution were predominantly identified as positively related to depressive symptoms [21]. A poor home or building environment has been repeatedly identified as positively correlated with depressive symptoms, and the same applies to a lack of green areas [21].

This study was conducted during the COVID-19 pandemic. This was a time when people spent more time at home due to contact restrictions and lockdowns [22]. Researchers argue that environmental factors may have been particularly important for mental health during the pandemic, as more time was spent in those same environments [23-25]. This is also indicated by the results showing an association between housing conditions (eg, available space) and depressive symptoms during the COVID-19 pandemic [23,26]. For this reason, environmental factors should be included in studies on depressive symptoms (especially during the COVID-19 pandemic). In addition, integrating environmental factors allows for a better understanding of depressive symptoms, namely, to what extent environmental factors are risk and protective factors for depressive symptoms [27]. Furthermore, as some environmental factors such as sociodemographics (eg, employment rate and age distribution), economic conditions (eg, investments per employee), social affairs (eg, percentage of households with children), and living conditions (eg, percentage of 1-person households) can be passively measured via GPS data, the prediction and identification of depressive symptoms can be achieved with much lower costs, effort, and in a faster manner. However, it is unclear how accurately self-reported individual depressive symptoms can be predicted purely on the basis of GPS signals.

Study Design

The aim of this study was to clarify to what extent environmental factors that can be passively measured via an individual's location tracked by GPS explained the statistical variance in individual depressive symptoms. In contrast to many studies that have focused on single predictors only [13], this study used a comprehensive approach and integrated a wide range of data available through GPS smartphone data (eg, sociodemographics, economic conditions, social affairs, and living conditions). Since this study was conducted during the COVID-19 pandemic, GPS-based COVID-19–specific variables such as the pandemic phase and the regional COVID-19 infection count were integrated as well.

The analyses were based on a data-driven statistical approach that allowed us to analyze a large number of predictor variables for individual depressive symptoms in an exploratory fashion without overfitting the data. Hence, there was no a priori selection of included variables based on any assumed connection to depressive symptoms, but all available variables of the data source were included.

Methods

Sample and Procedure

Data collection took place by means of the developed CORONA HEALTH app, a cooperative project between the German universities of Würzburg, Ulm, and Regensburg, and the German Robert Koch Institute. The CORONA HEALTH app was specifically designed to explore factors during the COVID-19 pandemic and allows for both cross-sectional and longitudinal data analyses [28]; in this paper, we exclusively used cross-sectional data. Participants were recruited by means of public relation measures (eg, press releases and social networks). Participation in this study was voluntary, and participants did not receive incentives for participation. The inclusion criterion (for the analyzed study) was a minimum age of 18 years. In this study, only those data from smartphones with Android operating systems were analyzed. To participate, participants had to download the app and were then requested to provide informed consent (including use of GPS data). The study information provided was based on the quality standards set out by Beierle et al [29].

Based on the recorded GPS signal during survey participation, we assigned each participant to the nearest district, which was the smallest possible regional unit. The only GPS-based passive data collected were the participants' location at the time of the questionnaire. This location was used to link participants to district-level sociodemographic and environmental data from official German statistical sources. For data protection reasons, the resolution of the location was reduced to an accuracy of 11.1 km. In Germany, the statistical offices of the counties and the federal government provide current average values for 160 indicators at the regional level in the so-called Regional Atlas [30]. All these available average values for population structure, housing conditions, and so forth, were assigned to each participant according to his or her respective district. Data were gathered from July 2020 to February 2021, coinciding with the COVID-19 pandemic. This period in Germany was marked by several waves of infections and accompanying contact-restricting measures and correspondingly restricted public life [22]. Based on the date of the first questionnaire completion, the COVID-19 incidence rate in the respective district and information on the pandemic phase [22] were determined and assigned to the individual dataset.

The conception and implementation of the app followed medical device regulations and were certified accordingly (see the study by Holfelder et al [31]). This study was approved by the ethics committee of the University of Würzburg (130/20-me).

Due to the inclusion of exclusively passive data, the dataset did not contain any individual sociodemographic information but rather the sociodemographic averages in the respective district. The following sociodemographic averages describe the sample: those aged 0-17 years accounted for 15% of the population (averaged across all districts), those aged 18-24 years accounted for 8.3%, those aged 25-44 years accounted for 29.7%, those aged 45-64 years accounted for 25.6%, and those older than 65 years accounted for 27.5%. It is important to note that while those aged 0-17 years were mentioned as comprising 15% of the population, this figure provides general context about the population, as individuals younger than 18 years were not included in the study sample. On average, 39.6% of the population in the districts graduated from school with a general matriculation standard, and an average of 6% did not have a school-leaving certificate.

The original sample had 1760 participants. Eighteen individuals were dropped in a plausibility check based on correspondence between similar items, straightlining, intraindividual response variability, and extreme outliers. Of the remaining sample of participants, 60.4% (1052/1741) had an Android operating system, and 28.1% (490/1741) consented to the collection of passive data. Of the remaining sample, only those districts with more than 20 participants were included to meet the condition of normally distributed data in the clusters. This resulted in a final sample of 249 participants. Details on the sample can be found in Table S1 in Multimedia Appendix 1.

Measures

The primary outcome of this study was depressive symptoms, measured using the German version of the Patient Health Questionnaire-9 (PHQ-9) [32]. The PHQ-9 is a validated self-report instrument consisting of 9 items (eg, "Over the last week how often have you experienced little interest or pleasure in doing things?"), with responses on a 4-point scale (0="Not at all" to 3="Almost every day"). The total PHQ-9 score ranges from 0 to 27, with higher scores indicating more severe depressive symptoms. A score of 0-4 suggests minimal depressive symptoms; 5-9, mild symptoms; 10-14, moderate symptoms; 15-19, moderately severe symptoms; and 20-27, severe symptoms. The internal consistency of the PHQ-9 in this sample was excellent, with a Cronbach α=0.85.

The PHQ-9 is widely used in both clinical and general populations and was chosen as the outcome measure because it allows for the assessment of the severity of depressive symptoms in a continuous format, which aligns with the study's objective to explore predictors of individual depressive symptoms. As a COVID-19 pandemic–specific variable, the number of infections per 100,000 inhabitants in the respective district at the time of assessment was included. These data were derived from official statistics reported by the Robert Koch Institute based on all laboratory-confirmed officially reported SARS-CoV-2 cases within the framework of the German Infection Protection Act [33]. In addition, the pandemic phase at the time of assessment was included in each case according to the classification by Schilling and colleagues [22] ranging from 1 (calendar weeks 10-20 in 2020) to 3 (calendar week 40 in 2020).

The respective regional environmental factors were determined using the district-level statistics of the Regional Atlas of the Federal Statistical Offices [30]. All variables available on the website on April 30, 2022, at the district level were included, with each construct included once. These included data on sociodemographics (eg, age group percentages in 2019, youth ratio in the regional population in 2021, percentage of the population without school-leaving qualifications in 2019, employment rate in 2020, disposable income per inhabitant in euros in 2020, and percentage of unemployed people in 2020), economy (eg, percentage of employed individuals by sector in 2019, investments per employee in thousand euros in 2019, and average length of stay of tourists in 2019), social affairs (percentage of households with children in 2011, percentage of children in care by age on March 1, 2021, proportion of fathers receiving parental benefits in 2014, and places in nursing homes per 1000 inhabitants aged 65 years and older in 2020), and living environment (eg, percentage of 1-person households in 2011, population density of inhabitants per square kilometer in 2020, percentage of area by use in 2015, and consumption-based charge for drinking water supply per cubic meter in 2019). A complete list of variables is shown in Table S1 in Multimedia Appendix 2. Due to the district clusters, the respective districts were included in the analyses as dummy variables. In addition, the pandemic phases were included as dummy variables. In total, the dataset included 121 variables.

Data Analyses

Using GPS coordinates, each participant was assigned to a district. To control for the nested data, the respective districts were included in the analysis as dummy variables. Two participants who had a GPS location outside Germany were excluded. The data contained only 3 missing values (in the depressive symptoms variable); these were replaced using a single imputation with 500 iterations using classification and regression trees (cart method) with the R package "mice" (ie, the mice package for multivariate imputation by chained equations was developed by Stef van Buuren and is supported by Utrecht University) [34]. Metric variables were *z* standardized.

For the prediction of individual depressive symptoms, we chose to compare ridge, lasso, and elastic net regression models [35]. The predictive performance, signaling the best fit, relied on the root-mean-square error, mean absolute error, and explained variance (R^2). Using a grid search, we implemented hyperparameter optimization. The analyses included automated variable selection. This allowed for a statistical check of which variables remained in the model with the best predictive performance, that is, the lowest degree of prediction errors [36]. To avoid overfitting, we split the dataset into a training (70%) and a test dataset (30%). In the training dataset, the final model was calculated using 10-fold cross-validation with 5-fold repetition [35]. In the test dataset, the model was evaluated for its predictive performance in a sample that had not been part of the model training. The result was a ranking by variable importance (Figures 1 and 2). Variables were ranked based on their contribution to the prediction of individual depressive symptoms.

Figure 1. Total variable importance as an indicator of the contribution to reduce the estimation error in the prediction of depressive symptoms in the lasso regression model.

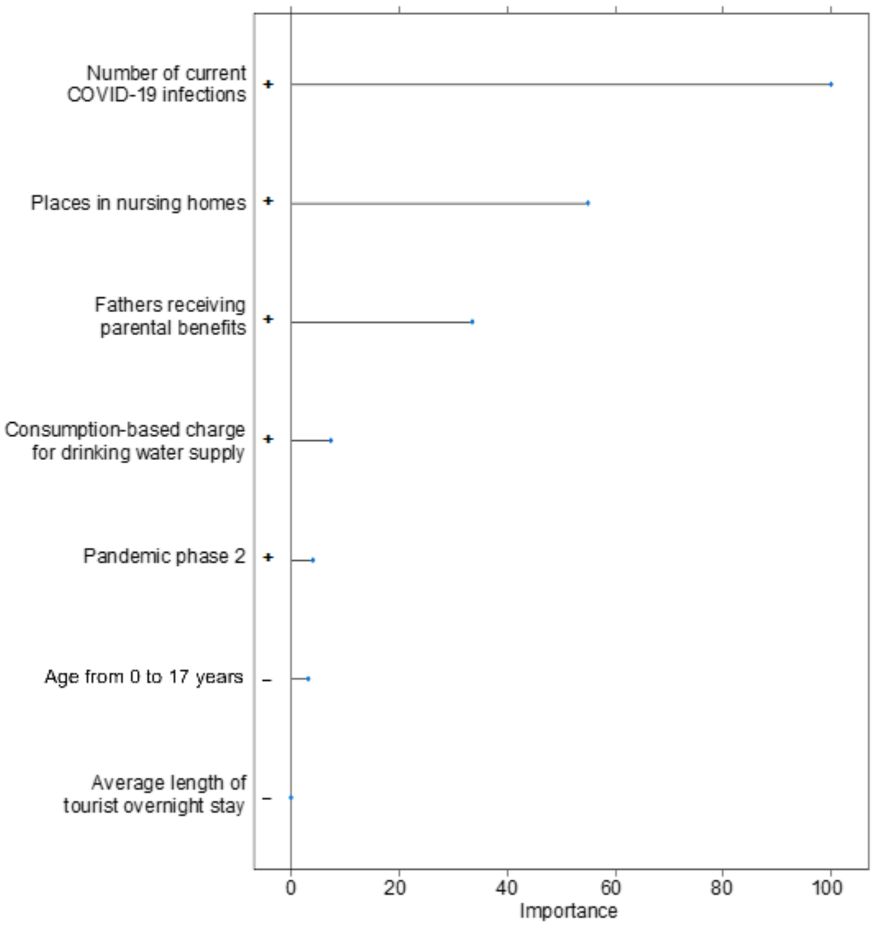
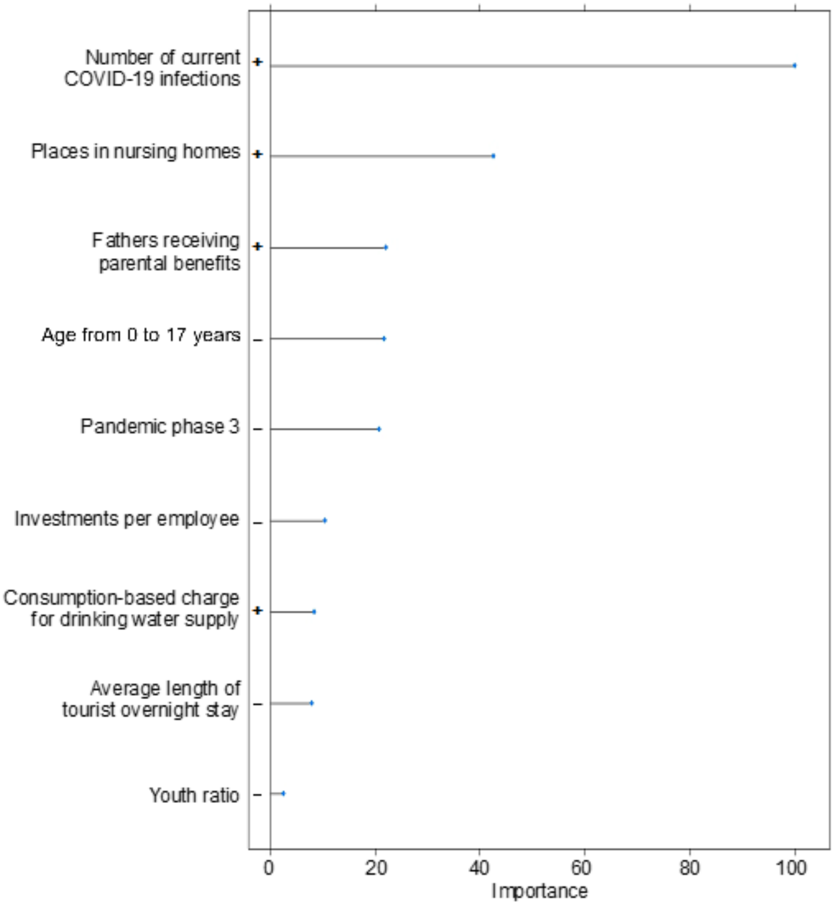


Figure 2. Total variable importance as an indicator of the contribution to reduce the estimation error in the prediction of depressive symptoms in the elastic net regression model.



Ethical Considerations

The conception and implementation of the app followed medical device regulations and were certified accordingly [31]. The original data collection for this study was approved by the ethics committee of the University of Würzburg (130/20-me). This approval explicitly covered both initial data collection and any potential future secondary analyses using the collected data. As such, no additional institutional review board approval or exemption was necessary for the present secondary analysis. In accordance with local regulations and institutional guidelines, the secondary use of existing, anonymized data does not require a separate review or approval. Specifically, the main institutional review board votum issued during the original data collection already included provisions for future secondary analyses. This is in line with German medical research standards, which state that when data are collected with informed consent that includes provisions for future use, and the data are anonymized, additional ethical approval is not required for secondary analyses (see Article 89 of the German Data Protection Regulation). All procedures adhered to institutional ethical standards for research involving human subjects, and all participant data were fully anonymized to protect privacy. Participation was voluntary, and no financial compensation was provided.

Results

The comparison of the individual models (ridge, lasso, and elastic net regression) showed the following differences: in the prediction of individual depressive symptoms, lasso regression had the smallest average root-mean-square error (5.59). The explained variance was second to highest (R^2=0.05). The elastic net regression produced the highest explained variance (R^2=0.06; Table 1). The listed characteristic values showed lasso and elastic net regression as the analyses with the best fit. Lasso regression reduced the dataset from 121 variables to 7 variables, and elastic net regression reduced it from 121 to 9 variables.

The lasso and elastic net regression models shared the first 3 predictors. The most important predictor was the number of current COVID-19 infections in the respective district. The second was the number of places in nursing homes, and the third was the proportion of fathers receiving parental benefits. Both models also included the 3 variables population share of the 0-17 years age group, average length of stay of tourists, and the consumption-based charge for drinking water.

Lasso regression showed the second pandemic phase as a relevant predictor (Figure 1). Elastic net regression further listed (in descending variable importance) the third pandemic phase, investment per employee and the youth ratio as relevant predictors (Figure 2).

Table 1. Model fit indices for predicting depressive symptoms resulting from stepwise, ridge, lasso, and elastic net regression based on 50 replicate samples[a].

	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
MAE[b]						
Ridge	3.628	4.127	4.515	4.448	4.746	5.524
Lasso	3.606	4.231	4.440	4.464	4.643	5.717
Elastic net	3.605	4.162	4.506	4.483	4.741	5.764
RMSE[c]						
Ridge	4.165	5.071	5.626	5.594	6.080	7.373
Lasso	4.216	5.244	5.630	5.585	5.942	7.104
Elastic net	4.169	5.219	5.677	5.618	5.912	7.162
R^2						
Ridge	0.000	0.003	0.019	0.048	0.079	0.228
Lasso	0.000	0.003	0.019	0.053	0.052	0.366
Elastic net	0.000	0.009	0.034	0.063	0.083	0.415

[a]Overall, elastic net regression had the best model fit due to the largest variance explained (R^2), and lasso regression had the best model fit when including the smallest mean absolute error and root-mean-square error.

[b]MAE: mean absolute error.

[c]RMSE: root-mean-square error.

Discussion

Principal Findings

This study aimed to identify correlates of depressive symptoms based on regional factors allocated via GPS (passive data). It should be noted that the only GPS-based passive data collected were the participants' location at the time of the questionnaire, which was then used to assign participants to regional sociodemographic and environmental data based on their district. For this purpose, we used a passive data collection method. This had the advantage of integrating a wide range of data without any effort on the part of the participants.

The results helped identify regional and freely available variables as risk and protective factors for individual depressive symptoms. The identified risk and protective factors are presented as follows, starting with the 3 aspects that had the greatest relevance in both models.

The weekly number of cases of COVID-19 infections in the respective district was positively associated with higher individual depressive symptoms. In many cases, high COVID-19 case numbers were associated with contact restrictions in everyday life imposed by law or by the population itself [37]. A connection between these contact restrictions and individual depressive symptoms has been discussed repeatedly [38-41]. Different arguments were used to explain this connection. The reduction in social contact promoted loneliness, which has been identified as a risk factor for individual depressive symptoms [42,43]. In addition, an increase in misconduct and home violence has been reported [44]. Moreover, the high number of cases might have been associated with increased fear of infection, which increased substantially during the pandemic [41], a lack of care capacities, or a severe course of the disease [45]. This could be related to individual depressive symptoms as an additional burden [46].

The proportion of fathers receiving a parental allowance was a risk factor for higher individual depressive symptoms. Parental allowance is a financial state benefit to mothers or fathers in Germany that is granted for a certain period during which the parent is not or only partially employed and devotes himself or herself to the care of their child. For methodological reasons, it was not possible to derive any causal associations from the results of our analysis. However, one possible explanation could be that paternal receipt of parental allowance might be an indicator for those families in which both parents are employed. These families were thus dependent on the functioning of the childcare infrastructure and therefore particularly challenged by the double burden of working from home and homeschooling for the duration of the pandemic. In a different study, increased individual depressive symptoms were also observed in parents of underage children during the COVID-19 pandemic, which also indicates the special burden on families [47].

In addition, the pandemic phase was a relevant factor for individual depressive symptoms. Phase 2 of the pandemic was positively related to individual depressive symptoms. The second phase of the pandemic, from the end of May to the end of September 2020, was accompanied by the opening of restaurants, gradual school openings, and the lifting of travel restrictions [22]. It is possible that with this return to regular daily life, depressive symptoms became more noticeable. In other words, it could be that it was only at the moment when a person was no longer able to cope with demands that he or she became aware of his or her own mental health condition. This could have been the case for those affected by depressive symptoms after the contact restrictions were removed and they returned to everyday demands. The same reasoning could apply to the negative correlation between phase 3 of the pandemic and individual depressive symptoms. The third pandemic phase was characterized by a nationwide partial lockdown at the beginning of November 2021 with tightened contact restrictions and a nationwide lockdown with moderately strict regulations from mid-December and the Christmas holidays [22]. Due to contact restrictions and holidays, there were fewer day-to-day demands to attend to during the period, such as homeschooling, daily logistics due to travel, and social obligations. In the case of individual depressive symptoms associated with reduced drive and anhedonia [48], these individual depressive symptoms would have been less noticeable during the lockdown, as there were fewer events to manage anyway.

In contrast to previous findings, a high proportion of the 0-17 years age group and a high youth ratio were associated with lower levels of individual depressive symptoms. In contrast, numerous studies have shown that stress and individual depressive symptoms in families increased during the pandemic [47,49,50]. Since only proportions of the population and not the absolute numbers were collected, a large share of the 0-17 years age group can also mean that the proportion of families was correspondingly large and thus the proportion of people living alone correspondingly smaller. Research showed that 1-person households correlated with lower well-being compared with households with 2-4 people during the pandemic [51]. Furthermore, correlations between loneliness and individual depressive symptoms were also found [52].

