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REVIEW

A Systematic Review of Artificial Intelligence Used to Predict Loneliness, Social Isolation, and Drug Use During the COVID-19 Pandemic

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Abstract: This systematic literature review evaluates the role of machine learning, artificial intelligence (AI), and social determinants of health (SDOH) in identifying loneliness during the COVID-19 pandemic. By examining various studies and articles through a comprehensive search of databases EBSCOhost, Medline Complete, Academic Search Complete, Directory of Open Access Journals, and Complementary Index, the research team sought to discern consistent themes and patterns. We identified four constructs central to understanding the impact of the pandemic on societal well-being: (1) the prediction of compliance with COVID-19 measures, (2) the prediction of loneliness and its effects, (3) the prediction of well-being and social inclusion, and (4) the prediction of drug use. Within these constructs, prevalent themes related to opioid overdose, stress levels, mental health, well-being, and cognitive decline emerged. The adherence to the PRISMA 2020 checklist has resulted in a PRISMA flow diagram that categorizes the selected literature. The findings of this review, including the proportion of studies predicting various attributes related to loneliness, demonstrate the critical intersections between machine learning, AI, SDOH, and the psychosocial phenomenon of loneliness amidst a global health crisis. The review results provide a summary of the occurrences and predictive percentages of each construct as determined by the literature, contributing to a nuanced understanding of the pandemic's multifaceted impact on loneliness, social isolation, and drug use. Using AI to predict these constructs has remarkable capabilities in identifying individuals at risk and facilitating timely interventions to mitigate adverse outcomes and promote mental health resilience in the face of challenges such as the COVID-19 pandemic. Moving forward, future research is warranted to refine AI algorithms, validate predictive models and utilize AI-based interventions in healthcare and mental health services while ensuring data security, and individuals' privacy.

Keywords: loneliness, social isolation, drug use, COVID-19, pandemic, social déterminants of health, artificial intelligence and machine learning

Introduction

The COVID-19 pandemic forced all nations in the world to adopt some drastic measures to contain the pandemic. While mitigating the spread of the COVID-19 virus, some measures such as total confinement or lockdown, quarantine, and social distancing have increased the prevalence of loneliness. Though not a disease, loneliness, defined by Majmudar, Mihalopoulos, Brijnath et al in 2022 as the "perceived social isolation" may lead to some negative health outcomes.[1] Loneliness is associated with cardiovascular disease, high blood pressure, decline in cognitive abilities and mental health, depression, dementia, suicide, eating disorders, substance abuse, and early preventable death.[2] While the COVID-19 pandemic has been found a major factor exacerbating loneliness, some social determinants of health such as poverty, unemployment, age, and gender, may also be associated with loneliness.[3] Scholars have developed survey instruments to determine loneliness, such as the mostly used UCLA loneliness scale, the Loneliness Rating Scale, and the Social and Emotional Loneliness Scale for Adults (SELSA).[4,5]

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Need for Research

The need for a study examining the impact of the COVID-19 pandemic on loneliness is underscored by the complex interplay of various social determinants of health that also contribute to this issue. Factors such as poverty, unemployment, age, and gender not only predispose individuals to loneliness but also exacerbate its effects during times of crisis. For instance, economic instability and job loss can lead to social withdrawal and increased stress, further deepening feelings of isolation. Older adults, who are already at higher risk for loneliness due to life transitions and mobility issues, faced heightened isolation during lockdowns. Similarly, gender differences in social networks and coping mechanisms mean that men and women may experience and respond to loneliness differently. By investigating these social determinants, the study aims to provide a nuanced understanding of loneliness during the pandemic, highlighting the multifaceted nature of this public health concern. This knowledge is critical for designing inclusive and effective interventions that address the specific needs of diverse populations, ultimately reducing the burden of loneliness and its associated health risks.

With the advance in information technology allowing the storage of big data, the use of artificial intelligence (AI) in research has been on the rise. In the late 70's the use of AI in healthcare focused on diagnosis and disease treatment.[6] Currently, AI can aid in defining and measuring the impact of social factors such as loneliness on health outcomes during the COVID-19 pandemic. Instances of AI predicting health outcomes include opioid overdose, stress levels, well-being, mental health, and cognitive decline. During the pandemic, research involving suicidal ideation and compliance with health measures was observable with the use of AI and machine learning.[4,6]

Purpose of Study

The purpose of this study is to systematically review how machine learning and AI have aided in the identification of loneliness, social isolation, and drug use during the COVID-19 pandemic. The novelty of this study lies in its comprehensive approach to systematically reviewing the application of machine learning and artificial intelligence in identifying loneliness, social isolation, and drug use during the COVID-19 pandemic. While previous research has highlighted the role of AI in healthcare, focusing on diagnostics and disease treatment, this study extends the scope to encompass the social dimensions of health exacerbated by the pandemic. Given the widespread and profound impacts of COVID-19 on mental health and social behaviors, understanding how AI can detect and predict these issues is crucial. The findings of this study are essential for developing targeted interventions and informing public health strategies to mitigate the adverse effects of loneliness and social isolation, thereby improving overall well-being and health outcomes in future public health crises.

Methods

The systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. It particularly followed the PRISMA 2020 checklist and employed the PRISMA 2020 flow diagram. The Methods section of the review specifically aligns with the PRISMA checklist criteria, detailing the process of selecting relevant articles from various databases.

Eligibility Criteria

This review included articles that met the specific eligibility criteria set by the research team, utilizing multiple iterations of EBSCO-hosted searches to encompass a broad range of studies relevant to the topic. Criteria for inclusion were publication date from January 1, 2020, to October 23, 2023, peer-reviewed status, full-text availability, and English language. Although initially focusing on US publications, this restriction was later removed to expand the pool of potential articles. The "academic journals" filter on EBSCOhost was applied to specifically target higher education studies. The review encompassed all types of articles and research methods, including additional reviews on similar topics, from which further articles were sourced for inclusion.

Search and Information Sources

The research team at Texas State University utilized several databases via EBSCOhost, including Medline Complete, Academic Search Complete, Directory of Open Access Journals, and Complementary Index, to find articles for the review. These sources were chosen for their high yield of relevant articles with minimal duplicates. The review focused on articles about machine learning's relation to loneliness and social determinants of health, including social status, policies and social protection, conducted between September 18 and October 23, 2023. The team used specific search strings with Boolean operators, opting for their own terms over the databases' suggested synonyms. The final search string was: [(machine learning or artificial intelligence) AND (loneliness or social isolation or social exclusion or lonely) AND (Employment status OR Income level OR Economic policies OR Social protection policies)]

Initial Article Selection

The review team held several meetings to select articles from the initial database search that met the review criteria. Collaboration and analysis were facilitated using a Microsoft Excel spreadsheet and other tools within a Microsoft Teams group site. The review process involved initial abstract screening, full-text examination, and checking the literature review/reference sections of articles, particularly for identified systematic reviews. For an article to be excluded during the title/abstract screening phase, at least two team members had to agree, and there was consensus among the team on the final selection of articles for the review.