In contrast to the present results, previous studies showed a correlation between nearby green spaces [25] or the quality of housing conditions (>60 m^2, view from the windows, and poor indoor quality) [23] and lower depressive mood. A systematic review confirmed this and identified poor housing, lack of green spaces, and both noise and air pollution as environmental factors that were associated with depressive mood across studies [21]. The reason for the deviation of the present results could be that availability alone was not the decisive predictor for the association with depressive symptoms. Using the example of green spaces, research conducted during the COVID-19 pandemic, for example, showed that although natural areas were visited more often, visits to parks decreased [25]. The authors further discussed to what extent it was the time spent in green spaces that was related to low depressive symptoms or whether the green space was explicitly visited to participate in sports or to maintain social contacts and whether these were actually relevant predictors [25]. Sonnentag et al [53] found that the psychological mechanisms underlying recovery seem to be enhanced in natural environments.

Strengths and Limitations

A central strength of this study is the application of a data-driven statistical approach that allowed us to analyze a large number of predictor variables in an exploratory fashion without overfitting the data. By these means, the approach allowed us to investigate which environmental factors had predictive power. The collection of passive data via smartphone made it possible to reach participants despite pandemic-related contact restrictions and to make a corresponding statement about the included predictors for the COVID-19 pandemic period.

The cross-sectional study design of this study was limiting; statements about causal relationships were therefore not possible. In addition, the final dataset was very small, which might have weakened the significance of the analyses. A limitation that other studies have also observed [12] is the limited predictive power of individual depressive symptoms based on the passive data used. The use of GPS data was also a limitation, as it included only the location at the time of questionnaire processing. This was not the same as the place of residence of the respective person. How long the respective person was exposed to the general conditions could therefore not be inferred from the data. In addition, the informative value of the GPS data regarding individual environmental conditions was limited due to the regional resolution: since large variances in the average values were possible, it was of course not possible to draw conclusions about individual cases. Moreover, the image of the environment was only very roughly described. However, it represented the smallest possible regional size at which data from statistical offices could be collected nationwide. In addition, a higher spatial resolution, for example, per block of houses, would make it impossible to anonymize the data, as too few people would remain in the respective cluster. The validity of this study is further limited by the nonrepresentative dataset. As this analysis was limited to data from Android smartphones and required agreement to the collection of passive data, selection bias could not be ruled out. This must be taken into account when evaluating the results of this study. In addition, neither changes in predictors over time nor long-term data collection was considered to depict cause and effect more validly. This study can therefore make statements only about correlations and not about cause and effect.

Conclusions

This study showed that regional average data on socioeconomics and living environment seemed to be limited predictors of individual depressive symptoms; for the pandemic period, individual depressive symptoms were predicted, although the predictors had a rather low explanatory value and are not transferable to postpandemic periods. This suggests that the spatial resolution would need to be modified or that the dataset would need to be supplemented with additional data sources. Nevertheless, the results help classify freely available average data as risk or protective factors for individual depressive symptoms.

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Authors' Contributions

JSE and MW developed the research questions and methodology in consultation with CC. MW and HS advised the planning of the statistical analyses. RP developed the app and data collection processes. JSE and MW performed the data analyses and wrote the manuscript in consultation with HS, RP, HB, and CC. All authors critically revised the paper and approved the final revision to be published.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Descriptive statistics of the present sample of 249 German-speaking adults across districts.
[DOCX File , 23 KB-Multimedia Appendix 1]

Multimedia Appendix 2

A list of variables from the Regional Atlas of Germany detailing sociodemographic, economic, and environmental data used in the study.
[DOCX File , 52 KB-Multimedia Appendix 2]

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Abbreviations

PHQ-9: Patient Health Questionnaire-9

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RESEARCH

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The role of personality traits and social support in relations of health-related behaviours and depressive symptoms

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Abstract

Background: Previous evidence has suggested that physically inactive individuals and extensive media users are at high risk for experiencing depressive symptoms. We examined personality traits and perceived social support as potential moderators of this association. Personality and perceived social support were included as two of the most frequently considered variables when determining predispositioning factors for media use phenomena also discussed in relation to physical activity.

Methods: We analysed cross-sectional data from 1402 adults (18–31 years old) who participated in a national health survey in Germany (KiGGS, Study on the health of children and adolescents in Germany, wave 2). The data included one-week accelerometer assessments as objective indicators of physical activity, self-reported media use, depressive symptoms, perceived social support and Big 5 personality traits. An elastic net regression model was fit with depressive symptoms as outcome. Ten-fold cross-validation was implemented.

Results: Amongst the main effects, we found that high media use was positively correlated with depressive symptoms, whereas physical activity was not correlated. Looking at support and individual differences as moderators, revealed that PC use was more strongly correlated with depressive symptoms in cases of low levels of perceived social support. Positive associations of social media use with depressive symptoms were more pronounced, whereas negative associations of moderate to vigorous physical activity with depressive symptoms were less pronounced in extraverts than they were in introverts.

Conclusions: Results highlight the importance of considering individual factors for deriving more valid recommendations on protective health behaviours.

Keywords: Depression, Personality, Social support, Health-related behaviours, Public mental health, Mental health monitoring

Introduction

Depression is amongst the most frequent diseases worldwide and is the main contributor of (nonfatal) morbidity [1]. In particular, young adults have high prevalence rates of depressive symptoms [2]. In addition to age, several other risk and protective factors for depressive symptoms have been identified, including health-related behaviours, that include risk and health protective behaviours [3–5]. Most health-related behaviours are modifiable, and behaviour change is an important component for preventing mental disorders [6]. Therefore, more detailed knowledge about the associations of

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depressive symptoms and specific health-related behaviours represents an essential starting point for public health research.

Current findings list extensive media use (e.g., high amounts of screen-time) and the lack of physical activity as major behaviour-related risk factors for depressive symptoms [7–9]. Both factors are also behavioural parameters that can be measured automatically via mobile devices and are thus effective and objective in terms of research economics (e.g., via accelerometers or smartphones). In light of their association with mental health, these factors are now also increasingly investigated by public health institutions; thus, validating the predictive accuracy of these health-related behaviours is relevant.

People who report extensive internet and social media use also more frequently report psychopathological symptoms [10].

In contrast to media use, physical activity has been reported to be negatively correlated with depressive symptoms and thus may serve as a protective factor [11]. Physical activity is defined as any bodily movement produced by skeletal muscles that requires energy expenditure [12]. The World Health Organization recommends at least 150 min of moderate-intensity physical activity or 75 min of vigorous-intensity physical activity per week for adults [13]. The lack of physical activity includes behaviour that involves a low level of energy expenditure while sitting or lying [13]. The present study focuses on media use and physical activity as important health-related behaviours affecting depressive symptoms.

To validate the relationship between health-related behaviours, such as media use and physical activity, and depressive symptoms, the individual differences must be taken into account [14–16]. Previous reports have proposed that associations of media use [17, 18] and physical activity [19, 20] with depressive symptoms are further qualified by individual-level factors such as personality and perceived social support.

To understand the role of personality traits, McCrae and Costa [21] pointed out the relevance of observing behavioural correlates. In line with this assumption, empirical evidence by Nagata and colleagues [22] showed how the correlation of physical activity with depressive symptoms differs after controlling for certain personality characteristics.

With regard to media use, Seidman [23] suggested that how individuals use and experience social media differs by personality, thus underpinning this assumption.

Despite these findings, many studies that have found relationships between high media use or a lack of physical activity and depressive symptoms did not examine the potential moderating function of personality [24].

Perceived level of social support [25] has been discussed as a major factor when investigating motivations and effects of media usage [26]; this variable may also function as a protective factor for mental health [27, 28]. Until now, evidence for the role of perceived social support on differences in associations between media use and depressive symptoms is still pending. Consequently, a profound understanding of the role of personality traits and perceived social support on the associations between health-related behaviours and depressive symptoms could be an important first step towards developing tailored prevention strategies.

The roles of personality traits and perceived social support in associations between media use and depressive symptoms

Previous studies have shown inconsistent results regarding individuals' susceptibility to media and have indicated differential effects depending on individual-level characteristics [24]. For example, small media effect sizes on mood have been explained with the selectivity of media use in accordance with the selective exposure theory [29]. The theory explains individuals' tendency to search for content and information that match their personal needs and beliefs. Valkenburg and colleagues [24] complemented selective exposure theory by concluding that media choices may also depend on dispositional factors such as personality.

Personality psychology often refers to the five-factor personality model [21], which is comprised of the dimensions of extraversion, neuroticism, conscientiousness, agreeableness and openness. Extraversion can be described as "energetic and thrill-seeking versus sober and solitary", neuroticism as "chronically predisposed to emotional distress versus emotionally stable", conscientiousness as "disciplined and fastidious versus laidback and careless", agreeableness as "kind and trusting versus competitive and arrogant" and openness as "curious and unconventional versus traditional and pragmatic" [30].

In fact, personality traits have been linked to different patterns of social media use in the past [31]. Valkenburg and colleagues [24] explained the differential effects of media use through cognitive, emotional and physiological processes that occur *during* media use. Individuals with low levels of self-esteem perceived more frequent social comparisons on the social media platform Facebook and compared themselves more often with others, which resulted in downward comparisons and self-devaluation [32]. Since low self-esteem has been related to the concept of neuroticism [33], emotionally labile people may more frequently experience downward comparisons and self-devaluation and hence have a more stressful user experience in social media compared with that of emotionally stable individuals. In sum, theories on the relationships between media use and depressive symptoms with a focus on personality are rare [34]. Following the summary of theories by Valkenburg and colleagues [24], another relevant individual-level factor that is related to the strength of media effects is social context. One aspect of social context is social support. Social support has been defined as the “social resources that persons perceive to be available or that are actually provided to them” [35]. This definition makes a crucial distinction: received support refers to retrospective reports about help received in the past. Perceived social support refers to a more or less stable expectation that help is available should the need arise. Although both forms of support are usually related, their association is only moderate in size, and they show distinct relations with indicators of physical and mental health [36]. In the present report, the potential moderating function of perceived social support was examined.

Seidman proposed that social media might be used to compensate for missing real-life social contacts [23]. Thus, when persons perceive themselves as receiving much support in real life, online compensation may be less sought after and likely less important for their mental well-being.

In conclusion, personality and perceived social support are important aspects of a thorough understanding of social media use and its relationship to mental health [23].

The role of personality traits and perceived social support in associations between physical activity and depressive symptoms

Another, relatively larger, body of research has investigated differential associations of physical activity with depressive symptoms [15, 16, 37]. However, the understanding of the underlying factors determining these differential effects remains insufficient [38].

According to a review by Kandola and colleagues [38], the association of physical activity and depressive symptoms depends on biological and psychosocial mechanisms. Theories explaining the association of physical activity and depressive symptoms with biological mechanisms have described depressive symptoms as elevated levels of pro-inflammatory markers and as a consequence of high cortisol due to hypothalamic-pituitary-adrenal (HPA) axis dysregulation [39]. Moreover, chronic stress has been suggested as a mediating mechanism behind associations of inflammatory or neuroendocrinological reactions and depressive symptoms [40]. Accordingly, physical activity that has been found to be correlated with a reduction in these biological mechanisms [38] may lead to lower depressive symptoms [41]. The association of physical activity and reduced depressive symptoms is thought to be higher with higher levels of biological dysregulation as a result of chronic stress. Since emotionally labile individuals frequently report chronic social stress, they may benefit from physical activity in particular [30].

In addition to the perspective on the personality of the individual, Kandola and colleagues [38] further explained the association of physical activity and depressive symptoms with psychosocial mechanisms. These theories proposed associations of depressive symptoms with low levels of perceived social support [42] that are more often observed in emotionally labile individuals and are rarely observed in extraverts [33, 43, 44]. Conversely, physical activity has been found to be associated with opportunities to extend the social network and thereby increase perceptions of social support [38]. The association of physical activity and reduced depressive symptoms is assumed to be higher at lower levels of perceived social support. The latter is supposed to be found in emotionally labile individuals.

Previous research has shown that high levels of physical activity were correlated with decreased levels of depressive symptoms by reinforcing energy and enthusiasm [23]. Highly extraverted individuals show characteristics that are typically described as energetic and talkative, regardless of their physical activity level [23]. Hence, physical activity may be particularly helpful for introverts, but not for extraverts.

The present study

The current study aimed to assess the relationship between health-related behaviours and depressive symptoms at the individual level.

Based on the theoretical and empirical background, we hypothesized that personality traits and perceived social support moderate the association between media use and depressive symptoms (hypothesis 1). We expected extraversion and perceived social support to buffer the positive association between high media use and depressive symptoms. By contrast, neuroticism was expected to increase the positive association between high media use and depressive symptoms.

In hypothesis 2, we assumed that personality traits and perceived social support moderate the association between physical activity and depressive symptoms. More precisely, we expected that extraversion and perceived social support would buffer the negative association between physical activity and depressive symptoms, whereas neuroticism would increase the negative association between physical activity and depressive symptoms.

The lack of prior theorizing and evidence does not allow us to form hypotheses on the moderating role of the personality dimensions of openness, conscientiousness and agreeableness in the associations between media use and physical activity with depressive symptoms. Thus, we explored their contributions to the prediction of depressive symptoms and their interaction with media use and physical activity in our analyses.

Method

Sample and procedure

This study used data from the second follow-up of the KiGGS cohort of the German Public Health Institute [45]. The KiGGS is a cross-sectional regularly conducted health interview and examination survey for children and adolescents that is combined with a longitudinal cohort sample [45]. Because of the longitudinal cohort structure, some of the study participants reached adulthood at the time of the second data collection. The current study analysed the self-report questionnaires that all participants had to complete. Additionally, the participants wore an accelerometer for 7 days. A detailed description of the recruitment procedure and study protocol can be found in the original publication by Mauz and colleagues [45, 46]. All the participants gave informed written consent for participation in the study. The second follow-up of the KiGGS survey was conducted in accordance with the amended Declaration of Helsinki and approved by the local independent Ethics Committee of the Medical University Hanover, Germany.

Since depressive symptoms were measured in individuals of full age only the original sample of $n = 2873$ is based on the adult participants of the KiGGS cohort in the second survey wave (KiGGS wave 2). Non-response (22.3%, $n = 642$), technical problems (16.0%, $n = 358$) or non-compliance (18.4%, $n = 345$) resulted in a sample size of $n = 1528$. A detailed analysis of participant attrition is described by Manz and colleagues [47]. The dropout analyses showed significant differences in socio-demographics as well as health behaviour, e.g. the response rate was significantly lower in men compared to women [47]. To partially prevent systematic bias, we controlled for the important socio-demographic factors by including the variables sex and education. In line with the scoring guidelines participants with more than one missing value in the depressive symptom inventory [48] were excluded, resulting in a final sample of 1402 young adults (mean age = 22.14 years, SD = 3.09, 46% male). Most of the participants had a moderate education level (81.9%), 11.8% had a high education level and 6.3% had a low education level, according to the CASMIN classification index [49]. A low education level is characterized by 8–9 years of schooling without formal graduation in combination with unknown, missing or completed vocational education training programmes. A moderate educational level is characterized by graduation from secondary school or advanced. A high educational level is characterized by a university degree or a degree from an university of applied science [49]. Table 1 summarizes the present sample characteristics. For the analyses, all first-order interactions were added as variables. The final dataset thus contained 190 variables.

Measures

Depressive symptoms

Depressive symptoms as outcome variables were measured with the PhQ-9 scale [50]. The instrument includes nine items indicating depressive symptoms (e.g., loss of energy and interest) answered on a 4-point scale from 0 ("not at all") to 3 ("almost every day"). A sum score was computed, and the internal consistency of the scale was Cronbach's Alpha = 0.81.

Media use

To measure media use, participants indicated the average duration of their daily media consumption for the categories of social media, PC, TV and console, which were graded on the following 6-point scale: 0 ("not at all") to 5 ("more than 4 hours"). The items were developed by Mauz and colleagues [45].

Physical activity

Accelerometer (GT3X+; ActiGraph LLC, Pensacola, FL, USA) data were used as an indicator of physical activity. Participants were instructed to wear the devices on their left or right hip for 7 consecutive days during the daytime. The wearing time was defined as the time the accelerometer was worn on the hip. The included participants had a wearing time of at least 8 h for a minimum of 4 days over a period of one week. The continuous accelerometer data were determined by the cut points of Troiano and colleagues [51] for adults, which define moderate to vigorous physical activity as at least 2020 counts per minute and lack of physical activity as less than 100 counts per minute (vertical axis used) referred to as sedentary behaviour. For the moderate to vigorous physical activity variable used in the current analysis, daily average values were calculated using only days with a wear time of at least 8 h. Further details of the accelerometer measurements in KiGGS Wave 2 and the device settings can be found elsewhere [52].

Personality

Personality as a predictor variable was measured with the 10-item version of the Big Five Inventory (BFI-10 [53];). The questionnaire consists of two items for each of the five dimensions extraversion, neuroticism, conscientiousness, agreeableness, and openness answered on a 5-point scale from 1 ("strongly disagree") to 5 ("strongly agree").

Table 1 Descriptive statistics of the sample of German young adults in total and grouped by sex

Variables	N = 1402					Female n = 754 (54%)					Male n = 648 (46%)				
	M	*(SD)*	*Median*	*Min.*	*Max.*	*M*	*(SD)*	*Median*	*Min.*	*Max.*	*M*	*(SD)*	*Median*	*Min.*	*Max.*
Age	22.14	3.09	22	18	29	22.07	3.11	22	18	28	22.22	3.07	22	18	29
Depressive symptoms[a]	5.42	4.04	4.000	0	25	5.91	4.24	5	0	25	4.85	3.71	4	0	24
MVPA[b]	48.00	22.21	45.04	2.88	173.25	44.00	19.78	41.696	2.88	120.41	52.65	23.93	48.90	7.00	173.25
Media Use[c]															
PC	2.95	1.25	2.5	0.5	4.5	2.99	1.26	2.5	0.5	4.5	2.90	1.24	2.5	0.5	4.5
TV	2.96	1.21	3	0.5	4.5	3.05	1.21	3.5	0.5	4.5	2.86	1.21	2.5	0.5	4.5
Social Media	1.94	1.04	1.5	0.5	4.5	2.11	1.10	1.5	0.5	4.5	1.74	0.93	1.5	0.5	4.5
Console	1.45	1.31	0.5	0.5	4.5	0.98	0.95	0.5	0.5	4.5	2.01	1.45	1.5	0.5	4.5
Perceived Social Support[d]	86.7	15.63	94.0	9.0	100	89.86	13.38	97.00	38.00	100	83.02	17.20	88.00	9.0	100
Personality[e]															
O	5.11	1.95	5	2	10	4.90	1.97	5	2	10	5.35	1.90	5	2	10
C	7.22	1.55	7	3	10	7.53	1.44	8	3	10	6.87	1.61	7	3	10
E	6.83	1.91	7	2	10	6.96	1.90	7	2	10	6.69	1.91	7	2	10
A	5.63	1.55	6	2	10	5.55	1.50	6	2	10	5.73	1.60	6	2	10
N	5.79	1.81	6	2	10	6.25	1.77	6	2	10	5.26	1.70	5	2	10

Note: *MVPA* Moderate to Vigorous Physical Activity; *O* Openness; *C* Conscientiousness; *E* Extraversion; *A* Agreeableness, *N* Neuroticism;

[a] Sum score of 9 items answered on a 4-point scale from 0 ("Not at all"), 1 ("On single days"), 2 ("On more than half of the days"), 3 ("Almost every day");

[b] Accelerometer data, averaged minutes per day over a period of one week;

[c] Self-reported average daily consumption answered on a 6-point scale from 0 ("Not at all"), 1 ("Up to 1 h"), 2 ("1 up to 2 h"), 3 ("2 up to 3 h"), to 4 ("3 up to 4 h"), 5 ("More than 4 h");

[d] Transformed sum score ranging from 0 to 100 based on 8 items answered on a 5-point scale from 1 ("Never") to 5 ("Always");

[e] Mean of two items for each dimension answered on a 5-point scale from 1 ("Disagree strongly") to 5 ("Agree strongly")

The mean values of the two items per dimension were computed. The inter-item correlations for the extraversion, neuroticism, conscientiousness, agreeableness and openness subscales were 0.50 ($p < .001$), 0.28 ($p < .001$), 0.25 ($p < .001$), 0.10 ($p < .001$) and 0.31 ($p < .001$), respectively.

Perceived social support

Perceived social support was measured using 8 items that address the perceived levels of social resources and social contacts (e.g., Is there someone in your life who listens to you when you feel the need to talk?; these items were modified according to Sherbourne & Stewart, [54]. Answers were given on a 5-point rating scale from 1 ("never") to 5 ("always") and were summarized and transformed to a standardized scale with a minimum of 0 and a maximum of 100 [54]. The internal consistency of the scale was Cronbach's Alpha = 0.90.

Covariates

Accelerometer wear time and correlates of depressive symptoms were included as control variables in the present study. This includes the socioeconomic status of the parents [55, 56], the participant's education level [57], age [58], sex [59] and personal resources. We operationalized personal resources with 5 self-developed items (e.g., meaningful life) rated on a 4-point rating scale from 1 ("not true") to 4 ("exactly right"). For example, previous research had identified a meaningful life as a preventive factor for suicide [60] and depression [61]. The internal consistency of the scale was Cronbach's Alpha = 0.80.

Data analyses

First, missing item values (education level had the greatest number of missing values ($n = 50$) and perceived social support had the fewest ($n = 1$)) were replaced at the score level by predictive mean matching (PMM) in R (package 'mice', version 3.8.0, Stef van Buuren). Within this process, five imputations per missing observation were generated and thereafter pooled for analyses. The procedure of multiple imputation made it possible to obtain the largest possible sample, as the analyses do not allow any missing values in the data set. The goal was to find a fitting and stable regression model to statistically predict depressive symptoms, considering all possible variables and first-order interactions. We performed stepwise, lasso, ridge and elastic net regression analyses to predict depressive symptoms by media use, physical activity, personality and perceived social support. Moreover, we included the participants' education level, age, sex, accelerometer wear time, personal resources and parental socioeconomic status as control variables in the models. Since the study's objective focuses on moderation effects, all possible first-order interactions were included. In addition, wear time was included as a main effect control variable. The continuous predictors were entered as z-standardized scores.

The advantage of this statistical approach is the utilization of a comparison of statistical models that offer an automated selection of significant variables in consideration of the entire data set (ridge and elastic net regression; 63). The reason behind this is that a valid result should be significant under the consideration of all possible alternative or parallel associations. By including all possible variables and first-order interactions, the analyses control for all variables and interactions simultaneously. Variables with low levels of contribution to the explanation of variance in depressive symptoms are statistically excluded. However, the inclusion of multiple variables overstresses a multiple linear regression model because of multicollinearity and overfitting but can be dealt with by lasso, ridge and elastic net regression and ten-fold cross-validation [62, 63]. The root mean square error (RMSE), mean absolute error (MAE) and R-squared served as the decision criteria for the best model fit. Additionally, we performed simple slope analyses for significant interactions (Table 2).

Results

Model comparison

Table 3 shows the model fit indices. The elastic net regression showed the best fit ($\alpha = 0.111$ and $\lambda = 0.25$) and had the smallest RMSE (Table 3).

Figure 1 shows the variable importance including the 20 best variables and interactions in descending order extracted by the elastic net regression model. Variable importance expresses the changes in the generalized cross-validation for each predictor and calculates the reduction in the statistic when each predictor's feature is added to the model, which occurs relative to the maximum [62]. A higher variable importance indicates a higher contribution to reduce the estimation error and to predict depressive symptoms. The model was able to reduce the dataset from 190 to 66 significant variables and explained 33.4% of the variance in depressive symptoms (Table 3). The importance levels of all remaining variables are shown Fig. A1 in the Additional file 1.

Main effects on depressive symptoms

Media use (social media, PC and TV) was positively associated with depressive symptoms whereas physical activity was not (Fig. 1). Neuroticism and agreeableness were positively correlated with depressive symptoms. Conscientiousness, perceived social support and age were negatively associated with depressive symptoms.

Personality and perceived social support as moderators of the relationship between media use and depressive symptoms

Personality traits moderated the positive association between media use and depressive symptoms (Figs. 2, 3 and 4).

Extraverts showed a stronger positive association of social media use with depressive symptoms (Fig. 2, Table 2). However, individuals with high levels of perceived social support showed a weaker positive association of PC use with depressive symptoms (Fig. 3, Table 2). The opposite pattern was found for individuals with low levels of openness. Persons with low levels of conscientiousness showed a stronger positive association of TV use with depressive symptoms, and persons with high levels of agreeableness showed a stronger positive association of TV use and PC use with depressive symptoms (Figs. 3 and 4, Table 2). Significant interactions of the predictors with control variables are visualized in Figs. A2 to A4 in the Additional file 1.

Personality and perceived social support as moderators of the relationship between physical activity and depressive symptoms

Personality traits moderated the association between moderate to vigorous physical activity and depressive symptoms (Fig. 5, Table 2). Individuals with low to average levels of extraversion and high levels of neuroticism showed a stronger negative association between moderate to vigorous physical activity and depressive symptoms. Additionally, extraverts showed a weaker positive association between sedentary behaviour and depressive symptoms. Perceived social support did not moderate the associations between physical activity and depressive symptoms.

Further exploratory results on interactions that were not within the present research scope can be obtained from the Supplementary Materials Table A1 and Figs. A2 to A4.

Discussion

In the present study, we investigated the role of personality traits and perceived social support as moderators of the relationships of physical activity and media use with depressive symptoms in a German population sample of young adults. We hypothesized that personality traits and perceived social support moderate (H1) the association between media use and depressive symptoms and (H2)

Table 2 Simple slope analyses for significant interactions resulting from elastic net regression on depressive symptoms

Predictor	*Moderator (1 SD below, 1 SD above and at the mean level)*		*Estimate*	*Std. Error*	*p*
MVPA	Extraversion [c]	4.92	−.017	.01	.007**
		6.83	−.011	.00	.018*
		8.74	−.005	.01	.467
	Neuroticism [c]	3.99	−.002	.01	.764
		5.79	−.008	.00	.074
		7.60	−.014	.01	.031 *
	Conscientiousness [c]	5.67	−.010	.01	.186
		7.22	−.010	.00	.044 *
		8.77	−.010	.01	.116
Sedentary behaviour	Extraversion [c]	4.92	.002	.00	.319
		6.83	−.001	.00	.406
		8.74	−.003	.00	.036 *
PC [a]	Agreeableness [c]	4.09	.319	.12	.007 **
		5.63	.503	.08	<.001 ***
		7.18	.687	.12	<.001 ***
	Openness [c]	3.16	.624	.12	<.001 ***
		5.11	.530	.09	<.001 ***
		7.06	.435	.12	<.001 ***
	Perceived Social Support [b]	71.06	.633	.11	<.001 ***
		86.70	.518	.08	<.001 ***
		102.33	.404	.12	.001 ***
TV [a]	Conscientiousness [c]	5.67	.532	.12	<.001 ***
		7.22	.317	.09	<.001 ***
		8.77	.102	.13	.419
	Agreeableness [c]	4.09	.300	.12	.014 *
		5.63	.419	.09	<.001 ***
		7.18	.537	.12	<.001 ***
Social Media [a]	Extraversion [c]	4.92	.367	.14	.011 *
		6.83	.475	.10	<.001 ***
		8.74	.583	.14	<.001 ***

Note: *MVPA* Moderate to Vigorous Physical Activity;

[a] Self-reported average daily consumption answered on a 6-point scale from 0 ("Not at all"), 1 ("Up to 1 h"), 2 ("1 up to 2 h"), 3 ("2 up to 3 h"), to 4 ("3 up to 4 h"), 5 ("More than 4 h");

[b] Transformed sum score ranging from 0 to 100 based on 8 items answered on a 5-point scale from 1 ("Never") to 5 ("Always");

[c] Mean of two items for each dimension answered on a 5-point scale from 1 ("Disagree strongly") to 5 ("Agree strongly")

the association between physical activity and depressive symptoms. By comparing different regression models, we selected the best model fit (elastic net) containing a selection of the most relevant predictors of depressive symptoms and their interactions. The results suggest that associations of media use and physical activity with depressive symptoms were moderated by personality and perceived social support, as discussed below.

The role of personality traits and perceived social support in associations between media use and depressive symptoms

In accordance with H1, our results show that personality traits and perceived social support moderated the association between media use and depressive symptoms.

Unexpectedly, positive associations between social media use and depressive symptoms appeared to be

Table 3 Model fit indices resulting from stepwise, Ridge, Lasso and Elastic Net Regression

MAE	*Min.*	*1st Qu.*	*Median*	*M*	*3rd Qu.*	*Max.*
Linear Model	.592	.664	.703	.702	.752	.818
Ridge	.548	.624	.652	.653	.688	.748
Lasso	.604	.674	.700	.703	.730	.799
Elastic Net	**.542**	**.601**	**.629**	**.630**	**.667**	**.724**
RMSE						
Linear Model	.757	.857	.936	.928	.988	1.102
Ridge	.670	.783	.865	.855	.908	1.012
Lasso	.710	.854	.913	.912	.977	1.150
Elastic Net	**.645**	**.780**	**.829**	**.828**	**.881**	**0.996**
R^2						
Linear Model	.068	.144	.209	.220	.286	0.512
Ridge	.081	.204	.261	.271	.335	0.488
Lasso	.057	.194	.228	.241	.294	0.408
Elastic Net	**.110**	**.261**	**.310**	**.334**	**.404**	**0.558**

Note: The best model fit resulting from Elastic Net Regression is highlighted in boldface

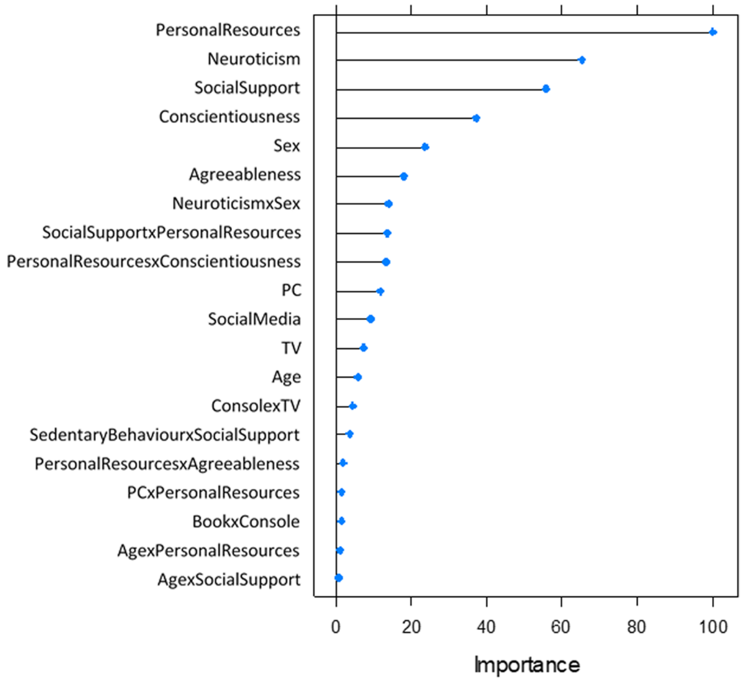

Fig. 1 Top 20 variable importance as indicator of the contribution to reduce the estimation error in the prediction of depressive symptoms

stronger amongst extraverted participants than amongst introverted participants. Considering the frequently reported positive associations between extraversion and mental health [64], we would have expected the opposite pattern. The present data do not allow for a substantive explanation, however, for future studies the selective exposure theory (SET [23];) represents a good starting point. SET proposes that extraverts tend to disclose their plain self [23] and thus may reveal more personal details compared with more restrictive user types and thereby provide a greater scope for negative and harmful feedback. For example, oversharing (i.e., the unrestrictive

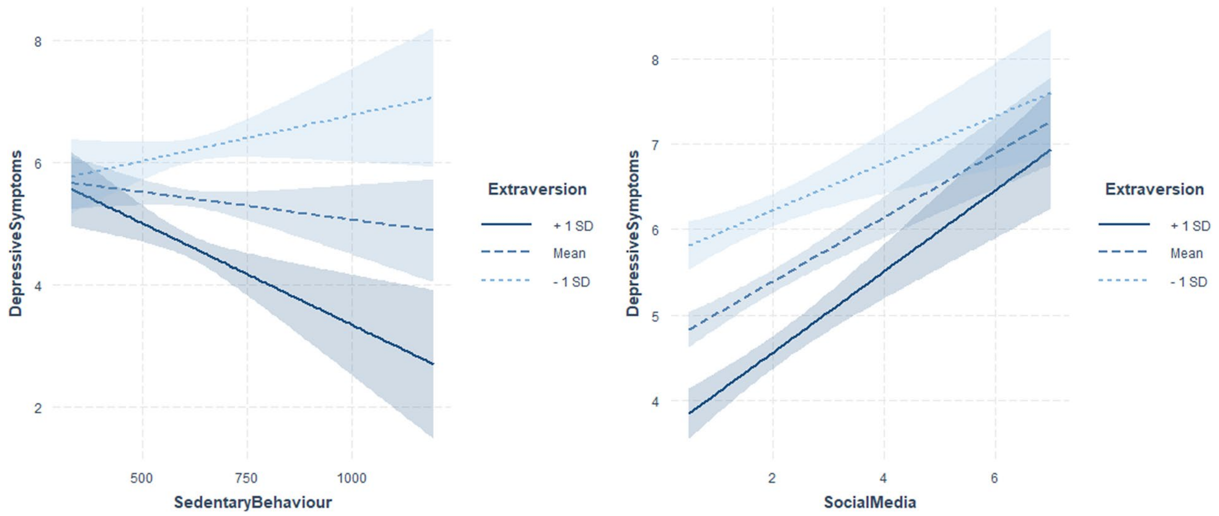

Fig. 2 Interaction plots showing simple slopes of health-related behaviours with the moderator extraversion predicting depressive symptoms (min = 0, max = 25) for 1 SD below (5.06), 1 SD above (8.86) and at the mean level of extraversion (*M* = 6.96). Coloured shading represents 95% CIs

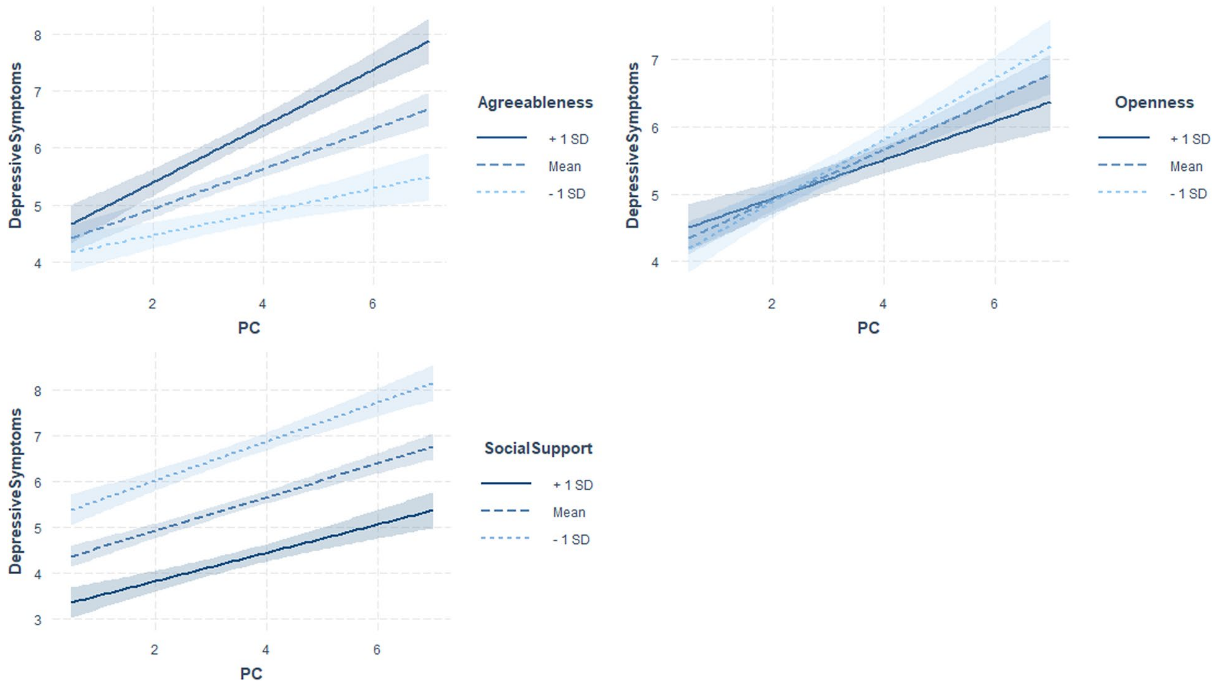

Fig. 3 Interaction plots showing simple slopes of PC use predicting depressive symptoms (min = 0, max = 25) for 1 SD below (4.04), 1 SD above (7.05) and at the mean level of agreeableness (*M* = 5.55); for 1 SD below (2.93), 1 SD above (2.93) and at the mean level of openness (*M* = 4.90); for 1 SD below (76.48), 1 SD above (103.24) and at the mean level of social support (*M* = 89.86). Coloured shading represents 95% CIs

behaviour of sharing information and pictures of one's life) has been reported as a potential risk of cyberbullying by social media users [65]. In accordance, other research has found that sharing attention-seeking posts leads to negative experiences for sharing individuals [65]. High levels of sharing behaviour may result in more frequent social comparisons in an atmosphere of optimized selves, e.g., on Facebook [32], that may in turn negatively

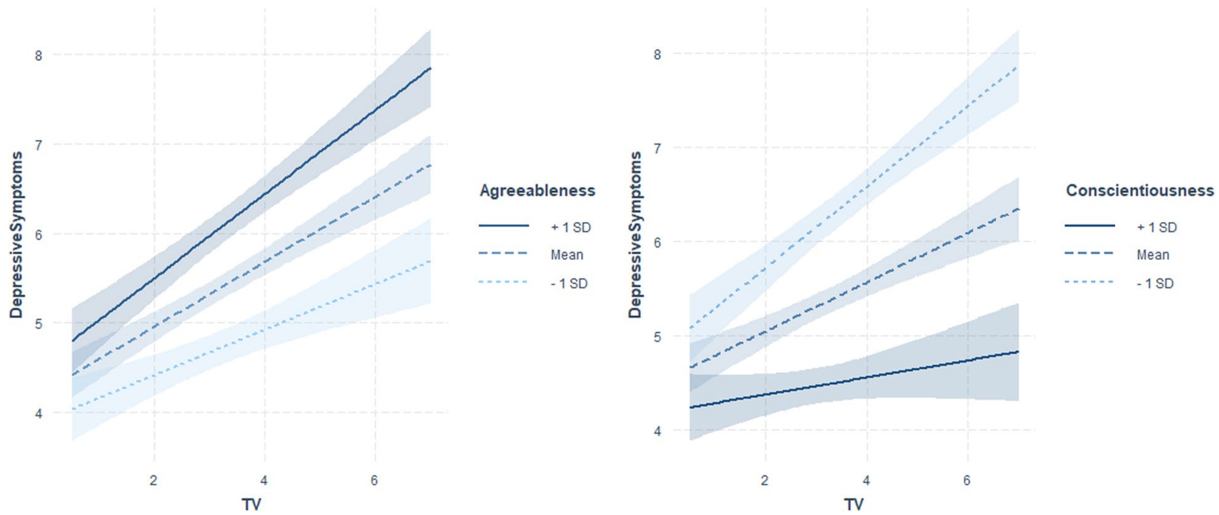

Fig. 4 Interaction plots showing simple slopes of TV use predicting depressive symptoms (min = 0, max = 25) for 1 SD below (4.04), 1 SD above (7.05) and at the mean level of agreeableness (*M* = 5.55); for 1 SD below (6.09), 1 SD above (8.97) and at the mean level of conscientiousness (*M* = 7.53) and for 1 SD below (0.03), 1 SD above (1.93) and at the mean level of playing console (*M* = 0.98). Coloured shading represents 95% CIs

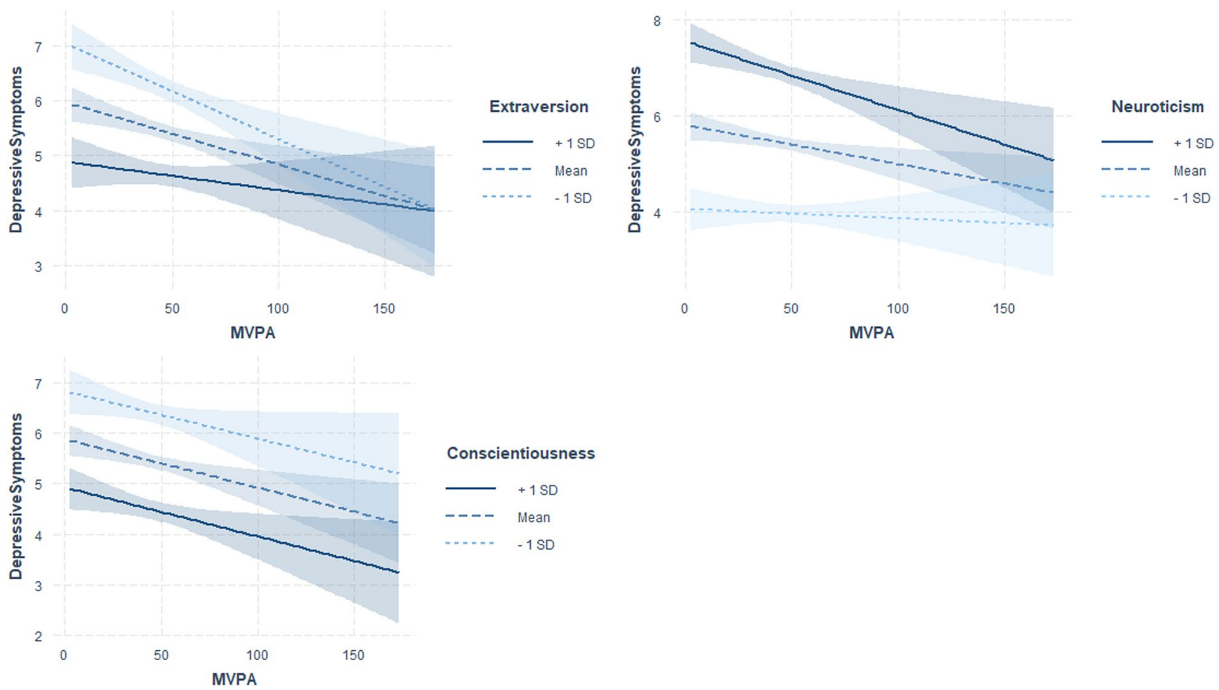

Fig. 5 Interaction plots showing simple slopes of moderate to vigorous physical activity (MVPA) predicting depressive symptoms (min = 0, max = 25) for 1 SD below (5.06), 1 SD above (8.86) and at the mean level of extraversion (*M* = 6.96); for 1 SD below (4.48), 1 SD above (8.02) and at the mean level of neuroticism (*M* = 6.25); for 1 SD below (6.09), 1 SD above (8.97) and at the mean level of conscientiousness (*M* = 7.53). Coloured shading represents 95% CIs

affect extraverts. Another possible explanation might be related to the fact that individuals with depressive symptoms tend to use social media more often than their counterparts [65], as do extraverts compared to introverts [11, 31]. It can be assumed that while in a depressive state, an extravert might show more frequent social media use than an introverted person due to generally engaging in more frequent social contacts in offline relationships. Consequently, the results could indicate that extraverts tend to use social media more often, particularly when experiencing depressive symptoms. In favour of this assumption, Määttänen and colleagues [66] more generally argued that personality-like affect states may be a better predictor of behaviour such as physical activity than trait measures. They emphasise the need for more detailed research based on a situational approach to help further understand causal relationships. However, these ad-hoc assumptions require further (longitudinal) investigations, including more detailed information on social media behaviour and content.