Article Exclusion

Figure 1 in the article outlines the process of excluding articles, starting from initial database searches to the final selection of 14 articles. The initial search yielded 181 articles focusing on the use of AI to predict loneliness in conjunction with social determinants of health factors. Despite using four databases, which increased the sample size, it resulted in 25 duplicates automatically removed by the EBSCOhost library search engine. After applying criteria like date range (2020–2023) (−56), English-only, full-text only (−16), and academic/peer-reviewed journals (−36), the count was reduced to 48. These articles were downloaded in full text and rigorously reviewed by the research team to ensure their relevance to the study's goals.

Results

After reviewing all articles and finalizing themes, the researchers convened to agree on a single affinity matrix. This involved reaching a consensus on categorizing articles based on their relevance to the use of AI in the prediction of loneliness during the post-COVID timeframe and as associated with SDOH factors. It was essential for all researchers to agree on the inclusion of each article in the respective thematic categories. These categories were not exclusive, allowing for articles to fit into multiple categories related to cost influence or reduction. A summary of the identified articles in the review and their topic details is presented in Table 1. The identified constructs and related articles supporting the review themes are presented in Figure 2.

The systematic literature review identified four key constructs in relation to COVID-19 measures and behavioral predictions. The first construct deals with the prediction of compliance with COVID-19 measures, showing a 30% instance of attribute occurrence across several study points, suggesting a moderate level of compliance prediction. The second construct focuses on the prediction of loneliness and/or its effects, with a 40% instance of attribute, indicating a significant concern for loneliness as an outcome of the pandemic. The third construct predicts well-being and social inclusion, with an even higher attribute instance at 45%, underscoring the substantial impact of COVID-19 on social and emotional well-being. Lastly, the Social Determinants of Health (SDOH) to predict drug use is the least represented construct, with a 5% instance of attribute, pointing to a relatively minor focus on drug use prediction in the current literature. These constructs highlight the multifaceted nature of the pandemic's impact on behavior and health outcomes.

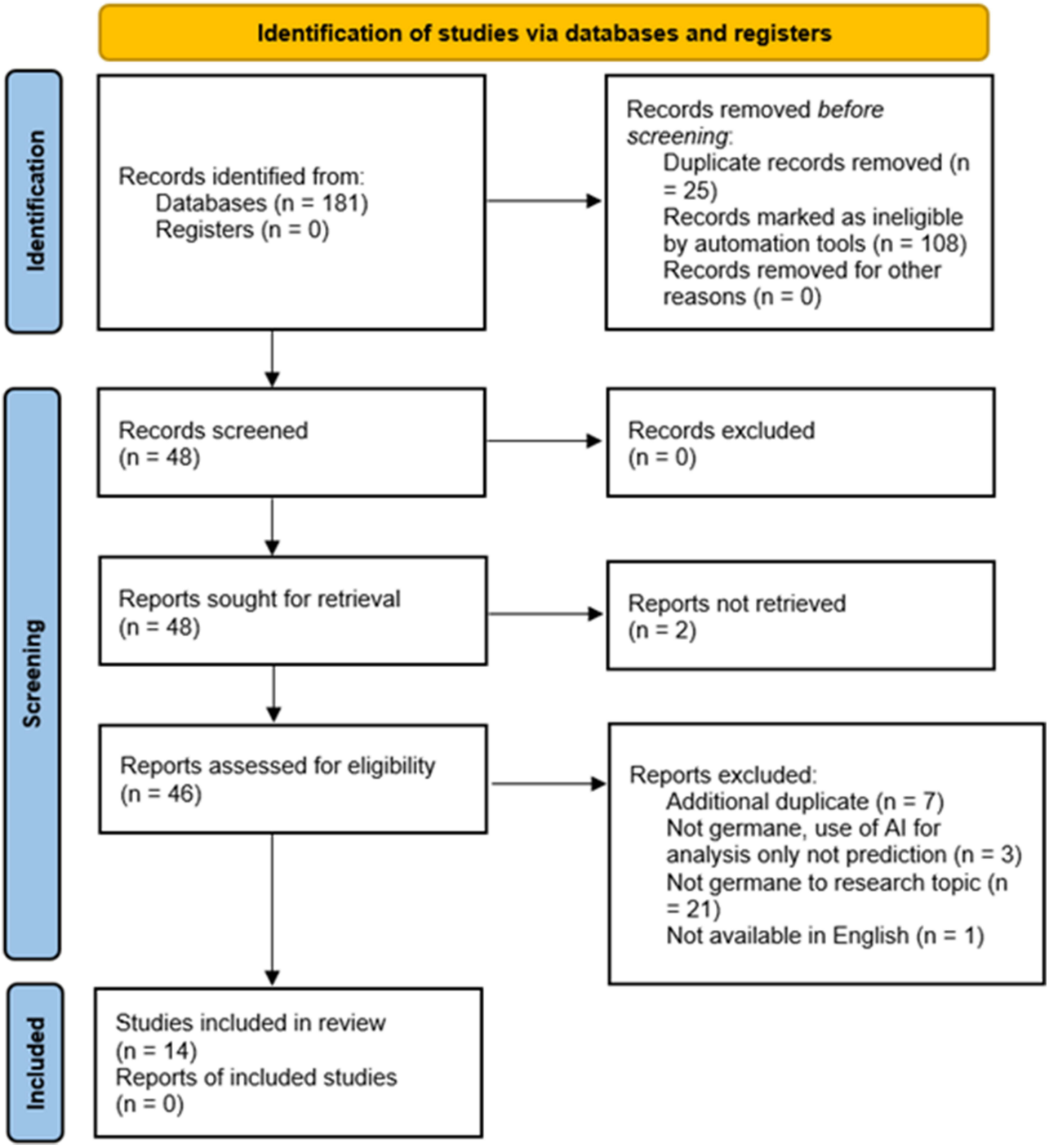

Figure 1 Preferred reporting items for systematic reviews and meta-analysis (PRISMA) figure that demonstrates the study selection process. Adapted from Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ.* 2021;372:n71.