Low levels of conscientiousness and high levels of agreeableness showed stronger positive associations of PC use with depressive symptoms as well as of watching TV with depressive symptoms. These findings are in line with previous results regarding the health risk behaviours of individuals with low levels of conscientiousness. A previous study reported that low levels of conscientiousness were related to risk behaviour; conversely, highly conscientious individuals seemed to be more motivated to meet health-related norms and recommendations [67]. Furthermore, conscientiousness, which is defined as an organized and disciplined personality, might have a compensatory function in terms of well-being, thereby enhancing the probability that everyday duties are met even while spending long hours in front of a TV screen. Consequently, low levels of conscientiousness in combination with excessive TV screen time might be associated with unattended daily responsibilities, resulting in a growing number of life problems. This argument matches a previous discussion that considered low levels of conscientiousness to be closely related to negative health consequences [68]. Similarly, the combination of low levels of conscientiousness and risk behaviour, such as extensive media use, seems to be associated with the risk of negative mental health consequences.

A possible explanation for the increased associations of media use with depressive symptoms among individuals with high levels of agreeableness could be that PC or TV use is in contradiction to their need for direct interpersonal contact [69]. In this case, TV use could be seen as a placeholder for a lack of social interaction, the latter being a particularly strong need for people with high agreeableness scores.

Furthermore, persons with low levels of openness showed a stronger positive association of PC use with depressive symptoms. In general, low levels of openness were shown to be related to social anxiety [70], and in the context of media use, such low levels may imply social withdrawal, which in turn represents a risk factor for depressive symptoms [71]. This argument is supported by results showing that loneliness is negatively related to openness [72]. However, this theory-based attempt to classify our results in terms of content requires further evidence.

Individuals with high levels of perceived social support showed a weaker positive association of PC use with depressive symptoms than did those with low levels of perceiving social support, as expected in H1. The restricting factor is that we do not have any information about the media content. Based on the idea that individuals have a fulfilling social life offline and engage with social media via their PC to strengthen social relationships [65, 73], the results suggest positive associations with mental health. The crucial fact that must be considered is that social media use should not function as compensation for unmet real-life needs, such as a lack of social relationships or perceived social support [65, 73]. Therefore, future research should take the media content and motivations of use into account to better understand the identified associations. The same applies for a better understanding of the role of neuroticism in associations between media use and depressive symptoms. In contrast to our expectations, neuroticism did not moderate the association between media use and depressive symptoms. Based on theoretical assumptions, we would have expected a negative effect resulting from differing use motives (i.e., emotional self-disclosure [23];, online behaviour (i.e., presenting an ideal self-image [23];) and processes *during* media use (i.e., social comparison [32];).

The role of personality traits and perceived social support in associations between physical activity and depressive symptoms

In line with H2, personality traits and perceived social support also moderated the relationship between physical activity and depressive symptoms.

We noted that extraverts showed a weaker negative association between moderate to vigorous physical activity and depressive symptoms as compared to introverts. Emotionally labile individuals showed a stronger negative association between moderate to vigorous physical activity and depressive symptoms than emotionally stable ones.

That the negative association between moderate to vigorous physical activity and depressive symptoms was weaker in extraverted young adults than in introverts, supported our hypothesis. Explanations can be derived from the biological mechanisms of physical activity summarized by Kandola and colleagues in their review [38]. Both the inflammation aspect and the neuroendocrinological aspect represent a biological imbalance that can affect depressive symptoms as a result of chronic stress. However, during a depressive episode, the level of extraversion seems to be temporarily decreased [74, 75]. Keeping this in mind, the results might indicate that high levels of extraversion and severe depressive symptoms are mutually exclusive and that high levels of extraversion can be seen as an indication of only mild to moderate depressive symptoms. Additionally, lower levels of depressive symptoms have been related to smaller biological imbalances [38]. Hence, physical activity, as a general potential compensatory factor, cannot reach its full potential in highly extraverted people due to an already more balanced biological state. In order to substantiate these theoretical considerations and to understand the contextual relationships, it is necessary to collect different physiological parameters. This corresponds to Määttänen and colleagues [76] who suspect situational changes in physiological parameters underlying depressive symptoms. Another idea is that the negative association of physical activity with depressive symptoms is also influenced by the social interactions [38] that occur during physical activities reducing social isolation. For highly extraverted individuals, this mechanism might be less effective due to an already fulfilled social life [77].

Moreover, our results suggest that emotionally labile individuals have a stronger negative association between moderate to vigorous physical activity and depressive symptoms. One possible explanation refers to a preconditioned biopsychological imbalance of emotionally labile persons. For example, neuroticism has been related to a disproportionate negative affectivity [30] and longer lasting recovery in response to stress (e.g., as indicated by cortisol release [78];). Thus, the collection of physiological parameters such as heart rate variability in follow-up studies could be beneficial for the investigation of individual depressive symptoms, as suggested by Määttänen and colleagues [76].

Low levels of extraversion showed a stronger positive association between sedentary behaviour and depressive symptoms. This finding is difficult to interpret since we have no information about the context of sedentary behaviour. A few results point towards toward the possibility that sedentary behaviour can be interpreted as a consequence of social withdrawal [79], which is listed as a risk factor for depression [71]. This would offer an explanation why introverts showed a stronger positive association between sedentary behaviour and depressive symptoms.

Strengths and limitations

This study is characterised by an extensive statistical approach that takes a broad variety of relevant variables into account. The statistical regularization procedure of the elastic net regression model led to a reduced bias-variance trade-off. Both aspects increased the validity of the results. Additionally, the validity profits from the broad population sample of young adults, representing a high-risk group for depressive symptoms. The results furthermore benefit from the use of accelerometer data as an objective indicator for physical activity and reduced distortion effects due to self-report measures.

However, several limitations must be taken into account when interpreting the results of the present study. First, the sample does not meet the criteria of representativeness due to longitudinal dropout of the cohort participants, selection bias, and further attrition due to non-response, technical problems or non-compliance regarding accelerometry. Thus, results cannot be generalized to the young adult population living in Germany. Second, the data quality of media use based on self-reports has been considered controversial [31] and represents only an indicator of screen time. Third, information on the motivation for media use and media content was not available. The measurement of personality with only two items per dimension is only a broad indicator and should be measured with more comprehensive inventories in future studies. As a result, the measurement of the effects of the personality variables may be severely underestimated, which would explain the contradiction with existing literature. Finally, we cannot clarify predictive direction because of the cross-sectional design of the dataset. Future research should establish a longitudinal design to further contribute to the understanding of differential effects of personality differences on the association of health risk behaviours with depressive symptoms.

Conclusion

The present results suggest that personality traits and perceived social support play a role in understanding individual differences in the associations between health-related behaviours such as media use and physical activity and depressive symptoms.

Furthermore, the results show that objective physical activity and media use data without further information on relevant individual characteristics do not allow general classification of their functioning as protective factors or risk behaviours. In particular, the present findings suggest that health protective effects of health-related behaviour may vary as a function of personality and perceived social support. Further replication and extended evidence on relevant individual characteristics involved in the moderation of depressive symptoms and health-related behaviour can help establish tailored intervention.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12888-022-03693-w.

Additional file 1: Fig. A1. Variable importance of all the included variables as indicator of the contribution to reduce the estimation error in the prediction of depressive symptoms. **Fig. A2.** Interaction plots showing simple slopes of health risk behaviours predicting depressive symptoms (min=0, max=25) for 1 SD below (8.45), 1 SD above (15.79) and at the mean level of socioeconomic status (M=12.12); for 1 SD below (3.63), 1 SD above (4.48) and at the mean level of education (M=4.05); for 1 SD below (19.04), 1 SD above (25.23) and at the mean level of age (M=22.14); for 1 SD below (55.59), 1 SD above (83.89) and at the mean level of personal resources (M=69.74). Coloured shading represent 95% CIs. **Fig. A3.** Interaction plots showing simple slopes of health risk behaviours predicting depressive symptoms (min=0, max=25) for 1 SD below (19.04), 1 SD above (25.23) and at the mean level of age (M=22.14); for sex (46 % male); for 1 SD below (55.59), 1 SD above (83.89) and at the mean level of personal resources (M=69.74); for 1 SD below (1.75), 1 SD above (4.17) and at the mean level of TV (M=2.96). Coloured shading represent 95% CIs. **Fig. A4.** Interaction plots showing simple slopes of health risk behaviours predicting depressive symptoms (min=0, max=25) for 1 SD below (25.79), 1 SD above (70.21) and at the mean level of MVPA (M=48.00); for sex (46 % male). Coloured shading represent 95% CIs. **Table A1.** Simple slope analyses for significant interactions resulting from elastic net regression on depressive symptoms.

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Authors' contributions
JSE developed the present research questions and methodology in consultation with CC. NRP advised the planning of the statistical analyses. KM was responsible for the data preparation. JSE performed the data analyses and wrote the manuscript in consultation with HB, KM, NRP and CC. All authors critically revised the article and approved the final revision to be published.

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Availability of data and materials
The dataset created and analysed in the current study is not publicly available because the consent of the study participants did not cover the publication of the data. However, the data are available on request from the corresponding author.

Declarations

Ethics approval and consent to participate
Ethical approval: The second follow-up of the KiGGS survey was approved by the local independent Ethics Committee of the Medical University Hanover, Germany. Guideline: The study was conducted in accordance with the amended Declaration of Helsinki.
Consent: All patients gave informed written consent for participation in the study."

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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Kapitel 5

Diskussion

Diskussion

Ziel der vorliegenden Dissertation war es, die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich am Beispiel der Forschung zu depressiven Symptomen zu bewerten. In einem ersten Forschungsprojekt wurde die Frage behandelt, inwiefern passive behaviorale Daten bei der Vorhersage einer depressiven Symptomatik einen Beitrag leisten, wenn gleichzeitig Befragungsdaten eingeschlossen werden. In einem zweiten Forschungsprojekt wurde die Vorhersageleistung für depressive Symptome allein auf Basis passiver über GPS ermittelter regionaler Daten untersucht. Das dritte Forschungsprojekt widmete sich der Rolle interindividueller Unterschiede bei der Interpretation passiver behavioraler Daten als Korrelate depressiver Symptome. Die Ergebnisse der einzelnen Forschungsprojekte werden nachfolgend diskutiert, daran anschließend legt eine übergeordnete Diskussion dar, welche Implikationen für Forschung und Praxis sich ergeben. Die Diskussion der Ergebnisse wie auch deren Implikationen wirft ethische Fragestellungen auf, die zum Abschluss der vorliegenden Dissertation diskutiert werden.

Beitrag passiver behavioraler Daten bei Vorhersage depressiver Symptome

Einzelne passive behaviorale Datenparameter leisteten einen Beitrag bei der Vorhersage depressiver Symptome unter Einbezug etablierter Befragungsdaten. Für die Vorhersage von depressiven Symptomen relevant waren die Nutzung von Messengerdiensten und Videotelefonie über das Smartphone (Edler, Terhorst, et al., 2024). Beide Aspekte dienten als Surrogatparameter für soziale Interaktion und schienen bei der rechnerischen Vorhersage depressiver Symptome relevant zu sein. Diese Ergebnisse entsprechen anderen Forschungsarbeiten, die soziale Interaktion auch über das Kommunikationsverhalten via Smartphone gemessen haben (zum

Beispiel mithilfe der Dauer und Anzahl von Anrufen, Anzahl von Nachrichten) (Currey & Torous, 2022; Dogan et al., 2017; Rohani et al., 2018). Eine systematische Übersichtsarbeit zeigte, dass einige Studien dabei auch einen Zusammenhang zwischen der sozialen Interaktion und Stimmungslagen fanden (Dogan et al., 2017). In einem anderen systematischen Überblick war das Bild der Zusammenhänge nicht einheitlich, der Zusammenhang von depressiven Symptomen mit Sozialverhalten gemessen durch passive behaviorale Smartphone-Daten (Telefonnutzung, physische Aktivität, Ort) zeigte sich nicht in allen Studien (Seppälä et al., 2019). Grund für dieses uneinheitliche Bild könnte sein, dass die zu den Analysen herangezogenen statistischen Kennwerte variieren: In manchen Studien wurden absolute Werte gewählt (zum Beispiel Anzahl besuchter Orte) (Di Matteo et al., 2021), in anderen die Smartphone-Nutzungsdauer und Anzahl eingehender wie ausgehender Anrufe verwendet (Razavi et al., 2020), in wieder anderen wurde zudem zwischen Wochentagen und Wochenenden unterschieden (Di Matteo et al., 2021; Saeb et al., 2016). Einige Autor*innen vermuteten, dass individuelle Nutzungsmuster mit den Ergebnissen korrelieren (Rohani et al., 2018), dies spräche für die Verwendung von standardisierten Kennwerten oder intraindividuellen Veränderungsmaßen in längsschnittlichen Studien. Auch gibt es das Argument, dass Vorhersagemodelle genauer sind, wenn zwischen Messzeitpunkten unterschieden wird, in denen eine Person frei über das eigene Verhalten entscheiden kann versus einer Datenerhebung zum Beispiel während der Arbeitszeit (Mohr et al., 2017; Saeb et al., 2016). Die aufgeführten Aspekte stellen alternative methodische Umsetzungen dar, unterschiedliche Operationalisierungen in Studien limitieren die Vergleichbarkeit der Ergebnisse. Vorstellbar wäre der Versuch, das vorliegende Ergebnis vom Forschungsprojekt 1 in Folgestudien unter Berücksichtigung methodischer Empfehlungen zu replizieren. Erst wenn jedoch studienübergreifend einheitliche

Paramater (zum Beispiel Telefonanrufe) und Kennwerte (zum Beispiel durchschnittliche Anrufdauer oder Anzahl eingehender Anrufe) definiert wurden, sind im Rahmen der Diskussion des Forschungsstandes Vergleiche der Ergebnisse möglich. Dieser Perspektive widerspricht die Datenerhebung vom Forschungsprojekt 1 während der COVID-19 Pandemie: Denkbar ist gleichermaßen, dass aufgrund des veränderten Kommunikationsverhaltens während der COVID-19 Pandemie die Ergebnisse aus dieser Zeit nicht mit postpandemischen Erhebungen vergleichbar sind. Dies würde bedeuten, es bedürfe weiterer Messungen, um eine postpandemische Vergleichsgrundlage zu erhalten.

Neben der variierenden Operationalisierung als Erklärung für diese uneinheitlichen Ergebnisse in der aktuellen Forschung, ist ebenso die fehlende Spezifität passiver behavioraler Daten als mögliche Ursache zu nennen. Im hiesigen Kontext bedeutet dies, dass durch die Messung zum Beispiel der Telefonnutzung nicht zuverlässig zwischen Vorliegen oder Abwesenheit depressiver Symptome unterschieden werden kann. Nicht jede Person mit depressiven Symptomen telefoniert weniger und nicht jede Person ohne depressive Symptome telefoniert viel - je unspezifischer die Messung, desto seltener sind wiederum konsistente Befunde zu erwarten. Da dieser Aspekt übergreifend über die einzelnen Forschungsprojekte hinweg relevant ist, wird er in der übergeordneten Diskussion der Ergebnisse wieder aufgegriffen.

Während die Nutzung von Videotelefonie und Messengerdiensten als passive behaviorale Datenparameter sozialer Interaktion sich in der Forschung zu depressiven Symptomen als relevant erwiesen hat, stellten sich zahlreiche weitere beobachtbare soziale Verhaltensweisen als (unter Berücksichtigung von Befragungsdaten) nicht relevant heraus (Edler, Terhorst, et al., 2024). Hierzu zählen die Nutzungsdauer von Telefonie, sozialen Medien und die Smartphone-Nutzung insgesamt (Edler, Terhorst, et al., 2024). In der Publikation zu den Ergebnissen wurde bereits umfangreich diskutiert, inwiefern die jeweiligen Verhaltensweisen inhaltlich nicht relevant sind oder aber indirekt dasselbe Konstrukt messen, das ebenfalls durch Befragungsdaten erhoben wurde (Edler, Terhorst, et al., 2024).

Das erste Forschungsprojekt dieser Dissertation widmete sich dem Beitrag passiver behavioraler Daten bei der Vorhersage depressiver Symptome unter Einbezug von Befragungsdaten. Es zeigte sich, dass Verhaltensparameter, die mit sozialer Interaktion in Zusammenhang stehen – konkret Nutzung von Videotelefonie und Messengerdiensten – im datenbasiert erstellten, besten Vorhersagemodell für das Vorliegen von depressiven Symptomen unter Berücksichtigung von Befragungsdaten enthalten sind. Für die Qualität des Vorhersagemodells ist eine Kombination beider Datenquellen zu empfehlen (Edler, Terhorst, et al., 2024).

Vor dem Hintergrund des Arguments der forschungsökonomischen Vorteile der Verwendung passiver behavioraler Daten, widmete sich das zweite Forschungsprojekt der Frage nach der Vorhersageleistung einer depressiven Symptomatik allein auf Basis von passiven (über GPS zugeordnete Durchschnittswerte von) frei zugänglichen regionalen Daten.

Vorhersage depressiver Symptome allein auf Basis passiver über GPS ermittelter regionaler Daten

Das Forschungsprojekt 2 dieser Dissertation konzentrierte sich dabei auf über GPS-Daten zugeordnete Durchschnittswerte auf Landkreisebene des Regionalatlas Deutschland der statistischen Ämter der Länder und des Bundes (Statistische Ämter des Bundes und der Länder, 2023) zu u.a. Soziodemografie, Wirtschaft (zum Beispiel

Anteil der Erwerbstätigen nach Branchen in Prozent im Jahr 2020) und Wohnbedingungen (zum Beispiel Anteil der Ein-Personen-Haushalte in Prozent im Jahr 2011) im Sinne eines datenbasierten explorativen Vorgehens zur Vorhersage einer depressiven Symptomatik (Edler, Winter, et al., 2024). Der für die Zuordnung genutzte GPS-Standort wurde einmalig bei der Bearbeitung des Fragebogens via Smartphone erhoben. Diese Auswertung des GPS-Standortes ist als eine zufällige Momentaufnahme des Standortes zu bewerten. Während die Arbeits- oder Ausbildungsstätte sowie der Wohnort Standorte sind, an denen erwachsene Personen die meiste Zeit verbringen und welche somit die höchste Wahrscheinlichkeit haben hier erfasst zu werden, ist eine gesicherte Aussage hierzu jedoch nicht möglich.

Die Erhebung von GPS-Standorten hängt nicht mit den Nutzungsmustern des Smartphones zusammen, ob intensive Kommunikation via Smartphone oder passives bei sich Tragen des Smartphones, der Standort wird gleichermaßen erhoben. Die Hypothese war daher, dass die Ergebnisse nutzer*innenübergreifend gültig sind, weil nicht mit der Intensität der Gerätenutzung zusammenhängend.

Die Ergebnisse zeigten, dass rein auf Basis des Standortes zum Zeitpunkt der Studienteilnahme insbesondere pandemiespezifische Variablen (zum Beispiel Anzahl der aktuellen COVID-19-Infektionen in dem jeweiligen Landkreis, Anzahl der Plätze in Pflegeheimen) als für die Vorhersage depressiver Symptome relevant identifiziert werden konnten (Edler, Winter, et al., 2024). Für den Public Mental Health-Bereich ist dies insofern relevant, als dass sich durch die Datenerhebung während der COVID-19 Pandemie neue Variablen zeigten, welche mit einem erhöhten Risiko für depressive Symptome einhergingen (Edler, Winter, et al., 2024). Die Ergebnisse des Forschungsprojektes 2 gaben somit erste Hinweise auf pandemiespezifische Risikogruppen für depressive Symptome, was für zukünftige pandemische Geschehen eine wertvolle Perspektive für frühzeitige Präventionsmaßnahmen sein könnte.