Discussion

While AI has emerged as a powerful force in various aspects of our lives, from healthcare to finance, the potential influence of AI on social relationships and the prevalence of social loneliness has also garnered attention.[3,4,6] Therefore, this systematic review conducted by our research team with a special focus on the roles of AI, machine learning, and SDOH in detecting loneliness, social isolation, and drug use during the COVID-19 pandemic highlights four major themes: 1) prediction of compliance with COVID measures, 2) prediction of loneliness and or its effects, 3) prediction of

Table 1 Summary of Findings (n = 14)

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Schell, et al[7]	Identifying Predictors of Opioid Overdose Death at a Neighborhood Level with Machine Learning *American Journal of Epidemiology*	• P (Population/Problem): Neighborhoods at risk for opioid overdose death. • I (Intervention): Examination of statewide data on opioid overdose death from Rhode Island (2016–2019) using machine learning methods (LASSO algorithm followed by variable importance rankings from a random forest algorithm). • C (Comparison): Not explicitly mentioned in the provided information. In many observational studies, the "comparison" might be inferred from the range of predictor values or groups within the data, or it might not be relevant. • O (Outcome): • Identification of predictors of opioid overdose death at the neighborhood level. • S (Study/Setting): Analysis of data from the American Community Survey for 742 US Census block groups in Rhode Island. The study employed double cross-validation, with 10 folds in the inner loop for training and 4 outer folds for testing.	• Machine learning was used to identify predictors of opioid overdose deaths at the neighborhood level.	• The study included a broad range of socioeconomic factors like education, income, residential stability, race/ethnicity, social isolation, and occupational status. • It highlighted the importance of considering various dimensions, including novel domains like social isolation and residential stability, in understanding opioid overdose risks.

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Table 1 (Continued).

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Cruz et al[8]	Using artificial intelligence to identify the top 50 independent predictors of subjective well-being in a multinational sample of 37,991 older European & Israeli adults *Nature*	• P (Population/Problem): 37,991 older adults from 17 European countries and Israel. • I (Intervention): The use of machine-learning algorithms to rank-order the strongest 50 (of an initial 94) SWB predictors from 15 categories. Further, the application of General Additive Modeling (GAM) and low-degree polynomials (ie, splines) to determine the independent effect sizes and significance levels for these top 50 SWB predictors. • C (Comparison): Comparison of social well-being (SWB) across 18 countries. Additionally, comparison of the impact and order of different SWB predictors. • O (Outcome): ○ Ranking and significance of the top 50 SWB predictors. ○ The order of impact of SWB determinants (eg, loneliness, social activity satisfaction, physical health, demographics, financial status, personality). ○ Differences in SWB across countries. ○ Identification of primary importance factors for SWB (eg, social factors, childhood experiences, healthcare status). • S (Study/Setting): A cross-sectional observational study involving a representative sample from 17 European countries and Israel.	• Notable findings include the paramount importance of social factors like loneliness and social activity satisfaction in determining SWB.	• Other significant predictors include self-reported health, income levels, and personality traits like neuroticism.

Ahmadzadeh et al[9]	Predictors of the rate of cognitive decline in older adults using machine learning *PLOS ONE*	• P (Population/Problem): 2733 participants aged 50–85 years from the English Longitudinal Study of Ageing. • I (Intervention): Implementation of a multivariate robust model using machine learning techniques to predict longitudinal cognitive changes over 12 years and to identify significant predictors of cognitive changes. • C (Comparison): Two categories of cognitive changes: minor cognitive decliners (86.4%) and major cognitive decliners (13.6%) over 12 years. • O (Outcome): o Prediction accuracy in distinguishing major cognitive decliners from minor cognitive decliners. o Identification of the top-ranked features influencing cognitive decline. o Understanding the least important features affecting cognitive decline. • S (Study/Setting): Longitudinal study from wave 2 (2004–2005) to wave 8 (2016–2017) of the English Longitudinal Study of Ageing.	• It aimed to predict cognitive decline over 12 years and identify significant predictors. • The study provides insights into identifying individuals at high risk of cognitive decline and highlights potential areas for intervention to delay or prevent cognitive decline in the elderly.	• Major findings emphasized the importance of various factors like age, employment status, socioeconomic status, self-rated memory changes, and social factors like loneliness.

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Table 1 (Continued).

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Muttaraju et al[10]	Data analysis of Global Perceived Stress Scores During COVID-19 *2022 4th International Conference on Circuits, Control, Communication, and Computing*	• P (Population/Problem): People around the world affected by the COVID-19 pandemic, specifically their mental health. • I (Intervention): Analyzing factors (demographic age, gender, marital status, employment status, effect of media, coping methods, trust in government, healthcare organizations) to understand their impact on perceived stress during the pandemic. • C (Comparison): Machine Learning techniques like XGBoost, AdaBoost, Decision Trees, Ordinal regression, k-Nearest Neighbors, Lasso, and Ridge regression. • O (Outcome): Relationship between perceived stress scores and the various features considered, especially the identification of major influencing features. • S (Study/Setting): Global population during the Covid-19 pandemic.	• This study identified loneliness during the pandemic as influenced by the stress scores. Also, loneliness is the strongest indicator of stress in this study. • Monitors stress levels related to SDOH during COVID-19. • Implements several machine learning techniques.	Trust in government, compliance with COVID-19 prevention measures, and concerns regarding the pandemic are the main factors influencing stress scores during COVID-19 compared to other variables analyzed in this study.

Ugwoke, P[11]	A framework for monitoring movements of pandemic disease patients based on GPS trajectory datasets *Wireless Networks*	• Population (P): COVID-19 patients in the Oshodi-Isolo Local Government Area of Lagos, Nigeria. • Intervention (I): Use of a GPS-based system to monitor the movements of COVID-19 patients. • Comparison (C): Not explicitly mentioned, but the study could be compared to other contact tracing methods. • Outcome (O): The ability to track the movements and predict future locations of COVID-19 patients. • Study Design (S): Observational study using GPS data and machine learning algorithms. • Create a framework to track and analyze patients during a pandemic using GPS monitoring. • Collection of patient information through GPS mobile apps to monitor movement and utilization of contract tracing and clustering algorithms to identify hot spots. • Less limitations than previous studies using Bluetooth technology but raises privacy concerns and financial issues.	• After evaluating different model predictions to monitoring the movements of COVID-19 patients, it was found that the DTR algorithm is more efficient in predicting their next probable location compared to other algorithms.	• Monitoring of movement based on COVID restrictions and loneliness may be a potential reason for movement and Results.

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Table 1 (Continued).

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Sarracino, F[12]	A year of pandemic: Levels, changes and validity of well-being data from Twitter. Evidence from ten countries *PLOS ONE*	• Population (P): General public in ten countries, with well-being data derived from Twitter posts. • Intervention (I): Analysis of Twitter data to measure changes in public well-being (GNH) during the pandemic. • Comparison ©: The study compares Twitter-derived well-being data with traditional survey data and other big data sources. • Outcome (O): Changes in public well-being (GNH) throughout 2020, and the validity of Twitter data for measuring these changes. • Study Design (S): Observational study using big data (Twitter posts) and machine learning algorithms for sentiment analysis. • Aimed to identify how happiness levels changed throughout 2020 across 10 countries during the Covid-19 pandemic. • Applied AI-generated emotional analysis filters on Twitter posts including "sadness in relation to loneliness" variable to calculate Gross National Happiness (GNH) scores. • GNH scores are shown to be associated with Covid-19 pandemic developments; including the surge of new cases, recovery of disease, and increase of policy stringency.	• Use of social media to monitor happiness levels during pandemic. Includes emphasis during different times of pandemic.	Daily happiness score is negatively correlated with new COVID-19 cases, containment policies, and disgust. Staying at home, surprise and generalized trust are directly related to daily happiness scores.

Ueda, M[13]	Emotional Distress During COVID-19 by Mental Health Conditions and Economic Vulnerability: Retrospective Analysis of Survey-Linked Twitter Data with a Semi-supervised Machine Learning Algorithm *Journal of Medical Internet Research*	• Population (P): Japanese Twitter users. • Intervention (I): Analysis of emotional distress through Twitter posts linked with survey data. • Comparison ©: Comparison of emotional distress levels during different periods of the COVID-19 pandemic. • Outcome (O): Changes in emotional distress levels among different groups, influenced by pandemic events. • Study Design (S): Retrospective analysis using a semi-supervised machine learning algorithm. • Understand the mental health conditions of individuals in Japan during the Covid-19 pandemic using social media posts. • Used machine learning framework to examine the emotional distress level of individuals based on demographics, socioeconomic status, mental health conditions, and Twitter handles between the years of 2019 and 2022. • Findings show levels of emotional distress raised during the initial school closure, peaked during the beginning of the state of emergency, and disproportionately affected low-income individuals.	• Page 9 discusses the SDOH and its effects on those coded as lonely as compared to the non-lonely. • Outside of the state of emergency, patterns of emotional distress did not differ between the lonely and non-lonely. • The study highlights the potential of social media data in understanding public mental health trends during a crisis.	• Used machine learning to identify mental health conditions of individuals in Japan during COVID-19. Emotional stress levels recorded (relation to loneliness). • Findings indicate increased emotional distress linked to government-imposed restrictions, school closures, and economic challenges.

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Table 1 (Continued).

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Shin[14]	Prediction of suicidal ideation in children and adolescents using machine learning and deep learning algorithm: A case study in South Korea where suicide is the leading cause of death *Asian Journal of Psychiatry*	• Population (P): Children and adolescents in South Korea. • Intervention (I): Machine learning and deep learning algorithms to predict suicidal ideation. • Comparison (C): The study compares various algorithms like logistic regression, random forest, XGBoost, MLP, and CNN. • Outcome (O): Prediction of suicidal ideation with an accuracy of about 90% using CNN. • Study Design (S): A retrospective analysis using big data from the Korea Youth Policy Institute, analyzed with various machine learning and deep learning algorithms. • Use of machine learning to predict suicidal ideation (suicidal thoughts) in the fields of health and medicine but not from a social science perspective. • Study of suicidal ideation in children and adolescents using 4 years of big data (2017–2020) from the Korea Youth Policy Institute. Supervised machine learning classification algorithms such as logistic regression, random forest, XG Boost, multilayer perception (MLP), and convolutional neural network (CNN) were used. • Suicidal ideation was predicted with an accuracy of ~90%. Logistic regression results show that sadness and depression increased suicidal thoughts by 25 times and anxiety, loneliness, and experience of abusive language increased suicidal thoughts by 3 times.	• Applied machine learning to determine thoughts of suicide in adolescents and the features that cause thoughts of suicide. • Loneliness as an independent variable in suicidal ideational tendencies/thoughts.	• It also addresses this with regards to social media and other interesting variables.

Hajdu[15]	Contextual factors predicting compliance behavior during the COVID 19 pandemic: A machine learning analysis on survey data from 16 countries *PLOS ONE*	• Population (P): Participants from 16 countries who responded to a survey on compliance during the COVID-19 pandemic. • Intervention (I): Analysis of various contextual factors influencing compliance behavior. • Comparison (C): The study does not have a direct comparison group, but compares various factors within the population. • Outcome (O): The level of compliance with COVID-19 lockdown regulations and the factors influencing this compliance. • Study Design (S): An observational study using machine learning to analyze survey data. • Investigating the factors associated with compliance and non-compliance in confinement situations across cultures during the COVID-19 pandemic. • Using machine learning - Analysis of survey data from 42,169 individuals from 16 countries (students from a university in Hungary) • The factors associated with confinement compliance consist of fear of getting infected, feeling of responsibility, feeling of being caged while at home, and perceived countrymen adherence • Factors associated with participation in risky activities include the anticipated number of people met while traveling, putative effectiveness of social distancing, activity importance and trust in people met at the activity	• Increased feelings of being caged while at home, responsibility, and fear of getting infected decreased the probability of leaving home. • The probability of risky places increased as the perceived putative effectiveness of social distancing decreased.	• A prediction of non-compliant behavior of voluntary isolation during COVID-19. • COVID social distancing compliance with loneliness as a predictor. This includes feeling "caged" while at home.

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Table 1 (Continued).

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Keeler[16]	The future of aging in smart environments: Four scenarios of the United States in 2050 *Futures*	• Population (P): Aging population in the United States by 2050. • Intervention (I): The development and integration of smart technologies in the context of aging. • Comparison (C): Comparison between four different future scenarios. • Outcome (O): Potential impacts on the aging population in terms of health, social integration, and interaction with technology. • Study Design (S): Speculative and scenario-based analysis using expert opinions and participatory methods. Scenario development using a participatory, intuitive logistics approach to construct scenarios of aging in smart environments in 2050 that illuminate the uncertainties, challenges, and opportunities presented by two mega trends; aging population and increasingly sensed people and environments (non-probability, purposive sampling of experts to participate in interviews) Based on a two-dimensional matrix (low/high social integration and low/high individual choice about technology), the four scenarios consist of how terribly strange to be 90, well assisted, live free and die free, final nesting place	• Discusses how AI may have a role in elder care in 2050, which could be connected to our research. The challenges presented in eldercare may relate to the SDOH. • Emphasizes the role of policy in shaping how society adapts to these technological advancements.	• Highlights the potential challenges in data management and privacy with increased reliance on smart technologies. • Aims to stimulate Discussions on preparing for diverse aging experiences influenced by technology and societal changes.