Das rein auf regionalen Durchschnittswerten der Bevölkerung, Wirtschaft, des Wohnumfeldes und Umgebung basierende Vorhersagemodell wies für depressive Symptome gleichzeitig eine eher geringe Erklärleistung auf. Dem entspricht die Aussage von Forschenden, dass je mehr individuelle passive behaviorale Verhaltensdaten in einem Modell enthalten sind, desto präziser die Vorhersage zum Beispiel depressiver Symptome (Sultana et al., 2020; Tuarob et al., 2017). Da unsere Studie lediglich Standortdaten inkludierte, können wir keine Aussage dazu treffen, wie präzise ein Vorhersagemodell unter Einbezug auch passiver behavioraler Nutzungsdaten (zum Beispiel Bildschirmzeit des Smartphones, Nutzungsdauer von Apps) für depressive Symptome wäre.

Das Forschungsprojekt 2 bietet Hinweise darauf, dass auch rein passive (nicht behaviorale) Daten bei der Vorhersage von depressiven Symptomen wertvoll sein können. Einige Forschende argumentieren, dass eine depressive Symptomatik jedoch individuell sehr verschieden aussehen kann (Lux & Kendler, 2010). Dies hätte die Folge, dass Verhaltensweisen für verschiedene Individuen unterschiedlich zu bewerten wären. Für die Bewertung behavioraler Daten wurden daher in dem dritten Forschungsprojekt ebenso interindividuelle Unterschiede berücksichtigt.

Interindividuelle Unterschiede der Zusammenhänge passiver behavioraler Daten mit depressiven Symptomen

Das Forschungsprojekt 3 der vorliegenden Dissertation untersuchte moderierende Effekte individueller Eigenschaften auf den Zusammenhang zwischen behavioralen Daten und depressiven Symptomen. Als behaviorale Daten wurde die durchschnittliche Nutzungsdauer unterschiedlicher Medien erfragt und die körperliche Aktivität mittels Akzelerometer gemessen. Als individuelle Eigenschaften wurden die

Persönlichkeitsfacetten Extraversion, Neurotizismus, Offenheit, Gewissenhaftigkeit und Verträglichkeit erfasst sowie die wahrgenommene soziale Unterstützung. Es zeigte sich, dass unabhängig von Persönlichkeitsfacetten und wahrgenommener sozialer Unterstützung die Nutzung sozialer Netzwerke, Computernutzung und TV-Konsum direkt mit depressiven Symptomen zusammenhingen (Edler et al., 2022). Es scheint demnach Verhaltensparameter zu geben, die (auch) direkt mit depressiven Symptomen zusammenhängen.

Das Forschungsprojekt 3 zeigte ebenso, dass Persönlichkeitsfacetten und wahrgenommene soziale Unterstützung den Zusammenhang zwischen Mediennutzung und depressiven Symptomen moderieren können: Zum Beispiel zeigte sich bei extravertierten Personen ein stärker positiver Zusammenhang zwischen Nutzung sozialer Medien und depressiven Symptomen. Auch zeigten sich Persönlichkeitsfacetten als Moderatoren des Zusammenhangs körperlicher Aktivität und depressiver Symptome: Zum Beispiel war bei Personen mit stark ausgeprägtem Neurotizismus ein stärker negativer Zusammenhang zwischen moderater wie auch starker körperlicher Aktivität und depressiven Symptomen sichtbar. Wahrgenommene soziale Unterstützung erwies sich für den Zusammenhang von körperlicher Aktivität mit depressiven Symptomen als nicht relevant (Edler et al., 2022).

Die Ergebnisse des Forschungsprojektes 3 der vorliegenden Dissertation zeigten, dass individuelle Unterschiede bei dem Zusammenhang von behavioralen Daten (Mediennutzung und körperliche Aktivität) und depressiven Symptomen bestehen (je nach Persönlichkeitsfacette und wahrgenommener sozialer Unterstützung). Berücksichtigung individueller Eigenschaften in Studien auf Basis passiver behavioraler Daten ist also sinnvoll. Da so zum einen sichtbar wird, welche Zusammenhänge (passiver behavioraler Daten und depressiver Symptome) persönlichkeitsübergreifend feststellbar sind und welche Zusammenhänge für bestimmte Personen bestehen.

Mit Blick auf die Wahl einheitlicher Verhaltensparameter und die Skalierung passiver behavioraler Daten wiesen die Ergebnisse des dritten Forschungsprojektes auf ein Problem hin: nicht für jede Persönlichkeitsfacette war zum Beispiel die Nutzungsdauer sozialer Medien gleichermaßen mit depressiven Symptomen verknüpft.

Dieses Ergebnis reiht sich ein in die Beobachtung von Han und Kolleg*innen, dass Anzeichen des (gleichen) psychischen Gesundheitszustands individuell verschieden sein können (Han et al., 2021). Bei der Vorhersage depressiver Symptome auf Basis behavioraler Daten ist daher personalisiert vorzugehen (Sükei et al., 2021), da die Zusammenhänge von Verhaltensparametern und depressiven Symptomen individuell verschieden sein können (Currey & Torous, 2022). Personalisierung kann zum einen umgesetzt werden durch längsschnittliche Analysen von Veränderungen innerhalb einer Person, zum anderen durch die Berücksichtigung individueller Unterschiede zum Beispiel durch den Einbezug möglicher Persönlichkeitsfacetten. Personalisierte Modelle (Narziev et al., 2020; Sultana et al., 2020) oder der Einschluss individueller Variablen verbesserten in verschiedenen Studien die Genauigkeit der Vorhersage depressiver Symptome deutlich (Opoku Asare et al., 2021; Sükei et al., 2021). Eine mögliche Schlussfolgerung aus diesen Ergebnissen wäre, dass ein ausschließlich personenübergreifend gültiges Set passiver behavioraler Daten zur Vorhersage depressiver Symptome nicht existiert. Für diese These spricht, dass auch in der Diagnostik bei zum Beispiel einer depressiven Symptomatik viele Symptome in zwei Richtungen ausgeprägt sein können: Mehr oder weniger Appetit, mehr oder weniger Schlaf, motorisch verlangsamt oder aktiviert (DSM) (American Psychiatric Association, 2013). Diagnostisch maßgebend ist dabei bei allen drei genannten Symptomen eine Veränderung weg von der individuellen Norm. Forschende regen daher zu einem

Umdenken an, weg von dem traditionellen Forschungsziel allgemeingültiger Ergebnisse, hin zu dem Fokus auf das Individuum zum Beispiel in der Vorhersage der individuellen Gesundheit oder optimalen Behandlung (Bzdok & Meyer-Lindenberg, 2018; Currey & Torous, 2022). Das hieße konkret, dass keine für alle Teilnehmenden an einer Studie gleichermaßen gültige Parameter passiver behavioraler Daten gesucht würden, sondern es um das Erkennen individueller Muster geht.
Die Forschung im Public Mental Health-Bereich hat jedoch die Aufgabe die Gesundheit der Gesamtbevölkerung zu untersuchen (World Health Organization. Regional Office for Europe, 1999), was ein personalisiertes Vorgehen ausschließt. Ein möglicher Umgang mit der fehlenden Verallgemeinerbarkeit passiver behavioraler Daten zur Vorhersage depressiver Symptome im Public Mental Health-Bereich könnte der Einbezug von individuellen Veränderungsmaßen sein oder der standardmäßige Einbezug soziodemografischer Informationen sowie von Persönlichkeitsfacetten als Kontrollvariablen (Han et al., 2021; Opoku Asare et al., 2021). Entsprechende individuelle Veränderungsmaße passiver behavioraler Daten müssten in Folgeuntersuchungen auf ihre Vorhersageleistung für depressive Symptome geprüft werden.

Als methodische Einschränkung ist die Operationalisierung der Mediennutzung zu sehen. Da die Selbstauskunft verzerrenden Effekten wie sozialer Erwünschtheit und Erinnerungseffekten unterliegt, ist eine Umsetzung als objektive Messung mittels passiver behavioraler Daten in Folgeuntersuchungen vorzuziehen. Die vorliegenden Ergebnisse gilt es in einem solchen neuen Studiendesign zu replizieren.

Projektübergreifende Diskussion passiver behavioraler Daten als neue Methode im Public Mental Health-Bereich

Ziel war es, passive behaviorale Daten als Korrelate depressiver Symptome zu untersuchen, um sie im Public Mental Health-Bereich zum Beispiel zur Vorhersage depressiver Symptome zu nutzen. Die Ergebnisse der vorliegenden Dissertation zeigten, dass in unterschiedlichen Forschungsfragen einzelne passive behaviorale Daten für die Vorhersage depressiver Symptome relevant waren. Der Anteil erklärter Varianz der einzelnen Parameter passiver behavioraler Daten war jedoch in einigen Fällen eher gering. Grund hierfür könnte sein, dass – wie bereits erwähnt – die hier untersuchten passiven behavioralen Daten nicht spezifisch waren. In anderen aktuellen Forschungsprojekten konnte demgegenüber mit einer Genauigkeit von 77% auf Basis passiver behavioraler Daten zwischen dem Vorliegen oder der Abwesenheit depressiver Symptome unterschieden werden (He et al., 2022).

In der eigenen Auswertung (im Forschungsprojekt 1) zeigte sich zudem durch die Nutzung automatisierter Variablenselektion, dass das beste Vorhersagemodell für depressive Symptome passive behaviorale Daten und Befragungsdaten kombiniert. Dies entspricht den Ergebnissen anderer Studien mit passiven behavioralen Daten, die zeigen, dass zum Beispiel soziodemografische Angaben, welche über Befragungen erhoben wurden, die Qualität der Ergebnisse steigern (Han et al., 2021). Da soziodemografische Angaben bei einer longitudinalen Datenerhebung nur einmalig abgefragt werden müssten und somit der Aufwand für eine Datenerhebung mittels Befragung nur punktuell zu leisten ist, während die Erhebung passiver behavioraler Daten in der Folge jedoch kontinuierlich fortlaufen kann, bleibt das Argument des forschungsökonomischen Vorteils passiver behavioraler Daten (Zachary et al., 2017) bestehen.

Für die Vorhersage depressiver Symptome im Public Mental Health-Bereich scheinen die untersuchten passiven behavioralen Daten als Korrelate einen Beitrag zu leisten, wobei sich rechnerisch (im Forschungsprojekt 1) die Kombination aus passiven behavioralen Daten wie auch Befragungsdaten als das Modell mit der besten Vorhersageleistung durchsetzte.

Jenseits der Vorhersage einer depressiven Symptomatik (auch) auf Basis passiver behavioraler Daten, gibt es die bereits vorgestellte in der Forschung diskutierte Perspektive, dass durch eine detaillierte Dokumentation von (digitalem) Verhalten ein neues, vollständigeres Verständnis des Störungsbildes ermöglicht würde (Mohr et al., 2017): in naturalistischem Setting (Torous et al., 2016), passiv (Birk & Samuel, 2022; He et al., 2022; Onnela & Rauch, 2016; Zarate et al., 2022), kontinuierlich und langfristig (Han et al., 2021). Durch diese neue Methode im Public Mental Health-Bereich könnten perspektivisch detailliert Verläufe abgebildet werden und dies nahezu in Echtzeit (Batra et al., 2017; Mohr et al., 2017). Dies könnte für ätiologische wie epidemiologische Fragestellungen im Public Mental Health-Bereich eine erkenntnisreiche neue methodische Herangehensweise sein, die es zu prüfen gilt.
Die Ergebnisse der vorliegenden Dissertation zeigten, dass passive behaviorale Daten durchaus neue Informationen bieten, sei es auf Basis von dokumentierten (digitalen) Verhaltensweisen oder auch durch (via GPS-Daten identifizierte und verknüpfte) regionale Informationen zur Umgebung. Nicht alle diese Informationen sind ohne weiteres in Form einer Befragung zu erfassen, da nicht jede Person über jedwede Information zur eigenen Umgebung verfügt (zum Beispiel wirtschaftliche Kennwerte). Manche Informationen wären durch Befragungen abbildbar, was jedoch einen deutlichen Mehraufwand für die Teilnehmenden bedeuten würde. Für die Verwendung passiver behavioraler Daten im Public Mental Health-Bereich spricht daher auch der zu Beginn beschriebene forschungsökonomische Vorteil (Zachary et al., 2017), welcher sich auch in den eigenen Forschungsprojekten (1 und 2) dieser Dissertation zeigte. Nach einmaliger Einrichtung der Infrastruktur (im Fall des Forschungsprojektes

1 und 2, Programmierung und Veröffentlichung der CORONA HEALTH App) war die Datenerhebung mit geringem Aufwand wiederholt möglich. Nach aktuellem Stand sind zudem kontinuierliche Erhebungen im Public Mental Health-Bereich kaum umsetzbar, es gibt keinerlei Apparatur um dauerhaft Stimmungen zu messen - passive behaviorale Daten als Korrelate könnten jedoch bei der wiederholten Vorhersage von Stimmungen hilfreich sein. Im Rahmen von kontinuierlichen repräsentativen Kohortenstudien zum Beispiel könnten mithilfe passiver behavioraler Daten Prävalenzen geschätzt und somit Trends frühzeitig identifiziert werden. Durch die Identifikation von Korrelaten passiver behavioraler Daten mit depressiven Symptomen ist zudem perspektivisch die Identifikation möglicher Hochrisikogruppen vorstellbar, so ein Vorhersagemodell eine starke Vorhersageleistung aufweist.

Auf Basis der Ergebnisse der vorliegenden Dissertation ist dies jedoch nicht möglich. Die vorliegende Dissertation stellt einen ersten Schritt dar, der zeigte, dass passive behaviorale Daten in unterschiedlichen Studiensettings durchaus mit depressiven Symptomen zusammenhängen und zur Vorhersage depressiver Symptome beitragen können.

Gleichzeitig bringt die Verwendung passiver behavioraler Daten Implikationen für die Forschung und Praxis im Public Mental Health-Bereich mit sich.

Der Einschluss von passiven behavioralen Daten bedeutet, dass die in der Einleitung beschriebene Forderung der Gleichwertigkeit (Kilgallon et al., 2022) leidet: ältere Bevölkerungsgruppen haben durchschnittlich eine geringere Smartphone-Nutzungsdauer (Andone et al., 2016; Bundesministerium für Familie, Senioren, Frauen und Jugend, 2020) und konkret auch eine geringe Nutzungsdauer sozialer Netzwerke (Cotten et al., 2022), weswegen für diese Gruppe weniger Daten zur Verfügung stehen, was sich auf die Qualität der Vorhersageleistung auswirken kann (Tuarob et al., 2017). Die Nutzungsmuster haben sich während der COVID-19 Pandemie verändert, hin zu einer vermehrten Nutzung virtueller Kommunikation (bei Personen mit höherem sozioökonomischen Status) (Nguyen, Hargittai, et al., 2021), was sich mildernd auf die mangelnde Gleichwertigkeit auswirken könnte. Gleichzeitig profitieren ausschließlich Menschen mit digitalem Kommunikationsverhalten von dieser Möglichkeit, eine depressive Symptomatik über ihre Smartphone-Daten vorhersagen zu können und zum Beispiel frühzeitig Hilfsangebote zu erhalten. Für die Forschung im Public Mental Health-Bereich gilt es diesen Aspekt daher zu berücksichtigen, um sicherzugehen niemanden systematisch zu benachteiligen, da der Auftrag u.a. die Untersuchung der psychischen Gesundheit der Gesamtbevölkerung ist (World Health Organization. Regional Office for Europe, 1999).

Ebenso ist die Frage nach der Modellgleichwertigkeit zu diskutieren, der Anforderung an ein Vorhersagemodell, dass es über unterschiedliche Gruppen und Zeiten die gleiche Leistung aufweist (Adler et al., 2022). So die erhobenen Zusammenhänge auf die Zeit der COVID-19 Pandemie beschränkt sind, ist die Modellgleichwertigkeit nicht gegeben. Bei Studien im Public Mental Health-Bereich ist die Verlässlichkeit der Ergebnisse jedoch grundsätzlich von großer Wichtigkeit, da sie Grundlage für Handlungsentscheidungen darstellen. Ohne eine Qualitätsprüfung auf Modellgleichwertigkeit mit derlei Modellen passive behaviorale Daten in der Forschung zu verwenden kritisierten Adler und Kolleg*innen (Adler et al., 2022). Gleichzeitig ermöglichen die Forschungsprojekte der vorliegenden Dissertation Aussagen über passive behaviorale Daten und deren Zusammenhang mit depressiven Symptomen in pandemische Zeiten, eine Datengrundlage, die insbesondere im Public Mental Health-Bereich äußerst relevant für zukünftige Pandemien sein könnte.

Aufgrund kontaktbeschränkender Maßnahmen hat sich u.a. die Nutzung von Kommunikationsmedien - wie bereits beschrieben - während der COVID-19 Pandemie verändert (Nguyen, Gruber, et al., 2021; Sun et al., 2020), insbesondere Personen mit höherem sozioökonomischen Status nutzten vermehrt virtuelle Kommunikation (Nguyen, Hargittai, et al., 2021). Denkbar ist also, dass diese Intensivierung der Kommunikationstechnologien eben jenem Kennwert für die Dauer der COVID-19 Pandemie Gewicht verlieh und somit für die Vorhersage depressiver Symptome relevant macht. Ob nach Abnahme kontaktbeschränkender Maßnahmen und Wiederherstellung persönlicher Interaktionen der Stellenwert dieses Messwertes in unverändertem Maße gegeben ist, bleibt zur Sicherung der Modellgleichwertigkeit zu prüfen.

Am Beispiel der eigenen Forschungsprojekte (1 und 2) zeigte sich, dass bei der Verwendung von Vorhersagemodellen mitunter das Kriterium der Modellgleichwertigkeit zu klären ist. Konkret bedeutet dies, dass es einer Replikation der Ergebnisse mit demselben Studienaufbau nach der COVID-19 Pandemie bedarf, um zu prüfen, ob sich die (Stärke der) Einflussfaktoren geändert haben. In einem Kommentar wurde kritisiert, dass derlei Reproduktion von Forschungsprojekten in der Verwendung passiver Daten ohnehin zu selten stattfindet, trotzdem Reproduzierbarkeit in der klinischen Forschung ein wichtiges Gütekriterium darstellt (Mohr et al., 2017). So ein Mehrwert passiver behavioraler Daten im Public Mental Heath-Bereich besteht, scheint dieser inhaltlich notwendige Mehraufwand gerechtfertigt.

Gleichzeitig sind die Ergebnisse der vorliegenden Dissertation ein erster Anhaltspunkt dafür, dass eine Datenerhebung zu depressiven Symptomen unter zu Hilfenahme passiver behavioraler Daten auch in einer pandemischen Zeit umsetzbar sein könnte, sprich unabhängig von geltenden Kontaktbeschränkungen. Dieser Aspekt ist gerade mit der Rückschau auf die COVID-19 Pandemie ein gewichtiges Argument, passive behaviorale Daten für die Verwendung im Public Mental Health-Bereich weiter zu evaluieren.

Methodische Einschränkungen passiver behavioraler Daten im Public Mental Health-Bereich

Die Erforschung depressiver Symptome mithilfe passiver behavioraler Daten im Public Mental Health-Bereich stellt eine neue Methodik dar. Die Diskussion methodischer Einschränkungen und abzuwägender Fragen zum methodischen Vorgehen ist daher elementarer Bestandteil bei der Beurteilung von Vor- und Nachteilen dieser neuen Methodik.

Zu Beginn wurde die Diskussion über die Bedeutung der Identifikation verallgemeinerbarer Parameter passiver behavioraler Daten dargestellt (Batra et al., 2017; Place et al., 2017; Rohani et al., 2018; Zarate et al., 2022). Die hierfür erforderlichen Analysen in bevölkerungsrepräsentativen und klinischen Stichproben stehen bislang aus (Dogan et al., 2017). In diesem Kontext müssen die vorliegenden eigenen Forschungsprojekte als Pilotstudien verstanden werden und reihen sich in die Liste einarmiger Beobachtungsstudien ein, deren Aussagen dadurch nicht verallgemeinerbar sind (Dogan et al., 2017).

Hohe Datenauflösung vs. Anonymisierung. Die technisch mögliche und wissenschaftlich wünschenswerte hohe Auflösung der erhobenen Daten wird durch das ethische und rechtliche Gebot der Einhaltung von Anonymisierung limitiert. So ist beispielsweise eine hohe Auflösung regionaler (GPS) Daten notwendig um aussagekräftige Ergebnisse zu erhalten (Han et al., 2021; Onnela & Rauch, 2016). Dieses Problem betraf die vorliegenden Arbeiten nicht, da im Forschungsprojekt 2 die Auflösung der GPS-Daten die zuzuordnenden öffentlich verfügbaren regionalen Daten vorgegeben war; die bestehenden Daten wiesen als kleinste räumliche Einheit die Landkreisebene auf (Statistische Ämter des Bundes und der Länder, 2023), entsprechend grob war die regionale Auflösung (Edler, Winter, et al., 2024). Perspektivisch führt die Verwendung passiver behavioraler Daten (insbesondere GPS) dazu, dass Daten in präziser räumlicher Auflösung vorhanden sind und genutzt werden könnten. Bereits in der Einleitung wurde auf die Herausforderung der Anonymisierung der Daten hingewiesen (Maher et al., 2019), diese ist bei der Verwendung von GPS-Daten nicht immer gewährleistet (Adler et al., 2022; Grande et al., 2020). Auch müssen bei der Analyse passiver behavioraler Daten (zum Beispiel bei der Auswertung von GPS-Daten zur Identifikation besuchter Orte) die Rechte Dritter berücksichtigt werden (Fisher & Appelbaum, 2017), deren Daten als Beifang mit erhoben werden könnten (Maher et al., 2019). Dies könnte der Fall sein zum Beispiel bei der Erfassung von Telefonanrufen und deren Absender*in oder Adressat*in. Eine mögliche Kollision mit den Rechten Dritter sollte bei der Studienkonzeption vorhergesehen und durch eine geänderte Datenerhebung verhindert werden.

Sollte die anonyme Erhebung der Daten nicht umsetzbar sein, gilt es darüber aufzuklären. Im Gegensatz zur Datennutzung zum Beispiel zur Optimierung der individuellen Behandlung ist die Freigabe der eigenen Daten für den Public Mental Health-Bereich nicht unmittelbar mit einem individuellen Nutzen verbunden. Dies kann die Bereitschaft zur Einwilligung beschränken (Maher et al., 2019), was die Rekrutierung für repräsentative Studien mit passiven behavioralen Daten im Public Mental Health-Bereich erschweren könnte.

Störungsvollbild vs. symptomorientiert. Die vorliegenden Forschungsprojekte bedienen sich bei der Umsetzung des vorherzusagenden Konstruktes depressiver Symptome des Summenwertes des PHQ-9 (Löwe et al., 2004). Dies stellt ein gängiges Vorgehen zur Messung des Schweregrades von depressiven Symptomen dar. Selbes gilt für die Verwendung des Summenwertes eines standardisierten Fragebogens, wie auch zum Beispiel des Beck Depression Inventars (Beck et al., 1996) um quantitativ zwischen „depressiv“ und „nicht depressiv“ zu unterscheiden (Fried & Nesse, 2015a). Das Vorgehen basiert dabei auf der Annahme, dass Depression eine psychische Störung mit verschiedenen Symptomen ist, die jeweils austauschbare und gleichwertige Indikatoren darstellen (Fried & Nesse, 2015a). Diesem Konzept widerspricht sowohl Theorie wie Empirie: das Diagnostic and Statistical Manual of Mental Disorders (DSM-5) beschreibt eine hierarchische Ordnung der Symptome (American Psychiatric Association, 2013), welche in dem Summenwert zum Beispiel des PHQ-9 (Löwe et al., 2004) und des Beck Depression Inventars nicht berücksichtigt wird (Beck et al., 1996). Empirisch zeigt sich zudem, dass depressive Symptome sehr heterogen sind (Fried & Nesse, 2015b). Auch können zwei Personen mit identischem Summenwert sehr unterschiedlich starke Einschränkungen erleben (Fried & Nesse, 2015a). Auch die Risikofaktoren für einzelne depressive Symptome können stark variieren (Lux & Kendler, 2010).

Fried und Nesse sehen in der Nutzung von Summenwerten die Ursache für fehlende Fortschritte in der Forschung zum Beispiel von biologischen Markern, da die Messung depressiver Symptome nicht valide sei (Fried & Nesse, 2015a), dies kann gleichermaßen für die hiesige Analyse passiver behavioraler Smartphone-Daten gelten. Die Autor*innen geben die Handlungsempfehlung, Untersuchungen anhand einzelner depressiver Symptome durchzuführen (Fried & Nesse, 2015a).

Wenn auch in der Herleitung der hiesigen Forschungsprojekte mit der Beobachtbarkeit einzelner Symptome argumentiert wurde, wurden diese letztlich zum Summenwert des PHQ-9 (Löwe et al., 2004) in Relation gesetzt. Dies kann einen limitierenden Effekt auf die Ergebnisse haben. Das Vorgehen wurde gewählt, da erst durch die Verwendung des Summenwertes ein Eindruck entsteht, inwiefern der Wert in einem pathologischen Bereich liegen könnte - ohne diesen mit einer Diagnose gleichsetzen zu können.

Konfundierende Effekte vs. Gleichwertigkeit. Zudem leiden die Ergebnisse von Studien auf Basis passiver behavioraler Daten (wie zum Beispiel Social Media Nutzung) unter konfundierenden Effekten (Harrigian et al., 2020). Je nach Plattform sozialer Netzwerke sind möglicherweise insbesondere Personen vertreten, deren Verhaltenspräferenzen den Anforderungen der jeweiligen Plattform entsprechen (Harrigian et al., 2020). Dies schränkt die Übertragbarkeit der Ergebnisse auf die Allgemeinbevölkerung deutlich ein, was als Mangel an Gleichwertigkeit zu sehen ist. Gleichwertigkeit steht in diesem Kontext für die – bereits beschriebene - soziodemographische Gerechtigkeit bei der Verwendung passiver behavioraler Daten (Kilgallon et al., 2022). Bei der Verwendung passiver behavioraler Smartphone-Daten kann der gleichwertige Nutzen darin beschränkt sein, dass in der Erwachsenenpopulation ältere Nutzer*innen eine weniger intensive Smartphone-Nutzung aufweisen (Andone et al., 2016; Bundesministerium für Familie, Senioren, Frauen und Jugend, 2020) und somit weniger Daten für die präzise Vorhersage zum Beispiel depressiver Symptome zur Verfügung stehen. Weniger verfügbare Daten führen zu einer schlechteren Vorhersageleistung in den rechnerischen Modellen (Tuarob et al., 2017). Somit wäre der Nutzen aufgrund ungenauerer Ergebnisse für ältere Bevölkerungsgruppen geringer und die Forderung nach Gleichwertigkeit nicht gewährleistet. Um Gleichwertigkeit bei der Verwendung passiver behavioraler Daten im Public Mental Health-Bereich sicherzustellen, müssten unterschiedlichste Gruppen identifiziert und in Datenerhebungen berücksichtigt werden. Eine Übersichtsarbeit stellte fest, dass keine der eingeschlossenen Studien zu passiven Daten im Public Health-Bereich Randgruppen (zum Beispiel Personen mit niedrigem sozioökonomischen Status oder ältere Personen) untersuchte (Shakeri Hossein Abad et al., 2021). Technisch ist das Auslesen einiger Kennwerte (Geolokalisierung, Anruf- und Textprotokolle) passiver behavioraler Daten via Smartphone nicht in selber Auflösung wie bei Endgeräten mit einem Android-Betriebssystem möglich (Keusch et al., 2020), gleichzeitig gibt es Hinweise darauf, dass sich die Nutzer*innen von Smartphone mit Apple- und Android-Geräten systematisch (zum Beispiel in Alter und Geschlecht) unterscheiden (Reinfelder et al., 2014; Shaw et al., 2016). Dies stellt ebenso eine Quelle möglicher konfundierender Effekte dar.

Da sich die aufgeführten Aspekte auch auf andere Merkmale jenseits der Soziodemografie (zum Beispiel Mediennutzungsverhalten) beziehen, geht dies über die für epidemiologische Studien im Public Mental Health-Bereich bereits geltende Anforderung der Repräsentativität hinaus.

Präzision vs. Transparenz der Ergebnisse. Die verwendeten Analysetechniken stellen zugleich eine Stärke und Schwäche der Methodik dar. Die Verfahren aus dem Bereich des maschinellen Lernens ermöglichen die Verarbeitung großer Datenmengen, die Berücksichtigung einer Vielzahl an Variablen, eine automatisierte Variablenselektion und das Verwenden von Trainings- und Testdatensätzen für validere Ergebnisse (Aleem et al., 2022). Gleichzeitig sind die in den vorliegenden Forschungsprojekten gewählten Modelle der Regressionen sehr grob in ihrer Modellierung der Daten und ungeeignet, nicht lineare Zusammenhänge und Muster zu erfassen (James et al., 2013). Eine wesentliche und weiterhin aktuelle Herausforderung besteht bei der

Verwendung passiver behavioraler Daten darin, dass bei der Wahl des Rechenverfahrens eine Abwägung zwischen Präzision und Interpretierbarkeit der Ergebnisse getroffen werden muss (Jacobson et al., 2020). So wurden auch in der vorliegenden Arbeit zugunsten der Interpretierbarkeit Verfahren gewählt, welche (bei nicht linearen Zusammenhängen) in ihrer Präzision nicht die maximal mögliche Performanz aufweisen. Alternative Vorgehen, beispielsweise durch den Einsatz neuronaler Netze, hätten möglicherweise eine präzisere Vorhersage der psychischen Gesundheit ermöglicht, jedoch eine Analyse des Modells und damit einen Einblick, welche Variablen zu dem Ergebnis geführt haben, unmöglich gemacht (Dao & Lee, 2020). Bei einer systematischen Verwendung passiver behavioraler Daten im Public Mental Health-Bereich ergibt sich dadurch die ethische Frage, wie zwischen der Präzision der Vorhersagemodelle und dem Anspruch, einen Einblick in die Prädiktoren zu haben, gewichtet werden sollte. Bzdok und Kolleg*innen empfehlen die Verwendung von Verfahren maschinellen Lernens (die keinen Einblick in das Vorhersagemodell ermöglichen) primär für Vorhersagen auf Individualebene im klinischen Setting (Bzdok & Meyer-Lindenberg, 2018). Ein Argument für die Verwendung auf Individualebene kann zum einen die sehr gute Vorhersageleistung sein (Narziev et al., 2020; Sultana et al., 2020; Zarate et al., 2022). Zum anderen liegt auf der Individualebene der Fokus auf dem Vorhersageergebnis zum Beispiel klinischer Symptome, die für das Ergebnis rechnerisch verantwortlichen Variablen sind in dem Anwendungsfall möglicherweise zweitrangig. Diese Empfehlung steht im Gegensatz dazu, dass diese Verfahren aktuell vermehrt auf Gruppenebene angewendet werden (Bzdok & Meyer-Lindenberg, 2018). Für die Bewertung von Studienergebnissen ist umso relevanter diese Vor- und Nachteile unterschiedlicher Verfahren mitzudenken.

Grundsätzlich könnte diese Diskussion Anleitung für die Wahl der rechnerischen Verfahren sein: Im Falle epidemiologischer Studien wie im Public Mental Health-Bereich wird versucht, inhaltliche Zusammenhänge zum Beispiel von Lebensbedingungen und depressiven Symptomen zu ermitteln. Dies spräche für Verfahren, die auch Aussagen über die Prädiktoren ermöglichen. Dieser Empfehlung folgend, wurden in den vorliegenden Forschungsprojekten entsprechende Analysen gewählt, und bewusst eine mögliche Reduktion in der Präzision der Ergebnisse in Kauf genommen.

Ethische Aspekte der Verwendung passiver behavioraler Daten im Public Mental Health-Bereich

Über die Diskussion der konkreten Forschungsergebnisse hinaus ergeben sich bei der Bewertung passiver behavioraler Daten im Public Mental Health-Bereich ethische Fragestellungen, die es für eine vollständige Diskussion dieser Datenquelle und Methodik zu thematisieren gilt (Kilgallon et al., 2022).

Beobachten von psychischen Krisen. Durch die Verwendung passiver behavioraler Smartphone-Daten findet eine Dokumentation von psychischer Gesundheit nahezu in Echtzeit statt (Batra et al., 2017; Mohr et al., 2017). Dieser Umstand bringt die ethische Verpflichtung mit sich, beim Erkennen unerwünschter Ereignisse zu reagieren (Jacobson et al., 2020; Kovach et al., 2011), was auch für die Verwendung im Public Mental Health-Bereich gilt. Denkbar wäre zum Beispiel, dass im Rahmen einer Studie Textanalysen erhoben und bei einer Person konkrete Suizidpläne identifiziert werden. In dieser Situation besteht die ethische Pflicht, zu reagieren (Kovach et al., 2011), um die Umsetzung möglicher realer Suizidpläne zu unterbinden. Um dies zu gewährleisten, müssten Forschende im Rahmen der Datenerhebung die zeitlich uneingeschränkte Verfügbarkeit von klinischem Personal sicherstellen (Jacobson et al., 2020). Einen Qualitätsleitfaden, wie die Umsetzung eines solchen Sicherheitsprozesses aussehen könnte, gibt es bisher nicht (Kovach et al., 2011). Inhaltlich müsste ein solcher Leitfaden u.a. die Prozesse zur Identifikation sowie zur Evaluation der Genauigkeit, zum Beispiel der Symptomverschlechterung, beinhalten (Kovach et al., 2011).

Einige Forschende warnen hier vor zu großem Vertrauen in die Nutzung passiver behavioraler Smartphone-Daten mit Blick auf die beschränkten Möglichkeiten angemessen auf Notfallsituationen reagieren zu können (Dogan et al., 2017). Die (zum Beispiel Suizid-) Präventionsleistung durch die neue Methodik in Echtzeit ist nur so wirksam, wie der Umgang mit der beobachteten Krisensituation angemessen ist, zum Beispiel durch aufsuchende klinische Notfallversorgung. Das bedeutet, es reicht beispielsweise nicht, wenn im Rahmen einer Erhebung und Auswertung passiver behavioraler Daten in Echtzeit Hinweise auf suizidale Absichten einer Person bestehen, dieser Person jedoch nicht zeitnah Hilfe geleistet wird und es zu suizidalen Handlungen kommt. Die datenbasierte Identifikation von Handlungsbedarfen sollte mit der automatisierten Beauftragung klinischen Fachpersonals einhergehen, Hilfe zu leisten, um das Potenzial der Echtzeitdatenerhebung voll auszuschöpfen. Aufgrund der bisher bestehenden Trennung von Gesundheitsversorgung und dem Public Mental Health-Bereich bedarf es für eben jenen Anwendungsfall passiver behavioraler Daten einer neuen Schnittstelle: Bei Krisen, identifiziert durch Daten erhoben im Public Mental Health-Bereich, müsste klinisches Personal beauftragt werden.

Offen ist auch inwiefern die Aufklärung über den Sicherheitsprozess im Falle von Suizidaussagen, das Antwortverhalten verändert (Siegel et al., 2017). Das Wissen, dass die Äußerung zum Beispiel von Suizidplänen zur Kontaktaufnahme durch klinisches Personal führt, mag Teilnehmende incentivieren Suizidpläne zu äußern, obwohl derlei Pläne nicht vorhanden sind, nur um Kontakt herzustellen. Ebenso ist denkbar, dass die Äußerung der realen Pläne daher explizit vermieden wird, um eine Kontaktaufnahme zu vermeiden (Jacobson et al., 2020).

Ungeklärt ist bisher zudem, was passieren soll, wenn die datenbasierte Vorhersage der psychischen Verfassung einer Person im Widerspruch zur Einschätzung der*des Kliniker*in steht (Ernala et al., 2019), und wer in einem solchen Fall die Verantwortung trägt (Chekroud et al., 2021). Des Weiteren ist offen, welche Folgen es hat, wenn die datenbasierte Vorhersage falsch ist (Ernala et al., 2019). So wäre es beispielsweise vorstellbar, dass im Zuge der Suizidprävention aufgrund falsch positiver Ergebnisse ein Sicherheitsprozess (zum Beispiel Aufsuchen durch klinisches Fachpersonal) initiiert wird und eine Kontaktaufnahme stattfindet, die von der kontaktierten Person als belastend oder stigmatisierend empfunden wird (Baumann, 2022). Auf der anderen Seite könnte ein falsch negatives Ergebnis zur Folge haben, dass eine Symptomverschlechterung nicht erkannt wird. So sich die Person darauf verlassen hat, im Falle einer Symptomverschlechterung aufgrund der Preisgabe passiver behavioraler Daten automatisiert kontaktiert zu werden, könnte die ausbleibende Kontaktaufnahme eine Enttäuschung vom Hilfssystem nach sich ziehen (Ernala et al., 2019). Dies wäre eine zusätzliche Belastung einer ohnehin unter Symptomen einer psychischen Störung leidenden Person. Was aus der Diskussion mitzunehmen ist, ist ein Bedarf an Anschlussstudien, um auf Basis der Ergebnisse den Sicherheitsprozess bestmöglich gestalten zu können.

Die Herausgabe personenbezogener Daten wie Standort und Telefonnummer im Falle eines klinischen Notfalls hieße zudem die Verletzung der Privatsphäre der Teilnehmenden (Jacobson et al., 2020) und stünde im Konflikt zu dem Ziel, die Daten anonym zu erheben. Selbst im Falle der Preisgabe personalisierter Daten liegen oft nicht ausreichend Informationen (zum Beispiel exakter Standort) vor, um im Notfall gezielt Hilfe leisten zu können.

Diese Liste möglicher Risiken und Herausforderungen in der Umsetzung von Präventionsmaßnahmen könnten dazu führen, dass bei Forschung mithilfe passiver behavioraler Daten sensible Themen (zum Beispiel suizidale Gedanken) systematisch ausgespart werden (Jacobson et al., 2020). Im Public Mental Health-Bereich würde dies gerade in der Forschung zu depressiven Symptomen eine große inhaltliche Einschränkung bedeuten und weniger präzise Daten in dem Feld zur Folge haben.
Diese potenziell negativen Folgen, Herausforderungen in der Umsetzung von (Suizid-) Präventionsmaßnahmen sind zu thematisieren und bei der Einführung passiver behavioraler Daten in der Forschung im Public Mental Health-Bereich mit umzusetzen.

Unerwünschte Nebenwirkungen. Ungeklärt ist auch inwiefern die Nutzung passiver behavioraler Daten Ängste bei den Nutzer*innen schüren könnte (Dogan et al., 2017; Onnela & Rauch, 2016). Fischer und Appelbaum erwägen, dass im klinischen Setting das Wissen um die Auswertung bestimmter passiver behavioraler Smartphone-Daten mit dem Ziel einer optimierten Diagnostik oder therapeutischen Versorgung zu einer verstärkten Nutzung des Smartphones durch die Patient*innen führen könnte (Fisher & Appelbaum, 2017). Mit Blick auf mögliche negative Effekte exzessiver Smartphone-Nutzung auf die psychische Gesundheit (Augner et al., 2023) ist dies als potenziell negative Nebenwirkung einzuordnen. Das Dokumentieren von Symptomen psychischer Störungen mithilfe passiver behavioraler Daten könnte diese auch verstärken und zu einer Beendigung der Teilnahme führen (Onnela & Rauch, 2016). Solche unerwünschten Nebenwirkungen gilt es vor abschließender Bewertung passiver behavioraler Daten im Public Mental Health-Bereich zu untersuchen und zu adressieren.

Grundsätzlich kann jedwedes Störgefühl auf Nutzer*innenseite, welches bei der Teilnahme einer Studie mit passiven behavioralen Daten entsteht, zum Abbruch der Studienteilnahme führen. So derlei systematisch erlebt wird, würde dies einen systematischen Dropout bedeuten und mit Blick auf die Verwendung im Public Mental Health-Bereich die Untersuchung der Gesamtbevölkerung erschweren. Die stark variierenden Dropout-Raten von 0-22% in Studien, die passive behaviorale Smartphone-Daten zur Untersuchung affektiver Erkrankungen nutzten (Dogan et al., 2017), legen eine Analyse des Dropouts zum Ausschluss einer Systematik nahe.

Auch um mögliche Vorbehalte zu reduzieren und Sicherheit der Daten zu vermitteln ist die umfangreiche Aufklärung der Nutzer*innen von großer Relevanz.

Informierte Einwilligungserklärung. Das Einholen einer informierten Einwilligungserklärung (informed consent) wird jedoch als herausfordernd in der Umsetzung beschrieben: sowohl die technischen Details der passiven behavioralen Smartphone-Daten als auch die Auswertung sind komplex und entsprechend schwer zu vermitteln (Ballantyne, 2020; Jacobson et al., 2020; Kilgallon et al., 2022). Maher und Kolleg*innen beschrieben in ihrer systematischen Übersichtsarbeit zu ethischen Aspekten der Nutzung passiver Daten in der Gesundheitsversorgung, dass die meisten Autor*innen die Prozesse, um informierte Einwilligungserklärungen einzuholen, als ungenügend bewerteten (Maher et al., 2019). Um dem entgegenzuwirken wurden unterschiedliche Vorgehensweisen vorgeschlagen, wie beispielsweise die erhobenen Daten sollten für die*den Nutzer*in sichtbar sein (Beierle et al., 2019), die Erlaubnisabfrage (zum Beispiel einzelner Parameter) sollte an der Steller (zum Beispiel in der App) platziert sein, an der es inhaltlich relevant ist (Beierle et al., 2019), individualisierbare wie revidierbare Zustimmung sollte möglich sein (Kaye et al., 2015), es sollten im Gesundheitskontext Alternativen dargestellt werden (Andreotta et al., 2022), eine interaktive Gestaltung der Aufklärung (Abujarad et al., 2017; Geier et al., 2021) oder mithilfe spielerischen Prüfens des Verständnisses mittels Quiz sollten genutzt (Abujarad et al., 2017).