Kolak, M[17]	Quantification of Neighborhood Level-Social Determinants of Health in the Continental United States *JAMA Network*	• Population (P): Populated census tracts across the continental United States, with a specific focus on Chicago. • Intervention (I): Quantification of neighborhood-level social determinants of health. • Comparison (C): Comparison of different neighborhoods based on SDOH indices. • Outcome (O): Association of SDOH with premature mortality rates in Chicago. • Study Design (S): Cross-sectional analysis using machine learning techniques to analyze census data. • Understand and quantify the social determinants of health across the US and analyze the SDOH in relation to early deaths in Chicago, Illinois. • Cross-sectional multivariate analysis using the US Census Bureau and clustering machine learning techniques. • A strong association was displayed between SDOH and premature death in Chicago; only 9.6% of the US population is categorized under extreme poverty, yet these areas displayed concentrated health crises.	• The research utilized cross-sectional data from US Census tracts and machine learning techniques for analysis. • Results indicate a significant association between SDOH indices and age-adjusted premature mortality rates in Chicago.	• The study emphasizes the importance of understanding SDOH at a neighborhood level for targeted health interventions. • Four SDOH indices were identified: advantage, isolation, opportunity, and mixed immigrant cohesion and accessibility.

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Table 1 (Continued).

Article Number and Author(s)	Article Title and Journal	Population/Intervention/Control/ Outcome/Study Information	Loneliness Observations	Employment status OR Income Level OR Economic Policies OR Social Protection Policies Observations
Khattak[18]	Knowledge, attitude, and perception of cancer patients towards COVID-19 in Pakistan: A cross-sectional study *International Journal of Environmental Research and Public Health*	• Population (P): Cancer patients in Pakistan. • Intervention (I): The intervention is not applicable in this case as this is an observational study. • Comparison (C): The study does not involve a direct comparison group. • Outcome (O): The level of knowledge, attitudes, and perceptions regarding COVID-19 among cancer patients. • Study Design (S): Cross-sectional survey-based study. • To determine cancer patients' knowledge, attitude, perception, and impact of COVID-19 on cancer patients • Cross sectional online survey (N= 300, respondents n =208) • Descriptive statistics and ANOVA • 90% knew about COVID, 90% were aware of the symptom, 94.5% were willing to accept social isolation, 98% reduced their use of public transportation, 90% practiced preventive measures, 94% stopped or changed cancer treatment during the pandemic	• Patients with cancer exhibited a good level of COVID-19 knowledge, awareness, positive attitude, and perception.	• Patients' gender, marital status, and employment status had a significant association with their knowledge scores. • Findings indicated a high level of COVID-19 knowledge and awareness among participants. • Majority practiced preventative measures like wearing face masks and social distancing. • The study revealed significant effects of the pandemic on cancer treatment, work, pay, and social isolation.

Libin[19]	Assessing the feasibility and effectiveness of household-pooled universal testing to control COVID-19 pandemic *PLOS Computational Biology*	• Population (P): Belgian population, specifically households. • Intervention (I): PCR test pooling for households and universal testing strategies. • Comparison (C): Comparing pool isolation and individual isolation strategies. • Outcome (O): Effectiveness in controlling the COVID-19 epidemic. • Study Design (S): A simulation study using an individual-based epidemiological model. To screen the entire population (household-pooled universal testing of the Belgian population). Weekly universal testing is able to control the epidemic even when many of the contact reductions are relieved. Universal testing in combination of contact reductions could be considered as a strategy to eradicate the virus	• Addresses isolation as a compliance issue with COVID pandemic and offers some loneliness details. • The study employs an individual-based epidemiological model to simulate the impact of these testing strategies.	• Findings suggest that weekly universal testing can control the epidemic, especially when combined with contact reduction measures. • The article discusses logistical considerations, compliance issues, and the potential effectiveness of this approach in controlling the spread of COVID-19.
Aguiar, M[20]	Modeling COVID-19 in the Basque Country from Introduction to control measure response *Nature*	• Population (P): The population of the Basque Country, Spain. • Intervention (I): The use of SHARUCD-type models for COVID-19 prediction and control measure assessment. • Comparison (C): The study does not involve a direct comparison group, but evaluates different scenarios based on model predictions. • Outcome (O): The effectiveness of control measures and predictions of the epidemic's course. • Study Design (S): A modeling study using the SHARUCD-type models to analyze COVID-19 data. • BMFT (multitask force created to assist Basque health managers) has been working to build a framework handling COVID-19 • Various approaches, such as stochastic processes, statistical methods, AI, and the collection of epidemiological data.	• Development and application of SHARUCD-type models to predict and analyze the spread of COVID-19. • The study incorporates data on tested positive cases, hospitalizations, ICU admissions, recovered patients, and deaths. • Evaluation of the effectiveness of control measures like lockdowns and social distancing.	• Analysis of the impact of control measures on the transmission rates and growth of the pandemic. • Insights into short-term and long-term predictions of the disease's spread based on current and potential future measures.

Abbreviations: AI, Artificial Intelligence; SDOH, Social Determinant(s) of Health; EBSCOhost, Elton B. Stephens Company Host; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; SELSA, Social and Emotional Loneliness Scale for Adults.

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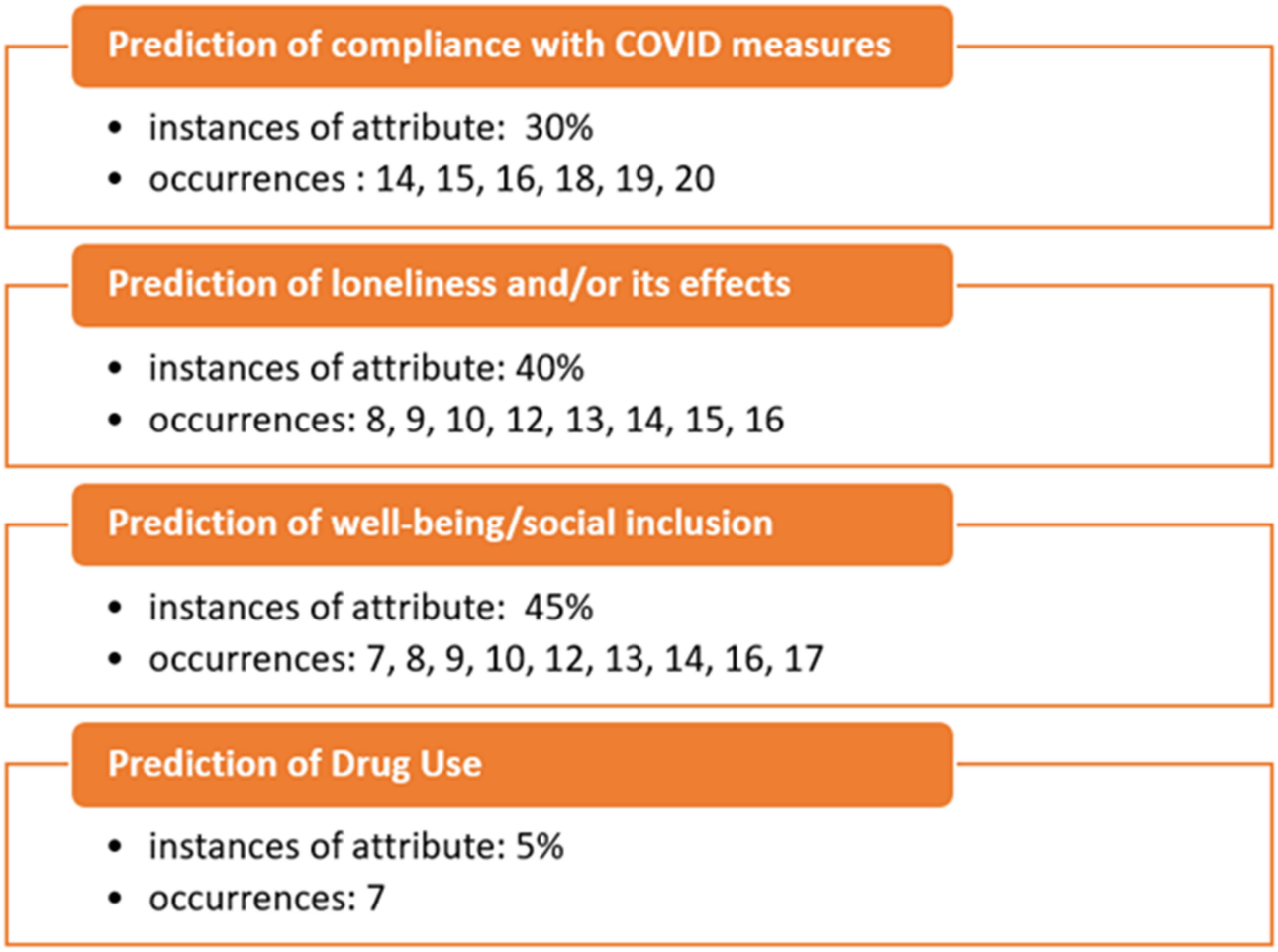

Figure 2 Occurrences of underlying themes (constructs) identified in the literature surrounding the use of AI in the prediction of loneliness as associated with SDOH.

well-being/social inclusion, and 4) the prediction of drug use. The following sections discuss our findings according to these themes.

Prediction of Compliance with COVID Measures

Predicting compliance with COVID-19 measures is a complex and multifaceted challenge with psychological, cultural, social, and economic dimensions. For instance, individuals' perception of the risk associated with COVID-19, and their trust in public health authorities play a vital role in their compliance and these factors are essential or critically important in determining whether or not individuals comply with health guidelines and regulations. In other words, how people perceive the risk of COVID-19 and how much they trust public health authorities are key elements that significantly influence their behavior regarding adherence to recommended health practices. Communicating the necessary measures effectively and disseminating information promptly impact individuals' ability to comply with COVID-19 measures. There is a profound trend toward integrating advanced analytical techniques to inform and enhance public policy and health strategies.[14–16,18–20] Advanced analytical techniques, such as machine learning and deep learning algorithms, were used to predict suicidal ideation among children and adolescents in South Korea with high accuracy, thereby providing critical data-driven insights to inform and enhance public policy on suicide prevention.[14] A predictive modeling method was used to delve into individual behaviors surrounding voluntary isolation, identifying the psychological and socio-cultural factors influencing compliance.[15] Additionally, advanced analytical techniques were used to construct scenarios of aging in smart environments in the United States in 2050, illuminating the uncertainties, challenges, and opportunities presented by the convergence of an aging population and increasingly sensed environments to inform and enhance public

policy on aging and healthcare.[16] Further, advanced analytical techniques were used to assess the knowledge, attitude, and perception of cancer patients in Pakistan towards COVID-19, providing critical insights to inform public health strategies and enhance policy decisions to better support this vulnerable population during the pandemic.[18] Such research collectively underscores the intricate relationship between technology and human conduct during public health crises. While another study investigates policy analysis,[14] previous research examines the connection between individual mental states and resulting behaviors.[15] This underscores a growing recognition of the necessity for policy measures that consider human psychology, a theme increasingly pertinent amid global health challenges. Hence, addressing mental health issues and offering appropriate support, while also comprehending and respecting cultural norms, could enhance adherence to COVID-19 protocols, aligning with these socio-cultural influences.[15]

Predictive modeling was also used to understand individual behaviors concerning voluntary isolation, pinpointing the psychological and socio-cultural drivers that affect compliance.[15] This emphasizes the theme of the interdependence between technology and human behavior in the context of public health emergencies. Additionally, a connection between individual mental states such as feelings of being caged, responsibility, and fear to behavioral outcomes was also identified by the research team.[14,15] This reflects a growing awareness of the need for policy interventions that are sensitive to human psychology, a theme that is becoming increasingly relevant in the face of global health challenges. Therefore, it is vital to address mental health concerns and provide the necessary support by understanding and respecting cultural practices while promoting measures that align with these socio-cultural drivers may improve compliance with COVID-19 measures.

Research mapped to this construct further underscores the importance of nuanced approaches to managing health crises. Specific behavioral insights provided by previous studies have profound implications for designing interventions that can effectively encourage public adherence to health advisories, which is crucial in controlling the spread of diseases.[15] Meanwhile, data-driven analyses can lead to a deeper understanding of the impact and reception of public policies, guiding governments in crafting more effective and responsive strategies during pandemics.[14] Through epidemiological data analyzed by AI, policymakers can evaluate the trajectory of infection rates, the efficacy of containment measures, and the impact on public health outcomes.[19] Furthermore, analyzing economic indicators elucidates the socio-economic consequences of policies, such as unemployment rates, and business closures.[19] Additionally, monitoring healthcare systems enables policymakers to gauge the strain on medical facilities, the availability of resources, and the adequacy of healthcare provisions.[20] While data-driven insights empower policymakers to adopt a proactive and adaptive approach to policymaking, they also help them identify vulnerable populations and develop targeted interventions to mitigate disparities and ensure equitable access to resources.[20] Moreover, employing tailored communication strategies based on data insights enhances public engagement, trust, and compliance with policies in global health crisis.[19,20]

Prediction of Loneliness and/or Its Effects

Loneliness is a serious preventable social issue and has been considered a national epidemic. For instance, Cigna reported that 61% (three in five adults) reported feeling lonely in 2020, indicating a seven-percentage point increase from 2018. This epidemic could cost the US an estimated $400 billion per year.[21] Though the COVID-19 pandemic played a role in the increase in loneliness prevalence among US adults, its after-effects such as the increased number of employees working from home may still play a role in loneliness.[21] The research team identified the prediction of loneliness and/or its effects as a construct in the literature. For instance, Shin et al used machine learning to identify suicidal thoughts.[14] In this study, AI was able to predict multiple variables of suicidal ideation in South Korean adolescents, one of which was loneliness.[14]