Bisher ungeklärt ist die Frage, wie im Kontext passiver behavioraler Daten eine Aufklärung zur Einwilligung aussehen soll, da zu Beginn der Datenerhebung die eigentliche Aussagekraft der Analysen noch nicht feststeht (Maher et al., 2019). Denkbar ist, dass eine Person einwilligt, nicht wissend, wie präzise zum Beispiel depressive Symptome auf Basis der erhobenen Datenquellen vorhersagbar sind. Wenn eine Vorhersage einer depressiven Symptomatik präzise möglich ist, findet diese bei der jeweiligen Person bereits statt. In der Aufklärung ist neben der Fragestellung daher zudem über mögliche Ergebnisse und deren Folgen aufzuklären. Hinzu kommen die bereits dargestellten unerwünschten Nebenwirkungen: solange mögliche negative Folgen nicht untersucht und ausgeräumt sind, müssten diese ebenso in der Aufklärung adressiert werden.

Besitzverhältnisse der Daten. Wie in der Einleitung dargestellt ist auch die Frage nach dem Besitz der erhobenen passiven behavioralen Daten zu beantworten (Maher et al., 2019) und im Rahmen der Einverständniserklärung zu erklären (Kilgallon et al., 2022). Die Herausforderung besteht darin, dass die Person, von der die Daten erhoben wurden, das Ausmaß möglicher Datenverwendung nicht überblickt, das Datenmissbrauchsrisiko und deren Folgen nicht abschätzen und somit auch keine angemessene Entscheidung über die Datennutzung treffen kann (Ballantyne, 2020). Den Schutz vor derlei Verletzung des Datenschutzes sollte auf Seiten der Gesetzgebung für Gesundheitsdaten und der Datenverwaltung geregelt werden

(Ballantyne, 2020). Das hieße, dass für den Fall der Verwendung passiver behavioraler Daten im Public Mental Health-Bereich Institutionen der Gesetzgebung wie Datenverwaltung für die Klärung und Gestaltung der Besitzverhältnisse der Daten hinzugezogen werden müssten.

Freiwilligkeit der Teilnahme. Darüber hinaus ist die Freiwilligkeit der Teilnahme nur schwer zu gewährleisten. Beim Einsatz passiver behavioraler Daten im Rahmen einer psychotherapeutischen Behandlung ist die betroffene Person gezwungen, sich zu entscheiden, ob sie zum Beispiel eine engmaschige Behandlung auch mithilfe passiver behavioraler Daten wünscht oder dies ablehnt und somit eine weniger engmaschige Begleitung in Kauf nimmt. In dieser Abwägungsentscheidung ist die Freiwilligkeit nicht mehr gegeben, da das Ablehnen der Datenverwendung die Person in der Behandlung benachteiligen würde. Dies ist der Fall, wenn passive behaviorale Daten als neuer Standard in der Public Mental Health-Forschung Einzug hielten und möglicherweise perspektivisch alternative Erhebung auf Basis von Befragungsdaten weniger würden. Aus ethischer Sicht muss im klinischen Setting ein alternatives Behandlungs- bzw. Begleitungsformat zum Beispiel über andere Kontaktwege angeboten werden, um Freiwilligkeit der Einwilligungserklärung zu gewährleisten.

Übertragen auf den Public Mental Health-Bereich könnte dies bedeuten, dass wenn eine Gruppe der Bevölkerung ebenso aussagekräftige Studienergebnisse als Grundlage für Präventionsmaßnahmen wünscht, für sie die Preisgabe passiver behavioraler Daten in diesem Kontext notwendig wird. Die unabhängige freie Entscheidung für oder gegen die Teilnahme ist damit in Frage gestellt.

Langzeitfolgen. Unter Einbezug der dargestellten ethischen Abwägungen verwiesen O’Doherty und Kolleg*innen auf die langfristigen Folgen der Verwendung passiver behavioraler Daten und dadurch bedingte Veränderungen der sozialen Umwelt. Auch sie empfahlen für die Bewertung passiver behavioraler Daten im Public Mental Health-Bereich den Einbezug weiterer Institutionen, konkret einen demokratischen Entscheidungsprozess (O'Doherty et al., 2016). Auch diese Empfehlung und deren Umsetzung wäre vor der Einführung passiver behavioraler Daten im Public Mental Health-Bereich zu gewährleisten.

Fazit

Passive behaviorale Daten haben das Potenzial einen technischen wie inhaltlichen Mehrwert für den Public Mental Health-Bereich zu bieten. Beachtenswert ist, dass einige Parameter passiver behavioraler Daten einen Beitrag zu der Vorhersage depressiver Symptome leisten, im Forschungsprojekt 1 neben etablierten selbst berichteten Maßen.

Es bestätigte sich durch die Forschungsprojekte 1 und 2 der vorliegenden Dissertation, dass passive behaviorale Daten auch hinsichtlich der Handhabbarkeit, technischen Eigenschaften und forschungsökonomischen Gesichtspunkte eine vielversprechende Datenquelle für den Public Mental Health-Bereich darstellen.

Durch die automatisierte Datenerhebung sind für den Public Mental Health-Bereich neue Formen der kontinuierlichen Datenerhebungen möglich. Dieses Vorgehen eröffnet perspektivisch die Möglichkeit, Trends in der Verbreitung depressiver Symptome frühzeitig zu identifizieren. Was eine zeitige Planung wie Umsetzung von Präventionsmaßnahmen ermöglicht. Zudem ermöglicht der Einbezug passiver behavioraler Daten eine kontinuierliche Dokumentation menschlichen Verhaltens, somit tiefere Einblicke in den Alltag der untersuchten Personen und gegebenenfalls neue Erkenntnisse zur Ätiologie einer depressiven Symptomatik.

Empfehlungen für die Verwendung passiver behavioraler Daten sind, dass insbesondere individuelle Nutzungsdaten und zudem personenspezifische Informationen für eine bessere Vorhersageleistung depressiver Symptome eingeschlossen werden sollten. Auch erhöht sich die Qualität der Ergebnisse, wenn die Daten hochaufgelöst sind.

Vor der Einführung dieser neuen Methode der Datenerhebung im Public Mental Health-Bereich bedarf es jedoch weiterer Vorarbeit. Insbesondere besteht der dringende Bedarf an verallgemeinerbaren definierten passiven behavioralen Datenparametern und nach Standards in der Art der Erhebung und Wahl der Analysemethode, um Forschungsergebnisse in Zukunft besser vergleichen zu können. Die Umsetzung ist insofern herausfordernd, als dass - wie das Forschungsprojekt 3 zeigte - die Zusammenhänge zwischen behavioralen Daten und depressiven Symptomen interindividuell in der Ausprägung variieren können. Eine mögliche Strategie wäre die Verwendung von Abweichungswerten der individuellen Norm der Kennwerte passiver behavioraler Daten. Darüber hinaus ist unter Einbezug gesetzgebender Institutionen die Klärung ethischer Fragen notwendig, welche über die Diskussion methodischer Fragen empirischer Forschung hinausgehen.

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Anhang A

Ergänzendes Material zu Kapitel 2

Table 1

Descriptive statistics of the present sample of N=490 German speaking adults in total and grouped by sex

	Total					Female					Male					Divers				
Variables	*N* = 490					*n* = 259 (53 %)					*n* = 225 (46 %)					*n = 6 (1%)*				
	M	*(SD)*	*Median*	*Min.*	*Max.*	*M*	*(SD)*	*Median*	*Min.*	*Max.*	*M*	*(SD)*	*Median*	*Min.*	*Max.*	*M*	*(SD)*	*Median*	*Min.*	*Max.*
Smartphone use [a]																				
videocalls	2.01	4.50	1	1	32	2.03	4.56	1	1	31	2.01	4.50	1	1	32	1	0	1	1	1
phone calls	33.15	52.69	1	1	178	28.50	49.11	1	1	175	38.75	56.17	1	1	178	23.67	55.52	1	1	137
social media	100.01	103.83	67.5	1	312	105.49	107.35	74	1	312	94.39	99.33	62	1	307	74.67	117.93	1	1	269
messaging	90.71	98.51	52.5	1	297	94.32	98.80	58	1	297	88.10	98.87	44	1	296	32.67	49.55	1	1	107
messenger	223.06	140.68	222.5	1	467	221.33	134.64	219	1	467	226.45	147.69	228	1	466	170.67	137.66	144	39	338
total smart-phone use	245.5	141.59	245.50	1	490	238.63	143.53	222	2	489	253.50	139.77	261	1	490	242.33	131.10	273	43	384
Stigmatisation																				
expectation [b]	6.24	1.77	6	2	10	6.33	1.70	6	2	10	6.14	1.85	6	2	10	6	2	6	3	9
experience [c]	1.86	0.43	2	0	2	1.87	0.40	2	0	2	1.85	0.46	2	0	2	2	0	2	2	2
Concerns [d]																				
lack of medical capacity	0.71	0.74	1	0	2	0.73	0.74	1	0	2	0.69	0.76	1	0	2	0.5	0.84	0	0	2
to infect someone	1.33	0.74	1	0	2	1.46	0.69	2	0	2	1.18	0.78	1	0	2	1.33	0.52	1	1	2
contracting COVID-19	1.19	0.73	1	0	2	1.25	0.72	1	0	2	1.10	0.74	1	0	2	1.67	0.52	2	1	2
getting seriously ill in case of COVID-19 infection	1.13	0.75	1	0	2	1.15	0.77	1	0	2	1.09	0.73	1	0	2	1.67	0.52	2	1	2
Loneliness [e]	8.81	3.10	9	3	15	9.09	3.00	9	3	15	8.54	3.18	8	3	15	6.67	3.50	5	3	12
Family climate																				
currently [f]	2.54	0.84	3	0	4	2.51	0.81	3	0	4	2.58	0.86	3	0	4	2.67	1.03	3	1	4
change [g]	0.64	0.63	1	0	2	0.65	0.66	1	0	2	0.63	0.60	1	0	2	0.83	0.75	1	0	2
Psychosocial distress [h]	7.89	4.69	7	0	20	8.53	4.64	8	0	20	7.17	4.68	6	0	18	7.33	4.03	6.5	3	13
General health status [i]	2.26	0.85	2	1	5	2.26	0.84	2	1	5	2.24	0.85	2	1	5	3	1.10	3	1	4

Coping [j]																				
escape-avoi-dant-focused	3.45	2.90	3	1	16	3.55	2.85	3	1	16	3.32	2.92	2	1	14	4	4.29	1.5	1	16
meaning-focused	9.40	3.63	10	1	19	10.13	3.63	10	1	19	9.10	3.59	9	1	19	8.5	2.07	8	6	11
problem-focused	9.91	3.70	10	1	19	10.53	3.45	10	1	19	9.19	3.86	9	1	19	10.67	3.61	11	5	16
Support-focused	1.86	0.43	2	0	2	1.87	0.40	2	0	2	1.85	0.46	2	0	2	2	0	2	2	2
Alcohol consumption [k]	0.98	1.11	1	0	4	0.91	1.06	1	0	4	1.08	1.16	1	0	4	0.17	0.41	0	0	4
Physical activity [l]																				
average last 3 months	2.64	1.30	3	1	5	2.67	1.31	3	1	5	2.61	1.29	2	1	5	2.67	1.37	2.5	1	5
last week	2.41	1.34	2	1	5	2.40	1.33	2	1	5	2.42	1.35	2	1	5	2.33	1.63	2	1	5
Personality [m]																				
openness	3.32	1.02	3	1	5	3.40	0.98	3	1	5	3.23	1.06	3	1	5	3.5	1.05	3.5	2	5
conscientious-ness	3.20	0.86	3	1	5	3.26	0.88	3	1	5	3.13	0.84	3	1	5	3.5	1.05	3.5	2	5
extraversion	2.64	1.07	3	1	5	2.80	1.05	3	1	5	2.48	1.08	2	1	5	1.83	0.75	2	1	3
agree-ableness	2.62	0.81	3	1	5	2.53	0.82	3	1	5	2.73	0.80	3	1	5	2.5	0.55	2.5	2	3
neuroticism	2.93	1.02	3	1	5	3.12	1.00	3	1	5	2.71	1.01	3	1	5	3	1.10	3	2	5
Loss of income	0.25	0.53	0	0	2	2.23	0.53	0	0	2	0.28	0.54	0	0	2	0.17	0.41	0	0	2

	N (%)	*n* (%)	*n* (%)	*n* (%)
Working status				
regular working hours	298 (61%)	154 (59%)	140 (62%)	4 (67%)
on short time	24 (5%)	10 (4%)	14 (6%)	
unability to pursue current occupation due to closed schools etc.	12 (2%)	9 (3%)	3 (1%)	
unability to pursue current occupation due to health protection measures	12 (2%)	7 (3%)	5 (2%)	
in quarantine	13 (3%)	7 (3%)	5 (2%)	1 (17%)
sick leave (other than COVID-19)	17 (3%)	10 (4%)	7 (3%)	
job-seeking	31 (6%)	14 (5%)	17 (8%)	
housewife/ househusband	22 (4%)	20 (8%)	2 (1%)	
pensioner	61 (12%)	28 (11%)	32 (14%)	1 (17%)
Workplace				
home office	180 (30%)	59 (32%)	48 (29%)	1 (25%)
regular workplace	195 (54%)	97 (52%)	95 (57%)	3 (75%)
partly home office. partly regular workplace	55 (15%)	30 (16%)	25 (15%)	
Mental Disorder				
no	271 (55%)	121 (47%)	149 (66%)	6 (100%)
yes	214 (44%)	136 (53%)	73 (32%)	
don't know	5 (1%)	2 (1%)	3 (1%)	

COVID-19				
Tested positive				
no	472 (96%)	247 (95%)	219 (97%)	6 (100%)
currently ill	9 (2%)	7 (3%)	2 (1%)	
recovered	9 (2%)	5 (2%)	4 (2%)	
Sick relatives				
no	454 (93%)	233 (90%)	215 (96%)	6 (100%)
currently ill	8 (16%)	6 (2%)	2 (1%)	
recovered	28 (6%)	20 (8%)	8 (4%)	

	No	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Working within health care system	414 (84%)	76 (16%)	210 (81%)	49 (19%)	200 (89%)	25 (11%)	4 (67%)	2 (33%)
Domestic violence								
last week	485 (99%)	5 (1%)	257 (99%)	2 (1%)	222 (99%)	3 (1%)	6 (100%)	
in the last year (except last week)	476 (97%)	14 (3%)	249 (96%)	10 (4%)	221 (98%)	4 (2%)	6 (100%)	
Chronic illness	229 (47%)	261 (53%)	118 (46%)	141 (54%)	111 (49%)	114 (51%)	6 (100%)	
COVID-19 relatives lost	476 (97%)	14 (3%)	252 (97%)	7 (3%)	218 (97%)	7 (3%)	6 (100%)	

Note: [a] Average daily consumption in minutes measured via smartphone;
[b] Sum score of 2 items answered on a 5-point scale from 1 (“Always”) to 5 (“Never”);
[c] Sum score of 2 items answered on a 2-point scale from 0 (“No”) to 1 (“Yes”);
[d] 3-point scale from 0 (“Not bothered”) to 2 (“Bothered a lot”);
[e] Sum score of 3 items answered on a 5-point scale from 1 (“Very often”) to 5 (“Never”);
[f] 5-point scale from 0 (“Very bad”) to 4 (“Very good”);
[g] 3-point scale from 0 (“Yes, it got worse”) to 2 (“Yes, it has improved”);
[h] Sum score of 11 items answered on a 3-point scale from 1 (“Not bothered”) to 5 (“Bothered a lot”);
[i] 5-point scale from 1 (“Very good”) to 5 (“Very bad”);
[j] Sum scores answered on a 4-point scale from 1 (“I haven't been doing this at all”), 2 (“I've been doing this a little bit”), 3 (“I've been doing this a medium amount”), 4 (“I've been doing this a lot”);
[k] 5-point scale from 0 (“None”) to 4 (“Six to seven times a week”);
[l] 5-point scale from 1 (“No sporting activity”) to 5 (“Regularly more than 4 hours a week”);
[m] Sum scores of 2 items answered on a 5-point scale from 1 (“Disagree strongly”) to 5 (“Agree strongly”).

Anhang B

Ergänzendes Material zu Kapitel 3

Table 1

Descriptive statistics of the present sample of N=249 German speaking adults in total across districts

Variables	*M*	*(SD)*	*Median*	*Min.*	*Max.*
PHQ-9	7.40	5.60	6	0	26
COVID-19 pandemic					
New infections	57.97	67.10	15	2	233
Sociodemographics					
Age groups in 2019[a]					
0-17 years	15.01	1.75	16	12	17
18-24 years	8.33	2.08	7	7	12
25-44 years	29.70	3.30	31	23	33
45-64 years	25.57	2.32	25	23	30
from 65 years	19.19	1.29	19	17	21
Youth ratio in 2021[b]	27.52	3.36	29	22	32
General higher education entrance qualification in 2021[a]	39.58	10.11	40	10	53
Without school leaving qualification in 2019[a]	6.02	1.43	6	4	8
Employment rate in 2020[a]	59.84	3.22	59	56	65
Disposable income per inhabitant in 2020[b]	25138.04	3488.70	25808	21327	32039
Proportion of unemployment benefit II recipients in 2019[a]					
up to 24 years	8.79	5.40	8	2	16
from 55 years	6.90	3.29	5	1	11
Economy					
Share of employed persons by sector in 2019[a]					
public and other services, education and health care	36.15	7.88	38	24	48
finance, insurance, trade, real estate and housing	21.37	4.74	24	15	28
trade, transport, hospitality, information and communication	27.35	2.61	26	25	32
service sectors	85.87	5.83	89	70	90
manufacturing industry	7.80	3.36	6	5	17
producing industry	13.09	4.89	11	9	26
construction industry	3.21	1.75	3	1	7

agriculture, forestry and fisheries	0.24	0.82	0	0	3
Investments per employee in 2019[c]	13.76	7.41	10	6	29
Average length of tourist stay in 2019[d]	1.68	0.47	2	1	2
Social affairs					
Households with children in 2011[a]	25.21	5.85	24	20	40
Childcare rate 0 to 2 years on 01.03.2021[a]	39.60	5.42	44	29	46
Childcare rate 3 to 5 years on 01.03.2021[a]	91.79	2.05	92	89	95
Fathers receiving parental benefits in 2014[a]	40.17	6.95	37	26	52
Places in nursing homes in 2020[e]	53.08	17.85	48	31	82
Living environment					
One-person household in 2011[a]	45.87	7.41	49	29	51
Population density in 2020[f]	2699.96	1607.34	2446	167	4777
Share of area in 2015[a]					
agriculture	22.28	18.05	22	4	61
settlement	42.73	15.26	46	7	58
recreation	8.61	4.34	8	0	13
traffic	12.61	3.06	12	6	16
forest	12.80	5.61	15	4	21
Consumption-based charge for drinking water in 2019[g]	1.32	0.47	1	1	2

Note: [a] in percent;
[b] per year in Euro;
[c] in thousand Euro;
[d] in days;
[e] per 1,000 inhabitants aged 65 and over;
[f] inhabitants per sqkm;
[g] in Euro per m^3.

Table 2

Variable list of the Regional Atlas of Germany produced by the Federal Statistical Office and the federal states

Sociodemographics	Politics
• population share of 0-17-year-olds in 2019 • population share of 18-24-year-olds in 2019 • population share of 25-44-year-olds in 2019 • population share of 45-64-year-olds in 2019 • population share of those aged 65 or older in 2019 • youth ratio in 2021 • old-age ratio in 2019 • average age of mother at birth of 1st child in 2019 • percentage of the population with general higher education entrance qualification in 2021 • percentage of the population without school leaving qualification in 2019 • employment rate in 2020 • share of 15-24-year-olds in the unemployed population in 2021 • share of 55-64-year-olds in the unemployed population in 2021 • proportion of children receiving financial social assistance in 2019 • share of those 55 years old or older in unemployment benefit II recipients in 2019 • proportion of those 24 years old or younger in unemployment benefit II recipients in 2019 • share of long-term unemployed in 2021 • share of foreigners in total population in 2019 • population share of 0-19-year-olds with a migration background in 2011 • population share of 20-59-year-olds with a migration background in 2011 • population share of those 60 years old or older with a migrant background in 2011 • naturalisation rate in 2019 • share of foreigners in the unemployed in 2021 • disposable income per inhabitant in euros in 2020 • basic income support rate for women aged 65 and over in 2021 • basic income rate of men aged 65 or older in 2021 • basic income support rate due to reduced earning capacity in 2019 • rate of employable SGB II beneficiaries for men in 2019 • rate of employable SGB II beneficiaries for women in 2019 • percentage of unemployed people in 2020	• voter turnout in the Bundestag election in 2017 • turnout in the European Election in 2019 • vote share in the AfD European Election in 2019 • vote share in the CDU CSU European Election in 2019 • vote share in the DIE LINKE European Election in 2019 • vote share in the FDP European Election in 2019 • vote share in the GRÜNE European Election in 2019 • vote share in the SPD European Election in 2019 • AfD second vote share in the Bundestag election in 2017 • CDU CSU second vote share in the Bundestag election in 2017 • DIE LINKE second vote share in the Bundestag election in 2017 • FDP second vote share in the Bundestag election in 2017 • GRÜNE second vote share in the Bundestag election in 2017 • SPD second vote share in the Bundestag election in 2017 Social affairs • percentage of households with children in 2011 • 0-2-year-old children in daycare facilities in 2021 • 3-5-year-old children in daycare facilities in 2021 • childcare rate for 0-2-year-olds in 2021 • childcare rate for 3-5-year-olds in 2021 • proportion of fathers receiving parental benefits in 2014 • hospital bed density in 2021 • places in nursing homes per 1,000 inhabitants for those aged 65 or over in 2020 • persons in need of care per 1,000 inhabitants for those aged 65 or over in 2021 • staff per 100 persons in need of outpatient care in 2021 • staff per 100 persons in need of full inpatient care in 2021 • proportion of men among pedagogical staff in child daycare facilities in 2021
Economy • employment density in 2019 • minimum protection rate in 2019 • share of employed persons in the construction industry in 2019 • share of employed persons in service sectors in 2019 • share of employed persons in the finance, insurance, real estate, and housing industries in 2019	Living environment • percentage of one-person households in 2011 • proportion of new residential buildings with 1 or 2 dwellings in 2019 • population density of inhabitants per square kilometre in 2020 • population development per year per 10,000 inhabitants in 2019 • average household size in 2021 • net migration per 10,000 inhabitants in 2019

- share of employed persons in the trade, transport, hotels and restaurants, information and communication industries in 2019
- share of employed persons in the agriculture, forestry and fishing industries in 2019
- proportion of employed persons in the public service and other services, education, and health industries in 2019
- share of employed persons in the producing sector in 2019
- share of employed persons in the manufacturing sector in 2019
- federal, state and local government employees per 1,000 inhabitants in 2019
- investments per employee in thousand euros in 2019
- gross domestic product per hour worked in 2017
- gross domestic product per person employed in 2019
- gross domestic product per inhabitant in 2020
- change in gross domestic product compared to that of the previous year in 2019
- gross wages per employee in 2019
- gross value added in the construction industry in 2019
- gross value added in service sectors in 2019
- gross value added in the finance, insurance, real estate, and housing industries in 2019
- gross value added in the trade, transport, hotels and restaurants, information and communication industries in 2019
- gross value added in the agriculture, forestry, and fishery industries in 2019
- gross value added in the public services and other services, education, and health sectors in 2019
- gross value added in the producing sector in 2019
- corporate insolvencies per 10,000 taxable companies in 2019
- average length of stay of tourists in 2019
- total amount of income per taxpayer in 2017
- business registrations per 10,000 inhabitants in 2020
- average farm size in 2016
- water delivery per inhabitant per day (in litres) in 2016
- consumption-based charge for drinking water supply per m^3 in 2019
- consumption-independent charge for drinking water supply per m3 in 2019
- share of land for agriculture in 2015
- share of land for settlement in 2015
- share of land for sport, leisure and recreation in 2015
- share of area for transport in 2015
- share of area for forest in 2015
- share of organic farming in 2020
- cattle per 100 ha of utilised agricultural area in 2016
- pigs per 100 ha of utilised agricultural area in 2016
- car ownership per 1000 inhabitants in 2021
- number of those injured in road traffic accidents per 100,000 inhabitants in 2019
- number of fatalities in road accidents per 100 000 inhabitants in 2019
- number of road traffic accidents per 10 000 inhabitants in 2019
- number of road traffic accidents per 10 000 motor vehicles in 2019
- number of overnight stays per inhabitant in 2019
- amount of household waste per inhabitant in 2019

Note: All county-level variables available on the Federal Statistical Office's website in the Regional Atlas on 30 April 2022 were considered, with each construct considered once.

Anhang C

Ergänzendes Material zu Kapitel 4

Appendix

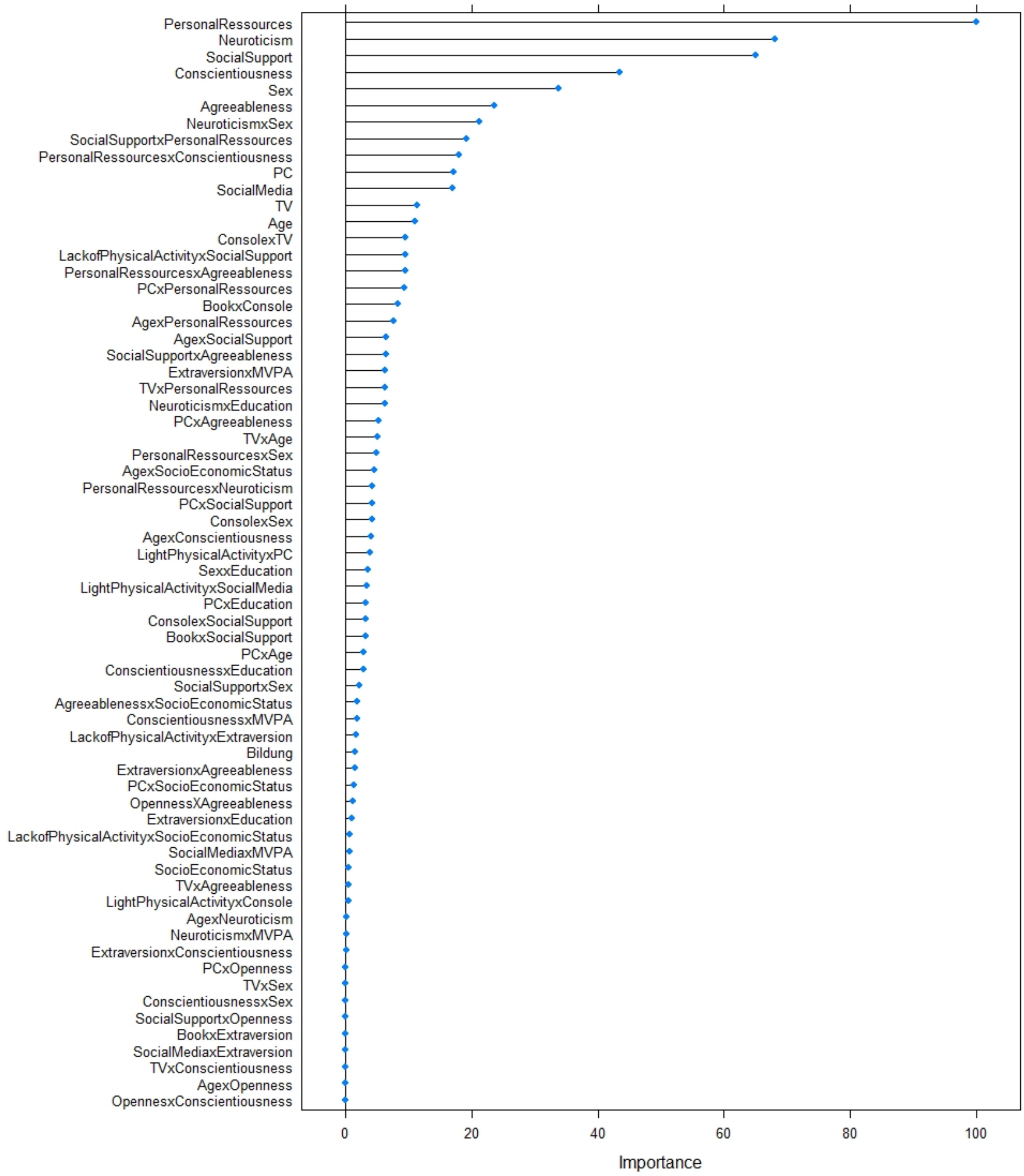

Fig. A1. Variable importance of all the included variables as indicator of the contribution to reduce the estimation error in the prediction of depressive symptoms.

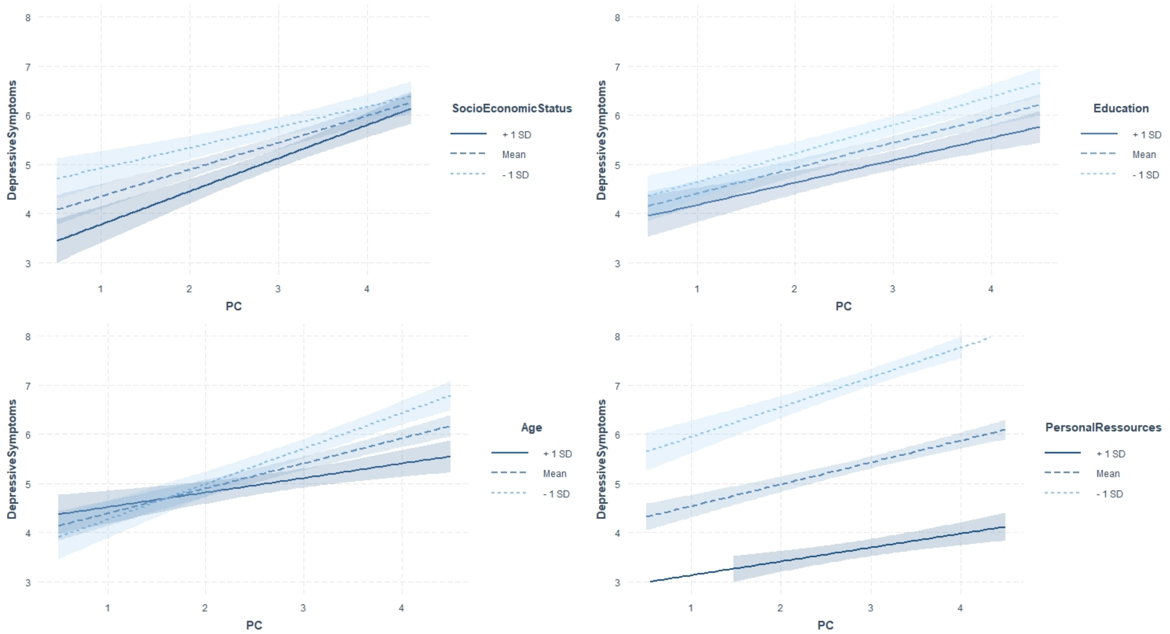

Fig. A2. Interaction plots showing simple slopes of health risk behaviours predicting depressive symptoms (min=0, max=25) for 1 SD below (8.45), 1 SD above (15.79) and at the mean level of socioeconomic status (*M*=12.12); for 1 SD below (3.63), 1 SD above (4.48) and at the mean level of education (*M*=4.05); for 1 SD below (19.04), 1 SD above (25.23) and at the mean level of age (*M*=22.14); for 1 SD below (55.59), 1 SD above (83.89) and at the mean level of personal resources (*M*=69.74). Coloured shading represent 95% CIs.

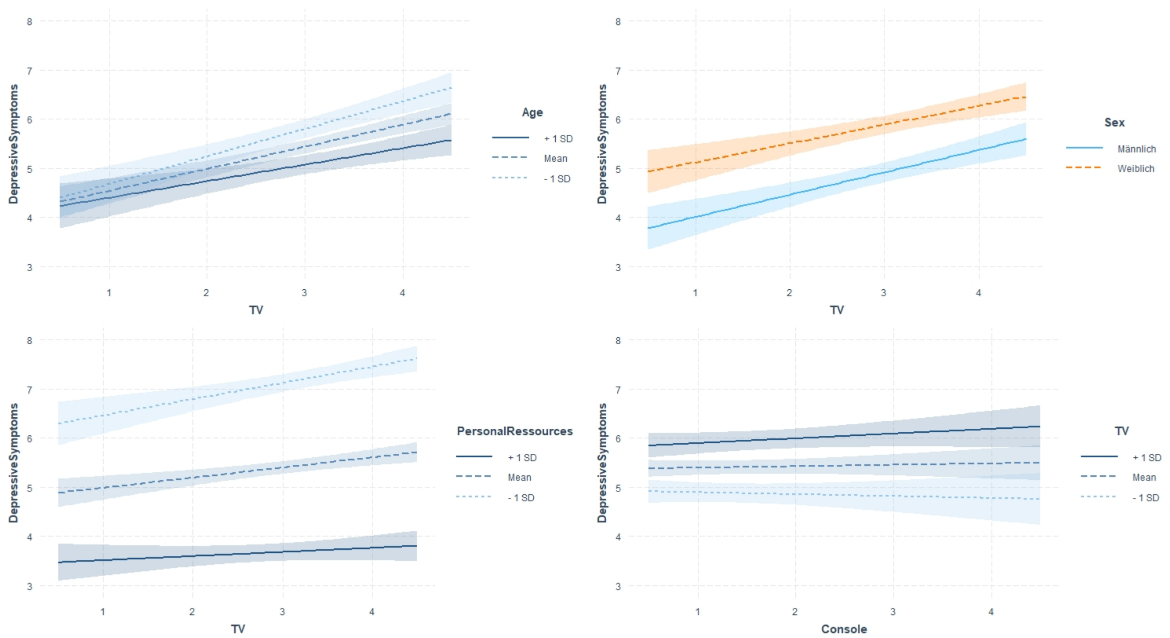

Fig. A3. Interaction plots showing simple slopes of health risk behaviours predicting depressive symptoms (min=0, max=25) for 1 SD below (19.04), 1 SD above (25.23) and at the mean level of age (*M*=22.14); for sex (46 % male); for 1 SD below (55.59), 1 SD above (83.89) and at the mean level of personal resources (*M*=69.74); for 1 SD below (1.75), 1 SD above (4.17) and at the mean level of TV (*M*=2.96). Coloured shading represent 95% CIs.

The role of personality traits and perceived social support in relations of health risk behaviours and depressive symptoms

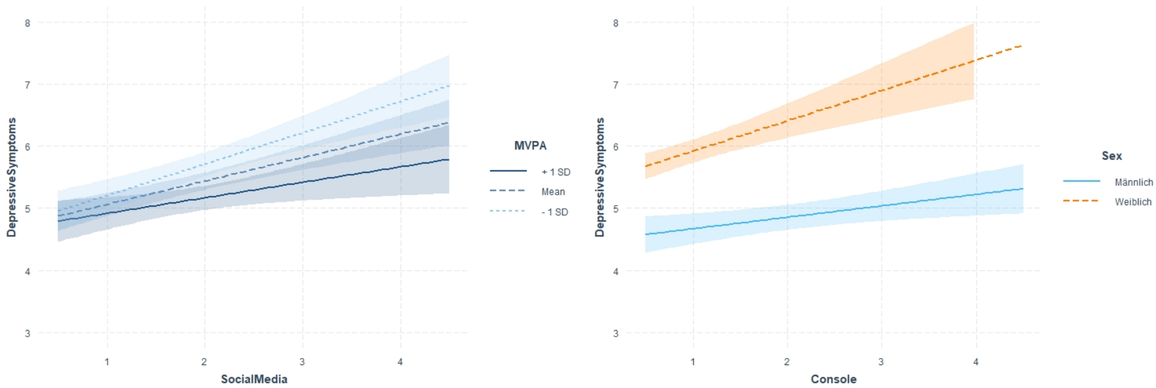

Fig. A4. Interaction plots showing simple slopes of health risk behaviours predicting depressive symptoms (min=0, max=25) for 1 SD below (25.79), 1 SD above (70.21) and at the mean level of MVPA (*M*=48.00); for sex (46 % male). Coloured shading represent 95% CIs.

Table A1
Results of the simple slope analyses for significant interactions resulting from elastic net regression on depressive symptoms

Predictor	*Moderator (1 SD below, 1 SD above and at the mean level)*		*Estimate*	*Std. Error*	*p*
MVPA	Social Media [a]	.90	-.006	.01	.379
		1.94	-.012	.00	.014 *
		2.98	-.018	.01	.012 *
PC [a]	Socioeconomic status	8.45	.419	.12	<.001 ***
		12.12	.547	.09	<.001 ***
		15.79	.674	.13	<.001 ***
	Education	3.63	.578	.11	<.001 ***
		4.05	.516	.09	<.001 ***
		4.48	.454	.12	<.001 ***
	Age	19.04	.721	.12	<.001 ***
		22.14	.508	.09	<.001 ***
		25.23	.295	.12	.013 *
	Personal Resources	55.59	.606	.11	<.001 ***
		69.74	.444	.08	<.001 ***
		83.89	.282	.11	.009 **
TV [a]	Age	19.04	.561	.12	<.001 ***
		22.14	.448	.09	<.001 ***
		25.23	.336	.13	.009 **
	Sex	Male	.454	.13	<.001 ***
		Female	.382	.12	.002 **
	Personal Resources	55.59	.330	.12	.005 **
		69.74	.207	.08	.011 *
		83.89	.084	.11	.466

Predictor	*Moderator (1 SD below, 1 SD above and at the mean level)*		*Estimate*	*Std. Error*	*p*
TV [a]	Console [a]	.14	.366	.12	.003 **
		1.45	.439	.09	<.001 ***
		2.76	.513	.12	<.001 ***
Console [a]	Sex	Male	.184	.11	.088
		Female	.488	.15	.001 **

Note: MVPA = Moderate to Vigorous Physical Activity; PA = Physical Activity;
[a] Self-reported average daily consumption answered on a 6-point scale from 0 ("Not at all"), 1 ("Up to 1 hour"), 2 ("1 up to 2 hours"), 3 ("2 up to 3 hours"), to 4 ("3 up to 4 hours"), 5 ("More than 4 hours");
[b] Transformed sum score ranging from 0 to 100 based on 8 items answered on a 5-point scale from 1 ("Never") to 5 ("Always");
[c] Mean of two items for each dimension answered on a 5-point scale from 1 ("Disagree strongly") to 5 ("Agree strongly").

Table A1

Simple slope analyses for significant interactions resulting from elastic net regression on depressive symptoms

Predictor		*Moderator (1 SD below, 1 SD above and at the mean level)*	*Estimate*	*Std. Error*	*p*
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[c] Mean of two items for each dimension answered on a 5-point scale from 1 (“Disagree strongly”) to 5 (“Agree strongly”).

Beitragsliste

Edler, J.-S., Manz, K., Rojas-Perilla, N., Baumeister, H., & Cohrdes, C. (2022). The role of personality traits and social support in relations of health-related behaviours and depressive symptoms. *BMC Psychiatry*, *22*(1), 52. https://doi.org/10.1186/s12888-022-03693-w

Edler, J.-S., Winter, M., Steinmetz, H., Cohrdes, C., Baumeister, H. & Pryss, R. (2024). Predicting depressive symptoms using GPS-based regional data in Germany with the CORONA HEALTH app during the COVID-19 pandemic: Cross-sectional study. Interactive Journal of Medical Research, 13. https://doi.org/10.2196/53248

Edler, J.-S., Terhorst, Y., Pryss, R., Baumeister, H. & Cohrdes, C. (2024). Messenger use and video calls as correlates of depressive and anxiety symptoms: Results from the CORONA HEALTH APP study of German adults during the COVID-19 pandemic. Journal of Medical Internet Research, 26. https://www.jmir.org/2024/1/e45530

Erklärung über Eigenanteil

Erklärung gemäß § 7 Abs. 3 Satz 4 der Promotionsordnung über den Eigenanteil an den veröffentlichten oder zur Veröffentlichung vorgesehenen eingereichten wissenschaftliche Schriften im Rahmen meiner publikationsbasierten Arbeit

I. Name, Vorname: Edler, Johanna-Sophie

Fachbereich: Erziehungswissenschaft und Psychologie

Promotionsfach: Psychologie

Titel: Passive behaviorale Daten im Public Mental Health-Bereich - Nutzung von Verhaltensdaten als Korrelate für eine depressive Symptomatik

II. Nummerierte Aufstellung der eingereichten Schriften
(Titel, Autor*innen, wo und wann veröffentlicht bzw. eingereicht):

1. Titel: Messenger use and video calls as correlates of anxiety and depressive symptoms – Results from the CORONA HEALTH APP study of German adults during the COVID-19 pandemic

   Autor*innen: Edler, Johanna-Sophie, Terhorst, Yannik, Pryss, Rüdiger, Baumeister, Harald & Cohrdes, Caroline

   Eingereicht am 10. Januar 2023 beim JMIR Mental Health (https://mental.jmir.org)

2. Titel: Predicting depressive symptoms using GPS-based regional data: a feasibility study with the CORONA HEALTH APP during the COVID-19 pandemic in Germany

   Autor*innen: Edler, Johanna-Sophie, Steinmetz, Holger, Cohrdes, Caroline, Baumeister, Harald & Pryss, Rüdiger

   Eingereicht im September 2023 bei JMIR Public Health and Surveillance (https://publichealth.jmir.org/)

3. Titel: The role of personality traits and social support in relations of health-related behaviours and depressive symptoms

   Autor*innen: Edler, Johanna-Sophie, Manz, Kristin, Rojas-Perilla, Natalia, Baumeister, Harald & Cohrdes, Caroline

   Veröffentlicht am 22. Januar 2022 in BMC Psychiatry, https://doi.org/10.1186/s12888-022-03693-w

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Dr. Kristin Manz

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Prof. Dr. Natalia Rojas-Perilla

Dr. Holger Steinmetz

Yannik Terhorst

Selbstständigkeitserklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig verfasst und ohne unerlaubte Hilfe angefertigt habe.

Alle Hilfsmittel, die verwendet wurden, habe ich angegeben. Die Dissertation ist in keinem früheren Promotionsverfahren angenommen oder abgelehnt worden.

Ort, Datum

Johanna-Sophie Edler