This same theme continued throughout other articles where machine learning or other research methods determined unhealthy behaviors using loneliness as one of its key variables. For instance, an analysis of factors that lead to high levels of stress during COVID-19, one variable being loneliness was identified.[10] Additionally, AI was used to identify variables affecting well-being, one of the highest indicators being loneliness.[8] A connection to loneliness as an adverse health outcome, (suicide ideation, stress, well-being) was also identified by the research team.[8,10,14] Another study focused on older adults and used machine learning to predict cognitive decline, one variable being social engagement.[9] Findings further

revealed that in healthy adults, reducing loneliness may be a shield against rapid cognitive loss.[9] This same study not only used AI to identify loneliness as a variable of poor health outcomes but discussed its prevention.[9] A similar theme in which suicide was the number one cause of death in adolescents in Korea, and the use of AI to identify loneliness as a factor in suicidal thoughts is a preventive measure to the actual suicide was observed.[14] Therefore, the use of AI to predict loneliness and identify suicidal thoughts holds a significant promise in developing targeted interventions to support individuals' mental health resilience. While AI techniques such as machine learning algorithms can analyze data from various sources to predict mental health, they can also forecast changes in well-being over time and detect early signs of mental health issues. Through AI predictive models, personalized resources and interventions such as self-care strategies, and social activities can be tailored to individuals' specific needs and preferences.

Prediction of Well-Being/Social Inclusion

The research team also found a theme regarding the use of AI to predict social well-being/social inclusions across multiple studies in the review. Social well-being, happiness, and social inclusion as well as its loneliness counterpart have been investigated in these studies by using survey data or longitudinal data.[8–10]

AI techniques, such as machine learning, generalized additive modeling, and low-degree polynomials, were utilized to identify factors associated with subjective well-being. This study covered 17 European countries and Israel, using a sample of 38,000 adults.[8] The results of the survey data indicate that the top predictors of subjective well-being consist of loneliness, the satisfaction with social activity, and social network, followed by physical health, demographics, financial status, and personality. Denmark has the highest subjective well-being score while Greece has the lowest. Also, subjective well-being decreases with age, but it has an inverted u-curve with respect to money.[8] A longitudinal study to assess the predictors of cognitive decline using machine learning on a sample of older adults from England and identified the top predictors consist of age, employment status, socioeconomic status, self-rated memory change, immediate work recall, feeling of loneliness, and vigorous physical activity.[9]

The factors associated with perceived stress and loneliness was found to be the top stressor of subjects experiencing loneliness in the review.[10] The change in gross national happiness level during the COVID-19 pandemic was based on longitudinal data from Twitter from 1 January, 2020 to December 31, 2020 from 10 countries was observed.[14] Further, the severity of the pandemic as well as policies to contain the spread of the pandemic are the top significant factors associated with reduced gross national happiness.[14]

AI technologies offer unprecedented opportunities to analyze vast amounts of data and extract actionable insights into social dynamics. By mining data from social media platforms, online forums, and digital communication channels, AI can identify patterns of social interaction, detect sentiment trends, and gauge the impact of policies and interventions on individuals' well-being.[8,10] Furthermore, AI-powered chatbots and virtual assistants can provide personalized support and companionship to individuals experiencing loneliness, enhancing their social connectedness and overall mental health resilience.[14]

Prediction of Drug Use

Understanding the social determinants of health (SDOH) and leveraging AI to predict drug use are essential components of public health research aimed at promoting health and well-being. Another theme presented throughout the pulled articles is the use of AI and SDOH to predict drug use. For instance, Schell et al used machine learning to identify neighborhood level predictors that may contribute to drug use and opioid overdose deaths in the Rhode Island area.[7] Despite having low opioid prescription rates, the opioid overdose death rate is twice the national average. The top predictors utilized were socioeconomic status, education, income, residential stability, race/ethnicity, social isolation, and occupational status. Social isolation is identified as a SDOH that contributes to drug overdose.[7]

Machine learning tools and predictive modeling are used to identify high-risk areas to prioritize prevention and intervention. Results concluded that there are 40 viable predictors that cause 17% of the 863 opioid deaths investigated. These predictors are categorized as old versus new, with the "new" domains being racial distribution, social isolation, and residential stability. Previous research has already identified several predictors. The most significant new predictor

identified is education, with high school-educated men being at a greater risk of opioid overdose death. This finding correlates with income and occupation also being important predictors.

Social isolation as a new predictor showed to have a strong association with increasing numbers of opioid deaths. The model shows that communities with unmarried people who are living alone have higher percentages of opioid overdose deaths. Due to its multidimensional nature, the exact correlation of social isolation and opioid deaths is unknown and needs additional research. The study concludes that there needs to be an increased focus on community-level interventions in areas of high overdose outbreaks. Predictive modeling may assist in policy making efforts to examine high-risk areas, target resources, and implement interventions.

Previous research also used AI to quantify the dimensions of SDOH in the United States and analyze public attitudes towards the COVID-19 vaccine using data from social media in the United Kingdom and the United States.[17,18] Another article demonstrates the development of a flexible COVID-19 mathematical modeling to predict the course of the epidemic and assess the effectiveness of partial lockdown policy to contain disease transmission in the Basque country.[4,5] While these articles are outside our topic, they showcase the potential of AI use in several fields of studies.

Future Research

As AI continues to evolve, it is essential to recognize both the potential benefits and risks associated with the integration of AI into social interactions by exploring the long-term impact of AI-generated content on social communication, connection, and loneliness. Future studies can explore the potential of AI in developing personalized interventions that address social loneliness based on individual preferences, and health conditions. Although we found some articles on the development of AI-based methodology to support government policy making during an economic crisis, more research on the impact of AI-based policymaking on social well-being and SDOH is warranted.[11] Also, the effectiveness of AI-driven simulations and social skills training in mitigating social loneliness needs to be evaluated.

Future research should build upon the findings of these studies to further explore the multifaceted impacts of the COVID-19 pandemic on employee well-being and organizational dynamics.[21] Given the significant influence of internal marketing on job satisfaction, future studies could examine additional internal marketing strategies and their long-term effects on employee performance and behavior in different cultural and economic contexts. Moreover, the relationship between job satisfaction and counterproductive work behaviors warrants deeper investigation to identify specific internal marketing practices that can mitigate negative employee outcomes.[21]

Additionally, the interplay between job insecurity, job instability, and job satisfaction highlighted in the second study suggests a need for more nuanced research into how these factors interact with organizational support mechanisms, such as supervisor support and promotion opportunities.[22] Future research could expand on this by exploring different sectors and job roles, as well as longitudinal studies to track changes over time. Furthermore, examining the role of digitalization and remote work, which have become prevalent due to the pandemic, could provide insights into how technological changes impact job satisfaction, stress levels, and overall employee well-being.[22]

Study Limitations

While studying the impact of AI and social loneliness has profound implications for mental health and social well-being, it is essential to recognize and address the limitations inherent in studies such as sample bias, measurement bias, and ethical concerns during the investigation of this complex research topic. Use of additional research databases, such as Web of Science and/or Scopus, could potentially further the number of relevant articles identified in the search process.

Conclusion

The data-driven analysis offers a robust framework to understand the effectiveness and reception of policies, enabling governments to craft more responsive strategies.[21] This review's findings highlight the usefulness of AI and machine learning in the analysis of government health policies, people's compliance to such policies, and the prediction of the factors associated with loneliness social isolation and drug use. Using AI to predict these constructs has remarkable capabilities in identifying individuals at risk and facilitating timely interventions to mitigate adverse outcomes and promote mental health resilience in the face of challenges such as the COVID-19 pandemic. Given the increased

availability of big data, the use of AI and machine learning in empirical studies has expanded. With respect to the use of AI in detecting loneliness, more studies are needed to corroborate the findings from prior studies that did not use AI. Moving forward, future research is warranted to refine AI algorithms, validate predictive models, and utilize AI-based interventions in healthcare and mental health services while ensuring data security, and privacy.

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References

1. Majmudar IK, Mihalopoulos C, Brijnath B, et al. The impact of loneliness and social isolation on health state utility values: a systematic literature review. *Qual Life Res*. 2022;31:1977–1997. doi:10.1007/s11136-021-03063-1
2. Ingram I, Kelly PJ, Deane FP, et al. Loneliness among people with substance use problems: a narrative systematic review. *Drug Alcohol Rev*. 2020;39(5):447–483. doi:10.1111/dar.13064
3. McQuaid RJ, Cox SML, Ogunlana A, Jaworska N. The burden of loneliness: implications of the social determinants of health during COVID-19. *Psychiatry Res*. 2021;296. doi:10.1016/j.psychres.2020.113648
4. Russell DW, Borji M, Tarjoman A. UCLA Loneliness Scale–Version 3. [Persian Version]. [Title denoted in this Source: sense of Loneliness Questionnaire]. *J Relig Health*. 2020;59:163–172. doi:10.1007/s10943-018-0708-x
5. DiTommaso E, Spinner B, Gantman A, Kapp SK, Orenski K, Laugeson EA. Social and emotional loneliness scale for adults. *J Aut Develop Dis*. 2012;42:1094–1103. doi:10.1007/s10803-011-1350-6
6. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. *Fut Healthc J*. 2019;6(2):94–98. doi:10.7861/futurehosp.6-2-94
7. Schell RC, Allen B, Goedel WC, et al. Identifying predictors of opioid overdose death at a neighborhood level with machine Learning. *American*. *J Epidemiol*. 2022;191(3):526–533. doi:10.1093/aje/kwab279
8. Vera Cruz G, Maurice T, Moore PJ, Rohrbeck CA. Using artificial intelligence to identify the top 50 independent predictors of subjective well-being in a multinational sample of 37,991 older European & Israeli adults. *Sci Rep*. 2023;13(1). doi:10.1038/s41598-023-38337-w
9. Ahmadzadeh M, Cosco TD, Best JR, Christie GJ, DiPaola S. Predictors of the rate of cognitive decline in older adults using machine learning. *PLoS One*. 2023;17(3):1–19. doi:10.1371/journal.pone.0280029
10. Muttaraju C, Kabber A, Parimala S, Anagani P, Srinivasa G. Data analysis of global perceived stress scores during covid-19. 2022 4th International Conference on Circuits, Control, Communication and Computing (I4C), Circuits, Control, Communication and Computing (I4C), 2022 4th International Conference on; 2022:95–102. doi:10.1109/I4C57141.2022.10057599.
11. Ugwoke PO, Bakpo FS, Udanor CN, Okoronkwo MC. A framework for monitoring movements of pandemic disease patients based on GPS trajectory datasets. *Wirel Netw J Mob Commun Comput Inform*. 2022;28(1):1–28. doi:10.1007/s11276-021-02819-4
12. Sarracino F, Greyling T, O'Connor K, Peroni C, Rossouw S. A year of pandemic: levels, changes and validity of well-being data from Twitter. Evidence from ten countries. *PLoS One*. 2023;16(2):1–24. doi:10.1371/journal.pone.0275028
13. Ueda M, Watanabe K, Sueki H. Correction: emotional distress during COVID-19 by mental health conditions and economic vulnerability: retrospective analysis of survey-linked twitter data with a semisupervised machine learning algorithm. *J Med Internet Res*. 2023;25:e47549.
14. Shin S, Kim K. Prediction of suicidal ideation in children and adolescents using machine learning and deep learning algorithm: a case study in South Korea where suicide is the leading cause of death. *As J Psych*. 2023;2023:88.
15. Hajdu N, Schmidt K, Acs G, et al. Contextual factors predicting compliance behavior during the COVID-19 pandemic: a machine learning analysis on survey data from 16 countries. *PLoS One*. 2022;17(11):1–15. doi:10.1371/journal.pone.0276970
16. Withycombe Keeler L, Bernstein MJ. The future of aging in smart environments: four scenarios of the United States in 2050. *Futures*. 2021;133:102830. doi:10.1016/j.futures.2021.102830
17. Kolak M, Bhatt J, Park YH, Padrón NA, Molefe A. Quantification of neighborhood-level social determinants of health in the continental United States. *JAMA network open*. 2020;3(1):e1919928. doi:10.1001/jamanetworkopen.2019.19928
18. Khattak S, Faheem M, Nawaz B, et al. Knowledge, attitude, and perception of cancer patients towards COVID-19 in Pakistan: a cross-sectional study. *Int J Environ Res Public Health*. 2022;19(13):7926. doi:10.3390/ijerph19137926
19. Libin PJK, Willem L, Verstraeten T, Torneri A, Vanderlocht J, Hens N. Assessing the feasibility and effectiveness of household-pooled universal testing to control COVID-19 epidemics. *PLoS Computational Biology*. 2021;17(3):1–22. doi:10.1371/journal.pcbi.1008688
20. Aguiar M, Ortuondo EM, Bidaurrazaga Van-Dierdonck J, Mar J, Stollenwerk N. Modelling COVID 19 in the Basque Country from introduction to control measure response. *Sci Rep*. 2020;10(1). doi:10.1038/s41598-020-74386-1
21. Cigna. Loneliness and its impact on the American workplace. Available from: https://legacy.cigna.com/static/www-cigna-com/docs/about-us/newsroom/studies-and-reports/combatting-loneliness/loneliness-and-its-impact-on-The-american-workplace.pdf. Accessed February 19, 2024.
22. Nemteanu MS, Dinu V, Dabija DC. Job insecurity, job instability, and job satisfaction in the context of the COVID-19 pandemic. *J Competitiven*. 2021;2:65–82. doi:10.7441/joc.2021.02.04